

## MODELING AND ANALYSIS

# Prognostics of a multistack PEMFC system with multiagent modeling

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**Abstract**

Current research on prognostics of PEMFC mainly focuses on one stack. However, in practice, the PEMFC stacks are assembled together to provide higher and more reliable power. In this paper, an original multiagent approach is proposed for predicting the remaining useful life-times of all stacks in a multistack PEMFC system. The predictions are updated dynamically by particle filtering when new stack loads are collected. The major contribution of the paper is not on degradation modeling of a single PEMFC, but on the cooperative prognostics of multiple PEMFC stacks in the same power system. A case study concerning a synthetic combined heat and power system with three PEMFC stacks is considered and the results show the effectiveness of the proposed approach.

**KEYWORDS**

Index Terms—multiagent approach, multistack system, particle filtering, PEM fuel cell, prognostics

## 1 | INTRODUCTION

High pollution of fossil energy motivates the development of renewable and environment-friendly energy sources. Fuel cells producing heat and electricity through chemical reactions are attracting the attention of industries and researchers in recent years. Among the different fuel cells types, Proton Exchange Membrane Fuel Cell (PEMFC) is the most developed one and is not far from large-scale deployment.<sup>1</sup> The chemical reaction between the hydrogen and oxygen in PEMFC produces electricity, heat, and water, with no poisonous gases emission.<sup>2</sup>

Unfortunately, PEMFC suffers a short life span, which makes it unsuitable for many applications.<sup>2</sup> The lifetime ranges from 1500 to 3000 hours, whereas the requirements

of mobile and stationary applications are around 5000 and 10 000 hours, respectively.<sup>3</sup> Besides mechanical and electronic improvements of PEMFCs, Prognostics and Health Management (PHM) can contribute to avoid irreversible degradation, extend lifetime, optimize service quality, and reduce maintenance costs.<sup>2</sup>

The approaches proposed in the literature for PHM of PEMFCs can be categorized into two classes: physics-of-failure based approaches and data-driven approaches.<sup>4-7</sup>

Physics-of-failure based approaches describe the physical relations among the different variables, for example, current, voltage, resistance, temperature, vapor transfer rate, by analyzing the chemical and physical reactions in the PEMFC.<sup>8,9</sup> Because of the complexity, multiphysics, multifailure, and multiscale characteristics of the PEMFC system, it is not

realistic to build a precise model of degradation and aging process. Empirical and simplified physical models are proposed in Refs 10-12 for modeling the degradation process. Extended Kalman filtering<sup>13,14</sup> and Particle Filtering (PF)<sup>15,16</sup> are two popular approaches for remaining useful life prediction based on the physical models. Data-driven approaches are also widely used for prognostics of PEMFC systems. Summation-wavelet extreme learning machine,<sup>17</sup> echo state network,<sup>18</sup> neural network,<sup>19</sup> relevance vector machine,<sup>20</sup> adaptive neuro-fuzzy inference system,<sup>21</sup> and ensemble<sup>17</sup> are some of the reported methods that have been adopted.

Proton Exchange Membrane Fuel Cell is normally used as a stack, where multiple cells are assembled together. The PEMFC stacks must be used together in transportation, space shuttle, Combined Heat and Power (CHP) systems, etc.<sup>22</sup> All previous works propose approaches for the prognostics of one PEMFC stack. In practice, however, one PEMFC stack provides limited power and may not be sufficient for industrial and civil applications. Also, its availability and reliability are relatively low as the damage of one cell can cause the stack failure. As a solution, multistack systems can be designed to provide higher and more reliable power. Applications of multistack systems in transportation are reported in Refs 23,24. However, works on prognostics of multistack system are very few. In Ref. 3 the authors try to maximize the Remaining Useful Life (RUL) of a multistack system, where the degradation of each stack is considered to be uniform and the same. A multistack system is also considered in Ref. 22 but, the prognostics is achieved separately for different stacks. Since the stacks are operated together for one same goal, their load and degradation may influence each other. Hence, it can be beneficial for the prognostics of one stack to consider the information of the other stacks.

In this paper, based on the degradation model proposed in Ref. 25 PF for the prognostics of one PEMFC stack with noisy load measurements is incorporated in a multiagent approach<sup>3,26</sup> for estimating simultaneously the RULs of multiple stacks in the same system. Each agent is modeled as a PF and performs the prognostics of one stack. And the different agents exchange information on their monitored load values at each time instance, to improve the likelihood of each particle in the PFs. To the best of the authors' knowledge, this is the first time that a systematic approach based on multiagent modeling is proposed for the prognostics of a multistack PEMFC system.

Due to the unavailability of real degradation data, a synthetic CHP system composed of three parallel PEMFC stacks is considered as case study. Results show that i) as expected, the PF can tackle effectively the noisy load measurements and ii) the proposed multiagent approach can estimate efficiently the RULs of multiple stacks, with superior results than individual PFs for one stack.

The remaining of the paper is structured as follows. The characteristics of the considered multistack PEMFC system

are described in Section II. The proposed approach is illustrated in Section III. Section IV describes the case study and analyses the experiment results. Some conclusions and perspectives are drawn in Section V.

## 2 | CHARACTERISTICS OF THE CONSIDERED MULTISTACK SYSTEM

### 2.1 | PEMFC stack degradation modeling

The degradation of a PEMFC stack can be modeled by data-driven and physics-of-failure based models.<sup>1,27</sup> In this work, a simplified physical model derived from a bond graph model for a PEMFC stack is adopted.<sup>25</sup> Bond graph can describe systematically a highly nonlinear and complex thermochemical system and it has been used for developing supervision and fault detection approaches.<sup>28</sup> A physical model relating the stack output voltage  $V_t$  and load current  $I_t$  can be obtained from the bond graph of a PEMFC stack.<sup>25</sup> As an electrochemical converter, the physics-based bond graph includes electrical system, thermal convection, thermal conduction, the hydraulic phenomenon, and the chemical reaction.<sup>25</sup> Mathematically, the relation between the PEMFC characteristics and the output voltage is expressed as

$$V_t = n_s (E_{0,t} - R_{ohm,t} I_t - AT \ln (I_t / I_{0,t}) - BT \ln (1 - I_t / I_{L,t})) \quad (1)$$

with  $n_s$  being the number of cells,  $E_{0,t}$  being the open circuit voltage at nominal pressure and temperature,  $R_{ohm,t}$  being the global resistance including membranes, connectors, end plates, etc.,  $I_{0,t}$  being the exchange current,  $I_{L,t}$  being the limiting current (maximal output current),  $A$  being the activation constant,  $B$  being the diffusion constant, and  $T$  being the operation temperature.

