A Particle Filtering Approach for On-Line Failure Prognosis in a Planetary Carrier Plate

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Abstract

This paper introduces an on-line particle-filtering-based framework for failure prognosis in nonlinear, non-Gaussian systems. This framework uses a nonlinear state-space model of the plant (with unknown time-varying parameters) and a particle filtering (PF) algorithm to estimate the probability density function (pdf) of the state in real-time. The state pdf estimate is then used to predict the evolution in time of the fault indicator, obtaining as a result the pdf of the remaining useful life (RUL) for the faulty subsystem. This approach provides information about the precision and accuracy of long-term predictions, RUL expectations, and 95% confidence intervals for the condition under study. Data from a seeded fault test for a UH-60 planetary carrier plate are used to validate the proposed methodology.

Keywords : Particle Filtering, Failure Prognosis, Planetary Carrier Plate.

1. Introduction

Critical aircraft assets (exhibiting attributes of reliability, robustness and high confidence under a variety of flight regimes) are required to be available when needed, and maintained on the basis of their current condition rather than on the basis of scheduled maintenance practices. Moreover, condition-based maintenance (CBM) requires that the health of critical components/systems be monitored and diagnostic/ prognostic strategies be developed to detect incipient failures and predict the remaining useful life (RUL) of the failing component. New and innovative technologies must be developed and implemented to address these concerns.

Bayesian approaches are particularly well suited to solve the problem of real-time state estimation (critical for FDI/prognosis purposes) since they incorporate process data (in the form of sequential observations) into the "a priori" state estimate by considering the likelihood of these observations [1]. Particularly, sequential Monte Carlo (SMC) methods – also referred to as particle filtering (PF) – provide a solid and consistent theoretical framework to handle model nonlinearities or non-Gaussian process/observation noise. Founded on the concept of sequential importance sampling (SIS), particle filtering has been the subject of a broad and intensive amount of research over the past years in many diverse disciplines including economics, biostatistics, and even statistical signal processing problems in the engineering domain such as time series analysis, radar and sonar target tracking, and communications [2].

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Although several applications of PF for FDI may already be found in literature [3]-[7], little work has been done in the prognosis arena. In this sense, this paper introduces a methodology that uses a nonlinear dynamic state-space model to represent the behavior of the system under faulty operating conditions and PF-based algorithms to predict the evolution of the state pdf in real time. As a result, the proposed approach not only provides information about the precision and accuracy of long-term predictions, but also allows computing expectations and 95% confidence intervals for the RUL.

The organization of the paper is as follows. Section 2 provides the basic theoretical background for Bayesian estimation and PF. Section 3 focuses on the description of the particle-filtering-based approach used to solve the prognosis issue. Section 4 describes a case study where the proposed framework has been successfully employed to predict the growth of an axial crack in an UH-60 planetary carrier plate, thus allowing estimating 95% confidence intervals for the RUL of this piece of equipment. Main conclusions and final remarks are stated in Section 5.

2. Theoretical Background

Nonlinear filtering is the process of estimating at least the first two moments of a state vector governed by a dynamic nonlinear, non-Gaussian state-space equation, given noisy observation data [8]. Although in principle the estimation procedure may be implemented in continuous-time systems, the present paper is solely focused on discrete-time systems, since the streaming measurement data is sent (and received) through digital devices in most of the applications relevant to FDI and prognosis.

Mathematically speaking, let $X = \{X_t,\ t \in \mathbb{N}\}$ be a $\mathbb{R}^{n_x}$ – valued Markov process characterized both by its initial distribution $p(x_0)$ and the transition probability $p(x_t \mid x_{t-1})$. Let $p(x_t \mid x_{t-1})$ be defined by (1), where $\{\omega_t\}_{t\geq 0}$ is a sequence of independent random variables [9].

$$x_t = f_t(x_{t-1}, \omega_t) \tag{1}$$

Noisy observations $Y = \{Y_t,\ t \in \mathbb{N}\}$ are assumed to be conditionally independent, given $X = \{X_t,\ t \in \mathbb{N}\}$. Equation (2) defines the marginal distribution $p(y_t \mid x_t)$, where $\{\upsilon_t\}_{t\geq 0}$ is a sequence of independent random variables, not necessarily Gaussian [9].

