Particle Filter-Based Method for Prognostics with Application to Auxiliary Power Unit

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Abstract. Particle filter (PF)-based method has been widely used for machinery condition-based maintenance (CBM), in particular, for prognostics. It is employed to update the nonlinear prediction model for forecasting system states. In this work, we applied PF techniques to Auxiliary Power Unit (APU) prognostics for estimating remaining useful cycle to effectively perform APU health management. After introducing the PF-based prognostic method and algorithms, the paper presents the implementation for APU Starter prognostics along with the experimental results. The results demonstrated that the developed PF-based method is useful for estimating remaining useful cycle for a given failure of a component or a subsystem.

Keywords: Particle filter (PF), data-driven prognostics, remaining useful cycle (RUC), condition-based maintenance (CBM), APU Starter prognostics.

1 Introduction

Condition-based maintenance(CBM) is an emerging technology that recommends maintenance decisions based on the information collected through system condition monitoring (or system state estimation) and equipment failure prognostics (or system state forecasting), in which prognostics still remains as the least mature element in real-world applications [1]. Prognostics entail the use of the current and previous system states (or observations) to predict the likelihood of a failure of a dynamic system and to estimate remaining useful life (RUL). Reliable forecast information can be used to perform predictive maintenance in advance and provide an alarm before faults reach critical levels so as to prevent system performance degradation, malfunction, or even catastrophic failures [2].

In general, prognostics can be performed using either data-driven methods or physics-based approaches. Data-driven prognostic methods use pattern recognition and machine learning techniques to detect changes in system states [3, 4]. The classical data-driven methods for nonlinear system prediction include the use of stochastic models such as the autoregressive (AR) model [5], the threshold AR model [6], the bilinear model [7], the projection pursuit [8], the multivariate adaptive

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regression splines [9], and the Volterra series expansion [10]. Since the last decade, more interests in data-driven system state forecasting have been focused on the use of flexible models such as various types of neural networks (NNs) [11, 12] and neural fuzzy (NF) systems [13, 14]. Data-driven prognostic methods rely on past patterns of the degradation of similar systems to project future system states; their forecasting accuracy depends on not only the quantity but also the quality of system history data, which could be a challenging task in many real applications [2, 15]. Another principal disadvantage of data-driven methods is that the prognostic reasoning process is usually opaque to users [16]; consequently, they sometimes are not suitable for some applications where forecast reasoning transparency is required. Physics-based approaches typically involve building models (or mathematical functions) to describe the physics of the system states and failure modes; they incorporate physical understanding of the system into the estimation of system state and/or RUL [17-19]. Physics-based approaches, however, may not be suitable for some applications where the physical parameters and fault modes may vary under different operation conditions [20]. On one hand, it is usually difficult to tune the derived models *in situ* to accommodate time-varying system dynamics. On the other hand, physics-based approaches cannot be used for complex systems whose internal state variables are inaccessible (or hard) to direct measurement using general sensors. In this case, inference has to be made from indirect measurements using techniques such as particle filtering (PF). Recently the PF-based approaches have been widely used for prognostic applications [21-25], in which the PF is employed to update the nonlinear prediction model and the identified model is applied for forecasting system states. It is proven that FP-based approach, as a Sequential Monte Carlo (SMC) statistic method [26, 27], is affective for addressing the issues that data-driven and physic-based approach face. In this work, we apply the PF method to Auxiliary Power Unit (APU) Starter prognostics by updating the models of the performance-monitoring parameters. This paper presents the developed PF-based methods for prognostics along with the experimental results from APU Starter prognostic application.

The rest of this paper is organized as follows. Section 2 briefly describes the background of the APU. Section 3 presents the PF-based method for prognostics; Section 4 provides some experimental results. Section 5 discusses the results and future work. The final section concludes the paper.

2 APU Overview

2.1 APU and APU Data

The APU engines on commercial aircrafts are mostly used at the gates. They provide electrical power and air conditioning in the cabin prior to the starting of the main engines and also supply the compressed air required to start the main engines when the aircraft is ready to leave the gate. APU is highly reliable but they occasionally fail to start due to failures of components such as the Starter Motor. APU starter is one of the most crucial components of APU. During the starting process, the starter accelerates APU to a high rotational speed to provide sufficient air compression for self-sustaining operation. When the starter performance gradually degrades and its output power decreases, either the APU combustion temperature or the surge risk will increase significantly. These consequences will then greatly shorten the whole APU life and even result in an immediate thermal damage. Thus the APU starter degradation can result in unnecessary economic losses and impair the safety of airline operation. When Starter fails, additional equipment such as generators and compressors must be used to deliver the functionalities that are otherwise provided by the APU. The uses of such external devices incur significant costs and may even lead to a delay or a flight cancellation. Accordingly, airlines are very much interested in monitoring the health of the APU and improving the maintenance.

