A Particle Filtering-based Framework for Real-time Fault Diagnosis and Failure Prognosis in a Turbine Engine

Marcos E. Orchard, Member, IEEE, George J. Vachtsevanos, Senior Member, IEEE

Abstract—This paper presents the implementation of an online particle-filtering-based framework for fault diagnosis and failure prognosis in a turbine engine. The methodology considers two autonomous modules, and assumes the existence of fault indicators (for monitoring purposes) and the availability of real-time measurements. A fault detection and identification (FDI) module uses a hybrid state-space model of the plant, and a particle filtering algorithm to calculate the probability of a crack in one of the blades of the turbine; simultaneously computing the state probability density function (pdf) estimates that will be used as initial conditions in the prognosis module. The failure prognosis module, on the other hand, computes the remaining useful life (RUL) pdf of the faulty subsystem in real-time, using a particle-filtering-based algorithm that consecutively updates the current state estimate for a nonlinear state-space model (with unknown time-varying parameters), and predicts the evolution in time of the probability distribution for the crack length. The outcome of the prognosis module provides information about precision and accuracy of long-term predictions, RUL expectations and 95% confidence intervals for the failure condition under study. Data from a seeded fault test is used to validate the proposed approaches.

Keywords: Particle filtering, fault detection, failure prognosis, turbine engine.

I. INTRODUCTION

Fault diagnosis and failure prognosis have become key issues in a world where the economic impact of reliability related issues and cost effective operation of critical assets is steadily increasing. Fault diagnosis involves the detection of abnormal conditions in the system and the identification of their locations and causes, a critical task in any health management system (HMS). Prognosis – as a natural extension to the fault detection and identification (FDI) problem – intends to characterize the evolution in time of the detected fault condition, thus allowing the estimation of the remaining useful life (RUL) of the affected subsystems or components. Several examples can be cited here in order to illustrate the range of applications for these types of algorithms: electro-mechanical systems, continuous-time manufacturing processes, structural damage analysis and even fault tolerant software architectures. Most of these applications have in common that they are highly complex, non-linear, and affected by large-grain uncertainty.

The task is particularly difficult when the system under study is operating in real time, especially in the case of prognosis. Most of the approaches currently available in the reliability arena involve intensive computations and the processing of large amounts of historical data [1]. More importantly, the obtained results do not necessarily include knowledge about the physics of the system and there is little room left for on-line updates in the predicted RUL when the system is behaving differently from what it is expected.

Recursive Bayesian approaches are particularly well suited to solve the issue of real-time estimation, since they incorporate process data into the “a priori” state estimate, by considering the likelihood of observations [2]. Particularly, sequential Monte Carlo (SMC) methods – also referred to as particle filters (PF) – provide a solid and consistent theoretical framework to handle model nonlinearities and/or non-Gaussian noise structures. Furthermore, PF allows information from multiple measurement sources to be fused in a principled manner.

Although several applications of PF for FDI may already be found in the literature [3]–[6], little work has been done in the prognosis arena, since no future measurements can be used to correct for model inaccuracies. In that sense, this paper proposes a general theoretical framework where both FDI and prognosis objectives are achieved in real-time, also showing a real application where such approach has been implemented successfully. This methodology allows the inclusion of customer specifications (statistical confidence in fault detection, minimum prediction window, etc.) in a simple and direct way. Moreover, all the outcomes are easily provided to plant operators through real-time updated graphs and may be easily coded and embedded in compact modules.

The organization of the paper is as follows. Section II provides the theoretical background for Bayesian estimation and PF, also indicating the state-of-the-art for the application of these methods in FDI and prognosis. Section III introduces the proposed approach for online FDI, and presents the results obtained for a real application example. Section IV focuses in the prognosis issue, providing the theoretical foundation and showing the results for the analysis of the crack growth in one blade of a turbine engine. Main conclusions and final remarks are stated in Section V.
II. THEORETICAL REVIEW

A. Bayesian Estimation and Particle Filtering

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 [7]. Within a Bayesian general formulation for the dynamic state estimation problem, the main goal of a nonlinear filtering procedure is to generate an estimation of the posterior probability density function (pdf) for the state, based on the set of received measurements [7].