The continuous operation time is discretized with time step  $\Delta t$ . For each discretized time, the Levenberg-Marquardt method can extract the values of the parameters  $E_{0,t}$ ,  $R_{ohm,t}$ ,  $I_{0,t}$ , and  $I_{L,t}$ . The time evolution of the four parameters is shown in Figure 1 from Ref. 25 estimated from real PEMFC degradation data. Significant changes of  $I_{L,t}$  and  $R_{ohm,t}$  are observed, both following approximately a linear trend. On the other hand,  $E_{0,t}$  and  $I_{0,t}$  remain nearly constant. Thus, in the physical model considered in this work, the open circuit voltage  $E_{0,t}$  and the exchange current  $I_{0,t}$  are assumed to be constant during the degradation process and always equal to the nominal values  $E_{0,n}$  and  $I_{0,n}$ . Denoting the nominal values of the global resistance and limiting current  $I_{L,n}$  and  $R_{ohm,n}$ , their evolution can be described by a time-dependent parameter  $\alpha_t$ , as shown in Equation (2-4):

$$R_{ohm,t} = R_{ohm,n} (1 + \alpha_t) \quad (2)$$

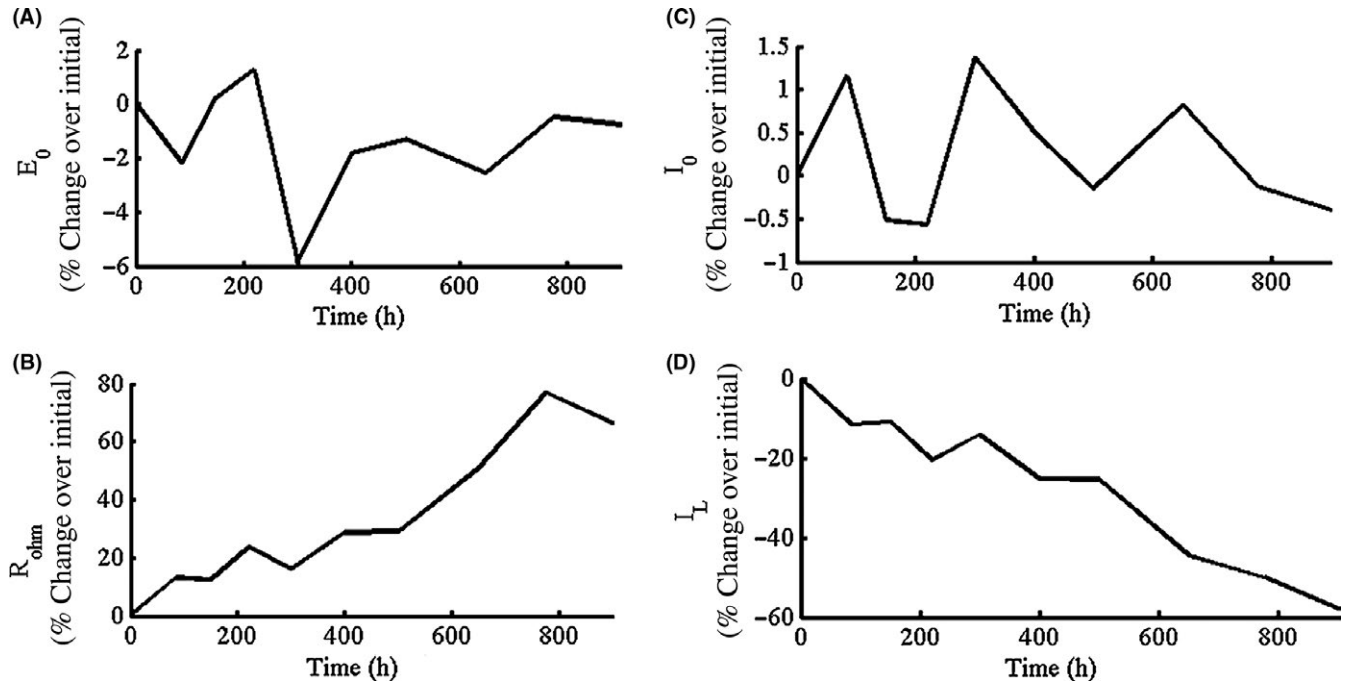


FIGURE 1 Deviation of  $E_{0,t}$ ,  $R_{ohm,t}$ ,  $I_{0,t}$  and  $I_{L,t}$  during the degradation process of a PEMFC<sup>25</sup>

$$I_{L,t} = I_{L,n} (1 - \alpha_t) \quad (3)$$

$$\alpha_t = \beta t + \nu_t \quad (4)$$

with  $\beta$  being the constant rate of change and  $\nu_t$  the process noise  $N(0, \sigma_{\nu}^2)$ .

Power conservation implies that Equation (1) can be rewritten as

$$V_t = n_s (R_{ohm,n} \alpha_t I_t - AT \ln(1 - I_t / I_{L,n}) + BT \ln(1 - I_t / I_{L,n} (1 - \alpha_t))) \quad (5)$$

More details on the model in Equation (5) can be found in Ref. 25. This simplified model has been verified to describe well the degradation process of a PEMFC.<sup>11,12,25</sup> Thus, it is used in Section IV for generating synthetic degradation data for the case study. For a real PEMFC, the value of  $\beta$  can be estimated with maximum likelihood estimation using Equation (5).

## 2.2 | Multistack PEMFC system

As explained in the Introduction, multistack systems are integrated for providing more reliable and higher power supply. Multiple stacks in a power system can be arranged in parallel, series or parallel-series.<sup>23</sup> The output of a multistack system can be current, power, and voltage. Without limiting the applicability of the proposed approach, the multistack system considered in this paper is supposed to be composed of three parallel PEMFC stacks.

