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Particle Filtering for Prognostics of a Newly Designed Product With a New Parameters Initialization Strategy Based on Reliability Test Data

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ABSTRACT In particle filtering-based prognostic methods, state and observation equations are used in which one or more parameters are uncertain. These parameters are estimated with collected monitoring data. The choices of the initial value ranges and distributions of the unknown parameters in the state and observation equations influence the performance of the particle filtering approaches, in terms of convergence, speed, and stability of prognostic results. For new products with little or even no degradation process data, uniform distributions over experience-based value ranges are the most common choice for parameters initialization. In this paper, the failure times' data collected during reliability tests executed before volume production are used for defining the initial value ranges and distributions of uncertain parameters. This is expected to increase the convergence speed of the parameters estimation with monitored data and to reduce the uncertainty of the predicted remaining useful life. Numerical experiments on synthetic degradation processes of PEM fuel cells and lithium-ion batteries are considered. The convergence speed of the parameters estimation and the sensitivity of the proposed method to the duration and number of product samples in the reliability tests are analyzed. Comparisons with particle filtering methods with standard initialization are also carried out to verify the effectiveness of the proposed new strategy for parameters initialization.

INDEX TERMS Prognostics, remaining useful life, particle filtering, parameters initialization, reliability test, failure times data.

I. INTRODUCTION

Prognostics aim at predicting the future evolution of a fault indicator of an equipment of interest, for estimating its Remaining Useful Life (RUL) [1]. Data-driven and PoF (Physics-of-Failure)-based methods are used for RUL prediction. For a newly designed product, little or even no degradation process data is available. Methods based on PoF models derived from failure mechanisms are, then, more suitable [24], [25]. However, in the PoF-based models there are uncertain parameters that need to be estimated with the monitoring data collected during online observation of the equipment.

In recent years, Particle Filtering (PF), a sequential Monte Carlo method for prognostics of nonlinear and/or non-Gaussian degradation processes [1], has become popular among researchers and engineers. Such method suits well the cases where equipment degradation state and observation equations are available, although with one or multiple uncertain parameters to be estimated with monitoring data [2]. PF has been successfully applied for prognostics of electronic products [3], [4], [5], mechanical systems [6], [7], batteries [2], [8], [9], mechatronic systems [10], [11], electric units [12], electrochemical devices [13], etc.

Starting from initial parameters value ranges and distributions over these ranges at initial time (named as parameters initialization in this paper), PF can progressively approach the true values of the uncertain parameters in the state and observation equations. The parameters initialization is crucial

for the convergence and stability of the prognostic results given by PF [6], [14]. Normally, in the literature the parameters value ranges are assigned by experts or determined by fitting historical degradation process data describing the time-dependent degradation level of the equipment of interest. As defining the initial distributions of the unknown parameters over the value ranges, different ways are available. One common way is fitting the available degradation process data [3]–[5], [8], which can come from the monitoring of the equipment [3] or from simulation of its degradation processes [5]. For cases without available degradation process data, e.g. for a newly designed product, the uniform distribution over the assumed value range is the most common choice [7], [9], [15]. Expert knowledge may also help defining the initial parameters distributions [14]. In [16], Gamma, deterministic and normal distributions for parameters initialization are discussed and compared.

In this paper, the parameters initialization for a newly designed product is considered. It is assumed that no historical degradation process data and limited expert knowledge are available for parameters initialization. This assumption is quite general for new equipment for which it is difficult to collect enough degradation process data for parameters initialization. To the best knowledge of the authors, uniform distributions over expert-informed value ranges is the only choice for parameters initialization in the published work on these cases [15], [17], [18]. However, such parameters initialization strategy may slow the convergence speed of the estimated parameters values or even bias the convergence of the prognostic results during the online prediction process. As indicated in [15], an improper initialization on the parameters value range may damage the overall performance of a PF. Thus, in this paper, a new strategy for parameters initialization is proposed considering failure times data from reliability tests. Before an equipment is put into volume production, reliability tests are performed to verify the reliability of the equipment. During these tests, a number of equipment samples are tested for a predefined period, which may fail or survive the test. Based on the failure times data, the equipment reliability can be derived [19]. In this paper, a Monte Carlo-based approach is proposed for the parameters initialization, using the failure times data obtained during the reliability tests. The likelihoods of the values of each unknown parameters combination with respect to the collected failure times data are calculated and the prior distribution of these parameters is obtained. From this, one can set the proper parameters initialization with a predefined confidence level. The benefits of the proposed framework include better parameters initialization, higher stability and lower uncertainty of the predicted RUL, than obtained with the conventional uniform distribution over expert-informed value ranges.

The proposed method is verified on simulated case studies concerning PEM fuel cell and lithium-ion battery degradation. Comparisons with PF using conventional parameters initialization are carried out. The sensitivity of the proposed method to the number of test product samples and duration of the reliability tests is also discussed.

The rest of the paper is structured as follows. Section 2 first reviews briefly the PF method and reliability test concept, followed with details of the proposed method for parameters initialization. Case studies concerning the prognostics of a PEM fuel cell and a Li-ion battery are illustrated in Section 3 with results analysis and comparisons. Some conclusions are drawn in Section 4.

II. METHODOLOGY

In this Section, the PF method and reliability test concept are briefly reviewed at the beginning to make the content self-contained. Further details can be found in related references, such as [20] and [21] etc. Then, the proposed method for parameters initialization is presented.

A. PARTICLE FILTERING

During the design process of a product, Failure Modes, Mechanism and Effect Analysis (FMMEA) may help building the relation between product degradation and the influencing factors [22]. Thus, even for new products, a degradation model can be available. With a known degradation model (state equation) and a measurement model (observation equation), PF can be widely used for prognostics. prognostic process can be divided into two main steps: state estimation and RUL prediction.

