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Research Article

The PV Corrosion Fault Prognosis Based on Ensemble Kalman Filter

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The degradation of photovoltaic (PV) modules remains a major concern on the control and the development of the photovoltaic field, particularly, in regions with difficult climatic conditions. The main degradation modes of the PV modules are corrosion, discoloration, glass breaks, and cracks of cells. However, corrosion and discoloration remain the predominant degradation modes that still require further investigations. In this paper, a model-based PV corrosion prognostic approach, based on an ensemble Kalman filter (EnKF), is introduced to identify the PV corrosion parameters and then estimate the remaining useful life (RUL). Simulations have been conducted using measured data set, and results are reported to show the efficiency of the proposed approach.

1. Introduction

In order to maximize the system availability and reduce the maintenance cost, the concept of fault prognosis has been proposed to estimate the damage propagation and then predict the fault appearance [1, 2]. More precisely, several approaches have been proposed to tackle this issue and could be categorized into three main families [3, 4]. The first category uses prognosis-based models. These models consider the damage as a continuous variable in which the evolution is defined by a deterministic or stochastic law (see [3, 5]). The second category of models uses measured data without requiring an equipment behavior (e.g., see [6, 7]). The third category is experience-based prognostic and requires, essentially, expert experience together with rigorous stochastic and probabilistic modelling.

This paper focuses on the first category that uses prognosis-based models that attracted the intention of several authors (see, e.g., [8–11]) and can be further categorized into two types. The first one concerns deterministic models (see, e.g., [9, 12, 13]). In this case, the techniques used to estimate degradation are based either on observers or on the Interacting Multiple Model. For example, the conventional observer approach that can be envisaged for studying determinist systems prognosis is highlighted in [14]. The second type is dedicated to the stochastic models (see, e.g., [15, 16]) and Bayesian filters [17, 18]. For stochastic models, which attract our attention, the prediction techniques can be classified according to their natures or uncertainties. For example, when the models are linear with Gaussian uncertainties, techniques based on the ordinary Kalman filter can be used, but, when models are nonlinear, the filtering may be performed with an extended Kalman filter [18, 19]. On the other hand, for systems with non-Gaussian uncertainty, classical filtering techniques are not adapted and present many convergence difficulties. In this case, several types of filters based on the Monte Carlo method could be used (see, e.g., [15, 16]).

This paper puts more emphasis on PV corrosion propagation prognostic and investigates further Bayesian method using EnKF. Previous studies have shown that this filter is more suitable for systems with complex phenomenon and

have been applied in many fields [20]. For example, it has been used to predict the flow of fluids in porous environment [21] or to predict the weather [22, 23]. In these two cases, the models that describe the systems' evolution are either highly nonlinear or having important dimensions.

It is worth noting that the performance study between the EnKF and other filters, mainly the PF, has been performed by many authors in different fields especially for nonlinear stochastic filtering problems (e.g., [24, 25]). For instance, the results of these studies show that the PF is computationally expensive and needs big sampling size to converge, especially, for systems with high dimensions. However, the EnKF gives more robust and promising results even if the sampling size is too small. For example, in the assumption of Gaussian uncertainties and nonlinear model (e.g., [25]), similar to our PV corrosion study, the prediction is better with EnKF. Indeed, the covariance matrix estimation is based on limited data assimilation component of ensemble forecasting. Besides, from this limited sampling size, the time of the algorithm convergence is still fast and consequently good for the purpose of prognosis. The obtained results from our numerical study, presented in Section 3, confirm also that EnKF outperforms the PF for nonlinear system with Gaussian uncertainties.

Throughout this paper, the general mathematical model that describes the evolution of the PV corrosion can be written as follows:

$$\begin{aligned} d_k &= f(d_{k-1}, \theta, u_{k-1}) + w_{k-1}^d, \\ y_k &= h(d_k, \theta) + w_k^y, \end{aligned} \tag{1}$$

where $d_k \in \mathbb{R}^{n_d}$ is the degradation variable. The function f_d and h are smooth functions. $u_k \in \mathbb{R}$ is the input vector of the system, $y_k \in \mathbb{R}$ is the output vector, and θ is an unknown parameter defining the damage speed. $w_k^d \sim \mathcal{N}(0, Q_k)$ and $w_k^y \sim \mathcal{N}(0, R_k)$ denote the modelling and measurement uncertainties where Q_k and R_k represent the covariance matrices.