For this study, we considered the data produced by a fleet of over 100 commercial aircraft over a period of 10 years. Only ACARS (Aircraft Communications Addressing and Reporting System) APU starting reports were made available. The data consists of operational data (sensor data) and maintenance data. The maintenance data contains reports on the replacements of many components which contributed the different failure modes. Operational data are collected from sensors installed at strategic locations in the APU which collect data at various phases of operation (e.g., starting of the APU, enabling of the air-conditioning, and starting of the main engines). The collected data for each APU starting cycle, there are six main variables related to APU performance: ambient air temperature (T_1), ambient air pressure (P_1), peak value of exhaust gas temperature in starting process (EGT_{peak}), rotational speed at the moment of EGT_{peak} occurrence (N_{peak}), time duration of starting process (t_{start}), exhaust gas temperature when air conditioning is enable after starting with 100% N (EGT_{stable}). There are 3 parameters related to starting cycles: APU serial number (S_n), cumulative count of APU operating hours (h_{op}) , and cumulative count of starting cycles(cyc). In this work, in order to find out remaining useful cycle, we define a remaining useful cycle (RUC) as the difference of cyc_0 and cyc. cyc_0 is the cycle count when a failure happened and a repair was token. When RUC is equal to zero (0), it means that APU failed and repair is needed. RUC will be used in PF prognostic implementation in the following.

2.2 APU Data Correction

The APU data collected in operation covers a wide range of ambient temperatures from -20^o to 40^o and ambient pressures relevant to the airport elevations from sea level to 3557ft. Since the ambient conditions have a significant impact on gas turbine engine performance, making the engine parameters comparable requires a correction from the actual ambient conditions to the sea level condition of *international standard atmosphere* (ISA). To improve the data quality, the data correction is performed based on the March number similarity from gas turbine engine theory. Two main parameters (EGT_{peak} (noted as EP) and N_{peak} (noted as NP)) related APU performance are corrected using Equation 1 and 2.

$$EP = EGT_c = \frac{EGT_{peak}}{\Theta^{a_{EGT}}} \tag{1}$$

$$\mathrm{NP} = N_c = \frac{N_{peak}}{\Theta^{a_N}} \tag{2}$$

Here the empirical exponents a_{EGT} and a_N are normally determined by running a calibrated thermodynamic computer model provided by engine manufacturers.

3 PF-Based Prognostics

3.1 PF-Based Prognostic Approach

In forecasting the system state, if internal state variables are inaccessible (or hard) to direct measurement using general sensors, inference has to be made from indirect measurements. Bayesian learning provides a rigorous framework for resolving this issue. Given a general discrete-time state estimation problem, the unobservable state vector $X_k \in R^n$ evolves according to the following system model

$$X_k = f(X_{k-1}) + w_k , \tag{3}$$

where $f : R^n \to R^n$ is the system state transition function and $w_k \in R^n$ is a noise whose known distribution is independent of time. At each discrete time instant, an observation (or measurement) $Y_k \in R^p$ becomes available. This observation is related to the unobservable state vector via the observation equation

$$Y_k = h(X_k) + v_k , \tag{4}$$

where $h : R^n \to R^p$ is the measurement function and $v_k \in R^p$ is another noise whose known distribution is independent of the system noise and time. The Bayesian learning approach to system state estimation is to recursively estimate the probability density function (*pdf*) of the unobservable state X_k based on a sequence of noisy measurements $Y_{1:k}$, k = 1, …, K. Assume that X_k has an initial density $p(X_0)$ and the probability transition density is represented by $p(X_k \mid X_{k-1})$. The inference of the probability of the states X_k relies on the marginal filtering density $p(X_k \mid Y_{1:k})$. Suppose that the density $p(X_{k-1} \mid Y_{k-1})$ is available at step k-1. The prior density of the state at step k can then be estimated via the transition density $p(X_k \mid X_{k-1})$,

$$p(X_k \mid Y_{1:k-1}) = \int p(X_k \mid X_{k-1}) p(X_{k-1} \mid Y_{1:k-1})\, dX_{k-1} . \tag{5}$$