A simplified architecture of the considered system is shown in Figure 2. At each time instance  $t$ , the output power

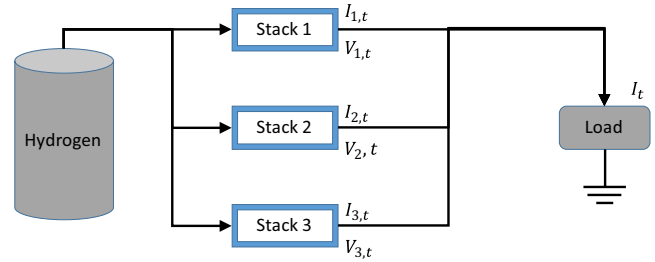


FIGURE 2 Architecture of the considered multistack system

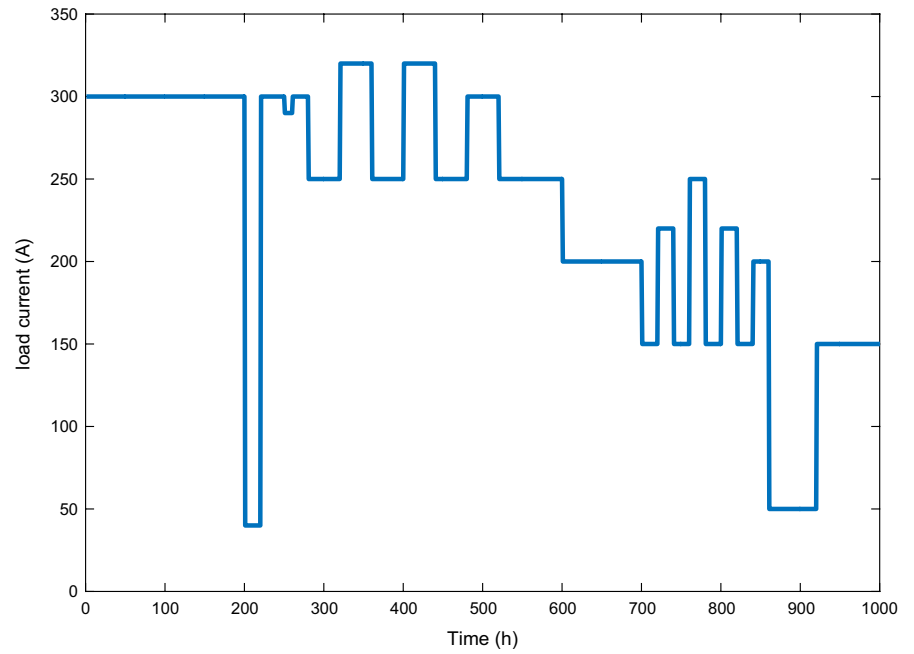
(current  $I_{i,t}$  and voltage  $V_{i,t}$ , for  $i=1,2,3$ ) of each stack is monitored by sensors. The measured output power ( $I_{i,t}^m$  and  $V_{i,t}^m$ ) is the true output power ( $I_{i,t}$  and  $V_{i,t}$ ) with added noise, as shown in Equation (6-7). Without limiting the applicability of the proposed approach, noise is supposed to follow a Gaussian distribution. The sum of the currents of all the stacks are always equal to the total load current, as shown in Equation (8).

$$I_{i,t}^m = I_{i,t} + \eta_{i,t} \text{ and } \eta_{i,t} \sim N(0, \sigma_{\eta_{i,t}}^2), i=1,2,3 \quad (6)$$

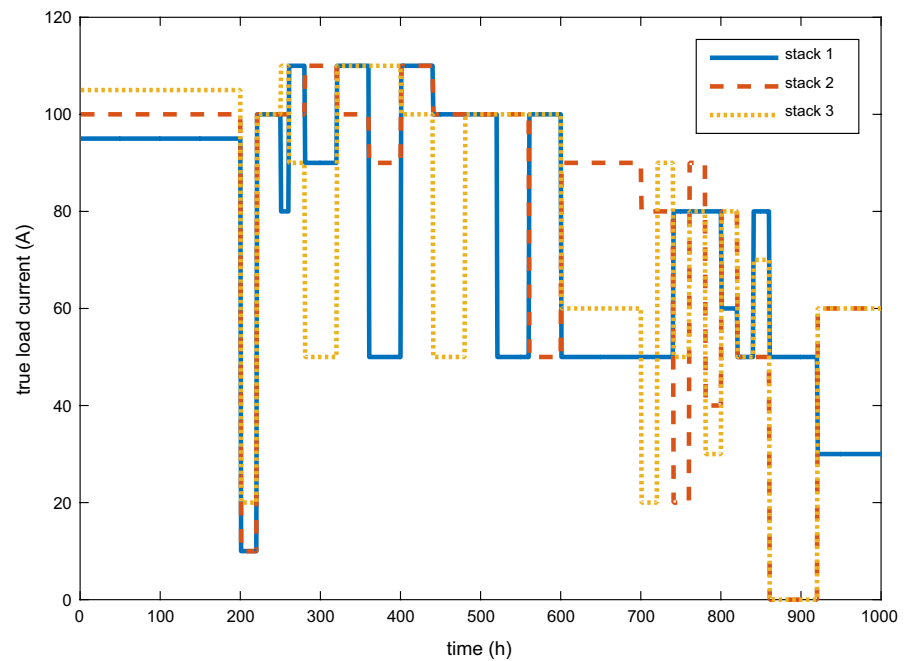
$$V_{i,t}^m = V_{i,t} + \omega_{i,t} \text{ and } \omega_{i,t} \sim N(0, \sigma_{\omega_{i,t}}^2), i=1,2,3 \quad (7)$$

$$I_{1,t} + I_{2,t} + I_{3,t} = I_t \quad (8)$$

For delivering a demanded load, each stack can deliver an output current within the interval  $[0, I_{L,i,t}]$ , with  $I_{L,i,t}$  the limiting current of the stack  $i$  at time  $t$ . Stop-and-start of PEMFC



**FIGURE 3** Total load demand of the CHP system for the experiments



**FIGURE 4** True load current of each stack for the experiments

stack inducing considerable damage and premature ageing<sup>10</sup> is not considered in this work.