Generally speaking, this mathematical model is used to describe the nominal system operation. Besides, the estimations consist in analyzing the difference between the sensed values and model outputs (i.e., residual). In our case, the state d evolution is modelled and combined with a hidden parameter θ which describes the damage speed, random noises, and observed measurements. In this case, the residual value is used to eliminate noise and then to restore the actual signal and unknown parameters. To summarize, the main contributions of this paper are the following:

(i) Introduce the PV corrosion parametric state model

(ii) Estimate the unknown parameter using a Bayesian filter

(iii) Analyze the damage propagation instead of estimating the RUL

This reminder of this paper is organized as follows. Section 2 describes the prognostic methodology and presents the filtering technique. In Section 3, the prognostic and numerical results are given. The conclusions and future work are presented in Section 4.

2. Problem Statement and Prognosis Methodology

2.1. Problem Statement. In this work, it is assumed that the structure of f_d is polynomial (see e.g., [8, 26]) and depends on an unknown parameter θ ([27]). In general, the corrosion of photovoltaic module is assessed by measuring its power loss during its lifetime compared to its initial values. Currently, there are a few corrosion PV models in the literature and further investigations are still required. For example, in [28], the authors propose a degradation model of the PV model given by

$$d_k = 1 - \exp(-b.k^a), \tag{2}$$

where a and b are the unknown parameters of the degradation model. In our work, we further investigate this model using prognostic-based Bayesian filter. The measurements are assumed to be available during a finite time horizon $[0, k_p \Delta h]$ where Δh is the sampling period of the time horizon and $k_p \in \mathbb{N}$.

The aim of the prognosis strategy is to estimate the parameter $\theta = [a, b]$ and analyze the degradation trajectories in order to estimate the RUL. It is worth noting that this strategy was originally used for continuous deterministic model based on observers' design (see [14]). Despite the relevance of the results obtained in prognostic, uncertainty was not taken into consideration. In our work, (2) is adapted as follows by taking into account the following inherent uncertainties:

$$d_k = 1 - \exp(-b.k^a) + w_d. \tag{3}$$

In order to overcome nonlinearity and uncertainties, we propose the EnKF filtering technique. Despite its similarity with particle filters, the EnKF combines the Monte Carlo method and the Kalman filter technique in order to estimate the parameters and to compute their covariance matrix even if the models are highly nonlinear [20]. However, this type of filters is limited to the estimation of moments of order 1 and order 2. Therefore, in this study, we deal only with Gaussian uncertainties.

This EnKF reconstruction consists on minimizing the error between the model (2) and the measurement set $Y_{k_p} = \{y_0, y_1, \dots, y_{k_p}\}$ obtained during a time horizon $[0, k_p \Delta h]$. Then, the corrosion trajectory analysis can be performed for the prognosis and the PV *RUL* estimation. Furthermore, the parameter θ estimation is carried out in a recurrent way, that is, at each time $k \in [\![1, k_p]\!]$. Indeed, when a new measurement y_k is available, θ can be adjusted by the filtering techniques. Thus, the parameter θ will be modelled by a variable θ_k which changes over time. More precisely, and because of the inherent uncertainties, the parameter's

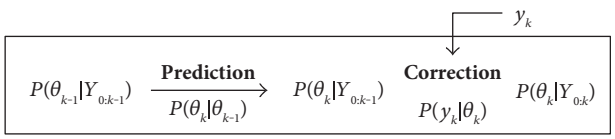

Figure 1: The Bayesian filtering steps for $k \in [\![1, k_p]\!]$.

dynamic is supposed to be given by a forced random path as follows:

$$\theta_k = \theta_{k-1} + w_{k-1}^{\theta}, \tag{4}$$

where $w_{k-1}^{\theta} \sim \mathcal{N}(0, Z_{k-1})$ is the additive noise and Z_{k-1} is the matrix of covariance associated to the uncertain parameter. Finally, taking into account (4) and the damage behavior (3), the PV state model can be written as follows:

$$\begin{aligned} d_k &= 1 - \exp(-b_k.k^{a_k}) + w_k^d, \\ \theta_k &= \theta_{k-1} + w_k^{\theta}, \\ y_k &= d_k + w_k^y. \end{aligned} \tag{5}$$

2.2. Bayesian Filtering. In a Bayesian framework, the estimation of θ_k consists in approximating the conditional expectation $P(\theta_k|Y_{k_p})$. For $k \in [\![1, k_p]\!]$, this probability law can be calculated into two steps as shown in Figure 1.