Mathematically speaking, let \( X = \{ X_t , t \in \mathbb{N} \} \) be a \( \mathbb{R}^n \) -valued Markov process characterized both by its initial distribution \( p(x_0) \) and the transition probability \( p(x_t | x_{t-1}) \). Moreover, let \( p(x_t | x_{t-1}) \) be defined by (1), the distribution of the random variable \( X_t | X_{t-1} \).

\[
X_t | X_{t-1} = x_{t-1} \sim f_t(\cdot | x_{t-1}) \tag{1}
\]

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 \( p(y_t | x_t) \).

\[
Y_t | X_t = x_t \sim g_t(\cdot | x_t) \tag{2}
\]

Let \( x_{0:t} \equiv \{ x_0, \ldots , x_t \} \) and \( y_{1:t} \equiv \{ y_1, \ldots , y_t \} \) denote, respectively, the signal and the observations up to time \( t \). It is of interest to estimate the posterior distribution \( p(x_{0:t} | y_{1:t}) \), the marginal distribution \( p(x_t | y_{1:t}) \) and the expectations \( (3) \) for any function \( f_t : \mathbb{R}^n \rightarrow \mathbb{R}^n \) integrable with respect to \( p(x_{0:t} | y_{1:t}) \) [2].

\[
I(f_t) = \mathbb{E}_{p(x_{0:t} | y_{1:t})} [ f_t(x_{0:t}) ] \triangleq \int f_t(x_{0:t}) p(x_{0:t} | y_{1:t}) dx_{0:t} \tag{3}
\]

This task can be basically achieved by performing two sequential steps, namely prediction and filtering [8]. 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.

\[
p(x_{0:t} | y_{1:t-1}) = \int p(x_t | x_{t-1}) p(x_{0:t-1} | y_{1:t-1}) dx_{0:t-1} \tag{4}
\]

On the other hand, the filtering step, which can be implemented by using the recursion formula (5), generates the posterior state pdf, by using Bayes formula:

\[
p(x_{0:t} | y_{1:t}) \propto p(y_t | x_t) \cdot p(x_t | x_{0:t-1}) \cdot p(x_{0:t-1} | y_{1:t-1}) \tag{5}
\]

Expressions (3), (4) and (5) do not have analytical solution in most cases. In that sense, SMC algorithms (particle filters) make feasible their evaluation through the use of efficient sampling strategies [8, 9].

B. Sequential Monte Carlo Methods: Particle Filtering

Consider a sequence of probability distributions \( \{ \pi(x_{0:t}) \} \), where it is assumed that we can evaluate \( \pi(x_{0:t}) \) pointwise up to a normalizing constant. SMC methods, also referred to as particle filters, are a class of algorithms designed to approximately obtain samples sequentially from \( \pi \), i.e. to generate a collection of \( N \gg 1 \) weighted random samples \( \{ w^{(i)}_t , x^{(i)}_{0:t} \}_{i=1}^N \), satisfying (6) [10].

\[
\sum_{i=1}^N w^{(i)}_t \phi_t(x^{(i)}_{0:t}) = \int \phi_t(x_{0:t}) \pi_t(x_{0:t}) dx_{0:t} \tag{6}
\]

where \( \phi_t \) is any \( \pi_t \)-integrable function.

In the particular case of the Bayesian Filtering problem, the target distribution \( \pi_t(x_{0:t}) = p(x_{0:t} | y_{1:t}) \) is the posterior pdf of \( x_{0:t} \), given a realization of the noisy observations \( Y_{1:t} = y_{1:t} \). Using (1) and (2), \( \pi_t(x_{0:t}) \) may be written as [9]:

\[
\pi_t(x_{0:t}) = p(x_0) \prod_{k=0}^{t-1} f_t(x_k | x_{k+1}) g_t(y_k | x_k) \tag{7}
\]

Assume that a set of \( N \) paths \( \{ x^{(i)}_{0:t} \}_{i=1}^N \) is available at time \( t=1 \) and that they distribute according to \( q_{t-1}(x_{0:t-1}) \), also referred to as the importance density function at time \( t=1 \). The objective is to efficiently obtain a set of \( N \) new paths (particles) \( \{ \tilde{x}^{(i)}_{0:t} \}_{i=1}^N \) approximately distributing according to \( \pi_t(x_{0:t}) \) [10].