The following assumptions are made for the illustration of the PF method:

1) The state equation can be represented as a first-order Markov process, i.e. the equipment state x_t at time t is only dependent on state x_{t-1} at previous time t − 1. The state equation describing the relation of the state (normally degradation state) at subsequent discretized time instances is expressed as:

$$x_t = f_{t-1}(x_{t-1}, \boldsymbol{\theta}_{t-1}, \omega_{t-1}), \tag{1}$$

with ω_{t-1} being a noise of known distribution and f_{t-1} being a known transition function with uncertain parameters $\boldsymbol{\theta}_{t-1}$. The variables ω_{t-1} and $\boldsymbol{\theta}_{t-1}$ can be time-variant or invariant. In this work, without restricting the generality of the proposed method, these parameters, i.e. f_{t-1}, ω_{t-1} and $\boldsymbol{\theta}_{t-1}$ are supposed to be time-invariant. The unit of the discretized time is arbitrary.

2) The equipment state can not always be precisely and/or directly measured. The relation between the true state and the measurement at time t is modeled as follows:

$$z_t = g_t(x_t, v_t), \tag{2}$$

with the measured value z_t being dependent only on x_t and a random noise v_t. The observation equation g_t and the noise v_t are supposed to be known and time-invariant in this work.

Measurements $\boldsymbol{Z}_{1:t} = [z_1, z_2, \ldots, z_t]$ from time 1 to t are available at time t. The objective of PF is to estimate the current degradation state x_t and the RUL of a product at time t.

1) STATE ESTIMATION

The state x_t at the current time t can by estimated by constructing the posterior Probability Density Function (PDF) $p(x_t \mid \boldsymbol{Z}_{1:t})$. Two steps, i.e. prediction and update, are performed.

Supposing that the posterior PDF $p(x_{t-1} \mid \boldsymbol{Z}_{1:t-1})$ at time $t-1$ is known, we build a sequential calculation process. The prediction step calculates the prior distribution of x_t using (1) and the Chapman-Kolmogorov equation, as follows:

$$p(x_t \mid \boldsymbol{Z}_{1:t-1}) = \int p(x_t|x_{t-1})p(x_{t-1}|\boldsymbol{Z}_{1:t-1})dx_{t-1}. \quad (3)$$

with $p(x_t|x_{t-1})$ being the conditional probability given by (1).

When a new measurement z_t is available, the update step estimates the posterior PDF $p(x_t \mid \boldsymbol{Z}_{1:t})$ with the following Equation (4):

$$p(x_t \mid \boldsymbol{Z}_{1:t}) = \frac{p(x_t \mid \boldsymbol{Z}_{1:t-1})\, p(z_t \mid x_t)}{\int p(x_t \mid \boldsymbol{Z}_{1:t-1})\, p(z_t \mid x_t)\, dx_t}, \quad (4)$$

where $\int p(x_t \mid \boldsymbol{Z}_{1:t-1})\, p(z_t \mid x_t)\, dx_t$ being a normalization term.

Since Equation (4) may involve high-dimensional integrals, it is not always possible to solve it analytically. Monte Carlo simulation is used to approximate the posterior PDF. By sampling N samples (i.e. particles) x_{t-1}^i from $p(x_{t-1} \mid \boldsymbol{Z}_{1:t-1})$, the PDF $p(x_{t-1} \mid \boldsymbol{Z}_{1:t-1})$ can be approximated by

$$p(x_{t-1} \mid \boldsymbol{Z}_{1:t-1}) \approx \sum_{i=1}^{N} \omega_{t-1}^i \delta(x_{t-1}^i - x_{t-1}), \quad (5)$$

with $\delta(\blacksquare)$ being a Dirac function and ω_{t-1}^i being the weight of particle x_{t-1}^i calculated with the following Equations (6):

$$\omega_{t-1}^i = \frac{\alpha_{t-1}^i}{\sum_{i=1}^{N} \alpha_{t-1}^i}, \quad (6)$$

with $\alpha_{t-1}^i = \frac{p(\boldsymbol{Z}_{1:t-1} \mid \boldsymbol{x}_{1:t-1}^i)p(\boldsymbol{x}_{1:t-1}^i)}{q(\boldsymbol{x}_{1:t-1}^i \mid \boldsymbol{Z}_{1:t-1})}$.

A common way is to consider $q\left(\boldsymbol{x}_{1:t-1}^i \mid \boldsymbol{Z}_{1:t-1}\right)$ as the transition function, i.e. $q(x_t \mid Z_{1:t}) = p(x_t \mid x_{t-1})$ and, then, the particle weight ω_t^i can be calculated as:

$$\omega_t^i = \frac{\alpha_t^i}{\sum_{i=1}^{N} \alpha_t^i}, \quad \text{with } \alpha_{t-1}^i = \alpha_{t-1}^i p\left(z_t \mid x_t^i\right), \quad (7)$$

with $p\left(z_t \mid x_t^i\right)$ being the likelihood of the i-th particle to the measurement at time t.

In case of a new product, both the degradation state x_t and the parameters $\boldsymbol{\theta}_t$ in Equation (1) are not known. PF needs to estimate, at the same time, x_t and $\boldsymbol{\theta}_t$. As in [15], we need simply extend (1) to the following equation set

$$\begin{aligned} x_t &= f_1(x_{t-1}, \boldsymbol{\theta}_{t-1}, \omega_1) \\ \boldsymbol{\theta}_t &= f_2(\boldsymbol{\theta}_{t-1}, \omega_2), \end{aligned} \quad (8)$$

with f_1 being the degradation state transition equation and f_2 being the parameters transition equation, which are both known. The parameters $\boldsymbol{\theta}_t$ are assumed to be independent of the measurements $\boldsymbol{Z}_{1:t}$ in this work. Now one just need to consider the state variable x in (3-7) as the combination of x and $\boldsymbol{\theta}$.

2) RUL PREDICTION

With the estimated posterior PDF $p(x_t \mid \boldsymbol{Z}_{1:t})$ for the present time, one can predict the future degradation evolution of the product. With (1), the prediction at any future time t + l, l = 1, 2, ... is calculated as follows:

$$\begin{aligned} &p(x_{t+l} \mid \boldsymbol{Z}_{1:t}) \\ &= \int \cdots \int \prod_{j=t+1}^{t+l} p(x_j|x_{j-1}) p(x_t|\boldsymbol{Z}_{1:t}) \prod_{k=t}^{t+l-1} dx_k. \end{aligned} \quad (9)$$

Assuming that the particle weights are unchanged and the generated error with unchanged particle weights is negligible in comparison with that caused by model inaccuracy, the predicted PDF $p(x_{t+l} \mid \boldsymbol{Z}_{1:t})$ can be approximated by [23]:

$$p(x_{t+l} \mid \boldsymbol{Z}_{1:t}) \approx \sum_{i=1}^{N} \omega_t^i \delta(x_{t+l} - x_{t+l}^i), \quad (10)$$

with x_{t+l}^i being obtained recursively by applying (1).