2.2.1. Prediction. By using the models (5) and without knowledge of the measurement y_k, the prior probability law is obtained via the Chapman-Kolmogorov equation:

$$P(\theta_k|Y_{k-1}) = \int P(\theta_k|\theta_{k-1})P(\theta_{k-1}|Y_{k-1})d\theta_{k-1}. \tag{6}$$

2.2.2. Correction. This step is dedicated to modify the prior probability law by introducing the measurement y_k. The obtained posterior probability law is given by using the Bayes formula as follows:

$$P(\theta_k|Y_k) = \frac{P(y_k|\theta_k)P(\theta_k|Y_{k-1})}{P(y_k|Y_{k-1})}. \tag{7}$$

The formula (6) and (7) are the optimal Bayesian filtering equations. In practical situations, the optimal algorithms to compute these equations are difficult, even impossible, to be implemented due to the complex integrations, which cannot be performed analytically. However, if the uncertainties are Gaussian, the results can be obtained by the elaboration of Kalman filters. In the sequel, the two steps, prediction and correction, are carried out through EnKF filtering Algorithm 1.

Initialization $k = 0$
Input $P_0(\theta)$, k_p
initializing $\{\theta_0^{i,p} \sim \mathcal{N}(0, P_0)\}_{i=1}^N$
while $(k \le k_p)$
prediction step
for $i = 1$ **to** N
$\hat{y}_{k+1}^{i,p} = 1 - \exp(-b_k^i.k^{a_k^i})$
end for
end prediction step
Input y_{k+1} the new observed value
correction step
fluctuation $\{y_{k+1}^i = y_{k+1} + w_k^{y,i}\}_{i=1}^N$
compute K_{k+1}^{θ}
for $i = 1$ **to** N
$\theta_{k+1}^{i,a} = \theta_{k+1}^{i,p} + K_{k+1}^{\theta}(y_{k+1}^i - \hat{y}_{k+1}^{i,p})$
end correction step
$\overline{\theta}_{k+1}^a = \frac{1}{N}\sum_{i=1}^N \theta_{k+1}^{i,a}$
$P_{k+1}^{\theta,y,a} = \frac{1}{N}\sum_{i=1}^N (\theta_{k+1}^{a,i} - \overline{\theta}_{k+1}^a)(y_{k+1}^{p,i} - \overline{y}_{k+1})$
end while
Output $P(\theta_k|Y_{k_p})$

Algorithm 1: EnKF.

3. Prognosis Results

In this section, we present the rules for estimating the RUL together with a numerical example.

3.1. RUL Estimation. The objective of prognosis is to estimate the RUL; therefore, looking at the considered uncertainties, this estimation is given as a conditional probability law of RUL, denoted $P(\mathrm{RUL}|Y_{k_p})$. For this purpose, let us consider $\mathrm{RUL}^i(k_p)$ as the necessary duration so that the nth step prediction of the ith future degradation members, noted as $\{d_{k_n}^i = 1 - \exp(-b_{k_p}^i k_n^{a_{k_p}^i})\}_{i\in[\![1,N]\!]}$, reaches the degradation threshold D_s. More precisely, the member's $\mathrm{RUL}^i(k_p)$ expression can be written as follows:

$$\mathrm{RUL}^i k_p = \operatorname*{Inf}_{n>p}\left\{k_n | d_{k_n}^i = D_s\right\} - (k_p \Delta h), \quad i \in [\![1, N]\!], \tag{8}$$

and the Monte Carlo probability law $P(\mathrm{RUL}|Y_{k_p})$ estimation based on the members $(\mathrm{RUL}^i(k_p))_{i=1,\ldots,N}$ is the following:

$$P\left(\mathrm{RUL}(k_p) = r|Y_{k_p}\right) = \frac{1}{N}\sum_{i=1}^N \Gamma_{[r-dr,r+dr[}\left(\mathrm{RUL}^i(k_p)\right), \tag{9}$$

where Γ is a function defined by

$$\Gamma_I(a)\begin{cases} 1, & \text{if } a \in I, \\ 0, & \text{else.} \end{cases} \tag{10}$$

The mean value of the RUL is estimated by

$$\widehat{\mathrm{RUL}}(k_p) = \frac{1}{N}\sum_{i=1}^N \mathrm{RUL}^i(k_p) \tag{11}$$

and the variance is given by

$$\mathcal{V}(k_p) = \frac{1}{N}\sum_{i=1}^N \left[\mathrm{RUL}^i(k_p) - \widehat{\mathrm{RUL}}(k_p)\right]^2. \tag{12}$$

Initialisation $k = k_p$
Input $\alpha \in]0, 1]$ desired confidence level
while $\left(\widehat{RUL}(k) \geq \sqrt{\frac{1}{N(1-\alpha)}\sum_{i=1}^{N}\left[RUL^i(k) - \widehat{RUL}(k)\right]^2}\right)$
$k = k + 1$
sample $\{RUL^i(k)\}_{i=1}^{N}$
$\widehat{RUL}(k) = \frac{1}{N}\sum_{i=1}^{N} RUL^i(k)$
$\mathcal{V}(k) = \frac{1}{N}\sum_{i=1}^{N}\left[RUL^i(k_p) - \widehat{RUL}(k_p)\right]^2$
end while
Output $k_\alpha^{\max} = k$

Algorithm 2: $k_\alpha^{\max}$ estimation.