For this purpose, the current paths \( x^{(i)}_{0:t} \) are extended by using the kernel \( q_t(\tilde{x}^{(i)}_{0:t}, x_{0:t-1}) = q_t(\tilde{x}^{(i)}_{0:t}, x_{0:t-1}) q_{t-1}(x_{0:t-1}) \), i.e. \( \tilde{x}^{(i)}_{0:t} = (x_{0:t-1}, \tilde{x}^{(i)}_t) \). The importance sampling procedure generates consistent estimates for (3), by approximating (7) with the empirical distribution [10]

\[
\tilde{x}^{N}_t(x_{0:t}) = \sum_{i=1}^N w^{(i)}_t \delta(x_{0:t} - \tilde{x}^{(i)}_{0:t}) \tag{8}
\]

where \( w^{(i)}_t \propto w_{0:t}(\tilde{x}^{(i)}_{0:t}) \) and \( \sum_{i=1}^N w^{(i)}_t = 1 \).

The most basic SMC implementation – the sequential importance sampling (SIS) particle filter – computes the value of the particle weights \( w^{(i)}_t \), by setting the importance density function equal to the a priori pdf for the state, i.e. \( q_t(\tilde{x}^{(i)}_{0:t}, x_{0:t-1}) = p(x_{0:t-1}) = f_t(\tilde{x}^{(i)}_{0:t}, x_{0:t-1}) \). In that manner, the weights for the newly generated particles are evaluated from the likelihood of new observations. The efficiency of the procedure improves as the variance of the importance weights is minimized.

The choice of the importance density function is critical in the performance of the particle filter scheme. Several approaches geared to improve the performance of the
algorithm, mainly based on the minimization of the evolution of the weight variance over time, have been suggested by different authors [11]-[16].

C. Resampling step: SIR Particle Filter

One of the main difficulties that must be addressed in the implementation of SIS particle filters is the degeneracy problem [17] since, after a few iterations, all but one particle will have a negligible weight [8], [9]-[10]. Several authors have proposed methods to overcome this problem [18]-[20], measuring the degeneracy in the particle population with \( \hat{N}_{\text{eff}} \), an estimate of the effective sample size \( N_{\text{eff}} \) [9].

\[
N_{\text{eff}} = N \left( 1 + \text{var}_{x(t)} \left( w_{i(t)} \right) \right)^{-1}, \quad \hat{N}_{\text{eff}} = \left( \sum_{i=1}^{N} (w_{i(t)})^2 \right)^{-1} \tag{9}
\]

Whenever \( \hat{N}_{\text{eff}} \leq N_{\text{thresh}} \), a fixed threshold, a resampling algorithm [8], [9], [13] is performed to eliminate particles with small weights, concentrating the computational efforts in those having large ones. Considering the latter, the algorithm for the sampling importance resampling (SIR) particle filter is as follows [9]:

**SIR Particle Filter Algorithm**

1) Importance Sampling

- For \( i = 1, \ldots, N \), sample \( \tilde{x}_{i}^{(t)} \sim \pi(x_{i}^{(t)} | x_{0:t-1}^{(t)}, y_{0:t}) \) and set \( \tilde{x}_{i}^{(t)} = (x_{i}^{(t)}, \tilde{x}_{i}^{(t)}) \).
- Evaluate the importance weights

\[
w^{(i)}(\tilde{x}_{i}^{(t)}) = w_{i}^{(t)}(\tilde{x}_{i}^{(t)}) = \frac{\pi^{(t)}(\mathbf{y}_{t}^{(t)} | \mathbf{x}_{t}^{(t)})}{\pi^{(t)}(\mathbf{y}_{t}^{(t)} | \mathbf{x}_{t}^{(t)})} \tag{10}
\]

\[
w_{i}^{(t)} = \frac{\pi^{(t)}(\mathbf{x}_{t}^{(t)} | \mathbf{y}_{t}^{(t)})}{\sum_{i=1}^{N} \pi^{(t)}(\mathbf{x}_{t}^{(t)} | \mathbf{y}_{t}^{(t)})} \tag{11}
\]

2) Resampling Algorithm

- If \( \hat{N}_{\text{eff}} \geq N_{\text{thresh}} \), \( \tilde{x}_{i}^{(t)} = \hat{x}_{i}^{(t)} \) for \( i = 1, \ldots, N \) otherwise.
- For \( i = 1, \ldots, N \), sample an index \( j(i) \) distributed according to a discrete distribution satisfying

\[
P(j(i) = l) = w_{l}^{(i)} \quad \text{for} \quad l = 1, \ldots, N.
\]