Given a failure threshold x_{th} and the predicted future degradation of each particle, the predicted RUL of the i-th particle is defined as the first time T_t^i that the predicted degradation state passes the predefined threshold:

$$\begin{aligned} &RUL_t^i \\ &= \left\{ T_t^i - t - 1 \mid f\left(x_{T_t^i - 1}\theta, \omega\right) < x_{th} \text{ and } f\left(x_{T_t^i}\theta, \omega\right) \geq x_{th} \right\}. \end{aligned}$$

Thus, the distribution of the predicted RUL of the product given by PF can be derived:

$$\mathrm{p}(\mathrm{RUL}_t \mid \boldsymbol{Z}_{1:t}, x_t < x_{th}) \approx \sum_{i=1}^{N} \omega_t^i \delta(RUL_t - RUL_t^i). \quad (11)$$

B. RELIABILITY TEST

For industry, it is important to verify that a designed product meets a required reliability level [24]. Reliability tests are designed for testing the failure modes and reliability of a specific product. Different ways are possible for estimating the reliability of the designed product from test results [26]. One common way is to test a number of products in operation under a predefined environment and load, for a predefined duration. The predefined test duration can be time, load cycles, charge/discharge cycles or any unit that can characterize the lifetime of product operation. The test can be accelerated or not, with respect to the load and working environment [27]. Some products may fail during the test and their failure times are recorded. The others may survive the test. With these information, one can calculate the reliability of the designed product.

C. PARAMETERS INITIALIZATION

For PF, parameters initialization, i.e. initializing the ranges and distributions of the unknown true degradation state and uncertain parameters in (8) at initial time, is necessary and important. A new product is reasonably supposed to have no degradation at initial time. In previous work, the value ranges are given according to experts' judgement and the commonly adopted distribution is the uniform distribution [15], [17], [18]. In this work, we focus on parameters initialization with failure times data collected during reliability tests. The main idea is to use Monte Carlo simulation for estimating the likelihood of each parameters combination to the failure times data. Then, one can calculate the likelihoods of different values for each parameter.

Suppose the reliability test duration is t_{rt} and N_{rt} new products are tested. The test results of the failure times FT_{rt} of the tested products fall into two categories: one contains the exact failure times of the products that fail during the test; the other contains uncertain information on the failure times of the products that do not fail during the reliability test. For these laters, one knows only that their failure times are larger than the duration of the reliability test. Assume that the first N_{rt1} products fail during the test, the rest $N_{rt2} = N_{rt} - N_{rt1}$ products survive the test. The proposed framework for parameters initialization is shown in Figure 1.

A conservative value range for each parameter in (8) is given by the expert, i.e. $\theta_i \in [a_i, b_i], i = 1, 2, \ldots, M$. For each parameter θ_i, K values, i.e. $\{\theta_i^j, j = 1, \ldots, K\}$ are sampled from its value range. Then, the number of possible parameters combinations is K^M. For each possible combination $\boldsymbol{\theta}_k = \left\{\theta_1^{l_1}, \ldots, \theta_M^{l_M}\right\}, k = 1, \ldots, K^M; l_1, \ldots, l_M \in [1, \ldots, K]$, a Monte Carlo simulation is adopted to estimate the RUL PDF $p_e\left(RUL_j \mid \boldsymbol{\theta}_k\right)$ at initial time and, then, we can estimate the likelihood of each parameters combination:

$$p\left(\boldsymbol{\theta}_k \mid FT_{rt}\right) = \prod_{i=1}^{N_{rt}} p\left(FT_{rt}^i \mid RUL_k\right), \tag{12}$$

with $p\left(FT_{rt}^i \mid RUL_k\right)$ being the likelihood of the RUL PDF $p_e\left(RUL_k \mid \boldsymbol{\theta}_k\right)$ for the k-th parameters combination to the failure time FT_{rt}^i of the i-th product. For the two different categories of failure times, the likelihood $p\left(FT_{rt}^i \mid RUL_k\right)$ is calculated, respectively, as

$$p\left(FT_{rt}^i \mid RUL_k\right) = \begin{cases} p(RUL_k = FT_{rt}^i \mid RUL_k \in p_e(RUL_k \mid \boldsymbol{\theta}_k)), \\ \quad for\ 1 \le k \le N_{rt1} \\ p(RUL_k > t_{rt} \mid RUL_k \in p_e(RUL_k \mid \boldsymbol{\theta}_k)), \\ \quad for\ N_{rt1} + 1 \le k \le N_{rt}. \end{cases} \tag{13}$$

Then, the likelihood of each parameter value can be calculated. For each parameter value $\theta_i^j, i = 1, \ldots, M; j = 1, \ldots, K$, its likelihood is the sum of the likelihood of all the combinations containing θ_i^j, as in Equation (14).

$$p'\left(\theta_i^j \mid FT_{rt}\right) = \sum p\left(\boldsymbol{\theta}_k \mid FT_{rt}\right),$$

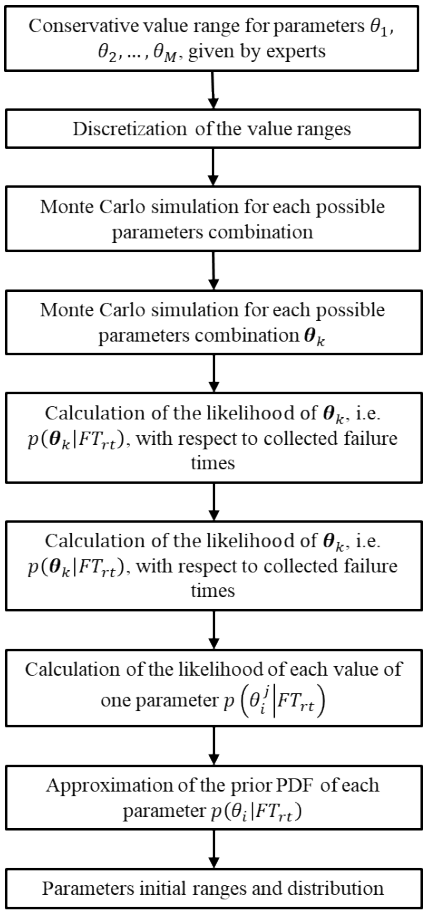

FIGURE 1. Illustration of the proposed framework for parameters initialization.