$$y_t = g_t(x_t, \upsilon_t) \tag{2}$$

Let $x_{0:t} = \{x_0, \ldots, x_t\}$ and $y_{1:t} = \{y_1, \ldots, y_t\}$ denote the signal and the observations up to time t. It is of interest to estimate the posterior distribution $p(x_{0:t} \mid y_{1:t})$ and the marginal distribution $p(x_t \mid y_{1:t})$ [1]. This task can be achieved by performing two sequential steps, namely prediction and filtering [2]. On one hand, prediction uses both the knowledge of the previous state estimate and the process model to generate the a priori state pdf estimate for the next time instant:

$$p(x_{0:t} \mid y_{1:t-1}) = \int p(x_t \mid x_{t-1})\, p(x_{0:t-1} \mid y_{1:t-1})\, dx_{0:t-1}\,. \tag{3}$$

On the other hand, the filtering step generates the posterior state pdf, as shown in (4):

$$p(x_{0:t} \mid y_{1:t}) \propto p(y_t \mid x_t) \cdot p(x_t \mid x_{0:t-1}) \cdot p(x_{0:t-1} \mid y_{1:t-1}) \tag{4}$$

Particle-filtering intends to approximate the conditional state probability distribution $p(x_{0:t} \mid y_{1:t})$ by a swarm of points called "particles". These particles contain samples from the state-space and a set of weights – associated with them – representing discrete probability masses. In the particular case of the Bayesian Filtering problem, the target distribution $\pi_t(x_{0:t}) = p(x_{0:t} \mid y_{1:t})$ is the posterior pdf of $X_{0:t}$, given a realization of the noisy observations $Y_{1:t} = y_{1:t}$. A basic implementation of the algorithm, the SIR particle filter, is as follows [9]-[10].

SIR Particle Filter

1. Importance Sampling

- For $i = 1, \cdots, N$, sample $\tilde{x}_t^{(i)} \sim \pi(x_t \mid \tilde{x}_{0:t-1}^{(i)}, y_{0:t})$ and set $\tilde{x}_{0:t}^{(i)} \triangleq (x_{0:t-1}^{(i)}, \tilde{x}_t^{(i)})$.
- Evaluate the importance weights

$$w(\tilde{x}_{0:t}^{(i)}) = w_{0:t-1}^{(i)} \cdot \frac{p(y_t \mid \tilde{x}_t^{(i)})\, p(\tilde{x}_t^{(i)} \mid x_{0:t-1}^{(i)})}{q_t(\tilde{x}_t^{(i)} \mid x_{0:t-1}^{(i)})} \tag{5}$$

$$w_{0:t}^{(i)} = w(\tilde{x}_{0:t}^{(i)}) \cdot \left(\sum_{i=1}^{N} w(\tilde{x}_{0:t}^{(i)}) \right)^{-1} \tag{6}$$

2. Resampling Algorithm

If $\hat{N}_{eff} \geq N_{thres}$

- $\tilde{x}_{0:t}^{(i)} = \tilde{x}_{0:t}^{(i)}$ for $i = 1, \cdots, N$; otherwise
- For $i = 1, \cdots, N$, sample an index $j(i)$ distributed according to a discrete distribution satisfying $P(j(i) = l) = w_t^{(l)}$ for $l = 1, \cdots, N$. For each particle, $N_t^{(i)} \in \mathbb{N}\,(i = 1, \cdots, N)$ offspring are created $\left(\sum_{i=1}^{N} N_t^{(i)} = N\right)$.
- For $i = 1, \cdots, N$, $\tilde{x}_{0:t}^{(i)} = \tilde{x}_{0:t}^{j(i)}$ and $\tilde{w}_t^{(i)} = N^{-1}$

After the resampling procedure, the particle population $\{\tilde{x}_{0:t}^{(i)}\}_{i=1\cdots N}$ is an i.i.d. sample of the empirical distribution (7), and thus the weights are reset to $\tilde{w}_t^{(j)} = N^{-1}$.