Correspondingly, the marginal filtering density is computed via the Bayes' theorem,

$$p(X_k \mid Y_{1:k}) = \frac{p(Y_k \mid X_k) p(X_k \mid Y_{1:k-1})}{p(Y_k \mid Y_{1:k-1})} , \tag{6}$$

where the normalizing constant is determined by

$$p(Y_k \mid Y_{1:k-1}) = \int p(Y_k \mid X_k) p(X_k \mid Y_{1:k-1})\, dX_k . \tag{7}$$

Equations (5)-(7) constitute the formal solution to the Bayesian recursive state estimation problem. If the system is linear with Gaussian noise, the above method simplifies to the Kalman filter. For nonlinear/non-Gaussian systems, there are no closed-form solutions and thus numerical approximations are usually employed [28].

The PF or so-called sequential important sampling (SIS), is a technique for implementing the recursive Bayesian filtering via Monte Carlo simulations, whereby the posterior density function $p(X_k \mid Y_{1:k})$ is represented by a set of random samples (particles) $\mathrm{x}_\mathrm{k}^\mathrm{i}(\mathrm{i} = 1,2,\dots,\mathrm{N})$ and their associated weights $\mathrm{w}_\mathrm{k}^\mathrm{i}(\mathrm{i} = 1,2,\dots,\mathrm{N})$.

$$p(x_k|Y_{1:k}) \approx \sum_{i=1}^{N} w_k^i \delta\left(x_k - x_k^i\right),\ \sum_{i=1}^{N} w_k^i = 1. \tag{8}$$

The $\mathrm{w}_\mathrm{k}^\mathrm{i}$, normally known as importance weight, is the approximation of the probability density of the corresponding particle. In a nonlinear/non-Gaussian system where the state's distribution cannot be analytically described, the $\mathrm{w}_\mathrm{k}^\mathrm{i}$ of a dynamic set of particles can be recursively updated through Equation 9.

$$\mathrm{w}_\mathrm{k}^\mathrm{i} \propto \mathrm{w}_{\mathrm{k}-1}^\mathrm{i} \frac{\mathrm{p}\left(\mathrm{y}_\mathrm{k}\middle|\mathrm{x}_\mathrm{k}^\mathrm{i}\right)\mathrm{p}\left(\mathrm{x}_\mathrm{k}^\mathrm{i}\middle|\mathrm{x}_{\mathrm{k}-1}^\mathrm{i}\right)}{\mathrm{q}\left(\mathrm{x}_\mathrm{k}^\mathrm{i}\middle|\mathrm{x}_{\mathrm{k}-1}^\mathrm{i},\mathrm{y}_\mathrm{k}\right)}, \tag{9}$$

where $q(x_k^i|x_{k-1}^i, y_k)$ is a proposal function called *importance density function*. There are various ways of estimating the importance density function. One common way is to select $q\left(x_k^i\middle|x_{k-1}^i, y_k\right) = p(x_k^i|x_{k-1}^i)$ so that

$$w_k^i \propto w_{k-1}^i p\left(y_k\middle|x_k^i\right). \tag{10}$$

3.2 Implementation for APU Prognostics

This section presents an implementation of PF-based prognostics for APU starter. As we mentioned in Section 2, two key parameters related to APU starter degradation are *NP* and *EP* from data correction. We conducted statistic analysis of these two parameters using data collected during 10 years' operation. It is clear that these two parameters are identical to show two phases: normal operation and degraded operation. In order to apply PF-based prognostic methods to these parameters, we take *EP* as an example to demonstrate the implementation. Figure 1 shows an example of *EP* moving average during evolution of APU degradation. It shows that the moving average $\mu_{X_{RUC}}$ and the moving standard deviation $\sigma_{X_{RUC}}$ are relatively stable in the normal phase, but increase dramatically in the degraded phase. In the normal operation phase, *EP* measurements satisfy a stationary Gaussian $\mathcal{N}(\mu_{nor}, \sigma_{nor}^2)$. The starter is healthy in this phase, and this healthy state is indicated by the starter signal which is a relative constant value equivalent to μ_{nor}. Meanwhile, the noise signal is a stationary white noise with variance of σ_{nor}^2. In the degraded phase, *EP* measurements satisfy a non-stationary distribution that cannot be analytically described. The starter is experiencing degradation in this phase, and the degradation level is indicated by the starter signal which is the estimation of the measurements. Meanwhile, the noise signal is a non-stationary white noise with a variance that varies with the degradation level of starter.