with

$$\boldsymbol{\theta}_k = \left\{\theta_1^{l_1}, \ldots, \theta_i^{l_i}, \ldots, \theta_M^{l_M}\right\} \text{ and } \theta_i^{l_i} = \theta_i^j. \tag{14}$$

Note that the likelihoods for all the K values of the same parameter are, then, normalized, i.e. $p\left(\theta_i^j \mid FT_{rt}\right) = p'\left(\theta_i^j \mid FT_{rt}\right) / \sum_{j=1}^{K} p'\left(\theta_i^j \mid FT_{rt}\right)$. The prior PDF $p\left(\theta_i \mid FT_{rt}\right)$ of the i-th parameter is approximated by

$$p\left(\theta_i \mid FT_{rt}\right) \approx \sum_{j=1}^{K} p\left(\theta_i^j \mid FT_{rt}\right) \delta(\theta_i - \theta_i^j). \tag{15}$$

With a predefined confidence level $1 - \alpha$ and the Cumulative Density Function (CDF) $P\left(\theta_i \mid FT_{rt}\right)$ derived from $p\left(\theta_i \mid FT_{rt}\right)$, the refined value range for θ_i is $\left[a_i', b_i'\right]$ with $P\left(\theta_i = a_i' \mid FT_{rt}\right) = \alpha/2$ and $P\left(\theta_i = b_i' \mid FT_{rt}\right) = 1 - \alpha/2$. Then, the PDF $p\left(\theta_i \mid FT_{rt}\right)$ is normalized on the selected value range and a sufficient number of initial particles can be sampled according to the prior distributions over the refined value ranges. The rest is to apply PF in Section 2.1 for state estimation and RUL prediction, as conventional PF.

III. CASE STUDIES

The performance of the proposed method for parameters initialization is verified by simulated case studies concerning the prognostics of PEM fuel cells and Li-ion batteries.

A. EXPERIMENT ON PEM FUEL CELLS

1) DEGRADATION MODEL

Proton Exchange Membrane (PEM) fuel cell is the most popular fuel cell, close to commercial deployment. Accurate prediction of its degradation process is important for energy management. In this work, the degradation model proposed in [28] is adopted. The model is briefly reviewed in this paper, and the interesting reader can refer to the related reference for additional details.

TABLE 1. Stack characteristics for the experiment.

Symbol	Physical meaning	Value
n_s	Number of cells	8
S	Surfaces	220 cm^2
T	Temperature	80 °C
P_{H2}, P_{O2}	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
β	Parameter characterizing the degradation speed	-
σ_v^2	Variance of the process noise of α_t	4*10^{-6}
σ_η^2	Variance of the measured load current noise	9
σ_ω^2	Variance of the measured voltage noise	0.09
α_{EoL}	Failure threshold of the PEMFC stack	0.15
$R_{ohm,n}$	General resistance at time t=0	0.3 Ω

Power conservation implies that the parameter introduced in Table 1 satisfies the following equation:

$$V_t = n_s(R_{ohm,n}\alpha_t I_t - BT\ln\left(1 - I_t/I_{L,n}\right) + BT\ln(1 - I_t/I_{L,n}(1-\alpha_t))) \quad (16)$$

with α_t being an unknown parameter that needs to be tuned with PF. One knows that α_t follows

$$\alpha_t = \beta t + \nu_t, \quad (17)$$

with β being the constant rate of change and ν_t the process noise $N(0, \sigma_{\nu_t}^2)$. Thus, one needs to estimate the value of β with the monitoring data. The monitoring data for a PEM fuel cell are its output voltage and current. The relations between the monitored values and the true values are

$$I_{i,t}^m = I_{i,t} + \eta_{i,t} \quad \text{and } \eta_{i,t} \sim N\left(0, \sigma_{\eta_{i,t}}^2\right), \quad (18)$$

$$V_{i,t}^m = V_{i,t} + \omega_{i,t} \quad \text{and } \omega_{i,t} \sim N\left(0, \sigma_{\omega_{i,t}}^2\right). \quad (19)$$

According to [28], the parameters setting in the previous functions is given in Table 1. The only unknown parameter is the value of the constant β.

2) RELIABILITY TEST DATA

In reliability test, twenty PEM fuel cells are tested for a duration of 1750 (with arbitrary time unit). Fourteen test samples fail during the test and the collected failure times data are shown in Figure 2.

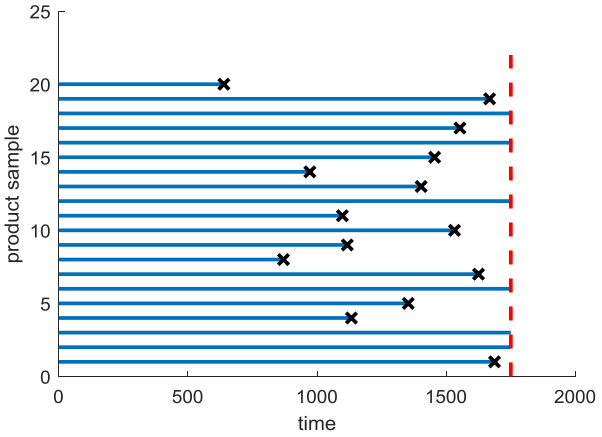

FIGURE 2. Failure times data of PEM fuel cells from the reliability test.

3) EXPERIMENT RESULTS

The conventional parameter initialization for β is a uniform distribution over an interval given by the expert. According to the results in [28], in this paper, the range of possible β values at initial time t = 0 is set to be $[0, 2 \times 10^{-4}]$.