- For \( i = 1, \ldots, N \), \( \hat{x}_{i}^{(t)} = \tilde{x}_{j(i)}^{(t)} \) and \( \hat{w}_{i}^{(t)} = N^{-1} \)

After the resampling procedure, the new particle population \( \{ \hat{x}_{i}^{(t)} \}_{i=1}^{N} \) is an i.i.d. sample of the empirical distribution (12), and thus the weights are reset to \( \hat{w}_{i}^{(t)} = N^{-1} \).

\[
\hat{w}_{i}^{(t)}(x_{0:t}) = \frac{1}{N} \sum_{i=1}^{N} N_{i}^{(t)} \delta(x_{0:t} - \hat{x}_{i}^{(t)}) = \frac{1}{N} \sum_{i=1}^{N} \delta(x_{0:t} - \hat{x}_{i}^{(t)}) \tag{12}
\]

III. PARTICLE FILTERING FOR DIAGNOSIS

The proposed fault diagnosis procedure fuses and utilizes the information present in a feature vector (observations) with the objective of determining the operational condition (state) of a system and the causes for deviations from desired behavioral patterns. From a nonlinear Bayesian state estimation standpoint, this task may be accomplished by the use of a particle-filtering-based module built upon the nonlinear dynamic state model (13).

\[
\begin{aligned}
x_{a}(t+1) &= f_{a}(x_{a}(t) + n(t)) \\
x_{b}(t+1) &= f_{b}(x_{b}(t), v(t)) \\
\text{Features}(t) &= h_{b}(x_{a}(t), x_{b}(t), v(t))
\end{aligned} \tag{13}
\]

Where \( f_{a}, f_{b}, h_{b} \) are non-linear mappings, \( x_{a}(t) \) is a collection of Boolean states associated with the presence of a particular operational condition in the system (normal operation, fault type #1, #2, etc.), \( x_{b}(t) \) is a set of continuous-valued states that describe the evolution of the system given those operational conditions, \( n(t) \) is zero-mean i.i.d. uniform white noise and \( \alpha(t), v(t) \) are non-Gaussian distributions that characterize both the process and feature noise, respectively.

One particular advantage of the proposed particle filtering approach is the ability to characterize the evolution in time of the above mentioned nonlinear model through modification of the probability masses associated with each particle, as new data from fault indicators are received. Furthermore, the output of the fault diagnosis module, defined as the current expectation of each Boolean state, provides recursively updated estimates of the probability for each fault condition considered in the analysis. In addition, pdf estimates for the system continuous-valued states provide the capability of performing swift transitions to failure prognosis algorithms, one of the main advantages offered by the proposed approach.

A. Detection of cracks in blades of a turbine engine

Consider the case where the particle filtering-based approach for FDI is applied for the detection of cracks in the blades of a turbine engine, see Fig. 1. Light probes on both the leading and the trailing edge of the blades have been installed in order to provide with the time-of-arrival (TOA) for each blade. Some pre-processing techniques were needed in order to generate a feature that can be used for detection purposes, the tangential blade position (TBP). Fig. 2 shows a schematic that illustrates the pre-processing steps, which basically start with the least square estimation of two parameters, namely \( A \) and \( B \), that relate the inter-blade spacing (IBS) with the square of the normalized rpm value.

In addition to the vibration-based feature, and after an exhaustive FRANC-3D structural analysis about the stresses on turbine blades undergoing a crack, it has been determined that (14) represents a model suitable for describing the crack growth under nominal load conditions [21].

\[
x_{a}(t+1) = f_{a}(x_{a}(t) + n(t))
\]
\[
\frac{dL}{dn} = \frac{1}{6\alpha \cdot L^2(n) + p(L(n))}
\]  
(14)

Where \( L \) is the length of the crack (in inches), \( n \) is the number of stress cycles applied to the material, \( \alpha \) is a model parameter to be estimated and \( p(L(n)) \) is a known fourth order polynomial determined with the help of the FRANC-3D structural model.

Assuming the existence of a 1-to-1 nonlinear mapping \( h(\cdot) \) between the feature information and the actual size of the crack in the blade, it is possible to implement a nonlinear model suitable for a particle filter-based FDI framework. The model is shown in (15), being \( \beta \) a known model parameter and where \( \omega(t) \) and \( \nu(t) \) have been selected as zero mean Gaussian noises for simplicity.

