

Article

Real-Time State of Health Estimation for Solid Oxide Fuel Cells Based on Unscented Kalman Filter

Yuanwu Xu ^{1,*}, Hao Shu ¹, Hongchuan Qin ², Xiaolong Wu ^{3,4}, Jingxuan Peng ² , Chang Jiang ², Zhiping Xia ², Yongan Wang ⁵  and Xi Li ^{2,4}

¹ School of Information Science and Engineering, Wuhan University of Science and Technology, Wuhan 430081, China; suuuyi2@gmail.com

² Key Laboratory of Image Processing and Intelligent Control of Education Ministry, School of Artificial Intelligence and Automation, Huazhong University of Science and Technology, Wuhan 430074, China; qinhc219@163.com (H.Q.); pjx@hust.edu.cn (J.P.); cjiang9010@outlook.com (C.J.); d202080870@hust.edu.cn (Z.X.); lixi_wh@126.com (X.L.)

³ School of Information Engineering, Nanchang University, Nanchang 330031, China; xiaolongwu@ncu.edu.cn

⁴ Shenzhen Research Institute, Huazhong University of Science and Technology, Shenzhen 518063, China

⁵ State Grid Hubei Maintenance Company, Wuhan 430077, China; wangyongancqu@126.com

* Correspondence: xyw201314@hotmail.com

Abstract: The evolution of performance degradation has become a major obstacle to the long-life operation of the Solid Oxide Fuel Cell (SOFC) system. The feasibility of employing degradation resistance to assess the State of Health (SOH) is proposed and verified. In addition, a real-time Unscented Kalman Filter (UKF) based SOH estimation method is further proposed to eliminate the disturbance of calculating the SOH directly utilizing measurement and electric balance model. The results of real-time SOH estimation with an UKF under constant and varying load conditions demonstrate the feasibility and effectiveness of the SOFC performance degradation assessment method.

Keywords: Solid Oxide Fuel Cell; state of health estimation; degradation resistance; Unscented Kalman Filter



Citation: Xu, Y.; Shu, H.; Qin, H.; Wu, X.; Peng, J.; Jiang, C.; Xia, Z.; Wang, Y.; Li, X. Real-Time State of Health Estimation for Solid Oxide Fuel Cells Based on Unscented Kalman Filter. *Energies* **2022**, *15*, 2534. <https://doi.org/10.3390/en15072534>

Academic Editor: Paola Costamagna

Received: 1 March 2022

Accepted: 29 March 2022

Published: 30 March 2022

Publisher's Note: MDPI stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.



Copyright: © 2022 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

The Solid Oxide Fuel Cell (SOFC) is the most efficient energy conversion device for converting hydrogen energy into electrical energy [1,2], with the advantages of high efficiency, fuel flexibility, and the strong ability of Combined Heat and Power (CHP) [3]. It has a wide range of application scenarios, from W-class to MW-class power levels, mainly involving portable power generation [4,5], transportation [6], and distributed power generation [7]. However, the performance of the SOFC, such as durability, reliability, and lifespan, lags behind current application requirements and has become a major obstacle to the large-scale deployment of SOFC systems [8,9]. In this case, real-time assessment of performance is crucial to ensure the SOFC productivity and further develop health management strategies.

The SOFCs are high-temperature (600–1000 °C) fuel cells employing solid ion-conducting electrolytes [10], and their working principle is shown in Figure 1a. The hydrogen in the fuel is continuously fed into the anode channel as a reductant and reaches the anode Triple Phase Boundary (TPB) by diffusion; the oxidant, usual oxygen in the air, is sent to the cathode channel and reaches the cathode TPB through diffusion. The electrochemical reactions are performed at the TPBs, where the oxygen ions migrate through the electrolyte to the anode and electrons flow to the cathode through the external circuit. The voltage and effective area of SOFC single cells are low (about 0.6–1.1 V, area less than 15 cm × 15 cm). To meet the power requirements of different applications, multiple single cells can be piled into stacks, and the current widely used planar design SOFC stack is shown in Figure 1).

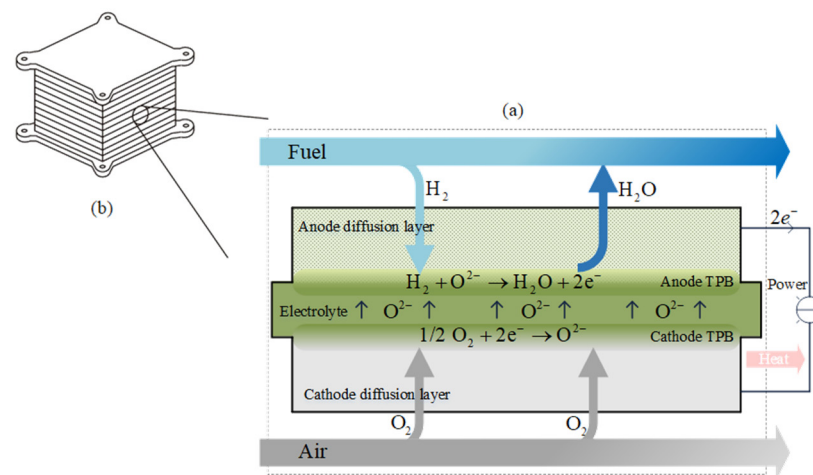


Figure 1. SOFC schematic; (a) Working principle; (b) Planar design SOFC stack.

The main causes of the SOFC performance degradation include thermal stress, sealants degradation, fuel shortage, materials oxidation/poisoning, etc., as shown in Figure 2. From the physical scale of post-experiment detection, it can be divided into macroscopic visible degradation and electrode microstructural degradation [11]. In addition, the operating conditions of the SOFC will also affect the performance degradation. Shi [12] used a zero-dimensional SOFC model combined with the degradation mechanism to simulate the micro SOFC-CHP system, and determined the effect of operating conditions on the SOFC lifespan. At present, it is generally considered that the SOFC needs to be operated at uniform reactant concentration and temperature to avoid performance degradation; serious deviation from this uniform operating conditions will lead to phase transition (oxidation of anode or reduction of cathode) and thus accelerate the degradation evolution of performance.

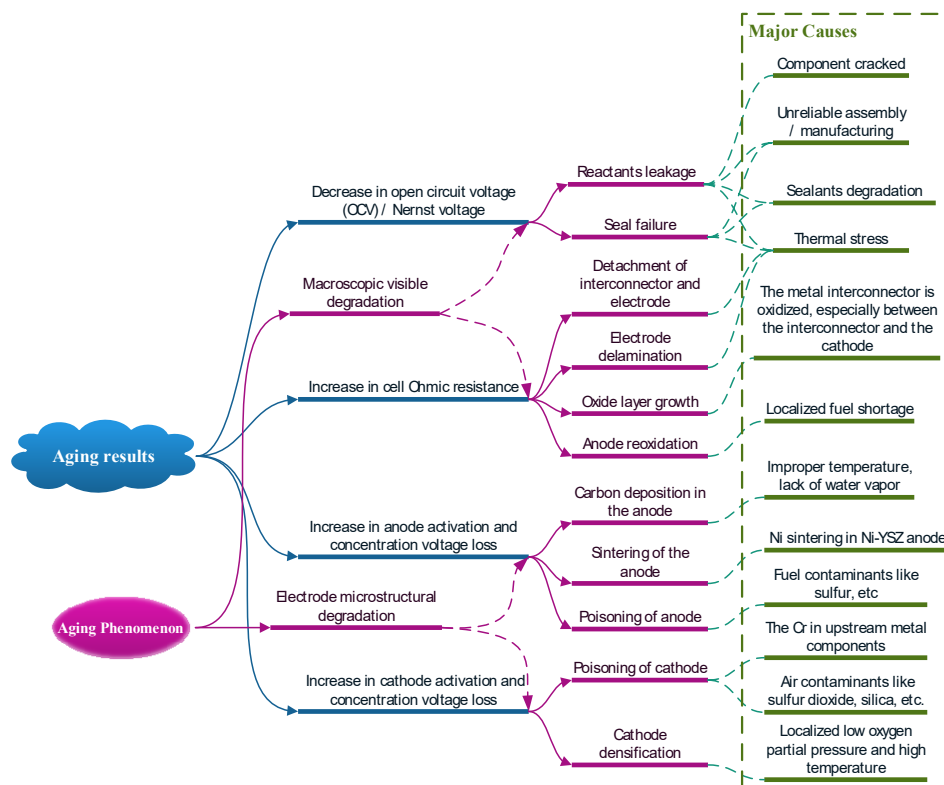


Figure 2. Main causes, phenomena, and results of SOFC degradation.