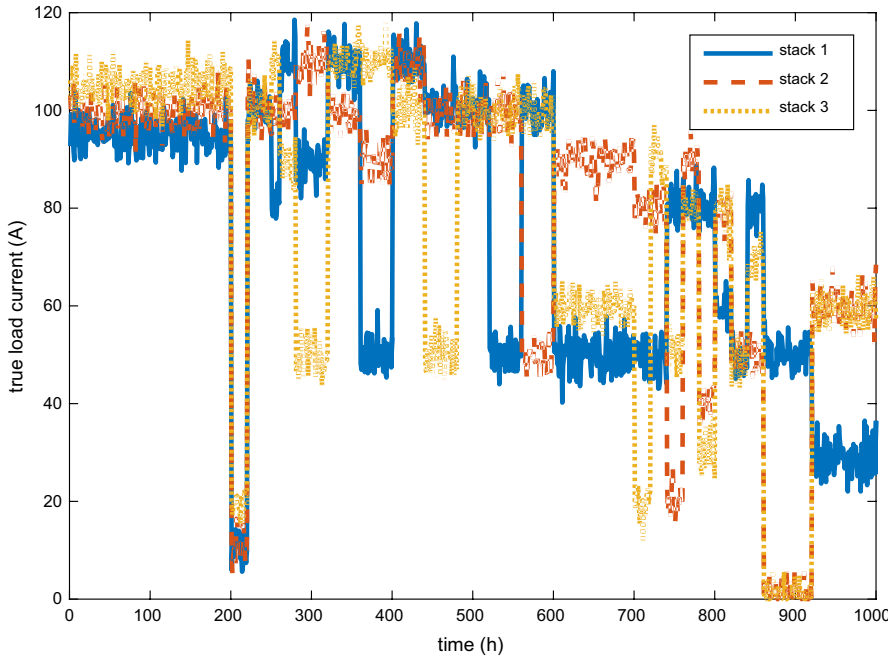
### 3 | PROPOSED APPROACH FOR MULTISTACK PEMFC SYSTEM

In this paper, uncertainties of the monitored outputs of a PEMFC stack are considered. In this section, the prognostics of a PEMFC stack with uncertain load is considered for the first time. Then, a PF-based multiagent

approach is proposed for the prognostics of a multistack PEMFC system.

#### 3.1 | Prognostics of a PEMFC stack with uncertain load using PF

In Equation (5), the only unknown parameter is  $\alpha$ , and one can observe from Equation (4) that its value depends on the unknown constant  $\beta$ . By adding an associated process noise  $\nu_k \sim N(0, \sigma_k^2)$ , it can be expressed as



**FIGURE 5** Monitored load current of each stack for the experiment

$$\alpha_k = \alpha_{k-1} + \beta \Delta t + \nu_k \quad (9)$$

where  $k$  being the discretized time starting from zero and  $t = k * \Delta t$ .

Denoting that  $x_k = [\alpha_k \ \beta]$ , the state equation can be represented as

$$x_k = f(x_{k-1}, \nu_k) = x_{k-1} \begin{bmatrix} 1 & 0 \\ \Delta t & 1 \end{bmatrix} + [\nu_k \ 0] \quad (10)$$

By Equation (5-7), the observation equation can be expressed as

**TABLE 1** Stack characteristics for the experiment

Symbol	Physical meaning	Value
$n_s$	Number of cells	8
$S$	Surfaces	220 cm <sup>2</sup>
$T$	Temperature	80 °C
$P_{H_2}, P_{O_2}$	Anode and cathode absolute pressure	1.5 bar
$Rh$	Relative humidity anode/cathode	50%
$I_{L,n}$	Maximal current at time $t = 0$	170 A
$\beta$	Parameter characterizing the degradation speed	
$\sigma_\nu^2$	Variance of the process noise of $\alpha_t$	$4 * 10^{-8}$
$\sigma_\eta^2$	Variance of the measured load current noise	9
$\sigma_\omega^2$	Variance of the measured voltage noise	0.09
$\alpha_{EoL}$	Failure threshold of the PEMFC stack	0.15
$R_{ohm,n}$	General resistance at time $t=0$	0.3 Ω

$$V_k^m = g(x_k, \omega_k, I_k^m) = n_s (R_{ohm,n} x_k(1) I_k^m - A T \ln(1 - I_k^m / I_{L,n}) + B T \ln(1 - I_k^m / I_{L,n} (1 - x_k(1)))) + \omega_k \quad (11)$$

$$I_k^m = I_k + \eta_k \text{ and } \eta_k \sim N(0, \sigma_{\eta_k}^2) \quad (12)$$

Note that the difference from the previous work using PF is that the uncertain measurements of a PEMFC considered in this work include the voltage and current, as shown in Equations (11) and (12). The state equation and observation equation define a Bayesian tracking system<sup>29</sup> given the initial state distribution  $p(x_0 | V_0^m, I_0^m) = p(x_0)$  and the independent monitored current and voltage values until time  $k_0$ . Because of the noise distribution and nonlinear relation between  $x_k$  and  $[V_k^m, I_k^m]$ , the optimal solution can not always be found analytically. PF approaches can give an approximate solution. A PF-based prognostic approach is composed of two main steps: state of health estimation and RUL prediction.

### 3.2 | State of health estimation

A number  $N_{PF}$  of particles are generated from the initial state distribution  $p(x_0 | V_0^m, I_0^m)$ . The weight of each particle  $w_o^j$  for  $j=1, \dots, N_{PF}$  is proportional to its probability density and  $\sum_{j=1}^{N_{PF}} w_o^j = 1$ . Then, for each observation time  $t$  between 1 and

$T$ , the state of health estimation follows three steps:

1. **Prediction:** Each particle  $x_{k-1}^j$ , for  $j=1, \dots, N_{PF}$  at time  $k-1$  is propagated to one particle  $x_k^j$  at time  $k$  by the state equation (11). The weight of  $x_k^j$  inherits that of  $x_{k-1}^j$  that is,  $w_k^j = w_{k-1}^j$ .