$$\tilde{\pi}_t^N(x_{0:t}) = \frac{1}{N}\sum_{i=1}^{N} N_t^{(i)} \delta(x_{0:t} - \tilde{x}_{0:t}^{(i)}) = \frac{1}{N}\sum_{i=1}^{N} \delta(x_{0:t} - \tilde{x}_{0:t}^{(i)}) \tag{7}$$

3. Particle Filtering for Prognosis in Stochastic Nonlinear Systems

Prognosis may be understood as the result of the procedure where long-term (multi-step) predictions – describing the evolution in time of a fault indicator – are generated with the purpose of estimating the remaining useful life (RUL) of a failing component/subsystem. Several approaches related to prognosis may be found in the literature. Few of them, however, offer appropriate tools for real-time estimation of the RUL as a continuous function of time [11].

A two-level procedure has been developed to address the failure prognosis problem. This procedure intends to reduce the uncertainty associated with long-term predictions by using the current state pdf estimate and a nonlinear dynamic state-space model. In a first prognosis level, p-step ahead predictions are generated based on an *a priori* estimate, adjusting their associated probabilities according to the noise model structure. A second prognosis level uses these predictions and the definition of critical thresholds to estimate the RUL pdf, also referred to as the time-to-failure (TTF) pdf. A detailed description of each level is now presented.

A. First Prognosis Level: Generation of Long-Term Predictions

The first prognosis level is related to the generation of a p-

step ahead long term prediction for the state pdf, which can be obtained in a recursive manner using both the model update equation (1) and the current state estimate, as shown in (8).

$$\tilde{p}(x_{t+p} \mid y_{1:t}) = \int \tilde{p}(x_t \mid y_{1:t}) \prod_{j=t+1}^{t+p} p(x_j \mid x_{j-1}) dx_{t:t+p-1} \approx \sum_{i=1}^{N} w_t^{(i)} \int \cdots \int p(x_{t+1} \mid x_t^{(i)}) \prod_{j=t+2}^{t+p} p(x_j \mid x_{j-1}) dx_{t+1:t+p-1} \quad (8)$$

The evaluation of these integrals, though, may be difficult and/or may require significant computational effort. Consider, however, the predicted conditional state pdf $\hat{p}(x_{t+k}^{(i)} \mid \hat{x}_{t+k-1}^{(i)})$, which describes the state distribution at the future time instant $t+k$ ($k = 1, \ldots, p$) when the particle $\hat{x}_{t+k-1}^{(i)}$ is used as initial condition. Assuming that the current weights $\{w_t^{(i)}\}_{i=1\ldots N}$ are a good representation of the state pdf at time t, then it is possible to approximate the predicted state pdf at time $t+k$, by using the law of total probabilities and the particle weights at time $t+k-1$, as it is shown in (9).

$$\hat{p}(x_{t+k} \mid \hat{x}_{1:t+k-1}) \approx \sum_{i=1}^{N} w_{t+k-1}^{(i)} \cdot \hat{p}(x_{t+k}^{(i)} \mid \hat{x}_{t+k-1}^{(i)}) \; ; \quad \hat{x}_t^{(i)} = \tilde{x}_t^{(i)} \; ; \; k = 1, \cdots, p. \quad (9)$$

One approach that can be implemented in order to estimate (9), is to predict the evolution in time of each particle by successively taking the expectation of the model update equation (1) for every future time instant, considering the state value associated to that particle as initial condition, as shown in (10).

$$\hat{x}_{t+p}^{(i)} = E[f_{t+p}(\hat{x}_{t+p-1}^{(i)}, \omega_{t+p})] \quad ; \quad \hat{x}_t^{(i)} = \tilde{x}_t^{(i)} \quad (10)$$

This approach for long-term predictions is the simplest in terms of computational effort, and thus very appropriate for real-time applications. Basically, it states that the error that can be generated by considering the particle weights invariant for future time instants is negligible with respect to other sources of error that may appear in practical applications, such as model inaccuracies or even in the assumptions made for process and measurement noise parameters.