The State of Health (SOH) is a recently emerging metric to describe the degradation of the SOFC performance. Generally, the operating voltage of the SOFC is considered a feasible SOH indicator. Yan [13] and Yang [14] evaluated the performance of the SOFC by measuring the voltage at constant current discharge under operating conditions. The operating voltage of the SOFC is the superposition of Nernst voltage, activation polarization, ohmic polarization, and concentration polarization. The main performance degradation mechanisms may affect one or more voltage components and cause the operating voltage to deviate from its normal value, as follows:

- Nernst voltage (generated by the thermodynamic properties of electrochemical reactions)—degradation mechanisms affecting this component are related to sealing failure or cell component cracked.
- Activation polarization loss (voltage drop due to electrochemical reaction)—the degradation mechanisms affecting this component are related to the change of active reactants/products in the electrochemical reactions.
- Ohmic polarization loss (voltage drop due to ionic or electronic conduction)—the degradation mechanisms affecting this component are related to the conductivity of the electrolyte, electrodes, connectors, and contact resistance.
- Concentration polarization loss (voltage drop due to mass transportation)—the degradation mechanisms affecting this component are related to active reactants/products diffusion in porous electrodes.

However, the SOFC operating conditions have a great impact on the voltage, as summarized by Dolenc [15], it is difficult to distinguish whether the voltage drop results from performance degradation or operating conditions change. It is a better approach to evaluate the degradation of the SOFC performance by using equivalent circuit parameters as SOH indicators. Gemmen [16] proposed to utilize Area Specific Resistance (ASR) as a key lumped parameter indicating the SOH. The ASR is insensitive to the change of reactants/products composition, so it is the preferred choice when comparing the performance difference caused by structural design or cell material. Chi [17] employed a parameter related to SOFC's internal ohmic resistance as a SOH indicator and further identified the relationship between the SOH's degradation rate and the varying-load operation. Compared with the operating voltage, the equivalent circuit parameters as the SOH indicator can superiorly reveal the SOFC performance degradation mechanisms and scale down the effects from operating conditions on SOH measurement. Therefore, an equivalent circuit parameter called degradation resistance is introduced into the SOFC electrical characteristic model to characterize the SOH in this study.

Due to the uncertainty in the measurement or modelling process, the direct calculation of the SOH using measurements or models is subject to significant disturbances. To mitigate this uncertainty and better evaluate the degradation of SOFC performance, several scholars have conducted targeted studies. Gallo [18,19] proposed an online SOH estimation algorithm based on Electrochemical Impedance Spectroscopy (EIS) analysis to accurately extract the equivalent circuit parameters indicating the SOFC performance degradation. Yan [20] used a fast EIS measurement to assess PEMFC's SOH and designed a corresponding fault-tolerant operation to eliminate the effect of faults on the performance degradation. However, performance degradation assessments based on EIS require additional measurement equipment. A more practical option is to estimate the unmeasurable equivalent circuit parameters with an online filtering algorithm, e.g., the SOH estimation through Bayesian filter, Kalman filter, or its variants.

This research discusses the feasibility of adopting SOFC's degradation resistance as the SOH indicator and proposes a real-time SOFC performance degradation assessment method based on the Unscented Kalman Filter (UKF). First, the rationality of using degradation resistance to characterize SOH is demonstrated by the identification results of experimental data. Then, the method of the real-time SOH estimation based on the UKF is proposed for the fact that direct calculation of degradation resistance will be greatly disturbed. Finally, the results of the online estimation of degradation resistance with the UKF under constant

and varying load operating conditions demonstrate the feasibility and effectiveness of the proposed performance degradation assessment method.

2. SOFC Electric Balance Model and SOH Indicator

2.1. Modelling of SOFC Electric Balance

The operating voltage of the SOFC single cell is determined by summing all voltage contributions, which is composed of Nernst voltage E_{Nernst} , activation polarization v_{act} , ohmic polarization v_{ohm} , and concentration polarization v_{con} :

$$v_s = E_{\text{Nernst}} - v_{\text{act}} - v_{\text{con}} - v_{\text{ohm}} \quad (1)$$

Assuming the hydrogen oxidation kinetics dominates the electrochemical reaction, the Nernst voltage E_{Nernst} is determined by:

$$E_{\text{Nernst}} = E^0 + k_E(\bar{T}_s - T^0) + \frac{R \cdot \bar{T}_s}{2F} \ln \frac{p_{\text{H}_2, \text{ch}} p_{\text{O}_2, \text{ch}}^{0.5}}{p_{\text{H}_2\text{O}, \text{ch}} \sqrt{p^0}} \quad (2)$$

where E^0 denotes the reversible voltage of the fuel-cell under usual conditions ($T^0 = 298.15 \text{ K}$, $p^0 = 1 \text{ atm}$), for SOFC, $E^0 = 1.229 \text{ V}$; k_E is related to the Gibbs free energy of the electrochemical reaction and can take the value of a constant, $k_E = 2.304 \times 10^{-4}$; $\bar{T}_s$ denotes the average temperature of SOFC, $\bar{T}_s = \frac{1}{2}(T_{\text{fuel}, \text{in}} + T_{\text{fuel}, \text{out}})$; $p_{\text{H}_2, \text{ch}}$, $p_{\text{O}_2, \text{ch}}$, and $p_{\text{H}_2\text{O}, \text{ch}}$ are the partial pressures of hydrogen, oxygen, and water vapor in the corresponding flow channels, respectively; $p_{\text{H}_2, \text{ch}}$, $p_{\text{O}_2, \text{ch}}$, and $p_{\text{H}_2\text{O}, \text{ch}}$ are calculated by the algebraic average of the corresponding quantities in the SOFC inlet and outlet, as follows:

$$\begin{cases} p_{\text{H}_2, \text{ch}} = \varphi_{\text{H}_2} p_{\text{fuel}}, \varphi_{\text{H}_2} = \frac{1}{2}(\varphi_{\text{H}_2, \text{in}} + \varphi_{\text{H}_2, \text{out}}) \\ p_{\text{H}_2\text{O}, \text{ch}} = \varphi_{\text{H}_2\text{O}} p_{\text{fuel}}, \varphi_{\text{H}_2\text{O}} = \frac{1}{2}(\varphi_{\text{H}_2\text{O}, \text{in}} + \varphi_{\text{H}_2\text{O}, \text{out}}) \\ p_{\text{O}_2, \text{ch}} = \varphi_{\text{O}_2} p_{\text{air}}, \varphi_{\text{O}_2} = \frac{1}{2}(\varphi_{\text{O}_2, \text{in}} + \varphi_{\text{O}_2, \text{out}}) \end{cases} \quad (3)$$

where p_{fuel} and p_{air} denote the average pressure of the fuel and air flow channels, $p_{\text{air}} = \frac{1}{2}(p_{\text{air}, \text{in}} + p_{\text{air}, \text{out}})$, $p_{\text{fuel}} = \frac{1}{2}(p_{\text{fuel}, \text{in}} + p_{\text{fuel}, \text{out}})$; φ_{H_2} , φ_{O_2} and $\varphi_{\text{H}_2\text{O}}$ denote the average molar fraction of hydrogen, oxygen and water vapor in the corresponding flow channels, respectively.

The activation polarization loss v_{act} is the result of the energy barrier that the reactants must overcome when a chemical reaction occurs at the electrode surface and that is calculated by the following empirical equation:

$$\begin{cases} v_{\text{act}} = v_{\text{act}0} + v_{\text{act}1} \\ v_{\text{act}1} = \frac{R \cdot \bar{T}_s}{F} \sinh^{-1} \left(\frac{i_s}{2i_{0, \text{an}}} \right) + \frac{R \cdot \bar{T}_s}{F} \sinh^{-1} \left(\frac{i_s}{2i_{0, \text{ca}}} \right) \end{cases} \quad (4)$$

where the voltage loss $v_{\text{act}0}$ is only related to temperature, which is identified by experimental data; The voltage loss $v_{\text{act}1}$ is calculated using the Butler-Volmer equation, which is correlated with the SOFC output current and the operating temperature; $i_{0, \text{an}}$ and $i_{0, \text{ca}}$ are the exchange currents at the anode and cathode, respectively, whose magnitudes are associated with the reactants concentrations and the SOFC operating temperature.