The proposed method uses the failure times data from the reliability test. The estimated Probability Density Function (PDF) of possible β values at initial time t = 0 by the proposed method is shown in Figure 3. The interval for possible β values at initial time t = 0 is set to be $[7.02\times10^{-5}, 1.12\times10^{-4}]$ with 95% confidence level. The best fitted distribution over this value range is the gamma distribution shown in Figure 3.

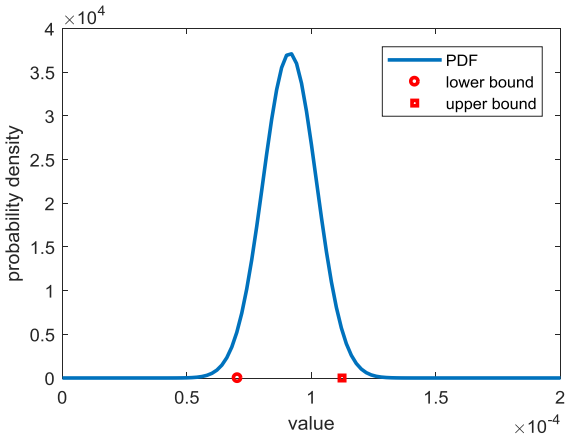

FIGURE 3. The posterior PDF of θ_1 given by the proposed method.

With these parameter initializations, PF can be adopted, with the monitored data, for adaptively estimating the β value and the RUL of the considered PEM fuel cell.

Figures 4 and 5 show separately the estimated β value given by the PF with the conventional parameter initialization, i.e. a uniform distribution over the value ranges given by the expert (noted as PF-U) and the PF with the parameter initialization method proposed in this paper (noted as PF-G). One may observe that the PF-G gives significantly

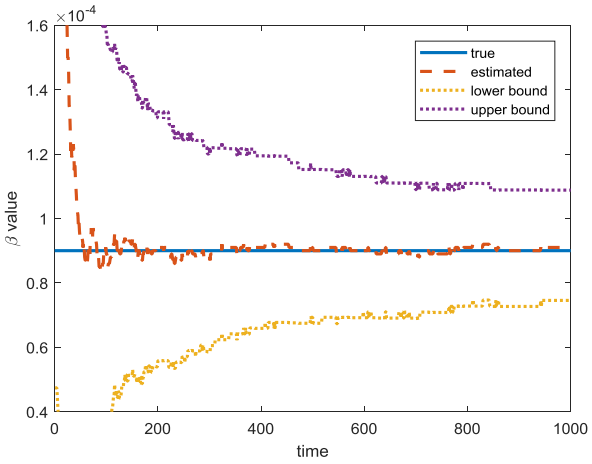

FIGURE 4. Estimated β value and 90% confidence interval of PF-U for PEM fuel cell.

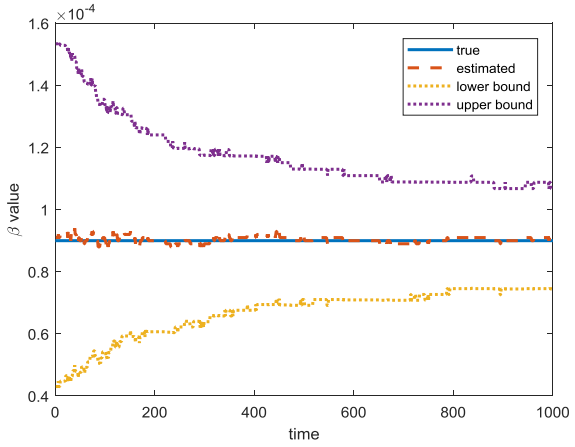

FIGURE 5. Estimated β value and 90% confidence interval of PF-G for PEM fuel cell.

more accurate estimated β values than PF-U for the first two hundred time-steps. This proves that the proposed parameter initialization method can increase the convergence speed for unknown parameters estimation in this case study. After the first two hundred time-steps, PF-G and PF-U give comparable results as expected.

Figures 6 and 7 show separately the estimated RUL given by PF-U and PF-G. Similar conclusions can be drawn as for the β value estimation: the proposed method reduces significantly the width of the 90% confidence interval for the first two hundred time-steps when there are not enough monitoring data collected from the degradation process.

B. EXPERIMENT ON LI-ION BATTERIES

1) DEGRADATION MODEL

Briefly, the degradation process of a Li-ion battery is characterized by two phases [15]: the first phase is the slow decrease of the battery capacity and the second phase is the fast decrease of the battery capacity. Usually, the state equation

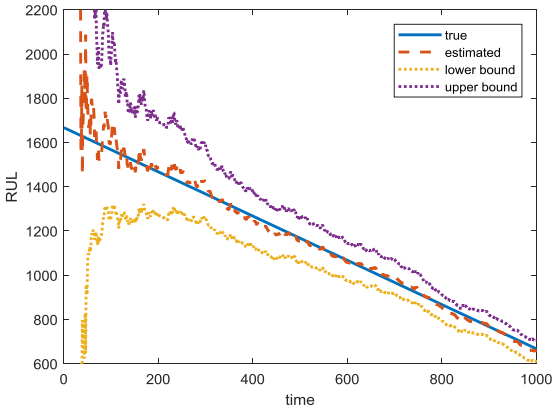

FIGURE 6. Predicted RUL and 90% confidence interval of PF-U for PEM fuel cell.

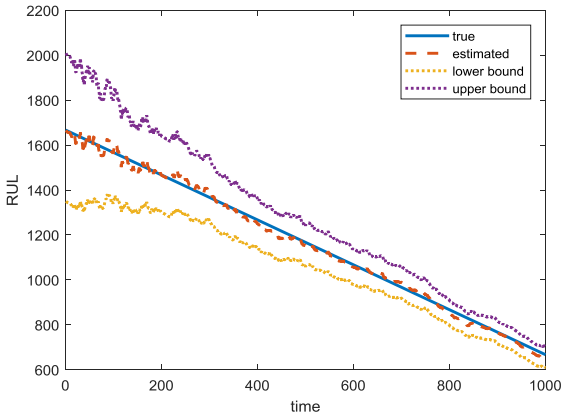

FIGURE 7. Predicted RUL and 90% confidence interval of PF-G for PEM fuel cell.