2. *Update*: As the measurements  $[V_k^m, I_k^m]$  at time  $k$ , the weight of each particle  $x_k^j$  is updated based on the likelihood of  $V_k^m$  as follows

$$w_k^j = w_k^j * p(V_k^m | x_k^j), \tag{13}$$

$$w_k^j = w_k^j / \sum_{j=1}^{N_{PF}} w_k^j \tag{14}$$

If the load current of the stack  $I_k$  is precisely known, the value  $p(V_k^m | x_k^j)$  in Equation (13) can be calculated with Equation (11). For the case of uncertain output current, the value  $p(V_k^m | x_k^j)$  should be calculated with

$$p(V_k^m | x_k^j) = \int_0^{I_{L,n}(1-\alpha_k^j)} p(V_k^m | x_k^j, I_k) * p(I_k | I_k^m) dI_k \tag{15}$$

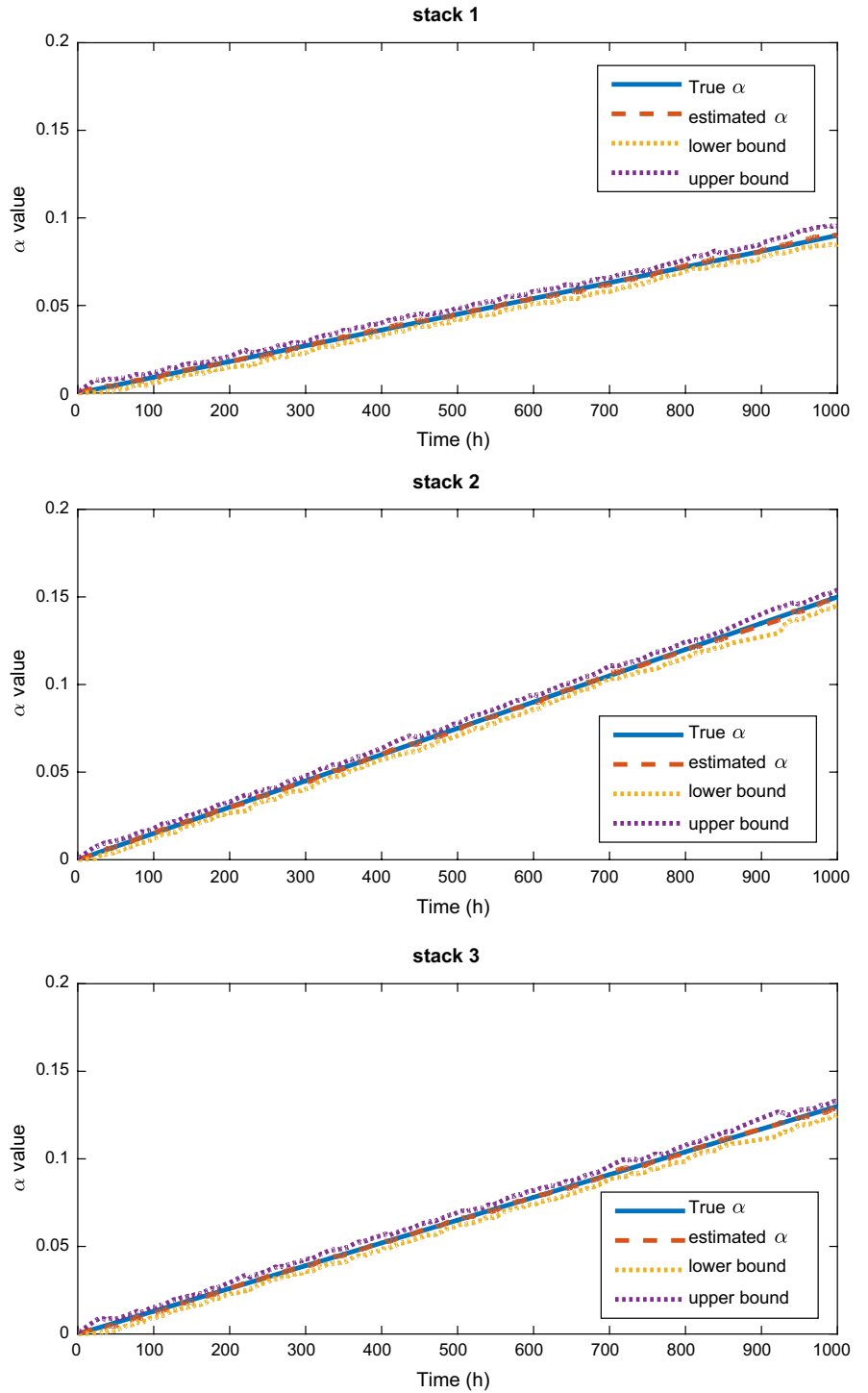


FIGURE 6 Estimated  $\alpha$  value with 90% confidence interval

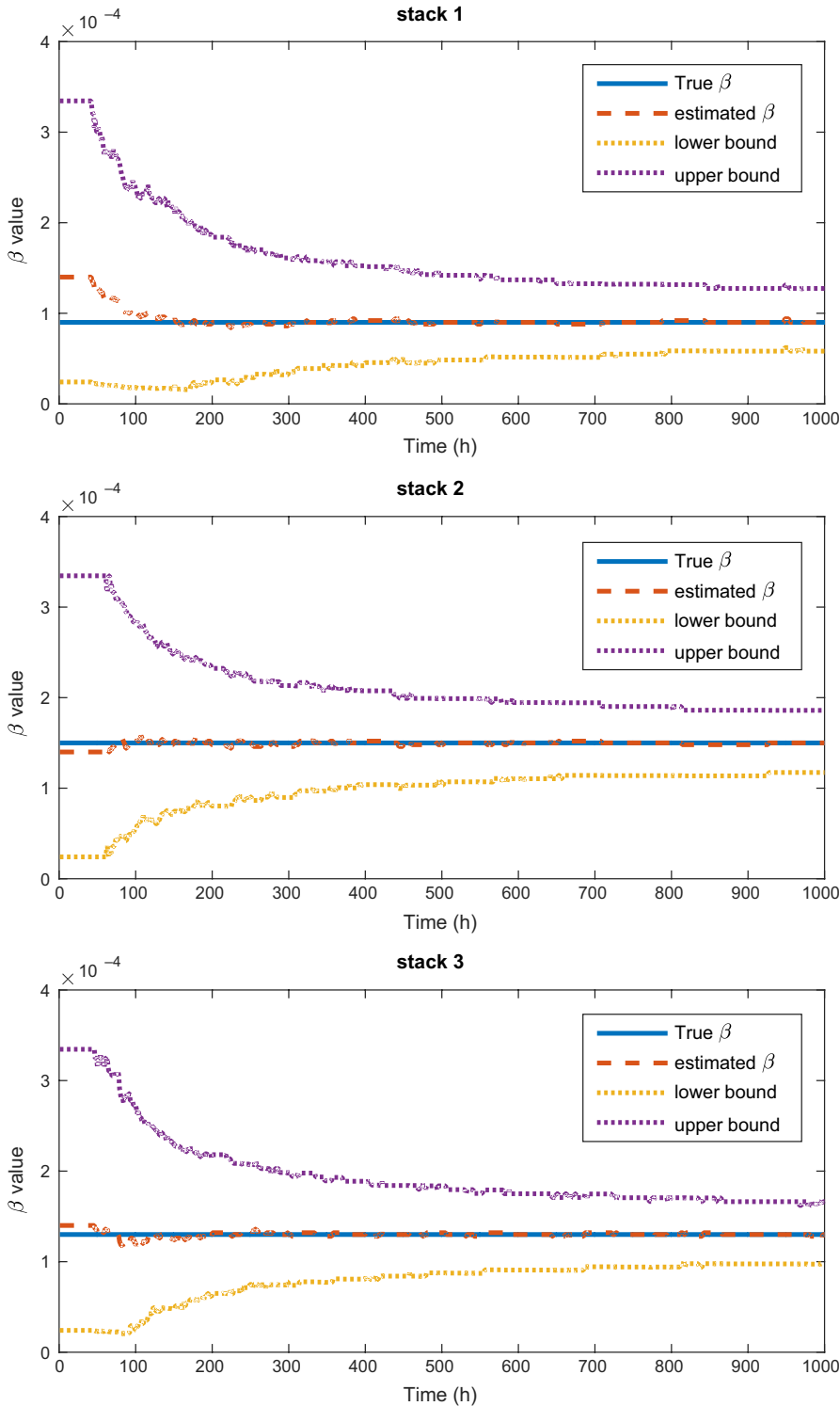
where  $I_{L,n}(1-\alpha_k^j)$  is the limiting current at time  $k$  for particle  $x_k^j$ , and  $p(V_k^m|x_k^j, I_k)$  and  $p(I_k|I_k^m)$  can be obtained from Equations (11) and (12), respectively.