The Ohmic polarization loss v_{ohm} is determined according to the cathode, anode, electrolyte, contact resistance and SOFC output current. The magnitude of the resistance is proportional to the resistivity, thickness, and inversely proportional to the effective area. Thus, v_{ohm} is given by:

$$\begin{aligned} v_{\text{ohm}} &= i_s \cdot \sum_i R_{\text{ohm}, i} \\ &= \frac{i_s}{S_a} \cdot (\rho_{\text{an}} \tau_{\text{an}} + \rho_{\text{el}} \tau_{\text{el}} + \rho_{\text{ca}} \tau_{\text{ca}} + r_{\text{contact}}) \end{aligned} \quad (5)$$

where τ_{an} , τ_{el} and τ_{ca} are the thickness of anode, electrolyte and cathode respectively; ρ_{an} , ρ_{el} and ρ_{ca} are the resistivity of anode, electrolyte and cathode respectively; $r_{contact}$ is used to explain the contact ASR of the non-ideal connection between the cells in the stack.

The concentration polarization loss v_{con} is caused by the mass transfer process of the reactants from the flow channel to the corresponding three-phase boundary, resulting in the SOFC operating voltage deviating from its equilibrium voltage. v_{con} is obtained by:

$$\begin{aligned} v_{conc} &= v_{conc,a} + v_{conc,c} \\ &= \frac{R \cdot \bar{T}_s}{2F} \ln \left(\frac{p_{H_2O,tpb} p_{H_2,ch}}{p_{H_2O,ch} p_{H_2,tpb}} \right) + \frac{R \cdot \bar{T}_s}{4F} \ln \left(\frac{p_{O_2,ch}}{p_{O_2,tpb}} \right) \end{aligned} \quad (6)$$

where $p_{H_2,tpb}$, $p_{O_2,tpb}$ and $p_{H_2O,tpb}$ are the effective partial pressures of hydrogen, oxygen, and water vapor in the three-phase boundary, respectively. The effective partial pressures can be described by the Stefan-Maxwell equation, as follows:

$$\begin{cases} p_{H_2,tpb} = p_{H_2,ch} - \frac{R \cdot \bar{T}_s \tau_{an}}{2F \cdot D_{eff,an}} \cdot \frac{i_s}{S_a} \\ p_{H_2O,tpb} = p_{H_2O,ch} + \frac{R \cdot \bar{T}_s \tau_{an}}{2F \cdot D_{eff,an}} \cdot \frac{i_s}{S_a} \\ p_{O_2,tpb} = p_{air} - (p_{air} - p_{O_2,ch}) \exp \left(\frac{R \cdot \bar{T}_s \tau_{ca}}{4F \cdot D_{eff,ca}} \cdot \frac{i_s}{S_a} \right) \end{cases} \quad (7)$$

where $D_{eff,an}$ and $D_{eff,ca}$ are the effective diffusion coefficients of the reactants at the anode and cathode, respectively.

2.2. SOH Indicator

As indicated in the studies [15,16], the most common manifestation of the SOFC performance degradation is a significant increase in resistance, which in turn induces a reduction in the operating voltage and power for the same operating conditions (i.e., a decrease in electrical output capability). Considering the presence of performance degradation of the SOFC and introducing the degradation resistance as a SOH indicator, the SOFC electric balance Equation (1) can be rewritten as:

$$v_s = (E_{nernst} - v_{act} - v_{con} - v_{ohm}) - i_s \cdot R_{ageing} \quad (8)$$

where R_{ageing} is an aggregate degradation resistance to account for the resistance increase due to the SOFC performance degradation, which takes the value of zero when performance degradation is not considered.

Define v_{nor} as the normal voltage, i.e., $v_{nor} \triangleq E_{nernst} - v_{act} - v_{con} - v_{ohm}$. Equation (8) is further simplified as follows:

$$v_s = v_{nor} - i_s \cdot R_{ageing} \quad (9)$$

The benefits of employing degradation resistance as a SOH indicator are that its value is insensitive to the operating conditions: (1) The performance degradation can be compared under varying load operations; (2) The voltage deviation due to different reactant fractions is attenuated or even eliminated.

To illustrate the feasibility of the degradation resistance as a SOH indicator, the parameter identification results of the SOFC polarization curve are used to verify Equation (8). The experimental SOFC stack was installed in an electric furnace and gradually preheated to 750 °C. After the temperature reached 750 °C, the average hydrogen (99 vol%) flow per cell into the anode was 2 Standard Litres per Minute (SLM), and the average air flow per cell into the cathode was 4 SLM. The voltage and current of the experimental process were measured and logged by the electronic load. The SOFC performance showed a significant degradation during 15 cycles. As shown in Figure 3, the symbols ∇ , $\triangle$, $\diamond$, and $\square$ mark the data collected during the 1st, 6th, 11th, and 15th cycles, respectively. The post-test inspections indicate that possible contributors to the evolution of the SOFC performance

degradation are interconnector oxidation and cathode contact material deterioration. For the specific process of the above experiment, please refer to the study of Pan [21].

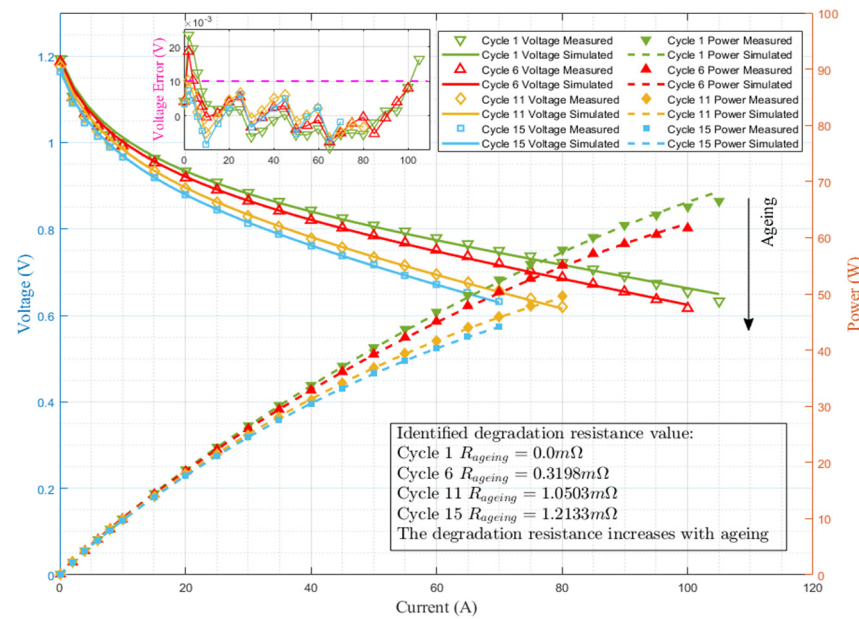


Figure 3. Identified degradation resistance results of polarization curve for the SOFC's SOH evolution.

The 1st cycle is regarded as the initial state of the degradation process. At this time, R_{ageing} is taken as zero, and other parameters of Equation (8) are identified by using the polarization curve data of the 1st cycle (See Appendix A for specific parameter values); then, keeping other parameters invariant, only the value of R_{ageing} is identified to match the data of the subsequent cycles. The results are added in Figure 3, where the coloured lines correspond to the curves plotted by the identified parameters. As can be seen in Figure 3, the polarization curve gradually deviates from its initial position as the number of cycles increases, mainly manifested as a decrease in output voltage and power. Specifically, R_{ageing} gradually increases from 0.0 mΩ in the 1st cycle to 1.2133 mΩ in the 15th cycle. The embedded plot in the upper left corner of Figure 3 shows the error between the identified model voltage and the experimentally measured voltage, and in the SOFC operating region (currents between 10 A and 70 A), the errors are less than 10 mV, which indicates that the identification results of Equation (8) can accurately capture the degree of SOFC performance degradation. Therefore, using the degradation resistor as the SOFC health status indicator is a feasible solution. Therefore, it is feasible to adopt the degradation resistance R_{ageing} as the SOFC's SOH indicator.