Therefore – from this standpoint – (10) is considered sufficient to extend the trajectories $\hat{x}_{0:t+k}^{(i)}$, while the current particle weights are propagated in time without changes. The computational burden of this method is significantly reduced and, as it will be shown in the Section 4, the method still offers a satisfactory view about how the system behaves for most practical applications.

B. Second Prognosis Level: Estimation and Statistical Characterization of the Remaining Useful Life (RUL) of Equipment

The final outcome for any prognosis algorithm is an estimate for the system RUL pdf, which is intrinsically entangled with the probability of failure at future time instants. This probability can be obtained from long-term predictions, when the empirical knowledge about critical conditions for the system is included in the form of thresholds for main fault indicators, also referred to as the hazard zones.

In real applications, it is expected for the hazard zones to be statistically determined on the basis of historical failure data, defining a critical pdf with lower and upper bounds for the fault indicator (H_{lb} and H_{ub}, respectively).

Since the hazard zone specifies the probability of failure for a fixed value of the fault indicator, and the weights $\{w_{t+k}^{(i)}\}_{i=1\cdots N}$ represent the predicted probability for the set of predicted paths, then it is possible to compute the probability of failure at any future time instant (namely the RUL pdf) by applying the law of total probabilities, as shown in (11). Once the RUL pdf is computed, combining the weights of predicted trajectories with the hazard zone specifications, it is well known how to obtain prognosis confidence intervals, as well as the RUL expectation.

$$\hat{p}_{TTF}(t) = \sum_{i=1}^{N} \Pr\left(Failure \mid X = \hat{x}_t^{(i)}, H_{lb}, H_{ub}\right) \cdot w_t^{(i)} \quad (11)$$

Expression (11) provides a solution for the prognosis problem that is very suitable for on-line applications, as the following case study shows.

4. Case Study: UH-60 Planetary Carrier Plate. Analysis of Axial Crack Growth

Consider the case of prognosis for the evolution of an axial crack on the plate of the UH-60 planetary carrier plate, shown in Figure 1.

Although this fault mode can lead to a critical failure condition in the aircraft, there was no certain way to determine its existence save by a detailed off-line inspection of this piece of equipment; a procedure which obviously involves large financial costs. Under this scenario, the use of algorithms capable of estimating the RUL by only analyzing vibration-based features becomes extremely attractive and would help to dramatically decrease operational and maintenance costs as well as avoid catastrophic events.

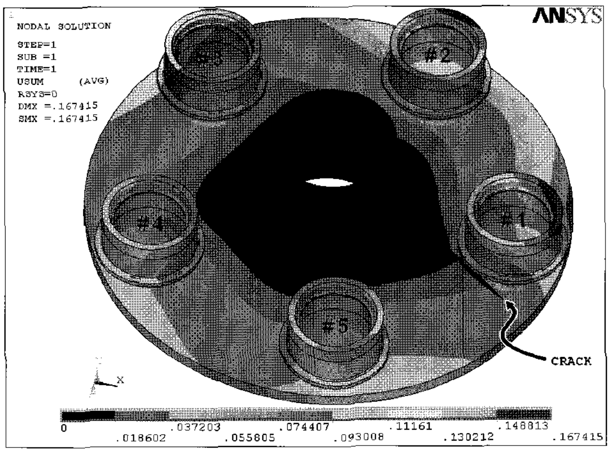


Figure 1. ANSYS model of the planetary carrier plate, showing crack location

With the purpose of testing the feasibility and efficiency of such techniques, a seeded fault test was conducted to collect fault data for a fixed known loading profile. In this test, the crack was grown until it reached a total length of 1.34", after which the gearbox was forced to operate emulating load changes that vary from 20% to 120% in 3 (min) ground-air-ground (GAG) cycles (see Figure 2).