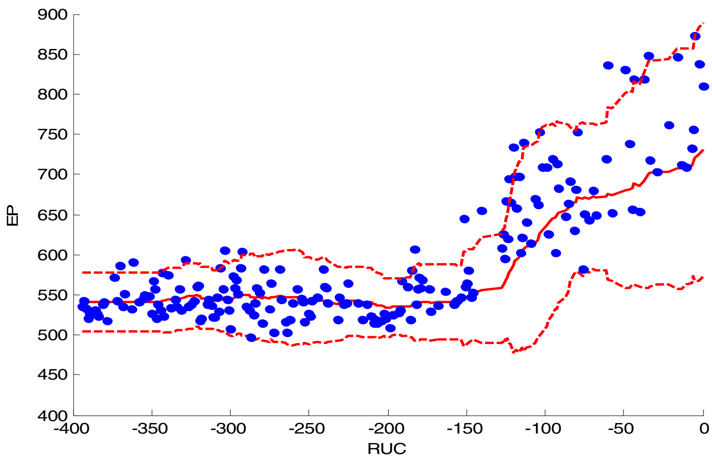

Fig. 1. an example of moving average for EP statistic analysis

Therefore, we can apply PF method to filter out the white noise and identify the degradation trend. To this end, we developed APU states estimation models for *EP*. These models are as follows:

$$\overline{EP}_k: \quad x_{1_k} = x_{1_{k-1}} \left(\frac{x_{3_k}}{x_{3_{k-1}}} \right) \exp\left[x_{2_k} (RUC_k - RUC_{k-1}) \right], \tag{11}$$

$$\lambda_k: \quad x_{2_k} = x_{2_{k-1}} + \omega_{2_k}, \tag{12}$$

$$C_k: \quad x_{3_k} = x_{3_{k-1}} + \omega_{3_k}, \tag{13}$$

$$EP_k: \quad y_k = x_{1_k} + v_k. \tag{14}$$

where the subscript k represents the kth time step and RUC_k represents the starting cycle in this kth time step. There are three system states, $\overline{EP}$, λ, C, and one measurement, EP, in this system state model. These states and measurement are also denoted as x_1, x_2, x_3 and y respectively. ω_2 and ω_3 are independent Gaussian white noise processes, the v is approximate by the standard deviation of RUC in the collected dataset.

The first system state, $\overline{EP}$, represents the starter signal. As described in Equation 11, its value at time step k is determined from the system states at the previous time step. The second system state λ represents the starter degradation rate. It is located in the exponential part of Equation 11. Therefore, the starter degradation rate between two adjacent starting cycles is indicated by e^{λ}. The higher λ is, the faster a starter degrades along an exponential growth. When $\lambda = 0$, no degradation develops between two starting cycles. The third system state C represents a discrete change of the starter degradation between two adjacent starting cycles. During the PF iterations, the systems states are estimated in the framework of recursive Bayesian by constructing their conditional *pdf* based on the measurements. Consequently, APU starter prognostic is implemented by λ estimation. Once the measurements stops, both λ and C are fixed with their most recent values. Thus the future degradation trend is expressed as an exponential growth of e^{λ}. The implementation of PF techniques is executed in an MATLAB environment.

4 Experimental Results

By implementing PF technique for ***EP***, we can use λ to perform APU starter prognostics. The idea is that λ is fixed at its most recent values updated by the available measurements. Then the future degradation trend is expressed as an exponential growth,e^{λ}, started from the latest $\overline{EP}$ estimations. The experiments were mainly conducted to learn the weight parameters for PF methods and to predict or estimate the ***EP*** using learned parameters. The triggering point for prediction is determined based on the statistic analysis given a failure mode. Figure 2 and 3 show the PF results when the prognostics is triggered at 650C and 750C for ***EP*** prediction corresponding to RUC at -100 and -50 starting cycles prior to the failure or replacement respectively. In these figures, we use "negative" numbers to represent the remaining cycles to failure event. Zero (0) represents the timing of failure event.