2.3. SOH Characterization

When EIS measurements are available for SOFC monitoring, R_{ageing} can be obtained by identifying the equivalent circuit model through Nyquist plots [13]. For conventional monitoring without EIS measurements, the common measurements are voltage, current, pressure, and temperature. In addition, the concentration of reactants within the SOFC can be observed by inlet flow and output current. In this case, the degradation resistance R_{ageing} needs to be derived from the known quantities mentioned above. When the normal voltage v_{nor} is calibrated, utilizing Equation (9), R_{ageing} can be calculated as follows:

$$R_{ageing}(t) = \frac{v_{nor}(i_s) - v_s(i_s, t)}{i_s(t)} \quad (10)$$

The test conditions of the SOFC in an electric furnace are very different from the operation in the system. In an electric furnace, the SOFC operating temperature can be

precisely controlled. In contrast, the system-related SOFC operation lacks independent temperature actuators because of the system efficiency requirements, and its operating temperature is maintained by the supply of high-temperature gas and waste heat from the power generation. Therefore, the SOH can be characterized without pre-calibrating the normal voltage in the case of electric furnace operation. Specifically, the calculation of the degradation resistance R_{ageing} can be simplified by a constant load current under constant thermodynamic conditions (temperature, reactant concentration, and pressure). It is assumed that SOFC begins to degrade at time t_0 and R_{ageing} begins to evolve with time. Applying Equation (9) at the beginning time t_0 and the measurement time t , the following equation holds:

$$\frac{v_s(i_s, t) - v_s(i_s, t_0) = v_{nor}(i_s) - i_s \cdot R_{ageing}(t) - (v_{nor}(i_s) - i_s \cdot R_{ageing}(t_0))}{v_s(i_s, t) - v_s(i_s, t_0) = -i_s \cdot (R_{ageing}(t) - R_{ageing}(t_0))} \quad (11)$$

Defining the degradation resistance $R_{ageing}(t_0)$ at the initial time as the initial zero point, then Equation (11) can be transformed into:

$$R_{ageing}(t) = \frac{v_s(i_s, t_0) - v_s(i_s, t)}{i_s} \quad (12)$$

3. UKF-Based Real-Time SOH Estimation

As the degradation resistance calculated directly using Equation (10) or (12) suffers from large noise, it is necessary to combine the measurements and model to estimate the SOH.

3.1. Degradation Process Model

Before the SOFC performance degradation estimation can be performed, it is necessary to develop a mathematical model describing the evolution of the SOH over time. For the degradation process model, the following assumptions are made:

- The degradation resistance characterizes the SOH, which does not change abruptly and can affect the measured voltage directly or indirectly.
- The dynamic of the SOH is slow relative to other dynamic processes, such as temperature and electrochemical reaction dynamics.

In the absence of a priori information on the SOFC degradation resistance, a linear drift model is used to describe the evolution of the SOH, as follows:

$$\begin{cases} R_{ageing}(t_{k+1}) = R_{ageing}(t_k) + T_s \cdot \dot{R}_{ageing}(t_k) + w_1(t_k) \\ \dot{R}_{ageing}(t_{k+1}) = \dot{R}_{ageing}(t_k) + w_2(t_k) \end{cases} \quad (13)$$

where, $\dot{R}_{ageing}$ represents the change rate of degradation resistance; w_1 and w_2 represent process noise corresponding to degradation resistance and change rate respectively; T_s represents the sampling period, $T_s = t_{k+1} - t_k$.

The measurement function for the SOH needs to be discussed in two cases. The first case is the power generation under constant condition when the evolution of the SOH can be simply equated to the change in voltage, and the measurement function is Equation (12). The second case is under varying load operating conditions when the measurement Equation (10) is valid, and the parameters required for normal voltage v_{nor} must be calibrated first for SOH estimation.

Based on the above assumptions and analysis, the state space model of the degradation process is as follows,

- Power generation under constant conditions:

$$\begin{cases} \theta_{k+1} = A \cdot \theta_k + w_k \\ y_k = H_1(\theta_k, u_k) + v_k \end{cases} \quad (14)$$

- Power generation under varying load operating conditions:

$$\begin{cases} \theta_{k+1} = A \cdot \theta_k + w_k \\ y_k = H_2(x_k, \theta_k, u_k) + v_k \end{cases} \quad (15)$$

where θ denotes the degenerate state vector, $\theta_k \triangleq [R_{ageing}(t_k), \dot{R}_{ageing}(t_k)]^T$; A denotes the system degenerate state transfer matrix, $A \triangleq \begin{bmatrix} 1 & T_s \\ 0 & 1 \end{bmatrix}$; y denotes the measured output, in this study the SOFC operating voltage is available for measurement, $y_k \triangleq v_s(t_k)$; u denotes the system input, $u_k \triangleq i_s(t_k)$; x denotes the system state, which is defined as the SOFC normal voltage, $x_k \triangleq v_{nor}(t_k)$, the state can be calculated directly from the calibrated SOFC stack model Equation (1); $H_1(\cdot)$ and $H_2(\cdot)$ respectively denote the measurement functions for the corresponding cases, $H_1(\theta_k, u_k) \triangleq v_s(i_s, t_0) - i_s \cdot R_{ageing}(t_k)$ and $H_2(x_k, \theta_k, u_k) \triangleq v_{nor}(t_k) - i_s(t_k) \cdot R_{ageing}(t_k)$; w denotes the process noise vector, $w_k \triangleq [w_1(t_k), w_2(t_k)]^T$; v_k denotes the measurement noise. Assuming that w and v are mutually independent and identically distributed zero-mean Gaussian noise, the corresponding covariance matrices are Q and R , respectively, with the values as follows:

$$\begin{cases} Q = \begin{bmatrix} q_1 & 0 \\ 0 & q_2 \end{bmatrix} \\ R = [r_1] \end{cases} \quad (16)$$

3.2. UKF-Based SOH Estimation

System identification can be applied to estimate the parameters of the degradation process model (Equations (14) and (15)). When performed offline, all measurements are available and regression methods (e.g., least squares) can be used for this task. Whereas the focus of this study is on online applications, at each time point only the measurement collected before the current moment are available, so the problem of SOH estimation can be solved with filters.

In general, filtering is more challenging than regression because the overall size and variability of the data are unknown. Common online filtering algorithms include recursive least squares, extended Kalman filter (EKF), and the UKF. In this study, the degenerate states in the state space (14) and (15) were estimated online with the UKF algorithm, which is described in Appendix B. The output of the UKF algorithm is the estimated SOH, which is expressed by $\hat{R}_{ageing}$.

Many studies [22,23] have shown that the process and measurement noise covariance have a great impact on the performance of the UKF. For the measurement noise covariance R , it can be determined according to the voltage sensor. For the matrix Q , as the degradation process of SOFC is assumed to be a linear drift model, if the model is accurate, then q_1 and q_2 are taken as zero, otherwise at least q_2 cannot be set as zero so that the UKF can track the change of degradation rate. Therefore, in this study, q_1 is set to zero, and q_2 is selected as a smaller value that is not zero.

4. SOH Estimation Results and Discussions

In this section, the SOH estimation is verified on two datasets, one from a constant condition power generation experiment in an electric furnace and the other from a varying load power generation experiment under a kW-class SOFC system platform.

4.1. Power Generation under Constant Conditions

The experimental SOFC stack consists of a single cell, as shown in Figure 4a. The size of the single cell is $11\text{ cm} \times 11\text{ cm}$, with a 1 cm seal around the edge, so the active area is $9\text{ cm} \times 9\text{ cm}$. The stack was installed in an electric furnace, as shown in Figure 4b. The stack temperature was controlled at $750\text{ }^{\circ}\text{C}$, high-purity hydrogen gas with a flow rate of 2 NL/min (Normal-Condition Litres per Minute) was used as the reductant and dry air with a flow rate of 2 NL/min was used as the oxidant. The stack was operated at a constant current of 30 A, its current and voltage were measured and logged to evaluate its performance degradation. The whole test lasted for nearly 4000 h until it was interrupted by an extended power failure, during which several equipment breakdowns also occurred and caused fluctuations in degradation behaviour. The complete test data curve is shown in Figure 4c. Detailed information about this experiment can be found in the study by Yan [24].