The FDI module itself discriminates between two Boolean states: absence of crack in any blade (normal condition) or presence of crack (fault condition) in at least one of them. As one value of the tangential blade position feature is calculated per blade and per cycle, the module is also able to pinpoint the blade which has been affected by a crack condition (fault identification).

\[
x_{c1}(t+1) = f_c\left(x_{c1}(t) + n(t)\right)
\]
\[
x_{c2}(t+1) = \left((1 + \beta)x_{c1}(t) - x_{c2}(t) + \alpha(t)\right)
\]
\[
f_c(x) = \begin{cases} 
[1 \ 0]^T, & \text{if } \|x-[1 \ 0]^T\| \leq \|x-[0 \ 1]^T\| \\
[0 \ 1]^T, & \text{else}
\end{cases}
\]
\[
x_{c1}(0) = \begin{bmatrix} 1 \\
0
\end{bmatrix}
\]
\[
x_{c2}(0) = \begin{bmatrix} 0 \\
1
\end{bmatrix}
\]

(15)

Results of the detection module for the case of one particular blade are shown in Fig. 3. Although it is possible to observe some changes in the probability of failure condition around the 230th cycle of operation, it is clear that only after the 280th cycle the evidence in the feature is strong enough to ensure the existence of a crack. After that particular time instant, the pdf estimate for the state \( x_c(t) \) together with \( h(\cdot) \) may be used for prognosis purposes.

IV. PARTICLE FILTERING FOR PROGNOSIS

A. Prognosis and generation of Long-term predictions

Prognosis can be essentially understood as the generation of long-term predictions describing the evolution in time of a particular signal of interest or fault indicator. Since prognosis intends to project the current condition of the indicator, it necessarily entails large-grain uncertainty. These facts suggest a prognosis scheme based on recursive Bayesian estimation techniques, combining the information from fault growth models and online data from sensors monitoring the plant.

Prognosis, though, is a problem that goes beyond the scope of filtering applications, since it involves future time horizons. Hence, it is necessary to project the current particle population in time, in absence of new observations. To solve this problem, a two-level procedure has been developed and subsequently tested in a case study.
1) First Prognosis Level: Long-Term Predictions

The first prognosis level is related to the generation of a p-step ahead long term prediction for the state pdf of a dynamic system, which can be obtained by using both the model update equation (1) and the current state estimation in a recursive manner, as it is shown in (16).

$$\tilde{p}(x_{t+p} | y_{t}) = \int \tilde{p}(x_{t} | y_{t}) \prod_{j=1}^{p} p(x_{t+j} | x_{t-j}) dx_{t-1+p}$$

$$\approx \sum_{i=1}^{N} w_{i}^{(p)} \int \tilde{p}(x_{t} | y_{t}) \prod_{j=1}^{p} p(x_{t+j} | x_{t-j}) dx_{t-1+p} \quad (16)$$

The evaluation of these integrals, though, may be difficult and/or may require significant computational effort. The proposed PF-based methodology simplifies and solves this problem, by successively taking the expectation of (1) to predict the evolution in time of each particle, considering the state value associated to the particle as initial condition.

$$\tilde{x}_{t+p}^{(i)} = E[f_{t+p}(\tilde{x}_{t-1+p}^{(i)}, \omega_{t+p})] \quad ; \quad \tilde{x}_{t}^{(i)} = x_{t}^{(i)} \quad (17)$$

In many practical applications, the error that can be generated by considering the particle weights invariant for future time instants is negligible with respect to other sources, such as model inaccuracies or wrong assumptions about process/measurement noise parameters.

Thus, from this standpoint, (17) is considered sufficient to extend the trajectories $\tilde{x}_{t+p}^{(i)}$ in those cases, while the current particle weights are propagated in time without changes. The computational burden of this method is considerably reduced and, as it will be shown in simulation results, it can give a satisfactory view about how the system behaves in time for most practical applications.

2) Second Prognosis Level: RUL pdf Estimation

Long-term predictions can be used to estimate the probability of failure in a process, given a hazard zone that is defined via a probability density function with lower and upper bounds for the domain of the random variable ($H_{lb}$ and $H_{up}$, respectively). Clearly, customer specifications or historical failure data may be used with this purpose.