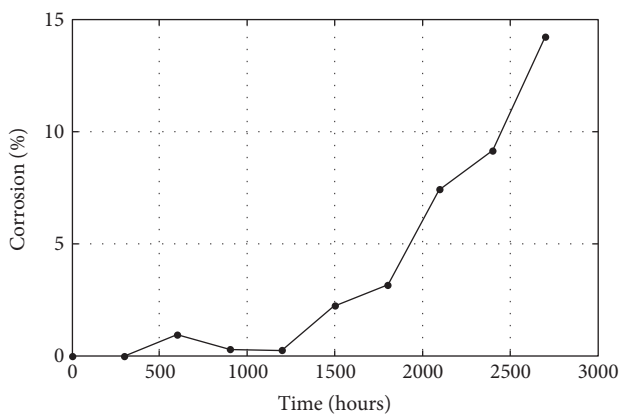

Figure 2: Degradation of polycrystalline silicon PV module under test 85/85.

Proposition 1. *Let $\alpha \in]0, 1[$ be the desired confidence rate. Let also $k_\alpha \in \mathbb{N}$ be a time index such that the following equation is satisfied, for all $k \in [k_p, k_\alpha]$ that*

$$\widehat{RUL}(k) \geq \sqrt{\frac{1}{N(1-\alpha)}\sum_{i=1}^{N}\left[RUL^i(k) - \widehat{RUL}(k)\right]^2}. \quad (13)$$

Thus, one can ensure, with a confidence rate equal to α, that no failure will occur within the time horizon $[k_p, k_\alpha]$.

For a confidence level α,k_α is the future time horizon defining the good function of the system. The maximum of this horizon, noted as $k_\alpha^{\max}$, can be obtained by using Algorithm 2.

3.2. Numerical Example. To predict the corrosion propagation on a polycrystalline PV module, data from an accelerated test based on extreme temperature and humidity is used. In fact, in this study, we use a large corrosion growth database of polycrystalline PV module that is reported in [29]. This data set consists of damage trajectory containing 10 measurement points (see Figure 2) based on a constant stress damp heat of T = 85°C and HR = 85%.

Table 1: Constants and simulation values.

Parameter b uncertainty	$\sigma_1 = 0.1 \times 10^{-12}$
Parameter a uncertainty	$\sigma_2 = 0.1$
Measure uncertainty	$\sigma_y = 0.05$
Damage uncertainty	$\sigma_d = 0.01$
Corrosion threshold	70%
Member's number	$N = 100$
Sampling time	$\Delta h = 250$ h
Measurement time horizon k_p	$k_p.\Delta h = 2500$ h

The recursive state form of the considered damage's model used in this simulation is developed by applying the Euler approximation to the temporal derivative of the model (see (3)) and introduced in the model (see (5)). More precisely, the resulting model is as follows:

$$\begin{aligned} d_{k+1} &= -d_k\left(1 + ab \times k^{a-1}\Delta h + 1\right) + ab \times k^{a-1}\Delta h w_k^d, \\ \theta_k &= \theta_{k-1} + w_k^\theta, \\ y_k &= d_k + w_k^y. \end{aligned} \quad (14)$$

The constants describing this model and the numerical values used in the simulations are given in Table 1.

3.2.1. The Parameter Estimation. To ensure a perfect prediction of the PV corrosion, the parameter filtering process has to reach the expected value in a finite time horizon. Therefore, we first study the influence of member's number and uncertainties on the parameter's convergence quality. Figure 3 illustrates the parameter's convergence for the different member's numbers according to three situations: low ($N = 10$), medium ($N = 50$), and high ($N = 200$). More precisely, for $N = 50$ or $N = 200$, and contrary to $N = 10$, the convergence is practically identical and fast. Therefore, to ensure a good RUL estimation, a member's number up to 50 is necessary and sufficient.

Now, to illustrate the influence of the measurement uncertainties, N is fixed to 100 by changing uncertainties. Figure 4 shows the convergence of the parameter over time under one of the following scenarios: scenario S1 ($\sigma_y = 0.01$), scenario S2 ($\sigma_y = 0.05$), and scenario S3 ($\sigma_y = 0.8$).

The convergence results show that, for the scenarios S1 and S2, the convergence reaches the expected values within the first five iterations. Therefore, the estimation is qualified to be satisfactory and perfect for a good RUL estimation, especially for S2 where the convergence is fast. In S1, the convergence results are less important than S2, but in general, it is very sufficient for a good RUL estimation. However, for S3, a slight divergence of the estimation is observed in the 8th iteration.