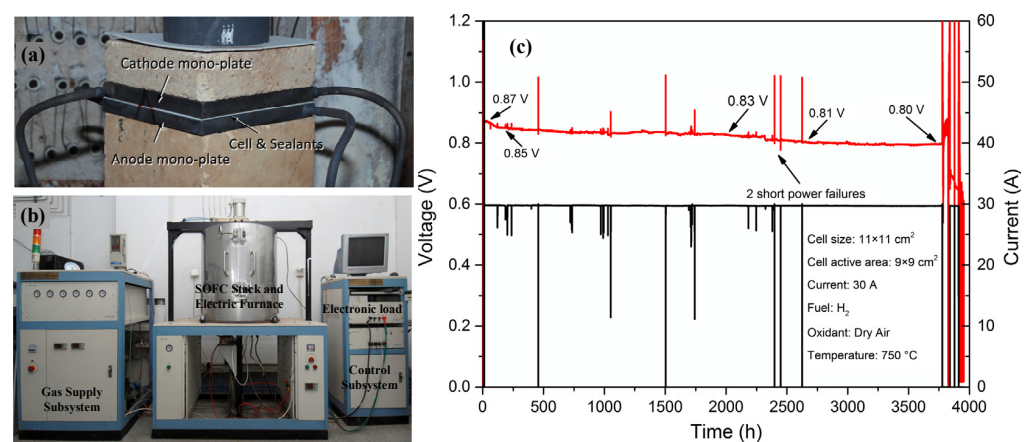


Figure 4. SOFC constant current power generation under constant conditions; (a) Single cell stack; (b) The profile of the testing facility; (c) Time dependence of the voltage and current.

As shown in Figure 4c, electromagnetic disturbances from the control subsystem caused several current fluctuations during the test, and the process resulted in a temporary voltage drop, that recovered quickly after the current disturbances were removed. In terms of the overall trend, the measured voltage reached a maximum value of 0.87 V from an initial 0.86 V after a transient of about 19 h and then dropped rapidly to 0.85 V after 120 h. The voltage dropped at a relatively constant rate to 0.83 V for the next 1800 h. Another quick decay (caused by two short power failures) emerges thereafter, and the voltage dropped to about 0.81 V at 2500 h. Finally, the voltage dropped steadily to about 0.80 V until the test experiment was interrupted by an external power failure at 3770 h.

The experimental dataset meets the conditions of state space Equation (14). The sampling period of the original data set is 10 s in Figure 4c, which is far less than the dynamics of degradation behaviour. Therefore, the original data set was resampled with a resampling interval of 1 h, and outliers during fault fluctuations were removed, and the period from 19 to 3719 h was selected to illustrate the effect of the SOH estimation. The pre-processed voltage measurements are shown in Figure 5.

The performance degradation is estimated using the method in Section 3. After appropriate adjustment and calibration, the process noise and measurement noise covariance are set to $Q = \text{diag}([0, 2.5 \times 10^{-7}])$ and $R = 9.0$, respectively. The SOH estimation results are shown in Figure 5.

As seen in Figure 5, firstly, the estimated voltage effectively tracks the measured voltage, and the UKF filters out the short-term fluctuation caused by the measurement noise. This result also shows the feasibility of assuming the degradation of the SOFC as a linear drift model; secondly, the UKF effectively estimates the degradation resistance, which not only filters out the short-term noise fluctuation, but also retains the long-term trend of degradation resistance. For a suitable estimator, the residual should be small amplitude

zero mean Gaussian white noise. Figure 6 shows the voltage residual, the calculated mean value of residual error is 0.0426 mV, which meets the requirements of a small amplitude zero mean value. Therefore, in the power generation test under constant conditions, the result of the SOH estimation with the UKF is robust and reliable.

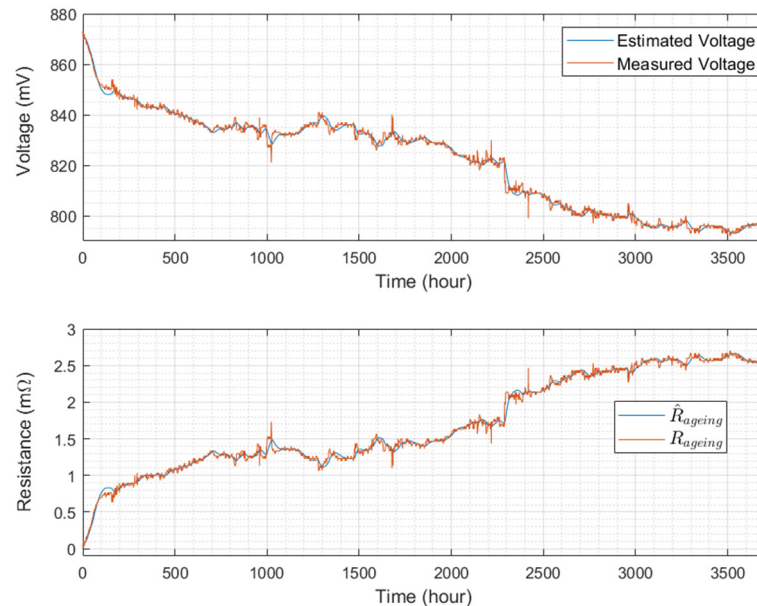


Figure 5. The SOH estimation results under constant conditions.

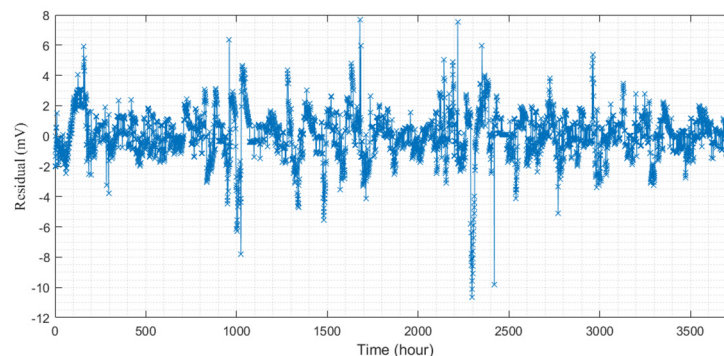


Figure 6. Voltage residual under constant conditions. The residual at each step is calculated by: $\text{Residual} = (\text{Measured Voltage}) - (\text{Estimated Voltage})$.

4.2. Power Generation under Varying Load Operating Conditions

This dataset is derived from the kW-class SOFC system platform of the previous study [25,26]. As shown in Figure 7, the test platform is composed of gas supply, hotbox, control subsystem, tested stack, etc. The tested stack consists of 27 single cells in series, with a single cell size of 15 cm $\times$ 15 cm and an active area of 13 cm $\times$ 13 cm. The maximum current during the test reached about 53 A, corresponding to a maximum power of about 1 kW. All measurements related to the SOFC stack are shown in Figure 8; the molar flow rate of the hydrogen-rich anode gas $\dot{N}_{fuel,in}$ at the SOFC inlet and the corresponding molar fraction vector $\Phi_{fuel,in}$ from the reformer operation, and the results are shown in Figure 9. It is worth noting that all measurements are converted to the corresponding quantities for a single cell.

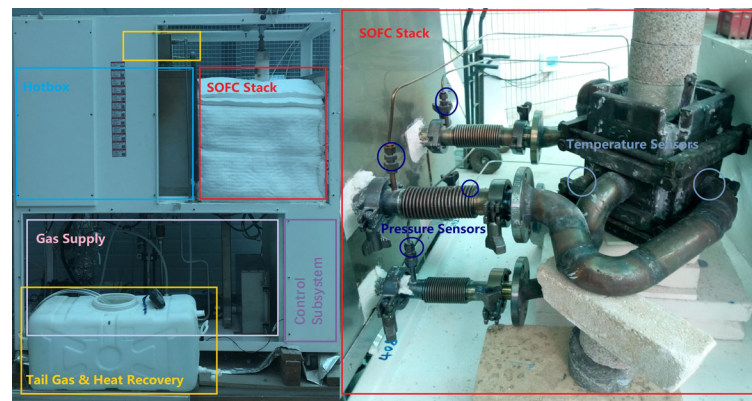


Figure 7. kW-class SOFC system platform.