3. *Resampling*: Repeating the previous steps for a number of iterations may skew the distribution of particles by observing that only one particle has non-negligible weight.<sup>30</sup> In this work, a systematic resampling algorithm is implemented

for its low computational burden.<sup>31</sup> Details can be found in the related reference and many other papers.

### 3.3 | RUL prediction

With the monitored data until time  $k_0$ , the RUL of a PEMFC stack is the time left before its health indicator reaches a predefined threshold. Different health indicators can be defined, for example,



**FIGURE 7** Estimated  $\beta$  value with 90% confidence interval

the output power, the cumulative energy, the efficiency with respect of the current.<sup>1</sup> In this paper the end of life is defined as the time that the value of  $\alpha_k$  reaches a predefined threshold  $\alpha_{\text{EoL}}$ .

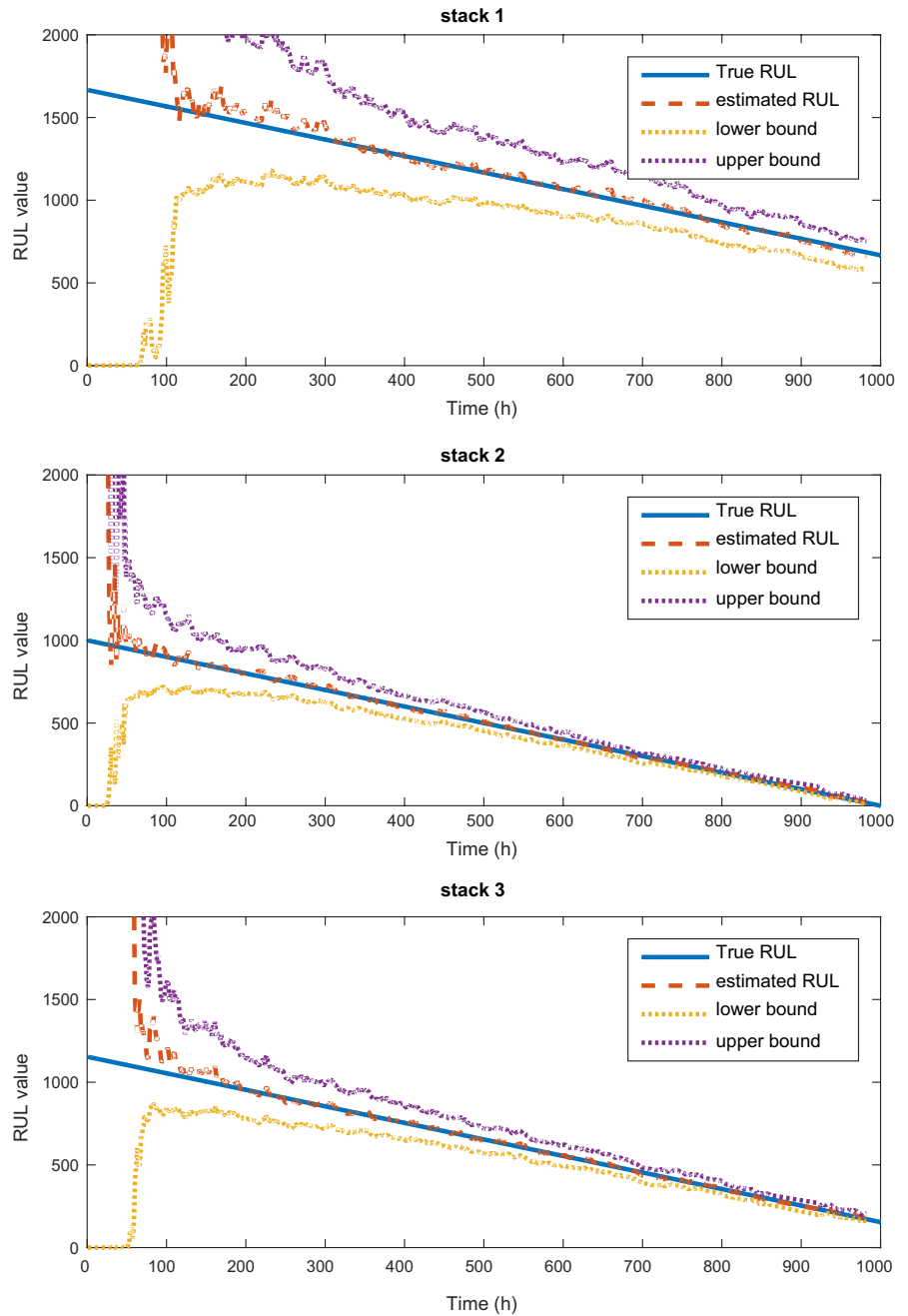
For each particle  $\alpha_T^j$  at time  $k_0$ , it can be propagated with Equation (9) until the end of life,  $\alpha_{k_{\text{EoL}}}^j \geq \alpha_{\text{EoL}}$ . The RUL given by the particle  $\alpha_k^j$  is noted as  $\text{RUL}^j = k_{\text{EoL}} - k_0$  and the corresponding probability density function of the RUL of the stack is obtained as

