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Wear rate-state interaction modelling for a multi-component system: Models and an experimental platform

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Abstract: This paper proposes a general deterioration model for a multi-component system. The deterioration process of a component depends upon the operational conditions, the component's own state, and also the state of other components. An experimental platform that aims to provide more insight into the true nature of degradation of multi-component systems is also described. Some preliminary experimental results demonstrate the feasibility and advantages of the proposed deterioration model for describing highly stochastic degradation processes in industrial engineering.

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1. INTRODUCTION

Predicting remaining useful lifetime is a key element for preventing failure of components, which incurs unexpected downtime leading to low plant efficiency and higher maintenance costs. However predicting remaining useful lifetime can be very challenging in a real world environment, due to the random nature of events that might happen and have an impact on the components degradation process. A key to having more accuracy while predicting these components' remaining useful lifetime is to be able to master their deterioration process. Many deterioration models have been proposed and successfully applied for various industrial systems, see Wang (2002) and Van Noortwijk (2009) for an overview. It is shown in the literature that the deterioration process may depend on the operational condition (load, temperature, vibration, humidity, maintenance operation, etc), see for instance Deloux et al. (2009), Song et al. (2014) and Do et al. (2015). It is also shown that the deterioration process of a system may depend on the current state of the system Si et al. (2012). However, in such works, the deterioration models can be only applied for singlecomponent systems.

Industrial machines keep becoming more complex, containing multiple interacting components forming subsystems within a system as a whole. Taking into consideration dependencies between components when modelling the deterioration behaviours of multi-component systems has recently shown an increase in popularity among researchers. Degradation interaction or state dependence, which implies that the state evolution of a component depends on both its state and the state of other components, has been introduced in Bian and Gebraeel (2014) for prognostics of system lifetime, and in Do et al. (2015), Rasmekomen and Parlikad (2016) for maintenance optimization. However, these works do not consider the operational condition impacts on the deterioration modelling. To face this issue, the first objective of this paper is to propose a general deterioration model for multi-component systems, which takes into account not only state dependence but also the operational condition effect. The second objective of the paper is to present an experimental platform developed, with the aim of providing the multi-component degradation model more insight about the true nature of deterioration for components with dependencies. In contrast with previous developed platforms, the experimental platform presented has sensors that are set up and configured in a way that would best capture wear interdependencies between components, the aim is to estimate the parameters of the presented degradation model in this paper.

Highly dynamic maintenance schedules are not well appreciated by OEMs and their clients, for logistic reasons among others. The experimental data that the developed platform will produce will compliment simulation data, and lead to more robust degradation models that in turn lead to more accurate remaining useful lifetime predictions, and thus more reliable maintenance scheduling can be done around that

Some experimental platforms have been proposed and used to provide data for RUL calculations. A bearing accelerated degradation test bed has been developed at femto Nectoux et al. (2012), the test bed PRONOSTIA was aimed at validating methods related to bearing health assessment, this experimental platform provided 3 test sets for the PHM challenge on RUL predictions. A bearing test bed is proposed Yan et al. (2009) Vibration readings were collected using 3 accelerometers for the accelerated degradation test, and a new vibration signal analysis method was developed to extract wear related features. Similarly a Bearing test bed has been developed by the centre for intelligent maintenance systems, 4 bearings were installed on a single shaft, and 3 experiments ran to bearing failure, The Morlet wavelet filter-based denoising method was applied for De-noising and extracting the weak signature from the noisy signal, and so perform reliable prognostics on the bearing data Qiu et al. (2006).

The remainder of this paper is organized as follows: The multi-component degradation model is presented in section 2, section 3 covers the developed experimental platform, some of the experimental data generated by the platform are presented in section 4 along with an analysis on the components' degradation dependence, and finally, section 5 concludes the paper.

2. MULTICOMPONENT SYSTEM MODELLING

Let us consider a system with multiple components interacting in series, where if one component fails the system fails. Each component i is subject to a continuous accumulation of deterioration in time, that is assumed to be described by a scalar random variable X_t^i . Component i fails if its deterioration level reaches the failure threshold L^i . When a component is not operating for whatever reason, its deterioration level remains unchanged during the stoppage period if no maintenance is carried out.

2.1 Rate-state interaction modelling

Between two adjacent maintenance activities, we assume that evolution of the deterioration level of component i is denoted by

$$X_{t+1}^i = X_t^i + \Delta X_t^i \tag{1}$$

Where ΔX_t^i is the increment in the degradation level of component *i* during one time unit.