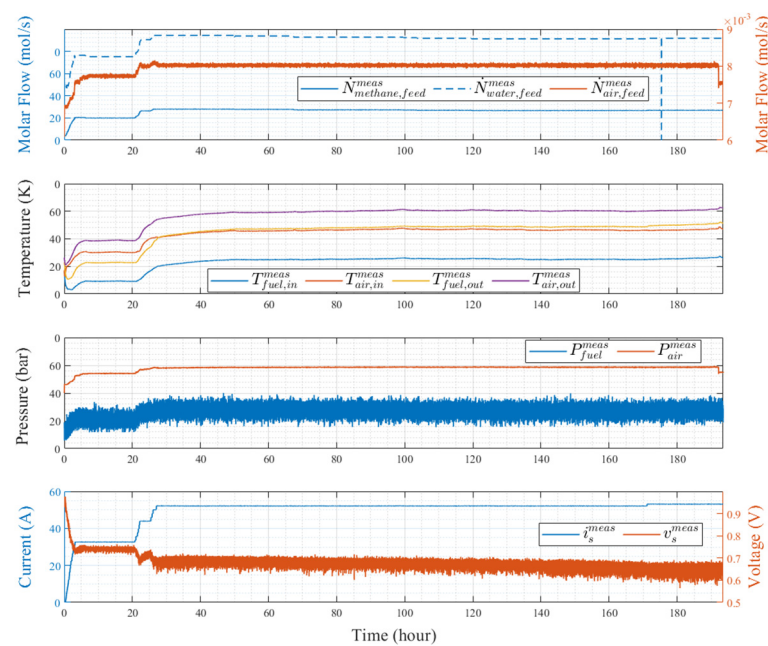


Figure 8. Relevant measurements of SOFC stack power generation under varying load operating conditions.

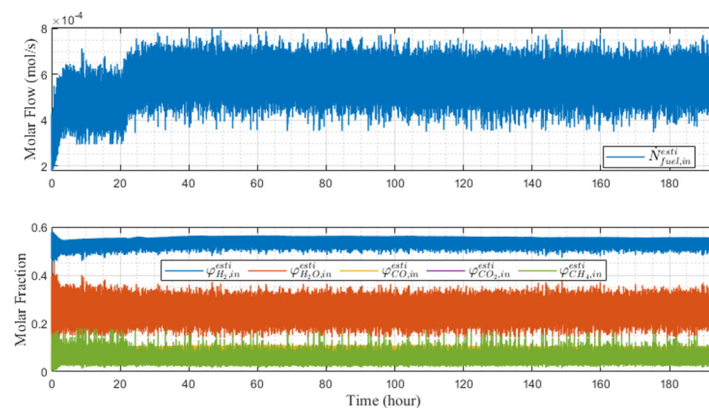


Figure 9. The SOFC inlet hydrogen-rich anode gas properties under varying load operating conditions.

As seen in Figure 8, the supplied methane, water, and air, as well as the controlled current, were switched many times during the test; the measured temperature, pressure and voltage also changed with the operating conditions. In addition, from the voltage measurement curve in Figure 8, it can be seen that there is an obvious degradation and attenuation trend of voltage from the 40th hour.

It shown in Figure 9 that the molar flow $\dot{N}_{fuel,in}$ and molar fraction vector $\Phi_{fuel,in}$ of hydrogen-rich anode gas at the SOFC inlet fluctuate violently. This is due to the sudden boiling in the process of water evaporation and gasification, which affects the operating pressure, voltage, and inlet fuel flow of SOFC [27]. In particular, the changing trend of SOFC voltage is submerged in noise, which is why this study needs to estimate the SOH with the UKF.

The experimental dataset meets the conditions of the state space Equation (15). The tested SOFC model was validated in a previous study [25], where the calculated normal voltage v_{nor} is also given. The sampling period of the dataset is 10 s, and the SOH is estimated using the method in Section 3. After proper adjustment and calibration, the process noise and measurement noise covariances are set as $Q = diag([0, 3.6 \times 10^{-18}])$ and $R = 9.0$, respectively. The estimated results of SOH are shown in Figure 10.

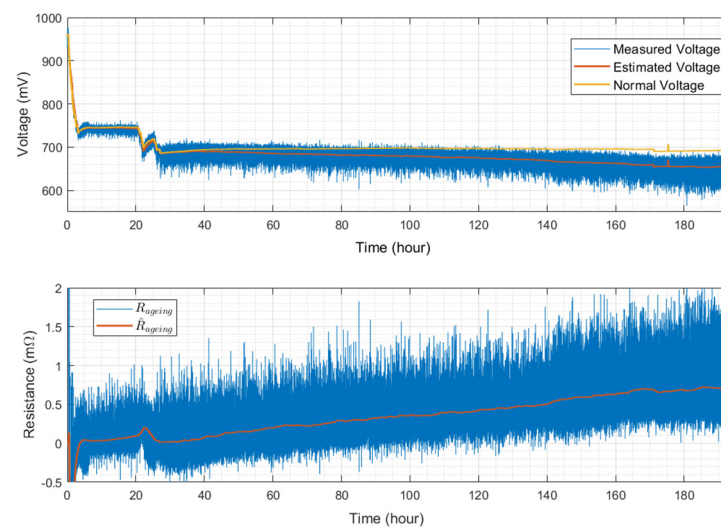


Figure 10. SOH estimation results under varying load operating conditions.

As shown in Figure 10, firstly, the UKF effectively tracked the long-term trend of the voltage and filtered out the noise; it is obvious that from the 40th hour onwards the UKF estimated voltage deviated from the normal voltage and the evolution of SOFC performance degradation gradually appeared, which indicates a significant reduction in the SOFC power generation capability after 40 h. Secondly, the UKF effectively estimates the degradation resistance (the measured degradation resistance is calculated from Equation (10)), while also preserving the long-term trend of the degradation resistance. This result is similar to that of Dolenc's study [15]; both the UKFs successfully integrated degradation process models and measurement data to effectively estimate the SOFC's SOH. The voltage residuals are plotted in Figure 11, and as mentioned before, the residuals should be small-amplitude zero-mean Gaussian white noise, and the calculated mean value of the residuals is -0.0560 mV, which meets the requirement of small-amplitude zero-mean. Therefore, the proposed degradation resistance as a SOH indicator combined with the UKF for the SOH estimation is feasible.

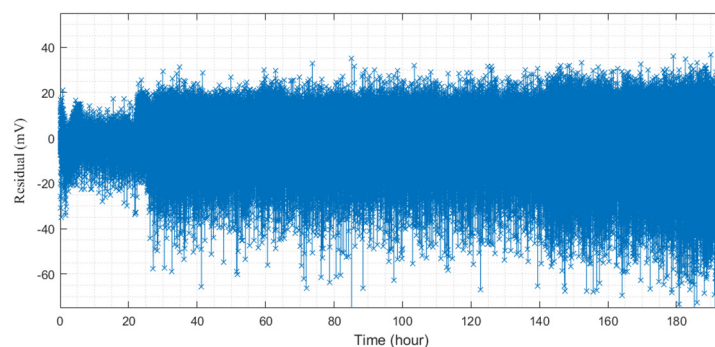


Figure 11. Voltage residual under varying load operating conditions. The residual at each step is calculated by: $\text{Residual} = (\text{Measured Voltage}) - (\text{Estimated Voltage})$.

5. Conclusions

The performance degradation of the SOFC has become one of the main challenges hindering its large-scale commercial application. Therefore, in this study, a method to evaluate the SOH of SOFC is discussed.

Voltage, as a general SOH indicator, must be measured under constant operating conditions, which brings inconvenience to the actual system. A better solution is to use equivalent circuit parameters as indicators for evaluating the SOFC performance degradation. Therefore, degradation resistance was introduced based on the SOFC electrical characteristic model to characterize the SOH, and the feasibility of the scheme was verified by experimental data. In addition, a degradation resistance estimation method with the UKF is proposed to evaluate the SOH. The results of real-time SOH estimation at constant and varying load conditions demonstrate the effectiveness of the method.

The SOFC performance degradation assessment is a prerequisite for prognosis and optimal maintenance decisions, which is important for achieving efficient and accurate management. The method proposed in this study can estimate the SOH of SOFC in real-time, but it can provide limited information for system maintenance. If the end of life and remaining useful life can be predicted based on the evolution trend of the SOH, then it can provide more intuitive and diverse information. Therefore, the method of the SOFC prognosis will be further investigated in the future based on the real-time SOH estimation.

Author Contributions: Conceptualization, Y.X.; data curation, C.J.; formal analysis, H.Q. and J.P.; investigation, C.J.; methodology, Y.X.; project administration, X.W. and X.L.; software, H.S.; validation, H.S.; visualization, H.S.; writing—original draft, Y.W.; writing—review and editing, Y.X., X.W., Z.X. and Y.W. All authors have read and agreed to the published version of the manuscript.