TABLE 2. Parameters values for data generation.

parameter	θ_1	θ_2	θ_3	θ_4
value	0.9191	-0.00080	-0.00023	0.04670
parameter	σ_1	σ_2	σ_m	x_{th}
value	0.0001	0.001	0.001	0.7172

used to describe the degradation process is as follows:

$$\begin{aligned} x(t) &= \theta_1 q_1(t) + \theta_3 q_2(t) \\ x_1(t) &= x_1(t-1)\, e^{\theta_2} + N(0, \sigma_1^2) \\ x_2(t) &= x_2(t-1)\, e^{\theta_4} + N(0, \sigma_2^2), \end{aligned} \tag{20}$$

with $x(t)$ being the degradation state, $x_1(t)$ and $x_2(t)$ being two independent first-order Markov processes, $N(0, \sigma^2)$ being a Gaussian process noise with zero mean and σ^2 variance, the time unit being a charge/discharge cycle and $\boldsymbol{\theta} = [\theta_1, \theta_2, \theta_3, \theta_4]$ being the unknown parameters to be estimated along with the degradation state in PF. Among these parameters, θ_1 and θ_4 are positive and θ_2 and θ_3 are negative.

The observation equation is:

$$z(t) = x(t) + N(0, \sigma_m^2), \tag{21}$$

with $N(0, \sigma_m^2)$ being the Gaussian measurement noise.

The degradation data of the test scenario is generated with respect to the parameters values and noise variances given in Table 2.

2) RELIABILITY TEST DATA

First, the distribution of the RULs of the Li-ion batteries generated with the values in Table 1 is shown in Figure 8. One can observe that the RULs are mostly located in the interval [123 126], but the RUL can also be smaller than 110 or larger than 130.

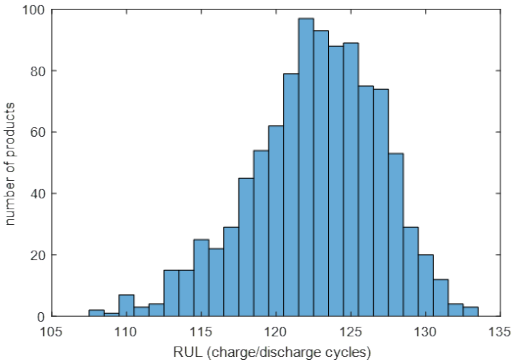

FIGURE 8. Distribution of the Li-ion batteries' RULs under the parameters values in Table 1.

One degradation scenario is selected to test the performance of the proposed method. Its true RUL is 130.

3) PARAMETERS INITIALIZATION

The original value range given by the experts, for each parameter is shown in the second line of Table 3. In case of no extra information, uniform distributions over the value ranges (given in the second line of Table 3) are assumed for parameters initialization in PF, as in [15].

TABLE 3. Parameters values for data generation.

Value range	θ_1	θ_2	θ_3	θ_4
Original one	[0.85 1.20]	[-0.001 0]	[-0.001 0]	[0.03 0.13]
Refined one	[0.85 1.25]	[-9.0e-4 0]	[-8.0e-4 0]	[0.02 0.08]

Suppose that during the reliability test, 35 product samples are tested and the test lasts for 130 charge/discharge cycles, i.e. the stop time is 130. The obtained failure times are shown in Figure 9. The cross in Figure 9 means that the corresponding product fails during the test.

From the original value ranges in Table 3, 15 values are sampled for each parameter. There are totally 15^4 possible parameters combination, i.e. $\boldsymbol{\theta} = [\theta_1, \theta_2, \theta_3, \theta_4]$. A Monte-Carlo simulation with 1000 trials is carried out for each parameters combination, starting from no degradation at time $t = 0$.

With the Monte-Carlo simulations' results, one can estimate the likelihood of the values of each parameter with Equations (12-14) in Section 2.2. Then, one can obtain the posterior PDF of each parameter with (15). The obtained PDFs are shown in Figures 10-13. The circles and squares in these figures represent, separately, the upper and lower bound of the parameters with respect to 95% confidence level.

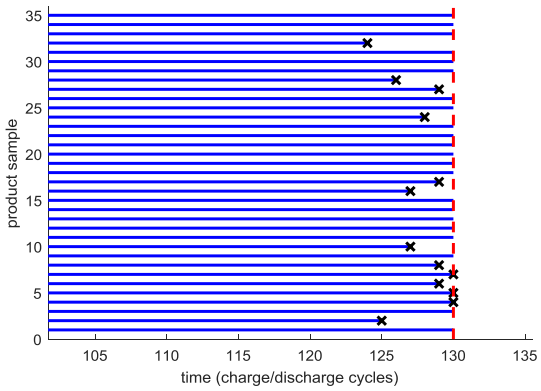

FIGURE 9. Failure time data of Li-ion batteries from the reliability test.

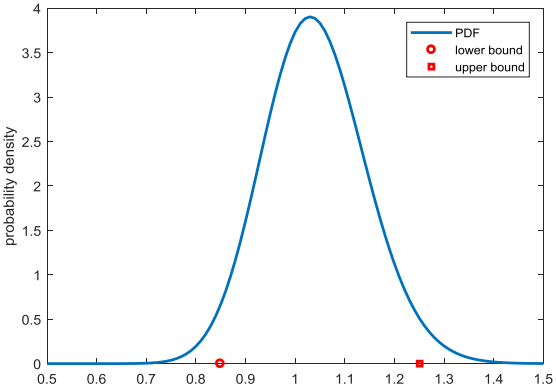

FIGURE 10. The posterior PDF of θ_1 given by the proposed method.