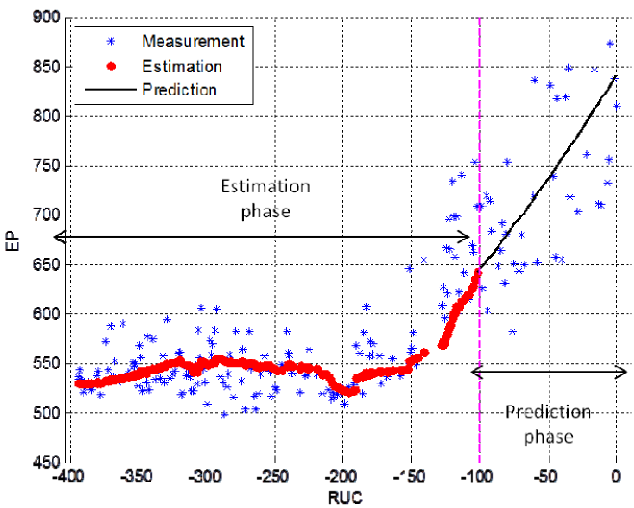

Fig. 2. PF prognostics result for EP (Triggered RUC= -100)

From the results, the APU starter prognostics can be easily performed by setting up a threshold for $\overline{EP}$. From the Figure 2, $\overline{EP}$ threshold is set at 840C. In other words, when ***EP*** estimation from the learnt PF model reached 650C, it starts to use ***EP*** prediction to perform prognostics and the RUC corresponding to triggered EP will be used as onset point of RUC estimation. If the ***EP*** prediction is reaching 840C, it means APU starter should be changed or replacement within 100 RUCs. In the Figure 2, the "star dots" represents the measurements; the red points are estimation from PF model during learning phase; and black line is ***EP*** prediction from the learnt PF models.

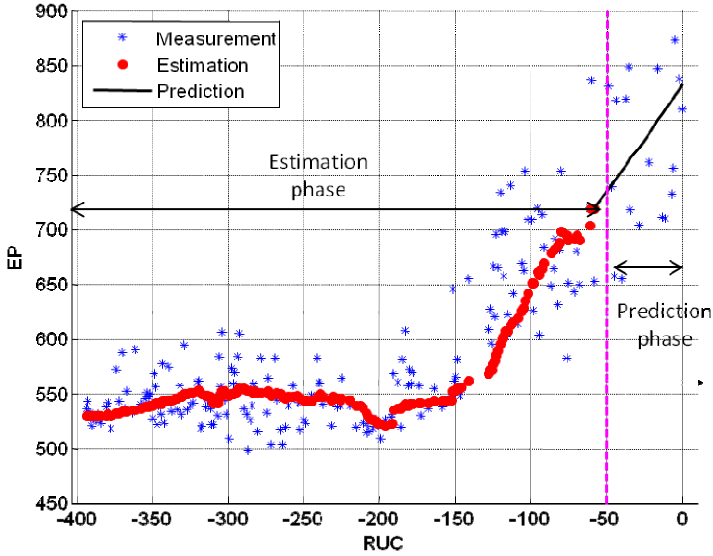

Fig. 3. PF prognostic result for EP (Triggered RUC= -50)

Similarly, Figure 3 shows the result of prediction triggered at ***EP*** = 750c correspond RUC = -50. From that point, the trained PF model starts to predict the ***EP*** for APU Starter prognostics.

5 Discussions

The experimental results above demonstrated that PF-based method is useful and effective for performing APU starter prognostics. If the threshold value is decided correctly, the RUC can be predicted precisely by monitoring APU EGT or engine speed (N) with the developed techniques. This result is useful for developing onboard prognostic systems, which makes the prognostic decision transparent and simplified. In turn, it promotes largely application of prognostic technique to real-world problems.

Since there is existing a large variance in the different failure models, the precise RUC prediction for a particular APU Starter is really challenged. However, our PF-based prognostic techniques suggested clearly that once the estimated $\overline{EP}$ is 50^oC higher than μ_{nor}, the APU starts the degradation phase. This information is also useful for helping make decision on predictive maintenance.

It is worth to note that the results of *NP* for APU starter prognostic are similar to *EP*. It is also assume that the APU starter degradation follows a certain exponential growth pattern when we implemented PF-based prognostic for APU starter. This may not be effective for repetitive fluctuations of the starter degradation. In the future we should integrate data-driven prognostic techniques with PF-based prognostics to develop a hybrid framework for prognostics.

The results in this work only demonstrated one failure mode, “Inability to Start”. The threshold value described above is determined only for this failure mode. For other failure modes, the corresponding statistics analysis is needed and the threshold values may vary. However, the developed PF-based method is still useful and applicable.

6 Conclusions

In this paper we developed a PF-based method for prognostics and applied it to APU Starter prognostics. We implemented the PF-based prognostic algorithm by using sequential importance sampling, and conducted the experiments with 10 years historic operational data provided by an airline operator. From the experimental results, it is obvious that the developed PF-based prognostic technique is useful for performing predictive maintenance by estimating relative precise remaining useful life for the monitored components or machinery systems.

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