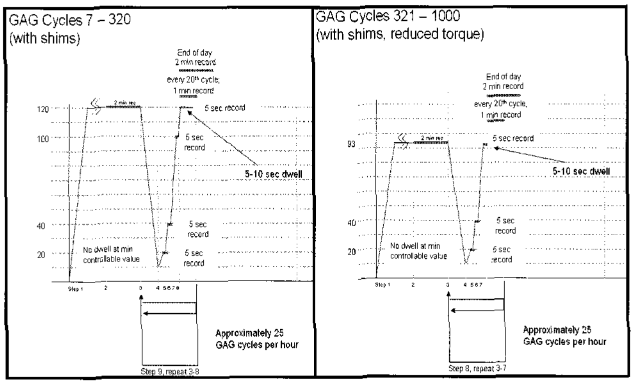


Figure 2. Loading profile diagram versus GAG cycles

A deterministic prognosis approach (based on concepts of material structure theory) was first considered to generate bounds for the failure time instant, given that the initial crack length is known. In this deterministic approach the crack growth evolution is described by using an empirical model such as the Paris' Law (12), given the proper set of coefficients [11], [12]:

$$\frac{dL}{dn} = C \cdot \left(U(n) \cdot \Delta K(n)\right)^m \qquad (12)$$

where L is the total crack length, C and m are material related coefficients, n is the cycle index, $U(n)$ is a parameter that models the effect of crack closure during cycle n and $\Delta K(n)$ is the crack tip stress variation during the cycle n, measured in ($MN/m^{3/2}$). Although simple, model (12) requires the computation of two critical parameters to be used in any prognosis routine: $\Delta K(n)$ and $U(n)$. The stress $K(n)$ may be estimated for a constant load (usually 100%) by using finite element analysis (FEA) tools such as ANSYS, for different crack lengths and crack orientation geometries. Considering a proportional relationship between the stress in the tip of the crack and the load percentage, it is in fact possible to construct a mapping relating both the current crack length and load variation per cycle with $\Delta K(n)$.

Albeit the former piece of information is helpful, it is insufficient to estimate the evolution of the crack length. On one hand, the closure effect parameter $U(n)$ cannot be efficiently measured and only empirical approximations exist for certain materials, such as Ti-6A1-4V. Even in the case of that material, only upper and lower bounds may be computed (see Figure 3), and thus it is impossible to compute expectations and/or determine statistically the validity of confidence intervals. Long term predictions and bounds generated by means of a deterministic model are reasonably good for regular maintenance scheduling, though insufficient for the on-line determination of confidence intervals and on-flight corrective actions.

The inclusion of process data, measured and pre-processed in an on-line fashion, or features related with the size of the crack improves tremendously the prospect of what can be achieved in terms of RUL estimation. Indeed, the use of features based on the ratio between the fundamental harmonic and the sidebands in the vibration data spectrum [12] gives the basis for the implementation of a particle-filtering prognosis framework. Under this approach, not only it is possible to estimate the expected growth of the crack, but also the unknown closure parameter in the crack growth model (12) and the RUL pdf, enabling the computation of any statistics such as expectations, confidence intervals, etc.

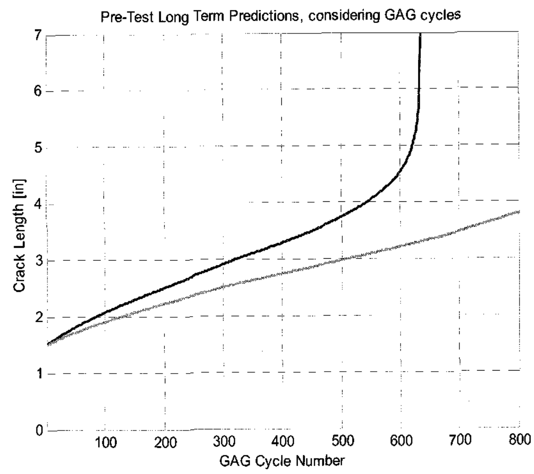


Figure 3. Deterministic bounds for crack length evolution vs. GAG cycles

The following crack growth state model (based on Paris' Law) has been implemented for purposes of on-line state and model parameter estimation:

$$\begin{cases} L(t+1) = C\cdot\alpha(t)\cdot\left\{\left(\Delta K_{inboard}(t)\right)^{m} + \left(\Delta K_{outboard}(t)\right)^{m}\right\} + \cdots \\ \qquad \cdots + L(t) + \omega_1(t) \\ \alpha(t+1) = \alpha(t) + \omega_2(t) \\ \Delta K_{inboard}(t) = f_{inboard}\left(\text{Load}(t), L(t)\right) \\ \Delta K_{outboard}(t) = f_{outboard}\left(\text{Load}(t), L(t)\right) \end{cases}, \quad (13)$$

$$\text{Feature}(t) = h(L(t)) + v(t)$$

where $L(t)$ is the total crack length estimation at GAG cycle t, $\alpha(t)$ is an unknown time-varying model parameter to be estimated (unitary initial condition), C and m are model constants related to material properties, ΔK is the variation in crack tips stress due to the load profile and the current crack length (estimated through off-line analysis of the system with ANSYS) and $\omega_1(t)$, $\omega_2(t)$ and $v(t)$ are non-Gaussian white noises.

Process model (13) necessitates a noisy estimate of the crack length based on the value of feature data to be used in on-line applications. This requirement is satisfied via a nonlinear mapping $h(\cdot)$, which is corrected or improved according to the ground truth crack length data that is acquired (at specific and very limited time instants) from strain gages sensors allocated on the surface of the planetary carrier plate.

As a result, in the proposed scheme, two update loops run in parallel. The first one, referred to as the *inner loop*, basically uses the feature data and the previous state pdf estimate to update the crack length and model parameter estimates and thus, the RUL pdf estimate through the prognosis approach discussed in Section 3. On the other hand a second loop, namely the *outer loop*, revises the nonlinear mapping $h(\cdot)$ between the vibration-based feature value and the crack length every time it gets an update from the strain gages allocated on the plate. It is expected, for future on-line applications, that the nonlinear mapping $h(\cdot)$ would be still valid, save for minor adjustments.

At any given time instant, each particle from the current particle population determines both an initial condition for a long term prediction and a probability associated with that prediction; see Figure 4 where each plausible long term prediction is depicted with a different color. The time instant when each predicted trajectory reaches a given threshold defines a probable failure time and thus, a realization of the remaining useful life (RUL) probability density function. RUL expectations, 95% confidence interval for long term predictions and ±3 sigma intervals may be computed once the RUL pdf is estimated through the described procedure. Table 1 shows the results for this particular case study, comparing all the statistics for long-term prediction with the ground truth data that was supplied from strain gages allocated on the plate surface.

Ground truth data points, i.e., strain gages crack length measurements, shown in Table 1 were provided incrementally up to 650 GAG cycles in a "*blind*" test format. Thus, for instance, the prediction result of Table 1 for GAG #36 (1.60") has been obtained at GAG #0 knowing only the initial crack length. Subsequently, the predicted value for GAG #100 (2.40") has been obtained at GAG #36 after the ground truth data value of 2.00" was used to adjust the nonlinear mapping $h(\cdot)$. The prediction for GAG #230 was made at GAG #100, and so on so forth.

Table 1. Prediction results for particle filtering-based approach for prognosis

Measured Crack Length		Confidence Intervals				
GAG	Length (inches)	-3σ	−95%	Mean	+95%	$+3\sigma$
0	1.34	N/A	N/A	1.34	N/A	N/A
36	2.00	0.74	1.03	1.60	2.17	2.46
100	2.50	1.93	2.09	2.40	2.71	2.87
230	3.02	2.73	2.79	2.90	3.01	3.07
400	3.54	3.41	3.54	3.80	4.06	4.19
550	4.07	3.85	4.11	4.30	4.60	4.75
650	4.52	4.20	4.48	4.71	5.08	5.70
750	6.78	6.38	6.42	6.61	6.76	6.84