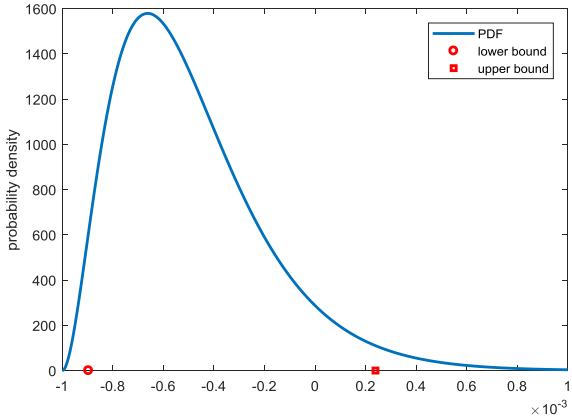

FIGURE 11. The posterior PDF of θ_2 given by the proposed method.

Note that these lower bounds and upper bounds are not the final value ranges for the parameters. For θ_2 and θ_3, their values need to be negative and the upper bounds with respect to 95% confidence level are 2.3919e-4 and 3.4795e-4, respectively: the final upper bounds for these two parameters in the parameters initialization for PF are zeros.

The final parameters value ranges for these parameters are shown in the third line of Table 3. The PDF of each parameter

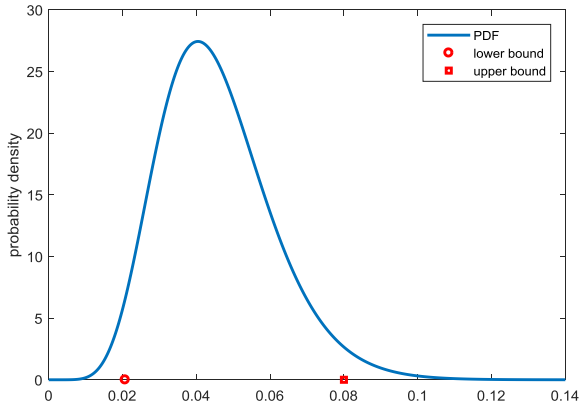

FIGURE 12. The posterior PDF of θ_3 given by the proposed method.

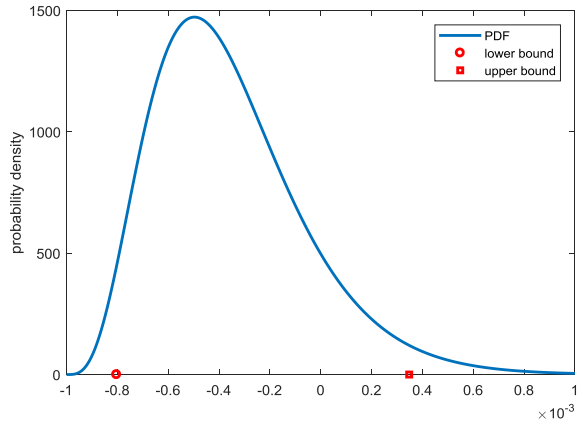

FIGURE 13. The posterior PDF of θ_4 given by the proposed method.

over its corresponding value range is the normalized PDF over the refined value ranges in Figures 10-13. From Table 3, one can observe that the value ranges given by the proposed method can be larger or narrower than the original ones given by the expert. And they are more reasonable according to the proposed method.

4) RESULTS COMPARISON

In this Section, comparisons are carried out between PF-G and PF-U.

The estimated RUL (dashed line) and true RUL (solid line) are shown in Figures 14 and 15 with 90% confidence interval (dotted line). It is shown that PF-G and PF-U give comparable results after 100 cycles, as a large enough number of measurements are collected at that time. However, PF-G gives more stable and more precise results than PF-U for the first 100 cycles. The predicted RUL of PF-G converges much faster to the true RUL with a narrower confidence interval.

The results of PF-G are influenced by the number of product samples and duration of reliability test. The longer the duration of the reliability test is, the better the predicted RULs are, as more product samples may fail during the reliability test and the parameters initializations are more reliable. The more product samples are used in the reliability test, the better

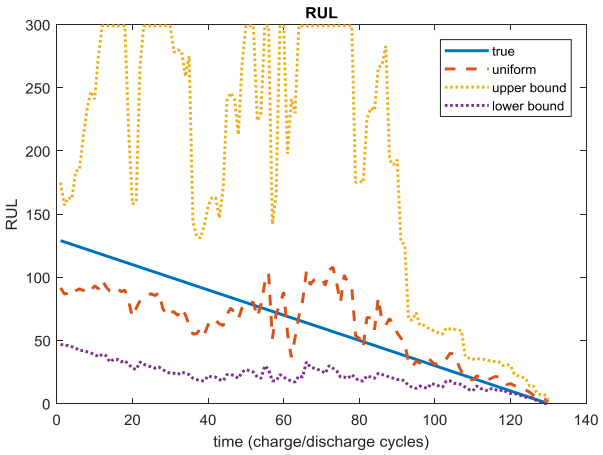

FIGURE 14. Predicted RUL and 90% confidence interval of PF-U.

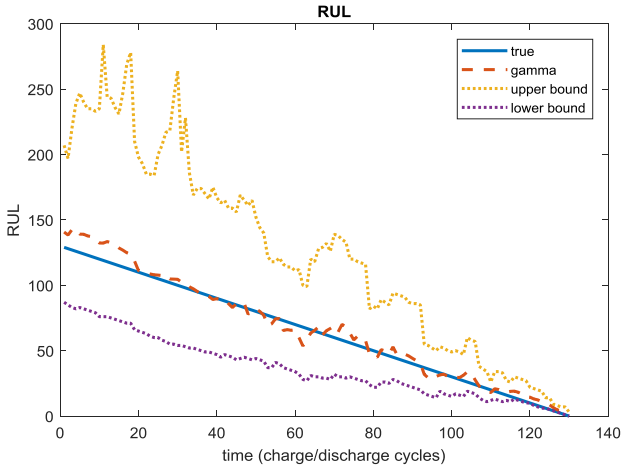

FIGURE 15. Predicted RUL and 90% confidence interval of PF-G.