The probability of failure at any future time instant, namely the RUL pdf, is estimated in real-time by combining both the weights $w_{i}^{(p)}$ of predicted trajectories and the specifications for the hazard zone, as shown in (18). Once the RUL pdf is computed, it is well known how to obtain prognosis confidence intervals, as well as RUL expectations.

$$\hat{p}_{TTF}(ttf) = \sum_{i=1}^{N} \text{Pr}(\text{Failure} | X = \tilde{x}_{t}^{(i)}, H_{lb}, H_{up}), w_{i}^{(p)} \quad (18)$$

To reduce the prognosis uncertainty and improve the accuracy of the RUL expectation, an outer correction loop has been included as part of the proposed second prognosis level. This outer loop is basically a data-driven learning paradigm. It computes a correction term $C_{n}$, the difference between the current RUL expectation and the one that was computed in the previous iteration. Once $p$ correction terms are obtained, a linear autoregressive model is built to establish a relationship between all past correction terms. In simple words, the outer correction loop intends to capture the pattern of past measurement-driven updates in a simple model, which can be used afterwards to estimate and correct for the accuracy of the current prediction.

B. Case study: Analysis of crack growth in blades of a turbine engine

Consider the problem discussed in Section III.A, where the objective is to analyze the growth in a crack on a turbine engine blade. As it was previously mentioned, vibration measures have been processed to come up with a feature directly related to the size of the crack in the blade, namely tangential blade position (TBP). A model-based update equation, based on the structural model (14), is shown in (19).

$$\begin{align*}
\hat{x}_{c3}(t+1) &= \left(1 + \frac{1}{6 \cdot x_{c3}(t) \cdot x_{c3}(t) + p(x_{c3})} \right) x_{c3}(t) + \omega_{1}(t) \\
\hat{x}_{c2}(t+1) &= \hat{x}_{c2}(t) + \omega_{2}(t) \\
\hat{x}_{c3}(280) &= E[\hat{x}_{c3}(280)] \\
\hat{y}(t) &= h^{-1}(\hat{x}_{c3}(t)) + \nu(t)
\end{align*} \quad (19)$$

The measurement equation is linear in $h^{-1}(\cdot)$, where $h(\cdot)$ is a known nonlinear mapping between the crack size and feature value. The state equation in non-linear, and the noise signal $\omega(n)$ is non-negative, and thus non-Gaussian. FDI results can be included as initial conditions for prognosis routines by assigning the resulting pdf estimate for the state $x_{c3}(t)$ at $t = 280$, from model (15), as the initial particle population for the state $x_{c3}(t)$ of the model (19). A hazard zone around 0.3 inches was defined according to customer specifications.

Results obtained, using an SIR particle filter for state estimation and the implementation of the proposed approach for the generation of long-term predictions [21], are shown in Fig. 4. Both the RUL pdf estimate and the long term prediction bounds have been computed considering only 40 cycles of data after the detection time, a population of 20 particles in the algorithm, and model (19). Results are excellent in terms of accuracy for both the estimated expected failure time and its 95% confidence interval, also offering a prediction window of about 300 cycles, a reasonable period to take corrective actions before the crack turns into a catastrophic failure.
Even considering that the 95% confidence interval is accurate enough for the purposes of this particular prognosis problem, and that it has been validated using the feature data beyond the 320th cycle of operation, it can be noticed that the predicted upper and lower bounds offer a precise representation for the trend of future feature data for a limited amount of time. In that sense, it is important to note that those bounds are constructed by using the current state estimate for $x_0(t)$ and that by no means this model parameter is fixed. In fact, its value depends on the length of the crack and hence, the current estimate is obsolete after a certain period of time. Thus, there is a compromise between the accuracy desired for prediction and the time window allowed for early prognosis, which must be large enough to both allow corrective actions and avoid catastrophic failures.

V. CONCLUSION

This paper is introducing an architecture for the development, implementation, testing and assessment of a particle-filtering-based framework for FDI and failure prognosis. The proposed framework for FDI has been successful and very efficient in pinpointing abnormal conditions in very complex and nonlinear processes, such as the detection of cracks in a turbine engine blade. Regarding prognosis, it was shown that the proposed approach is suitable for online implementation, providing acceptable results in terms of precision and accuracy. A successful case study (with real failure data) has been presented, offering insights about how model inaccuracies and/or customer specifications (hazard zone or prediction window definitions) may affect the algorithm performance.

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