$$p\left(\text{RUL}_{k_0}^j | V_{1:k_0}^m, I_{1:k_0}^m\right) \approx \sum_{j=1}^{N_{\text{PF}}} w_{k_0}^j \delta_{\text{RUL}^j}(d\text{RUL}^j) \quad (16)$$

where  $\delta_{\text{RUL}^j}(d\text{RUL}^j)$  denotes the Dirac delta function located at  $\text{RUL}^j$ .

### 3.4 | Prognostics of a multistack PEMFC system

The prognostics of a multistack PEMFC system can be approached by performing the prognostics of each stack individually, as in Ref. 22. However, dependencies may exist between different stacks, for example, because of similar degradation process or functional dependencies. In this paper, the sum of the load currents of different stacks should satisfy the relation in Equation (8). In case of dependencies, it would be beneficial to take them into account during the prognostics. Multiagent approaches offer an adequate framework to do so, where different agents collaborate with each other to



**FIGURE 8** Estimated RUL value with 90% confidence interval



realize their own objectives (i.e., prognostics of the PEMFC stack, in this paper).<sup>26</sup>

In this work, one agent using the PF in Section IIIA is formulated for the prognostics of each PEMFC stack. For the considered system presented in Section IIB, three agents are formulated. With distributed computation, these agents can work in parallel. The difference between an individual PF for prognostics in Section IIIA and a multiagent system lies in the calculation of the likelihood. The agents in the proposed multiagent system are not working independently. Each time the monitored data of these stacks output are available, these agents exchange their monitored current values and, thus, each stack knows the monitored current values of all the stacks in the system. The likelihood of the particle  $x_{i,k}^j$  of the stack  $i, i = 1, 2, 3$  is, then, calculated as

$$p\left(V_{i,k}^m | x_{i,k}^j\right) = \int_0^{\min(I_k, I_{L,n}(1-\alpha_{i,k}^j))} p\left(V_{i,k}^m | x_{i,k}^j, I_{i,k}\right) * p\left(I_{i,k} | I_{1,k}^m, I_{2,k}^m, I_{3,k}^m\right) dI_{i,k} \quad (17)$$

where the index  $i$  indicates the  $i$ -th stack.

The difference between Equations (15) and (17) is that in (17) the a posterior probability density function of  $I_{i,k}$  is dependent not only on the monitored current load of stack  $i$  but also on the values of the other stacks, because their current loads should satisfy the relation in Equation (8). The posterior probability density function  $p\left(I_{i,k} | I_{1,k}^m, I_{2,k}^m, I_{3,k}^m\right)$  in Equation (17) for example, for  $i = 1$  is calculated as

$$p\left(I_{1,k} | I_{1,k}^m, I_{2,k}^m, I_{3,k}^m\right) = p\left(I_{1,k} | I_{1,k}^m\right) * p\left(I_{2,k} + I_{3,k} = I_k - I_{1,k} | I_{2,k}^m, I_{3,k}^m\right) \quad (18)$$

**TABLE 2** Root mean squared error of the results given by single PF and multiagent approach for small measurement noise

	Single PF in section IIA	Multiagent approach in Section IIB
Estimated current		
Stack 1	3.07	2.46
Stack 2	2.98	2.40
Stack 3	2.98	2.41
$\alpha$		
Stack 1	$7.26 * 10^{-4}$	$7.13 * 10^{-4}$
Stack 2	$6.33 * 10^{-4}$	$6.18 * 10^{-4}$
Stack 3	$6.24 * 10^{-4}$	$6.00 * 10^{-4}$
RUL		
Stack 1	70.43	68.04
Stack 2	12.37	11.70
Stack 3	23.11	22.34

where  $I_k$  is the total load of the multistack system at discrete time  $k$ .  $p\left(I_{2,k} + I_{3,k} = I_k - I_{1,k} | I_{2,k}^m, I_{3,k}^m\right)$  is calculated as

$$p\left(I_{2,k} + I_{3,k} = I_k - I_{1,k} | I_{2,k}^m, I_{3,k}^m\right) \approx \int_{I_{2,k}=0}^{\min(I_{L,n}(1-\alpha_{2,k}), I_k - I_{1,k})} p\left(I_{2,k} | I_{2,k}^m\right) * p\left(I_{3,k} = I_k - I_{1,k} - I_{2,k} | I_{3,k}^m\right) dI_{2,k} \quad (19)$$

where  $\alpha_{2,k}$  is the estimated value of  $\alpha_k$  in Equation (4) of stack 2 at time  $k$ .

Similarly, posterior probability densities  $p\left(I_{2,k} | I_{1,k}^m, I_{2,k}^m, I_{3,k}^m\right)$  and  $p\left(I_{3,k} | I_{1,k}^m, I_{2,k}^m, I_{3,k}^m\right)$  can be derived based on the exchanged information. After the tack state of health estimation, each agent follows the same RUL prediction process in Section IIIA.

## 4 | EXPERIMENTS AND DISCUSSIONS

In the experiment, due to the unavailability of PEMFC degradation data, a synthetic CHP system composed of three stacks is considered, following the degradation model described in Section II. The system has been operated for 1000 hours before failure. The failure of one stack can cause the failure of the system. The total load demand of the CHP system and the true load current of each stack are shown in Figures 3 and 4, respectively. The load demand is given by the authors. The monitored load current of each stack is shown in Figure 5. The value of  $\alpha_0$  is set to 0 and  $\beta$  has equal probability to take the values in interval  $[0 \ 3 * 10^{-4}]$  at time 0.