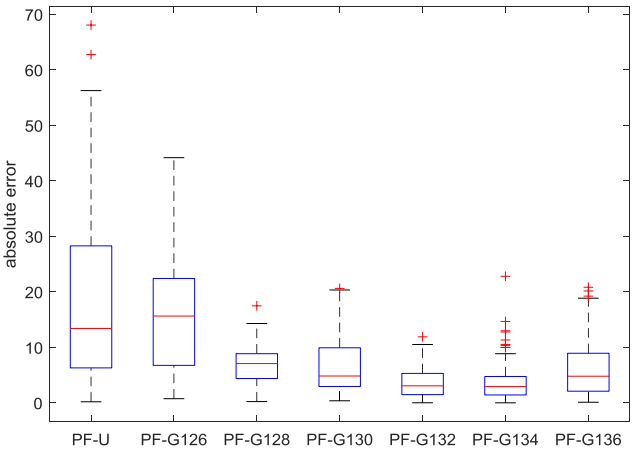

FIGURE 16. Comparison of absolute error between PF-U and PF-G with 35 product samples and different durations of reliability test.

the predicted RULs are, as more failure time information are collected and we can better estimate the value ranges of the parameters and their prior distributions.

Figure 16 shows the boxplot of the absolute errors of PF-G and PF-U between the predicted RULs and the true RULs at different charge/discharge cycles. PF-G is with 35 product

samples and different reliability test durations. In Figure 16, the x tick label PF-G128 means the corresponding box plot is the results of PF-G with a reliability test duration of 128. One can observe that PF-G can always give more stable and precise results than PF-G in the experiments. When the reliability test duration becomes longer, the performance of PF-G tends to improve. The Figure shows also that when the reliability test duration is too short, e.g. 126, few of the product samples fail during the test, making PF-G less stable and PF-G gives only slightly better results than PF-U. This proves that the quality of the failure time data is very important. If few failure times of the product samples are precisely known, PF-G can not improve significantly the prognostic results.

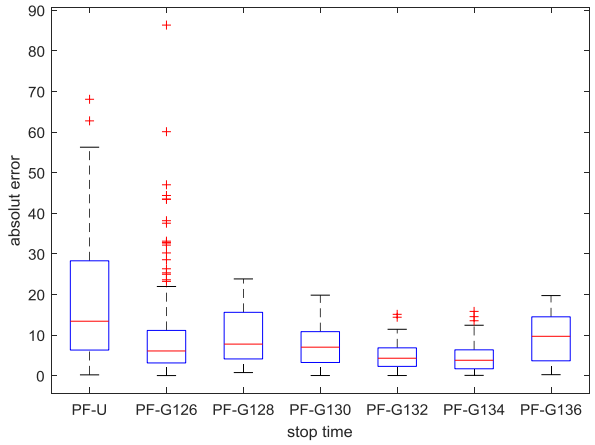

FIGURE 17. Comparison of absolute error between PF-U and PF-G with different stop time of reliability test over 10 product samples.

Another experiment with 10 product samples is carried out for analyzing the PF-G's sensitivity to the reliability test duration. Figure 17 shows the boxplot of the absolute errors between the true RULs and the predicted RULs given by PF-U and PF-G with only the first 10 product samples in Figure 9. Based on Figures 16 and 17, one may draw the conclusions that: 1) the longer the reliability test time, the better the prognostic results of PF-G; 2) PF-G gives always more stable and precise predicted RUL than PF-U.

In order to show precisely the influence of the number of product samples on the performance of PF-G, another experiment is carried out. In this experiment, the reliability test duration is fixed at 128. We test the performance of PF-G with different numbers of product samples used in the reliability test. The results together with the results of PF-U are shown in Figure 18. The x tick label PF-G20 means that the corresponding boxplot is the results of PF-G with the reliability test on the first 20 product samples in Figure 9. It is shown again that PF-G gives better results than PF-U in the simulation and that more production samples can improve the performance of PF-G.

Note that the quality of the failure time data is also important for the prognostic results of PF-G. As shown in Figure 18, the results with 25, 30 and 35 product samples are not better than that with only 20 samples. The reason for this is that the

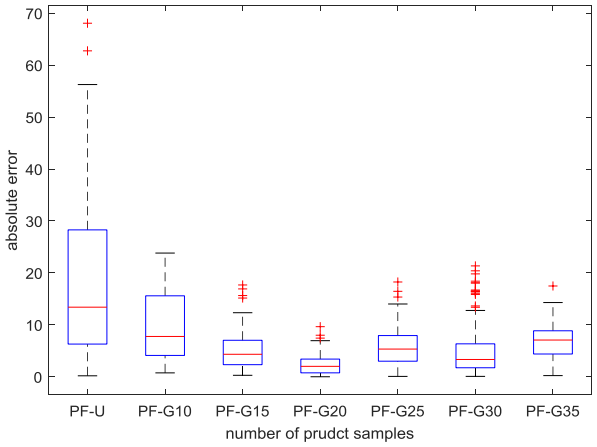

FIGURE 18. Comparison of absolute error between PF-U and PF-G with different numbers of product samples in the reliability test with a duration of 128.

collected failure times for the product samples are too diverse. The true failure time of the test scenario is 130 and the failure times of the product samples numbered from 20 to 35 are either much smaller or larger than 130, as shown in Figure 9. Thus, the uncertainty of the collected failure times may influence the results.

IV. CONCLUSIONS

One of the difficulties for applying PF is the parameters initialization at initial time. In case of a new product, no degradation process data is available and a common way for parameters initialization is assuming uniform distributions over value ranges given by experts. Such initialization is not always reliable and effective. Thus, a new method is proposed in this work for parameters initialization. In the proposed method, failure time data collected from reliability tests during the design process are used to estimate the likelihood of each parameter value via Monte Carlo simulation. Then, for each uncertain parameter in the state and observation equations, the value range with a predefined confidence level can be derived along with the PDF over this value range.

The effectiveness of the proposed framework is verified through simulated case studies on prognostics of PEM fuel cells and Li-ion batteries. In the experiment, the predicted RULs are more stable and the uncertainties of the prognostic results are significantly reduced, especially at the beginning when little measurements are available.

The proposed method has some assumptions that may restrict its application. First, the proposed method is restricted to new products with no degradation at the beginning. Second, the transition of the parameters should be known or fixed. The future work will focus on the development of the proposed method for wider applications by relaxing these assumptions.

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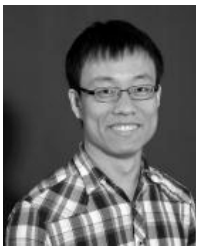

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