In summary, we conclude that when the convergence is slow, the estimation can occur outside the horizon "the window of the measurement time" and prognosis results are automatically affected.

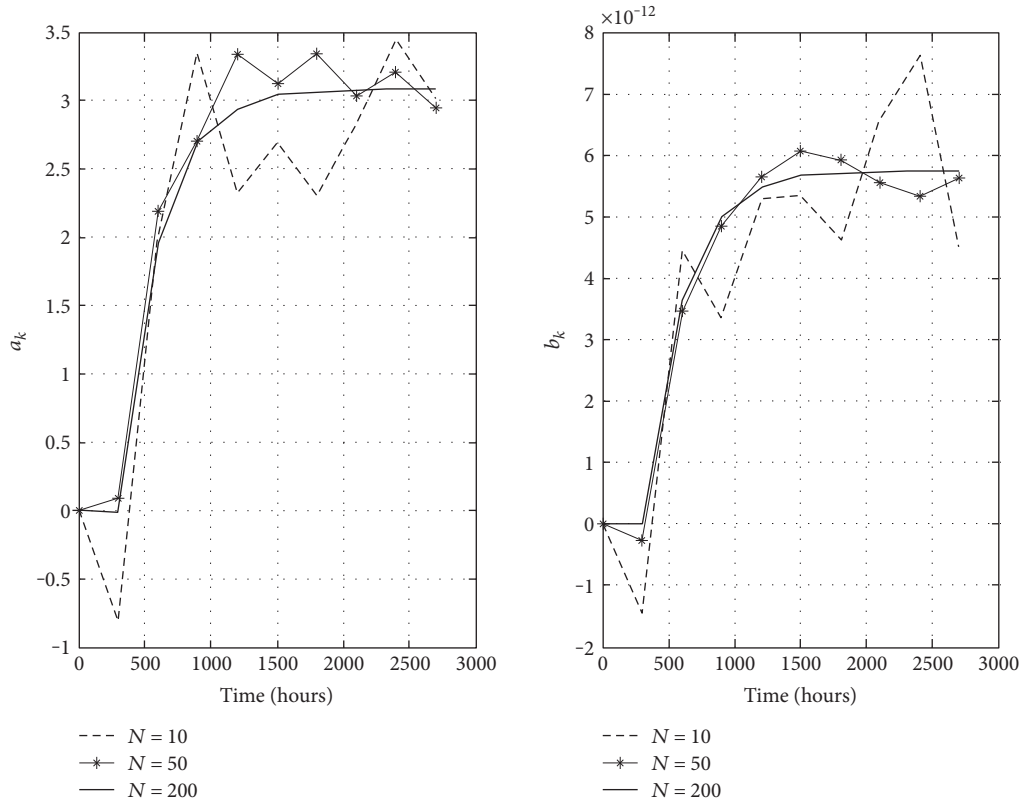

Figure 3: The member's number influence on the parameter convergence.