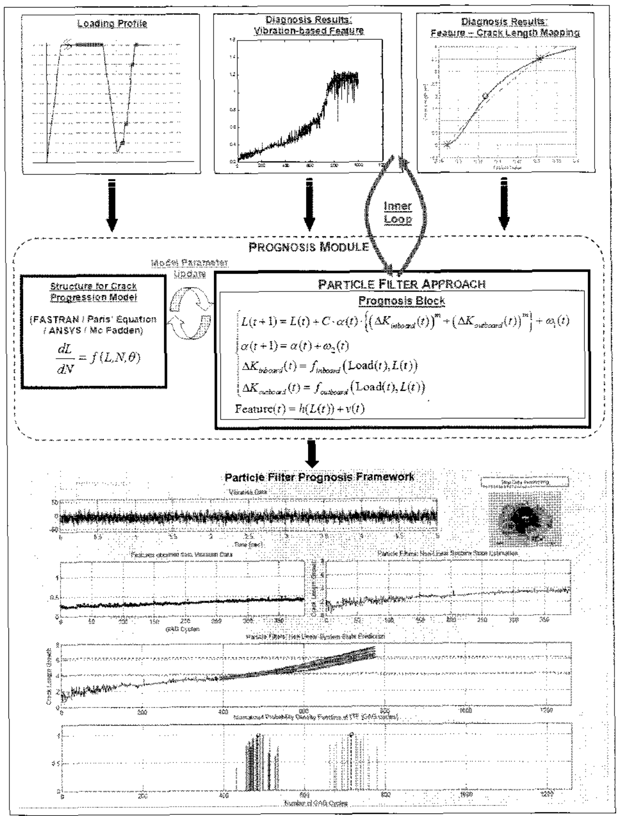


Figure 4. Particle filtering-based approach for prognosis. Crack growth in a planetary carrier plate

Every time a new point of ground truth data is included, a more accurate initial condition for the prediction algorithm is estimated, and hence the overall precision of the algorithm is enhanced. The modularity of the proposed approach allows even modifying the set of thresholds considered in the analysis, every time that it is required to increase the hazard level.

The accuracy of the algorithm has been validated at every step of the "*blind*" test, confirming the robustness of the approach with respect to changes in the load profile (depicted in Figure 2) and/or in the signal to noise ratio of the feature-based noisy crack length estimate, which steadily improved as the crack length increased.

In this sense, it is interesting to note how the estimate of the model parameter is indicative of changes in the testing operating conditions, as it is shown in Figure 5 where the load profile change at the GAG cycle #320 results evident.

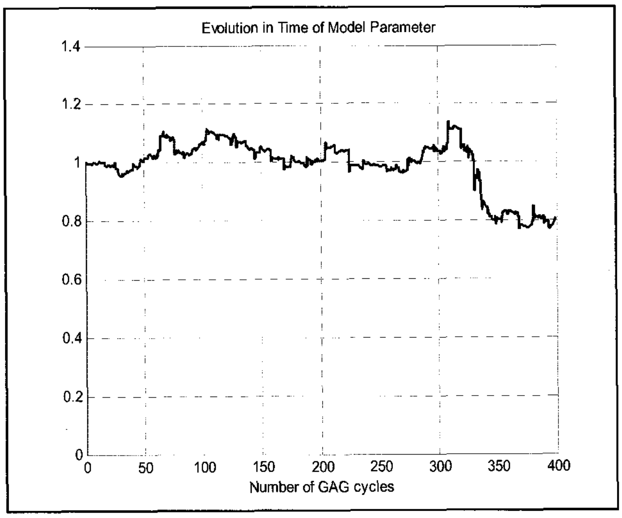


Figure 5. Time-varying model parameter vs. GAG cycles

Finally, it is important to mention that the proposed methodology has been compared with an EKF-based approach for long term prediction. Other approaches such as IMM or Unscented Kalman Filter were not considered since they implied a significantly higher computational burden than the proposed approach. Results were always favorable for the proposed particle filtering-based prognosis scheme in terms of accuracy and precision of the RUL pdf estimate.

The particle filtering framework for the prediction of the RUL may be easily implemented in real time on-board a HUMS or other health monitoring platform for on-line applications; in fact, an integrated architecture that combines vibration data processing, feature extraction, fault diagnosis and failure prognosis based on this concept is described in [13].

