Remaining Useful Life Estimation for Degradation and Shock Processes

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Abstract—**Remaining useful life (RUL) estimation by monitoring in-situ health of components and systems permits decision-makings in the condition based maintenance policy relying on actual operational states. In this paper, we consider systems subject to competing failures, and determine the remaining useful life distribution at the end of monitoring time. Soft failures consider both the degradation and damage from a shock process to the system, whereas, the hard failures are based on shock process. Both failures are connected by the ratio constant between damages and loads. The particle filter is applied for the statement estimation and online prediction of remaining useful life based on degradation and shock failure risks in the framework of prognostics and health management (PHM). A Micro-Electro-Mechanical System example demonstrates numerical analysis.**

Keywords-remaining useful life; particle filter; degradation and shock processes

I. Introduction

In reliability modeling, the competition among different processes is challenging for multiple failure processes [1]. Two typical failure modes classify failures of units or systems into catastrophic failure by some sudden shock and degradation failure by physical deterioration [2].The fusion of shock model and degradation model provides condition monitoring information for the maintenance decision-making [3, 4], especially for condition based maintenance [5]. Random shocks induce sudden damage increments to the degradation failure [6]. Since the degradation path is central to remaining useful life estimation in prognostics and health management (PHM), remaining useful life (RUL) is presented dependent on a degradation path approach, combined with Bayesian updating and expectation maximization algorithm [7].

Recently the on-line prediction of RUL for complex products and systems with various kinds of failure modes are emphasized by operators for the purposes of monitoring real time reliability and maximizing availability economically [8]. Undertaken by a significant research for predicting RUL of engineering assets in application of PHM, the prognostics are classified into three approaches [9]: 1) data-driven based approaches; 2) Physics-of-failure (PoF) approaches; 3) hybrid approaches. Physics-of-failure approaches, combined with potential failure mechanisms and failure sites, use the information of in-situ life cycle loads and canary devices to estimate RUL for devices. Data-driven based approaches contain the directly observed state process, such as regression-based models, Brownian motion with drift (Wiener processes), Gamma processes, Markovian-based models, and indirectly observed state process including stochastic filtering based models, especially Kalman filtering approach and particle filter approach.

Derived from sequential importance sampling and Bayesian theory, on-line particle filter based framework works for the fault diagnosis and failure prognosis in real time, approximating the probability density function, by a swarm of particles for points and weights for probability mass [10]. A state dynamic model and a measurement model construct the particle filter state estimation and prognostics estimation of the remaining useful life of nonlinear components and non-Gaussian processes for high accuracy [11], almost converged. Resampling algorithm solves the effects of the degeneracy problem in particle filter. Tutorials on particle filter provide MATLAB codes for these methods [12].

The paper is organized as follows. In section 2, we provide system updating model for degradation and shock model. In section 3, generic particle filter is applied for on-line diagnosis and failure prognosis. Section 4 presents a numerical example from industry to demonstrate the proposed model. Section 5 concludes the study.

II. Degradation and Shock Failure Systems

In terms of PHM framework, the hybrid models for multiple failures are applied in the system for updating process with relevant formations. Assumptions of system changed by adapted models for exact failure modes in corresponding failure processes.

A. Soft Failure Process

To simplify the demonstration the both process, we choose a linear path to model the degradation process.

$$X(t) = \varphi + \beta t \tag{1}$$

$X(t)$ is the degradation value. The initial value φ and the degradation rate β can be either constants or random variables. In following example of this paper $\varphi = 0$ and $\beta \sim N(\mu_\beta, \sigma_\beta)$

.There is some other alternative degradation processes such gamma process and so on.

The damage from shock is $S(t)$,

$$S(t)=\begin{cases}\sum_{i=1}^{N(t)} Y_i, & \text{if } N_t(t)>0,\\ 0, & \text{if } N_t(t)=0,\end{cases} \tag{2}$$

Y_i is the damage value of shock in normal distribution, and $N_t(t)$ represents the number of shock. Then the system updates function for the soft failure process is

$$\mathbf{x}_k=\begin{cases}\mathbf{x}_{k-1}+\beta*\Delta t & \text{if } \mathbf{x}<H, \text{and } N(k)=0\\ \mathbf{x}_{k\text{-}1}+\beta*\Delta t+Y_k & \text{if } \mathbf{x}<H, \text{and } N(k)=1\\ \mathbf{x}_{\max} & \text{if } \mathbf{x}\geq H\end{cases} \tag{3}$$

$\mathbf{x}_k$ stands for the system condition instead of just the failure path, so the above function only shows the situation when there is no any hard failure in the degradation path. At the iteration k, $N(k)$ is 0 when there is not shock, $N(k)$ is 1 when there is a shock.