For the experiment, the characteristics of the three stacks are the same as in Table 1, except that the degradation rate  $\beta$  of the three stacks are  $9 * 10^{-5}$ ,  $15 * 10^{-5}$ , and  $13 * 10^{-5}$ , respectively. The true values of  $\beta$  are known in this synthetic experiment, but for a real PEMFC system, it needs to be

**TABLE 3** Root mean squared error of the results given by single PF and multiagent approach for large measurement noise

	Single PF in section IIA	Multiagent approach in Section IIB
Estimated current		
Stack 1	5.77	4.71
Stack 2	5.79	4.74
Stack 3	5.68	4.54
$\alpha$		
Stack 1	$1.05 * 10^{-3}$	$9.39 * 10^{-4}$
Stack 2	$1.26 * 10^{-3}$	$1.01 * 10^{-3}$
Stack 3	$9.93 * 10^{-4}$	$7.73 * 10^{-4}$
RUL		
Stack 1	60.91	52.54
Stack 2	22.27	21.52
Stack 3	26.87	21.28

estimated with the monitoring data. Thus, the RULs of the three stacks with a threshold  $\alpha_{\text{EoL}} = 0.15$  are 1667, 1000, and 1154, respectively. The variances of measurement noises are set according to the work in Refs 1 and 13. The noise level is set to be higher than in the corresponding references to show more clearly the online estimation process.

#### 4.1 | Prognostic results of the proposed multiagent approach

One agent based on PF is formulated for the prognostics of each stack. The likelihood is a posterior probability of each particle given the monitored current and voltage values of all the three stacks. The estimated values of  $\alpha$ ,  $\beta$ , and RUL of each stack are shown in Figures 6, 7, and 8, respectively. It is observed that the proposed approach gives satisfactory accuracy after  $t = 100$ . For the first 100 hours, the prediction interval with 90% confidence level is very large, as the distribution of  $\beta$  at  $t = 0$  is supposed to be uniform over the interval  $[0, 3.2 \times 10^{-4}]$  and, thus, it is difficult to estimate the true  $\beta$  value with few data points. The convergence and stability of the proposed method are shown clearly in these figures.

#### 4.2 | Comparison with the results of an individual PF

As mentioned in Section II, for the case of uncertain load current of PEMFC stack, the likelihood can be calculated as Equation (15) using a single PF in Section IIA or as Equation (17) using the proposed multiagent approach in Section IIB. The difference lies in the available prior knowledge. For a single PF, the prior knowledge is only the monitored current of the corresponding stack, whereas in a multiagent approach each PF (agent) has the monitored current values of all the stacks. The comparison of the two approaches is shown in Table 2, with reference to the Root Mean Squared Error (RMSE) of the estimated current,  $\alpha$ , and RUL ( $t > 100$ ) of each stack. The estimated load current of stack  $i$  at time  $T$  is calculated as

$$\widehat{I}_{i,k} = \int I_{i,k} P(I_{i,k} | I_{i,k}^m) dI_{i,k} \quad (20)$$

$$\widehat{I}_{i,k} = \int I_{i,k} P(I_{i,k} | I_{1,k}^m, I_{2,k}^m, I_{3,k}^m) dI_{i,k} \quad (21)$$

for the single PF and multiagent approaches, respectively.

The comparison of the RMSE of the estimated current in Table 2 clearly shows that the estimated load current given by Equation (21) is closer to the true load current than that of Equation (20). It is also shown that the proposed approaches in Section III work well for the prognostics of the PEMFC stack with noisy load measurements. The proposed multiagent

approach gives better results than a single PF which considers only the monitored load of the corresponding stack.

Another experiment has been carried out with large measurement noise, that is  $\sigma_v^2 = 0.25$  and  $\sigma_\eta^2 = 36$ . The results are shown in Table 3. One can observe that the proposed multiagent approach gives significantly better results than single PF. In comparison with the results in Table 2, it can be concluded that both the multiagent approach and single PF tackle well the situation with small measurement noise, whereas the proposed method also performs well in the situation of large measurement noise and is less sensitive to the measurement noise.

The computational time for a single PF of one stack is 16 h 21 min and that of the multiagent approach for the whole system is about 18 h 42 min, by using distributed computation. The calculation is carried out with 70 parallelized tasks on an SGI® UV™ 30 server (72 cores, 2.1-2.6GHz, 60G memories).

## 5 | CONCLUSION

Proton Exchange Membrane Fuel Cell is an alternative choice of environment friendly energy source. Current research on the prognostics focuses mostly on one PEMFC stack, whereas, research on multistack PEMFC systems is very limited.

In this paper, PF is firstly used for tackling the of one PEMFC stack with noisy load measurements. Then, a multiagent approach based on PF is proposed for the prognostics of a multistack PEMFC system. The different agents in the multiagent approach exchange the monitored load current values to improve the accuracy of the estimated load of each stack.

A case study concerning a synthetic CHP system made of three parallel PEMFC stacks is implemented. The results show that the proposed multiagent approach captures well the values of  $\alpha$ ,  $\beta$ , and RUL for each stack, after a sufficient amount of monitored data becomes available. In comparison with the single PF proposed for one stack with uncertain load, the multiagent approach gives better results.

In this work, the communication of different agents is limited to the exchange of monitored load values. In the future, other useful information on the estimated  $\alpha$ ,  $\beta$ , and RUL could also be shared among the agents, if the stacks have a certain kind of physical dependencies. Only PF method with one physical model is considered in the current work. More work needs to be done for data-driven methods and other degradation models.

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## NOMENCLATURE

$A$	activation constant
$\alpha_{EoL}$	failure threshold of the PEMFC stack
$B$	diffusion constant
$E_{0,t}$	open circuit voltage at nominal pressure and temperature
$\sigma^2$	noise variance of load current measurement
$\sigma_{i,t}^2$	noise variance of voltage measurement
$I_{0,t}$	exchange current
$I_{L,t}$	limiting current
$I_{i,t}^m$	load current measurement of the $i$ -th stack at time $t$
$I_t$	total load current at time $t$
$n_s$	number of cells in one stack
$p(A B)$	conditional probability of A given B
$R_{ohm,t}$	global resistance
$RUL$	remaining useful life
$T$	operation temperature
$V_t$	stack output voltage
$V_{i,t}^m$	voltage measurement of the $i$ -th stack at time $t$

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