From a practical point of view, the deterioration increment of a component at time t may depend on the operational condition (mission profile), its own current state as well as the current of state of other components. In this way, we suggest a general stationary model for the increment ΔX_t^i :

$$\Delta X_t^i = \Delta O_t^i + \Delta X_t^{ii} + \sum_{i \neq i} \Delta X_t^{ji}$$
 (2)

where:

- ΔO_t^i is the increment in the deterioration level of component *i* caused by the operational condition during one time unit, namely the operation effect. ΔO_t^i may be specified as deterministic or as a random variable;
- ΔX_t^{ii} represents the increment in the deterioration level of component i induced by itself during one time unit, namely the intrinsic effect. This means that ΔX_t^{ii} depends only on the state of component i at time t. In the same manner, ΔX_t^{ii} may be specified as deterministic or as a random variable;
- ΔX_t^{ji} is the increment in the deterioration level of component i induced by component j during one time unit, called the interaction effect. ΔX_t^{ji} represents the state interaction between the two components j, i and may be specified as deterministic or as a random variable.

Several variants of the proposed model can be specified:

Case 1: $\Delta O_t^i > 0$, $\Delta X_t^{ii} = 0$ and $\Delta X_t^{ji} = 0$ with $\forall j \neq i$: neither intrinsic effect nor interaction effect and the proposed model becomes a basic model describing the homogenous

degradation behaviour of independent components, see for instance Van Noortwijk (2009).

Case 2: $\Delta O_t^i > 0$, $\Delta X_t^{ii} > 0$ and $\Delta X_t^{ji} = 0$ with $\forall j \neq i$: no interaction effect and the proposed model becomes a basic model describing the non-homogenous degradation behaviour, see Si et al. (2012).

Case 3: $\Delta O_t^i = 0$, $\Delta X_t^{ii} = 0$ and $\Delta X_t^{ji} > 0$ with $j \neq i$: here the components i and j ($j \neq i$) are stochastically dependent but the increment in the deterioration level of component i depends only on the state of component j. For this case, the proposed model corresponds to the model introduced in Rasmekomen and Parlikad (2016) where the interaction effect (ΔX_t^{ji}) is described by a normal distribution whose parameters depend on the deterioration level of component j.

Case 4: $\Delta O_t^i > 0$, $\Delta X_t^{ii} = 0$ and $\Delta X_t^{ji} > 0$ with $j \neq i$: components i and j ($j \neq i$) are stochastically dependent and the increment in the deterioration level of component i does not depends on the state of the component its self, see Do et al. (2015), Bian and Gebraeel (2014).

Case 5: $\Delta O_t^i > 0$, $\Delta X_t^{ii} > 0$ and $\Delta X_t^{ji} > 0$ with $j \neq i$: the components i and j ($j \neq i$) are stochastically dependent and the increment in the deterioration level of component i depends on the operational condition, the state of component i as well as the state of component j.

As an example, we consider the case 4 and extend the model proposed for condition-based maintenance of a two-component system in Do et al. (2015) to multi-component systems. In that way,

$$\Delta X_t^i = \Delta O_t^i + \sum_{i \neq i} \mu^{ji} * \left(X_t^j \right)^{\sigma^{ji}} \tag{3}$$

where ΔO_i^t is described by a gamma law with shape parameter α^i and scale parameter β^i . μ^{ji} and σ^{ji} are nonnegative real numbers that quantify the influence of component j on the deterioration rate of component i. Fig. 1 illustrates the degradation evolution of a 3-component system with rate-state interaction modelled by eq. (3) with

$$\alpha = \begin{pmatrix} \alpha^1 \\ \alpha^2 \\ \alpha^3 \end{pmatrix} = \begin{pmatrix} 4.944 \\ 4.350 \\ 5.193 \end{pmatrix}, \beta = \begin{pmatrix} \beta^1 \\ \beta^2 \\ \beta^3 \end{pmatrix} = \begin{pmatrix} 3.919 \\ 1.09 \\ 2.257 \end{pmatrix}$$

and,

$$\sigma = [\sigma^{ji}] = \begin{pmatrix} 0 & 0.54 & 0.729 \\ 0.785 & 0 & 0.836 \\ 0.838 & 0.555 & 0 \end{pmatrix},$$

$$\mu = [\mu^{ji}] = \begin{pmatrix} 0 & 0.254 & 0.108 \\ 0.384 & 0 & 0.346 \\ 0.242 & 0.118 & 0 \end{pmatrix}$$

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