B. Hard Failure Process

Mean value of which μ_Y is simple in direct proportion to that of the load of the shock μ_W, $\mu_Y=a\mu_W$, with a ratio a. We assume that damage by shock and the shock load is i.i.d. variables subjected to the normal distribution, $Y_i \sim N(\mu_Y,\sigma_Y^2)$ and $W \sim N(\mu_W,\sigma_W)$, which could be changed according to actual situation. If there is not soft failure process, the hard failure occurs only when the shock exits and, the shock size is larger than the hard failure threshold, which could be shifted to other levels based on several cases. The shock times are subjected to homogeneous poisons process with parameter λ .We generate Poisson process by $T_1 \sim \text{Exponential}(\lambda)$, which presents the interval between two consecutive shock times. The time τ equals 1 in order to represent time by the iteration number with a time resolution. In addition, at k iteration, $N(k)$ is a sign function, randomly generated by shock time arrival distribution to represent whether the shock happens or not.

$$\mathbf{x}_k=\begin{cases}0 & \text{if } \mathbf{x}<\mathbf{x}_{\max}, \text{and } N(k)=0\\ 0 & \text{if } \mathbf{x}<\mathbf{x}_{\max}, \text{and } N(k)=1, \text{and } W_k<D\\ \mathbf{x}_{\max} & \text{if } \mathbf{x}<\mathbf{x}_{\max}, \text{and } N(k)=1, \text{and } W_k\geq D\\ \mathbf{x}_{\max} & \text{if } \mathbf{x}\geq \mathbf{x}_{\max}\end{cases} \tag{4}$$

C. System Description

We already separately provide the system update function for soft failure process and hard failure process. Now we consider both of them at the same time and the mathematical formulations of whole process are:

$$\mathbf{x}_k=\begin{cases}\mathbf{x}_{k-1}+\beta*\Delta t & \text{if } \mathbf{x}<H, \text{and } N(k)=0\\ \mathbf{x}_{k\text{-}1}+\beta*\Delta t+Y_k & \text{if } \mathbf{x}<H, \text{and } N(k)=1, \text{and } W_k<D\\ \mathbf{x}_{\max} & \text{if } \mathbf{x}<H, \text{and } N(k)=1, \text{and } W_k\geq D\\ \mathbf{x}_{\max} & \text{if } \mathbf{x}\geq H\end{cases} \tag{5}$$

D is a constant for hard failure threshold.

In this section, we build up the model for the whole system in terms of updating sequentially.

III. PARTICLE FILTER

Particle filter based RUL estimation is divided into two steps by the existing field data with the inspection time. The system is described by discrete time step, $t_k=k\Delta t$, with a sequential dynamic model for updating system state, and a measurement model for measurement data $\mathbf{z}_k$. $\mathbf{f}_k$, state transition function, stands for updating system model, with $\boldsymbol{\omega}_{k-1}$ for all independent identically distributed (i.i.d.) process noise. $\mathbf{h}_k$ is measurement function with a measurement noise vector $\mathbf{v}_k$.

$$\mathbf{x}_k=\mathbf{f}_k(\mathbf{x}_{k-1},\boldsymbol{\omega}_{k-1}) \tag{6}$$

$$\mathbf{z}_k=\mathbf{h}_k(\mathbf{x}_k,\mathbf{v}_k) \tag{7}$$

The state estimation contains two parts: one part is to predict system based on the data from previous distribution $p(\mathbf{x}_{k-1}\mid\mathbf{z}_{1:k-1})$ and dynamic system model $p(\mathbf{x}_k\mid\mathbf{x}_{k-1})$ by equation; the other part is to update distribution by the field data $\mathbf{z}_{1:k}$ via Bayes rule.