Funding: This research was supported by the National Natural Science Foundation of China (grant number: U2066202, 61873323); Science, Technology, and Innovation Commission of Shenzhen Municipality (grant number: JCYJ20210324115606017); Jiangxi Provincial Natural Science Foundation (grant number: 20212BAB212013).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A. Parameter Values of SOFC Electric Balance Model

	Units	Value
<i>Geometric properties</i>		
Anode thickness, τ_{an}	[m]	5×10^{-6}
Cathode thickness, τ_{ca}	[m]	5×10^{-6}
Electrolyte thickness, τ_{el}	[m]	1×10^{-5}
Cell's active area, S_a	[m ²]	0.0081
<i>Constants</i>		
Gas constant, R	[J/(K·mol)]	8.314
Faraday constant, F	[C/mol]	96485.3
Nernst Voltage		
Reversible voltage, E^0	[V]	1.229
Primary coefficient, k_E	[V/K]	2.304×10^{-4}
Normal temperature, T^0	[K]	298.15
Standard atmosphere, P^0	[bar]	1.0132
<i>Activation polarization</i>		
Voltage drop, v_{act0}	[V]	$0.05-3.10 \times 10^{-5} \times T$
Anode exchange current, $i_{0,an}$	[A]	$3.0 \times 10^7 \times p_{H_2} \times p_{H_2O}^{-0.5} \times \exp(-1.32 \times 10^4/T)$
Cathode exchange current, $i_{0,ca}$	[A]	$9.8 \times 10^6 \times p_{O_2}^{0.25} \times \exp(-1.44 \times 10^4/T)$
<i>Ohmic polarization</i>		
Anode resistivity, ρ_{an}	[Ω·m]	$9.5 \times 10^7 \times \exp(-1150/T)/T$
Cathode resistivity, ρ_{ca}	[Ω·m]	$4.2 \times 10^7 \times \exp(-1200/T)/T$
Electrolyte resistivity, ρ_{el}	[Ω·m]	$3.34 \times 10^4 \times \exp(-10300/T)$
Contact ASR, $r_{contact}$	[Ω·m ²]	4.87×10^{-6}
<i>Concentration polarization</i>		
Anode effective diffusion coefficient, $D_{eff,an}$	[m ² /s]	0.0041
Cathode effective diffusion coefficient, $D_{eff,ca}$	[m ² /s]	0.01

Appendix B. UKF Algorithm

Assume that the state transition and measurement equations have additive process and measurement noise terms. The following expressions constitute a general model of nonlinear discrete-time systems:

$$\begin{aligned} x_{k+1} &= G(x_k, u_k) + w_k \\ y_k &= H(x_k) + v_k \end{aligned} \quad (A1)$$

where $G(\cdot)$ is the nonlinear state transition function, $H(\cdot)$ is the measurement function; x is a system state vector, y is a measured output vector, u is the input vector; w and v are process and measurement noise respectively, both of which follow gauss distribution and have the following statistical characteristics:

$$\begin{cases} E(w_k) = 0, Cov(w_k, w_j) = Q_k \delta_{kj} \\ E(v_k) = 0, Cov(v_k, v_j) = R_k \delta_{kj} \\ Cov(w_k, v_j) = 0 \end{cases} \quad (A2)$$

where $E(\cdot)$ is the mathematical expectation and $Cov(\cdot)$ is the covariance matrix; Q and R are process and measurement covariance matrices respectively; δ_{kj} is Dirac function.

The main steps of UKF algorithm are as follows:

Step 1: Prediction

Calculate sigma points $\hat{x}_{k-1|k-1}^{(i)}$.

$$\begin{cases} \hat{x}_{k-1|k-1}^{(0)} = \hat{x}_{k-1|k-1}, i = 0 \\ \hat{x}_{k-1|k-1}^{(i)} = \hat{x}_{k-1|k-1} + \left(\sqrt{cP_{k-1|k-1}} \right)_i, i = 1, 2, \dots, n \\ \hat{x}_{k-1|k-1}^{(i)} = \hat{x}_{k-1|k-1} - \left(\sqrt{cP_{k-1|k-1}} \right)_i, i = n+1, n+2, \dots, 2n \end{cases} \quad (\text{A3})$$

where $c = \alpha^2(n + \kappa)$ is the scaling parameter based on number of states n , and the parameters α and κ ; $(\sqrt{cP})_i$ is the i -th column of the square root of matrix cP , and $\sqrt{cP}(\sqrt{cP})^T = cP$.

Use the nonlinear state transition function to compute the predicted states.

$$\begin{cases} \hat{x}_{k|k-1}^{(i)} = G(\hat{x}_{k-1|k-1}^{(i)}, u_{k-1}), i = 0, 1, \dots, 2n \\ \hat{x}_{k|k-1} = \sum_{i=0}^{2n} \omega_m^{(i)} \hat{x}_{k|k-1}^{(i)} \\ \omega_m^{(0)} = 1 - \frac{n}{\alpha^2(n+\kappa)} \\ \omega_m^{(i)} = 1/(2\alpha^2(n+\kappa)), i = 1, 2, \dots, 2n \end{cases} \quad (\text{A4})$$

Compute the covariance of the predicted state.

$$\begin{cases} P_{k|k-1} = \sum_{i=0}^{2n} \omega_c^{(i)} (\hat{x}_{k|k-1}^{(i)} - \hat{x}_{k|k-1})(\hat{x}_{k|k-1}^{(i)} - \hat{x}_{k|k-1})^T + Q_{k-1} \\ \omega_c^{(0)} = (2 - \alpha^2 + \beta) - \frac{n}{\alpha^2(n+\kappa)} \\ \omega_c^{(i)} = \omega_m^{(i)} = 1/(2\alpha^2(n+\kappa)), i = 1, 2, \dots, 2n \end{cases} \quad (\text{A5})$$

Step 2: Update

Calculate sigma points $\hat{x}_{k|k-1}^{(i)}$.

$$\begin{cases} \hat{x}_{k|k-1}^{(0)} = \hat{x}_{k|k-1}, i = 0 \\ \hat{x}_{k|k-1}^{(i)} = \hat{x}_{k|k-1} + \left(\sqrt{cP_{k|k-1}} \right)_i, i = 1, 2, \dots, n \\ \hat{x}_{k|k-1}^{(i)} = \hat{x}_{k|k-1} - \left(\sqrt{cP_{k|k-1}} \right)_i, i = n+1, n+2, \dots, 2n \end{cases} \quad (\text{A6})$$

Use the measurement function to compute the predicted measurements.

$$\begin{cases} \hat{y}_{k|k-1}^{(i)} = H(\hat{x}_{k|k-1}^{(i)}, u_k), i = 0, 1, \dots, 2n \\ \hat{y}_k = \sum_{i=0}^{2n} \omega_m^{(i)} \hat{y}_{k|k-1}^{(i)} \\ \omega_m^{(0)} = 1 - \frac{n}{\alpha^2(n+\kappa)} \\ \omega_m^{(i)} = 1/(2\alpha^2(n+\kappa)), i = 1, 2, \dots, 2n \end{cases} \quad (\text{A7})$$

Estimate the covariance of the predicted measurement.

$$\begin{cases} P_{yy} = \sum_{i=0}^{2n} \omega_c^{(i)} (\hat{y}_{k|k-1}^{(i)} - \hat{y}_k)(\hat{y}_{k|k-1}^{(i)} - \hat{y}_k)^T + R_k \\ \omega_c^{(0)} = (2 - \alpha^2 + \beta) - \frac{n}{\alpha^2(n+\kappa)} \\ \omega_m^{(i)} = \omega_c^{(i)} = 1/(2\alpha^2(n+\kappa)), i = 1, 2, \dots, 2n \end{cases} \quad (\text{A8})$$

Estimate the cross-covariance between $\hat{x}_{k|k-1}^{(i)}$ and $\hat{y}_k$.

$$P_{xy} = \frac{1}{2\alpha^2(n + \kappa)} \sum_{i=1}^{2n} (\hat{x}_{k|k-1}^{(i)} - \hat{x}_{k|k-1})(\hat{y}_{k|k-1}^{(i)} - \hat{y}_k)^T \quad (A9)$$

Compute the Kalman gain K_k .

$$K_k = P_{xy}P_{yy}^{-1} \quad (A10)$$

Update the estimated state and state estimation error covariance.

$$\begin{cases} \hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k(y_k - \hat{y}_k) \\ P_{k|k} = P_{k|k-1} - K_k P_{yy} K_k^T \end{cases} \quad (A11)$$