5. Conclusion

This paper introduces an architecture for the development, implementation, testing, and assessment of a particle-filtering-based framework for failure prognosis. The proposed method (SIR particle filter and an expectation-based long term prediction generation) was successfully tested in a case study, using real failure data from a seeded fault test in a UH-60 planetary carrier plate, providing an excellent insight about the effect of model inaccuracies and customer specifications (e.g., hazard zone definition, desired prediction window) in the algorithm performance. Furthermore, the obtained results show that the proposed approach is suitable for on-line implementation.

References

[1] Doucet, N. de Freitas, and N. Gordon, "An introduction to Sequential Monte Carlo methods," in *Sequential Monte Carlo Methods in Practice*, A. Doucet, N. de Freitas, and N. Gordon, Eds. New York: Springer-Verlag, 2001.

[2] M. S. Arulampalam, S. Maskell, N. Gordon, and T. Clapp, "A Tutorial on Particle Filters for Online Nonlinear/Non-Gaussian Bayesian Tracking," *IEEE Transactions on Signal Processing*, vol. 50, no. 2, February 2002.

[3] V. Kadirkamanathan, P. Li, M. H. Jaward, and S. G. Fabri, "Particle filtering-based fault detection in non-linear stochastic systems," *International Journal of Systems Science*, vol. 33, no. 4, pp. 259 – 265, 2002.

[4] X. Koutsoukos, J. Kurien, and F. Zhao, "Monitoring and Diagnosis of Hybrid Systems Using Particle Filtering Models," *International Symposium on Mathematical Theory of Networks and Systems*, 2002.

[5] P. Li, and V. Kadirkamanathan, "Particle Filtering Based Likelihood Ratio Approach to Fault Diagnosis in Nonlinear Stochastic Systems," *IEEE Transactions on Systems, Man, and Cybernetics — Part C: Applications and Reviews*, vol. 31, no. 3, 2001.

[6] V. Verma, G. Gordon, R. Simmons, and S. Thrun, "Particle Filters for Rover Fault Diagnosis," *IEEE Robotics & Automation Magazine*, pp. 56 – 64, June 2004.

[7] N. de Freitas, "Rao-Blackwellised Particle Filtering for Fault Diagnosis," *IEEE Aerospace Conference Proceedings* (Cat. No. 02TH8593), pt. 4, pp. 1767 – 1772, 2002.

[8] A. J. Haug, "A Tutorial on Bayesian Estimation and Tracking Techniques Applicable to Nonlinear and Non-Gaussian Processes," *MITRE Technical Report. MTR* 05W0000004, The MITRE Corporation, 2005.

[9] C. Andrieu, A. Doucet, and E. Punskaya, "Sequential Monte Carlo Methods for Optimal Filtering," *in Sequential*

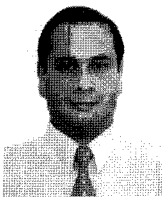
Monte Carlo Methods in Practice, A. Doucet, N. de Freitas, and N. Gordon, Eds. New York: Springer-Verlag, 2001.

[10] A. Doucet, S. Godsill, and C. Andrieu, "On Sequential Monte Carlo sampling methods for Bayesian filtering," *Statistics and Computing*, vol. 10, no 3, pp. 197-208, July 2000.

[11] A. Ray, and S. Tangirala, "Stochastic Modeling of Fatigue Crack Dynamics for On-Line Failure Prognosis," *IEEE Transactions on Control Systems Technology*, vol. 4, no. 4, pp. 443 – 451, 1996.

[12] R. Patrick, *A Model Based Framework for Fault Diagnosis and Prognosis of Dynamical Systems with an Application to Helicopter Transmissions*, Ph.D. Thesis, Department of Electrical and Computer Engineering, Georgia institute of Technology, 2007.

[13] M. Orchard, *A Particle Filtering-based Framework for On-line Fault Diagnosis and Failure Prognosis*, Ph.D. Thesis, Department of Electrical and Computer Engineering, Georgia institute of Technology, 2007.



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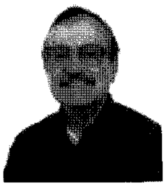

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