$$p(\mathbf{x}_k|\mathbf{z}_{1:\text{k-1}})=\int p(\mathbf{x}_k\mid\mathbf{x}_{k-1})\,p(\mathbf{x}_{k-1}\mid\mathbf{z}_{1:k-1})\,d\mathbf{x}_{k-1} \tag{8}$$

$$p(\mathbf{x}_k|\mathbf{z}_{1:\text{k-1}})=\frac{p(\mathbf{z}_k\mid\mathbf{x}_k)\,p(\mathbf{x}_k\mid\mathbf{z}_{1:k-1})}{\int p(\mathbf{z}_k\mid\mathbf{x}_k)\,p(\mathbf{x}_k\mid\mathbf{z}_{1:k-1})\,d\mathbf{x}_k} \tag{9}$$

To solve this complex integral, we use particles with weights to describe distribution. Then the posterior density function can be approximated by

$$p(\mathbf{x}_{0:k}\mid\mathbf{z}_{1:k})\approx\sum_{i=1}^{N_s} w_k^i\,\delta(\mathbf{x}_{0:k}-\mathbf{x}_{0:k}^i) \tag{10}$$

IV. NUMERICAL EXAMPLES

The numerical data in Table I is from Sandia National Laboratories and part of assumption is from reference [13], describing a micro-engine. Rubbing surface wear degradation is the main failure mode, companied by the shock threaten from a certain level. Then the object is subjected to a degradation and shock failure process.

Results of filtered observation are illustrated in Fig. 1, which are the estimated states from the generated random observation from an random degradation state. There is a jump between the two degradation state for the existing of the abrupt damage in degradation path, which affects the estimated state and the RUL distribution.

TABLE I. DEGRADATION AND SHOCK PROCESSES EXAMPLE VALUES

Parameters	Value	Sources
H	0.00125 μm^3	Tanner and Dugger
D	1.4 Gpa	Tanner and Dugger
φ	0 μm^3	Tanner and Dugger
β	$N(8.4823e\text{-}9, 6.0016e\text{-}10)\mu m^3$	Tanner and Dugger
λ	5e-5	Assumption
Y_i	$N(1.2e\text{-}4, 2e\text{-}5)\mu m^3$	Assumption
W_i	$N(1.2, 0.2)$Gpa	Assumption
a	1e-4 μm^3/Gpa	Assumption

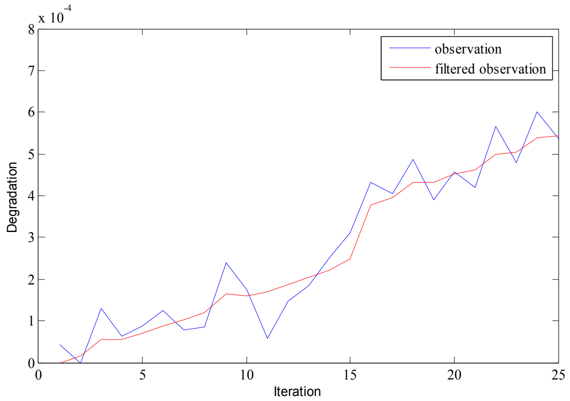

Figure 1. The filtered observation.

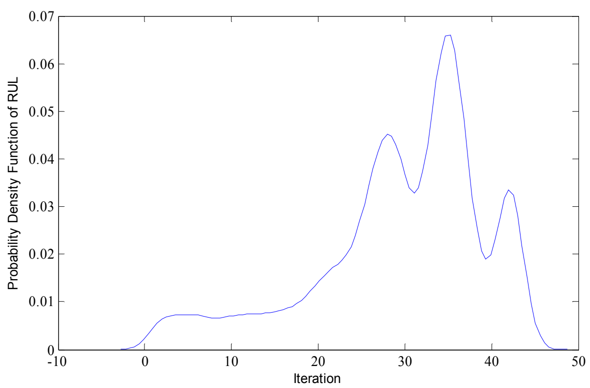

Figure 2. Probability density function of RUL.

Moreover, we calculate the probability density function for RUL. Fig. 2 plots the probability density function of RUL for degradation and shock processes.

V. CONCLUSION

In this paper, we present a PHM framework that jointly considers the degradation and shock processes. In particular, this paper models the degradation and shock processes by sequentially updating the system health condition. Particle filter is used to carry out the estimation and prognostics of the health states, respectively. Finally, the probability density distributions of RUL are illustrated. In Future, the more complicated system subject to degradation and shock processes will be analyzed for the estimation of RUL.

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