References

1. Fernandes, M.D.; Bistrizki, V.; Domingues, R.Z.; Matencio, T.; Rapini, M.; Sinisterra, R.D. Solid Oxide Fuel Cell Technology Paths: National Innovation System Contributions from Japan and the United States. *Renew. Sustain. Energy Rev.* **2020**, *127*, 109879. [\[CrossRef\]](#)
2. Peng, J.; Huang, J.; Wu, X.; Xu, Y.; Chen, H.; Li, X. Solid Oxide Fuel Cell (SOFC) Performance Evaluation, Fault Diagnosis and Health Control: A Review. *J. Power Sources* **2021**, *505*, 230058. [\[CrossRef\]](#)
3. Steinberger-Wilckens, R. European SOFC Technology—Status and Trends. *ECS Trans.* **2011**, *35*, 19. [\[CrossRef\]](#)
4. Cimenti, M.; Hill, J.M. Direct Utilization of Liquid Fuels in SOFC for Portable Applications: Challenges for the Selection of Alternative Anodes. *Energies* **2009**, *2*, 377–410. [\[CrossRef\]](#)
5. Fan, J.; Lu, Y.; Ding, J.; Meng, A.; Tang, Z.; Ye, J. SOFC Detector With OCA Approach to Quantify Trace Gases Dissolved in Transformer Oil. *IEEE Sens. J.* **2020**, *20*, 648–655. [\[CrossRef\]](#)
6. Fernandes, M.D.; de P. Andrade, S.T.; Bistrizki, V.N.; Fonseca, R.M.; Zacarias, L.G.; Gonçalves, H.N.C.; de Castro, A.F.; Domingues, R.Z.; Matencio, T. SOFC-APU Systems for Aircraft: A Review. *Int. J. Hydrog. Energy* **2018**, *43*, 16311–16333. [\[CrossRef\]](#)
7. Ghanem, R.S.; Nousch, L.; Richter, M. Modeling of a Grid-Independent Set-Up of a PV/SOFC Micro-CHP System Combined with a Seasonal Energy Storage for Residential Applications. *Energies* **2022**, *15*, 1388. [\[CrossRef\]](#)
8. Cooper, S.J.; Brandon, N.P. Chapter 1—An Introduction to Solid Oxide Fuel Cell Materials, Technology and Applications. In *Solid Oxide Fuel Cell Lifetime and Reliability*; Brandon, N.P., Ruiz-Trejo, E., Boldrin, P., Eds.; Academic Press: Cambridge, MA, USA, 2017; pp. 1–18. ISBN 978-0-08-101102-7.
9. Wu, X.; Xu, L.; Wang, J.; Yang, D.; Li, F.; Li, X. A Prognostic-Based Dynamic Optimization Strategy for a Degraded Solid Oxide Fuel Cell. *Sustain. Energy Technol. Assess.* **2020**, *39*, 100682. [\[CrossRef\]](#)
10. Huang, B.; Qi, Y.; AKM, M.M. Introduction. In *Dynamic Modelling and Predictive Control in Solid Oxide Fuel Cells: First Principle and Data-Based Approaches*; John Wiley & Sons, Ltd.: Hoboken, NJ, USA, 2012; pp. 1–7. ISBN 978-1-118-50105-4.
11. Mukerjee, S.; Leah, R.; Selby, M.; Stevenson, G.; Brandon, N.P. Chapter 9—Life and Reliability of Solid Oxide Fuel Cell-Based Products: A Review. In *Solid Oxide Fuel Cell Lifetime and Reliability*; Brandon, N.P., Ruiz-Trejo, E., Boldrin, P., Eds.; Academic Press: Cambridge, MA, USA, 2017; pp. 173–191. ISBN 978-0-08-101102-7.
12. Shi, W.; Zhu, J.; Han, M.; Sun, Z.; Guo, Y. Operating Limitation and Degradation Modeling of Micro Solid Oxide Fuel Cell-Combined Heat and Power System. *Appl. Energy* **2019**, *252*, 113444. [\[CrossRef\]](#)
13. Yan, D.; Liang, L.; Yang, J.; Zhang, T.; Pu, J.; Chi, B.; Li, J. Performance Degradation and Analysis of 10-Cell Anode-Supported SOFC Stack with External Manifold Structure. *Energy* **2017**, *125*, 663–670. [\[CrossRef\]](#)
14. Yang, J.; Huang, W.; Wang, X.; Li, J.; Yan, D.; Pu, J.; Chi, B.; Li, J. Study on Component Interface Evolution of a Solid Oxide Fuel Cell Stack after Long Term Operation. *J. Power Sources* **2018**, *387*, 57–63. [\[CrossRef\]](#)
15. Dolenc, B.; Boškoski, P.; Stepančič, M.; Pohjoranta, A.; Juričić, D. State of Health Estimation and Remaining Useful Life Prediction of Solid Oxide Fuel Cell Stack. *Energy Convers. Manag.* **2017**, *148*, 993–1002. [\[CrossRef\]](#)
16. Gemmen, R.S.; Williams, M.C.; Gerdes, K. Degradation Measurement and Analysis for Cells and Stacks. *J. Power Sources* **2008**, *184*, 251–259. [\[CrossRef\]](#)
17. Chi, Y.; Qiu, Y.; Lin, J.; Song, Y.; Hu, Q.; Li, W.; Mu, S. Online Identification of a Link Function Degradation Model for Solid Oxide Fuel Cells under Varying-Load Operation. *Int. J. Hydrog. Energy* **2022**, *47*, 2622–2646. [\[CrossRef\]](#)
18. Gallo, M.; Costabile, C.; Sorrentino, M.; Polverino, P.; Pianese, C. Development and Application of a Comprehensive Model-Based Methodology for Fault Mitigation of Fuel Cell Powered Systems. *Appl. Energy* **2020**, *279*, 115698. [\[CrossRef\]](#)
19. Gallo, M.; Polverino, P.; Mougin, J.; Morel, B.; Pianese, C. Coupling Electrochemical Impedance Spectroscopy and Model-Based Aging Estimation for Solid Oxide Fuel Cell Stacks Lifetime Prediction. *Appl. Energy* **2020**, *279*, 115718. [\[CrossRef\]](#)

20. Yan, C.; Chen, J.; Liu, H.; Kumar, L.; Lu, H. Health Management for PEM Fuel Cells Based on an Active Fault Tolerant Control Strategy. *IEEE Trans. Sustain. Energy* **2021**, *12*, 1311–1320. [[CrossRef](#)]
21. Pan, J.; Yang, J.; Yan, D.; Pu, J.; Chi, B.; Li, J. Effect of Thermal Cycling on Durability of a Solid Oxide Fuel Cell Stack with External Manifold Structure. *Int. J. Hydrog. Energy* **2020**, *45*, 17927–17934. [[CrossRef](#)]
22. Yan, Q.; Huang, J.; Yang, Z.; Hasegawa, Y.; Fukuda, T. Human-Following Control of Cane-Type Walking-Aid Robot Within Fixed Relative Posture. *IEEE/ASME Trans. Mechatron.* **2022**, *27*, 537–548. [[CrossRef](#)]
23. Zhang, Q. Adaptive Kalman Filter for Actuator Fault Diagnosis. *Automatica* **2018**, *93*, 333–342. [[CrossRef](#)]
24. Yan, D.; Zhang, C.; Liang, L.; Li, K.; Jia, L.; Pu, J.; Jian, L.; Li, X.; Zhang, T. Degradation Analysis and Durability Improvement for SOFC 1-Cell Stack. *Appl. Energy* **2016**, *175*, 414–420. [[CrossRef](#)]
25. Xu, Y.; Wu, X.; Zhong, X.; Zhao, D.; Sorrentino, M.; Jiang, J.; Jiang, C.; Fu, X.; Li, X. Mechanism Model-Based and Data-Driven Approach for the Diagnosis of Solid Oxide Fuel Cell Stack Leakage. *Appl. Energy* **2021**, *286*, 116508. [[CrossRef](#)]
26. Wu, X.; Xu, Y.; Xue, T.; Zhao, D.; Jiang, J.; Deng, Z.; Fu, X.; Li, X. Health State Prediction and Analysis of SOFC System Based on the Data-Driven Entire Stage Experiment. *Appl. Energy* **2019**, *248*, 126–140. [[CrossRef](#)]
27. Xue, T.; Wu, X.; Zhao, D.; Xu, Y.; Jiang, J.; Deng, Z.; Fu, X.; Li, X. Fault-Tolerant Control for Steam Fluctuation in SOFC System with Reforming Units. *Int. J. Hydrog. Energy* **2019**, *44*, 23360–23376. [[CrossRef](#)]