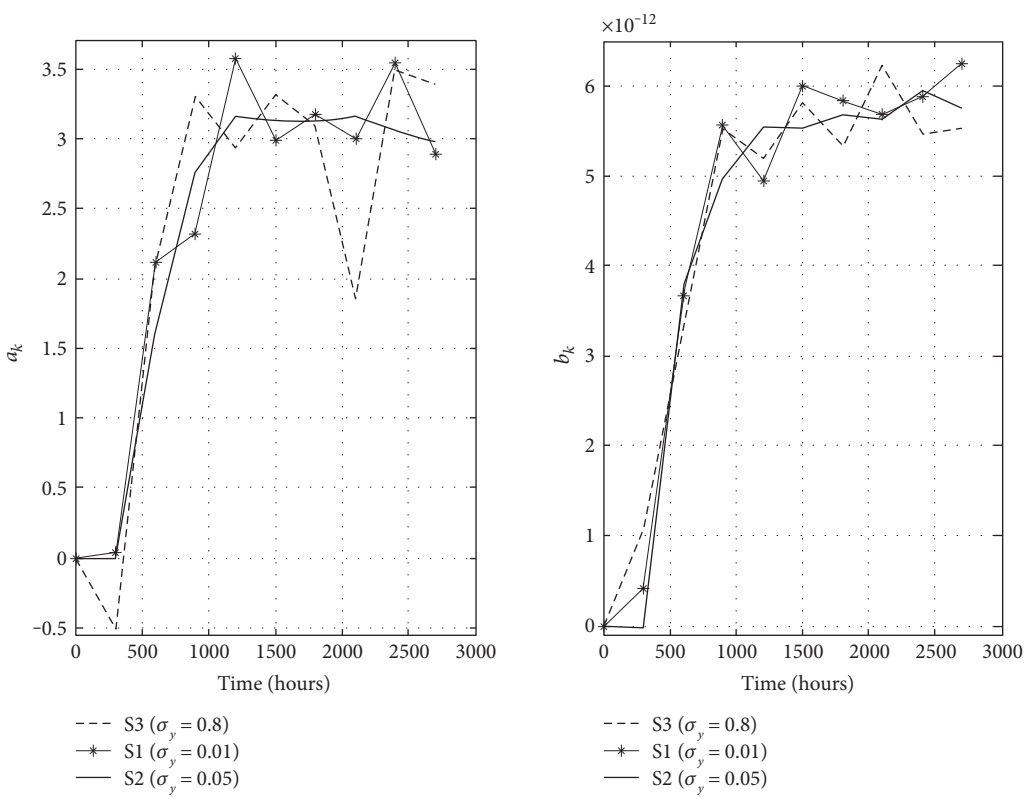

Figure 4: The uncertainty influence on the parameter convergence.

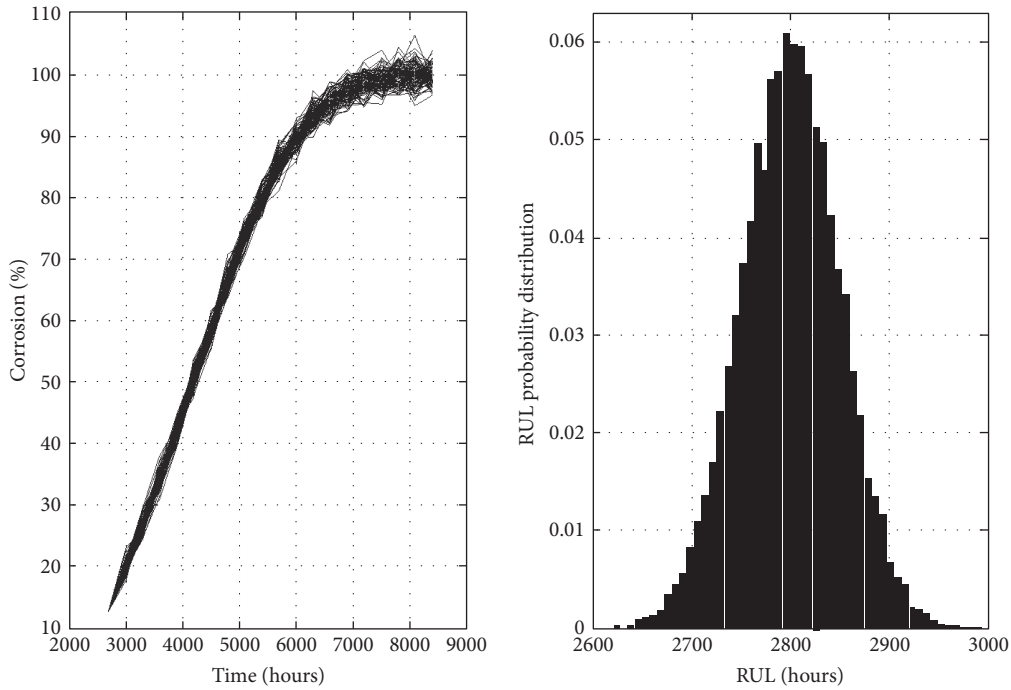

Figure 5: The RUL probability mass function and the damage trajectory estimation.

From results shown in Figures 3 and 4, we have selected the medium situation $(N = 50)$ combined with the scenario S2 $(\sigma_y = 0.05)$. We have conducted 100 Monte Carlo simulations of the future corrosion propagation, and the estimated RUL probability mass is shown in Figure 5. This figure shows that the mean of RUL is about 2800 h. This value could be used for maintenance purpose.

3.2.2. Analysis and Discussion. Now, in order to illustrate the relevance of the EnKF estimation compared to other particle filters, mainly, sequential importance sampling (SIS) and sequential importance resampling (SIR), a prognosis performance analysis based on accuracy and statistical dispersion criteria is introduced. Simulation results have been included to show the effectiveness of EnKF against SIS and SIR. In fact, in the literature, several metrics are used to measure those criterions (see, e.g., [30]). Therefore, in this study and for simplicity reason, we choose the relative accuracy (RA) and median absolute deviation (MAD) to measure, respectively, the prediction precision and the dispersion of the particles $(\mathrm{RUL}_i(k))_{i=1,\ldots,N}$ around the median, which is very important to compute the exactitude. More precisely, those indicators are given as follows:

$$\mathrm{RA}(k) = 100 \times \left(\frac{|\mathrm{RUL}_r(k) - \widehat{\mathrm{RUL}}(k)|}{\mathrm{RUL}_r(k)}\right),$$
$$\mathrm{MAD}(k) = \left(\frac{\mathrm{median}_j\left(\mathrm{RUL}_j(k) - \mathrm{median}_i(\mathrm{RUL}_i(k))\right)}{\mathrm{median}_i(\mathrm{RUL}_i(k))}\right), \tag{15}$$

where RUL_r denotes the true value of the RUL. Note that the confidence level related to the RUL estimation (see Figure 2) is derived from 95% of members or particles closest to the real $\mathrm{RUL}(k)$. After computing those indicators, the RA variation reaches 95% for the EnKF, while for SIS and SIR, it reaches 89% and 91%, respectively. Therefore, in terms of accuracy, the EnKF method gives a better RUL accuracy than SIS and SIR. However, in terms of member's $\mathrm{RUL}_i(k)_{i=1,\ldots,N}$ dispersion around the median, the results show that MAD related to EnKF, equal to 9.30%, is worse than 3.58% computed from the SIR member's dispersion; however, it is better than 12.83% computed from the SIS dispersed members. We conclude that, in terms of a combined accuracy-exactitude performance analysis, the EnKF presents the best prognosis compromise. Furthermore, other metrics can be developed; for instance, robustness, benefit, and convergence to illustrate even more the relevance on the EnKF.

4. Conclusion and Future Work

In this paper, the methodology of the PV corrosion prognostic with Bayesian filtering is introduced. More exactly, the filtering is conceived for the systems having strong nonlinearity like the corrosion model. The general methodology of the prognostic is elaborated into two steps. The estimation of the degradation parameter through an ensemble Kalman filter and prediction for estimating the remaining useful life (RUL). A numerical example, based on an accelerated corrosion test dataset, is used to illustrate the effectiveness of the proposed methodology for estimating RUL. In our future work, other filters will be implemented in others to show the relevance of the proposed methodology. This methodology will be also implemented to study RUL in real scenario under our Research and Development project.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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References

[1] G. Vachtsevanos, F. Lewis, M. Roemer, A. Hess, and B. Wu, *Intelligent Fault Diagnosis and Prognosis for Engineering Systems*, John Wiley and Sons, Hoboken, NJ, USA, 2006.

[2] C. S. Byington, P. W. Kalgren, R. Johns, and R. J. Beers, "Prognosis enhancements to diagnostic system for improved condition based maintenance," in *IEEE Systems Readiness Technology Conference*, pp. 320–329, CA, USA, September 2003.

[3] M. J. Roemer, C. S. Byington, G. J. Kacprzynski, and G. Vachtsevanos, "An overview of selected prognostic technologies with reference to an integrated PHM architecture," in *First International Forum on Integrated System Health Engineering and Management in Aerospace*, Napa Valley, CA, USA, October 2005.

[4] C. S. Byington, M. J. Roemer, and T. R. Galie, "Prognostic enhancements to diagnostic systems for improved condition-based maintenance [military aircraft]," in *IEEE Aerospace Conference Proceedings, 2002*, vol. 6, pp. 6-2815–6-2824, Big Sky, MT, USA, March 2002.

[5] D. Chelidze, "Multimode damage tracking and failure prognosis in electromechanical system," *SPIE Conference*, vol. 4733, pp. 1–12, 2002.

[6] T. Brotherton, G. Jahns, J. Jacobs, and D. Wroblewski, "Prognosis of faults in gas turbine engines," in *2000 IEEE Aerospace Conference Proceedings*, vol. 6, pp. 163–171, Big Sky, MT, USA, 2000.

[7] A. Eleuteri, R. Tagliaferri, L. Milano, S. De Placido, and M. De Laurentiis, "A novel neural network-based survival analysis model," *Neural Networks*, vol. 16, no. 5-6, pp. 855–864, 2003.

[8] J. Luo, K. R. Pattipati, L. Qiao, and S. Chigusa, "Model-based prognostic techniques applied to a suspension system," *IEEE Transactions on Systems, Man and Cybernetics, Part A: Systems and Humans*, vol. 38, no. 5, pp. 1156–1168, 2008.

[9] J. Luo, M. Namburu, K. Pattipati, L. Qiao, M. Kawamoto, and S. Chigusa, *Model-Based Prognostic Techniques, Anaheim, CA, USA*, Institute of Electrical and Electronics Engineers Inc., Piscataway, NJ, USA, 2003.

[10] S. Moaveni, *Finite Element Analysis: Theory and Application with ANSYS*, Pearson Prentice Hall, 2008.

[11] T. Takagi and M. Sugeno, "Fuzzy identification of systems and its applications to modeling and control," *IEEE Transactions on Systems, Man, and Cybernetics*, vol. SMC-15, pp. 116–132, 1985.

[12] D. Chelidze, *A Nonlinear Observer for Damage Evolution Tracking, [Ph.D. thesis]*, College School of Engineering Science and Mechanics, Pennsylvania State University, University Park, PA, USA, 2000.

[13] A. Chatterjee, J. P. Cusumano, and D. Chelidze, "Optimal tracking of parameter drift in a chaotic system: experiment and theory," *Journal of Sound and Vibration*, vol. 250, no. 5, pp. 877–901, 2002.

[14] D. Gucik-Derigny, R. Outbib, and M. Ouladsine, "A comparative study of unknown-input observers for prognosis applied to an electromechanical system," *IEEE Transactions on Reliability*, vol. 65, no. 2, pp. 704–717, 2016.

[15] M. Donga and D. Heb, "Hidden semi-Markov model-based methodology for multi-sensor equipment health diagnosis and prognosis," *European Journal of Operational Research*, vol. 178, no. 3, pp. 858–878, 2007.

[16] M. Chen, S. Liu, and L. Tieszen, "State-parameter estimation of ecosystem models using a smoothed ensemble Kalman filter," in *Summit on Environmental Modelling and Software, International Environmental Modelling and Software Society, 3rd Biennial Meeting*, Burlington, 2006.

[17] K. Le Son, A. Barros, and M. Fouladirad, "Utilisation d'un proessus de wiener pour le pronostic: csas d'étude sur données de test," in *Université de Technologie de Troyes Institut Charles Delaunay, Réunion du GT S3*, Paris, 2010.

[18] R. Leroux, *Inference Bayesienne Pour la Reconstruction d'ecoulements Complexes Application Au Prol NACA0012, [Ph.D. thesis]*, Universite de Poitiers Faculte des Sciences Fondamentales et Appliquees, 2012.

[19] B. S. Bhangu, P. Bentley, D. A. Stone, and C. M. Bingham, "Nonlinear observers for predicting state-of-charge and state-of-health of lead-acid batteries for hybrid-electric vehicles," *IEEE Transactions on Vehicular Technology*, vol. 54, pp. 783–794, 2005.

[20] G. Evensen, "Sequential data assimilation with nonlinear quasi-geostrophic model using Monte Carlo methods to forecast error statistics," *Journal of Geophysical Research*, vol. 99, no. C5, pp. 143–162, 1994.

[21] K. Yang and J. Xue, "Continuous state reliability analysis," in *Proceedings of 1996 Annual Reliability and Maintainability Symposium*, pp. 251–257, Las Vegas, NV, USA, 1996.

[22] M. J. Zuo, J. Renyan, and R. C. M. Yam, "Approaches for reliability modeling of continuous-state devices," *IEEE Transactions on Reliability*, vol. 48, no. 1, pp. 9–18, 1999.

[23] W. Q. Meeker, L. A. Escobar, and C. J. Lu, "Accelerated degradation tests: modeling and analysis," *Technometrics*, vol. 40, no. 2, pp. 89–11, 1998.

[24] D. Pasetto, M. Camporese, and M. Putti, "Ensemble Kalman filter versus particle filter for a physically-based coupled surface–subsurface model," *Advances in Water Resources*, vol. 47, pp. 1–13, 2012.

[25] Z. Yu, X. Fu, H. Lü et al., "Evaluating ensemble Kalman, particle, and ensemble particle filters through soil temperature prediction," *Journal of Hydrologic Engineering*, vol. 19, no. 12, 2014.

[26] L. Heidari, *Calage d'Historiques de Réservoirs Pétroliers par le Filtre de Kalman d'Ensemble et des Méthodes de Paramétrisation, [Ph.D. thesis]*, École nationale supérieure des mines de Paris, 2011.

[27] M. Orchard, *A Particle Filtering-Based Framework for on-Line Fault Diagnosis and Failure Prognosis, [Ph.D. thesis]*, Georgia Institute of Technology, Atlanta, GA, USA, 2007.

[28] R. Pan, J. Kuitche, and G. Tamizhmani, "Degradation analysis of solar photovoltaic modules: influence of environmental factor," in *2011 Proceedings - Annual Reliability and Maintainability Symposium (RAMS)*, pp. 1–5, Lake Buena Vista, FL, USA, 2011.

[29] R. Laronde, A. Charki, and D. Bigaud, "Reliability of photovoltaic modules based on climatic measurement data," *International Journal of Metrology and Quality Engineering*, vol. 1, no. 1, pp. 45–49, 2010.

[30] A. Saxena, J. Celaya, E. Balaban, S. Saha, B. Saha, and M. Schwarbacher, "Metrics for evaluating performance of prognostic techniques," in *2008 International Conference on Prognostics and Health Management*, pp. 1–17, Denver, CO, USA, 2008.