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Dynamic-weighted ensemble for fatigue crack degradation state prediction

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ABSTRACT

This paper proposes a prognostic framework for online prediction of fatigue crack growth in industrial equipment. The key contribution is the combination of a recursive Bayesian technique and a dynamic-weighted ensemble methodology to integrate multiple stochastic degradation models. To show the application of the proposed framework, a case study is considered, concerning fatigue crack growth under time-varying operation conditions. The results indicate that the proposed prognostic framework performs well in comparison to single crack growth models in terms of prediction accuracy under evolving operating conditions.

1. Introduction

Cracks are among the most common degradations in equipment of several major industries, including manufacturing [1,2], construction [3,4], aerospace [5–7], automotive [8,9], energy [10,11], etc. A study conducted by the American Society of Civil Engineers (ASCE) [4] has revealed that more than 80% of the collapses of American bridges in steel were caused by fatigue and fracture in structural elements. In [5], it has been shown that in aerospace industry, cracks develop in most critical components of rotorcrafts, such as the main rotor blade, the major cabin frame cap splice, and the tail boom. These unexpected degradations increase the operation risk and can cause severe economic losses in case of breakdowns [12–15]. Thus, for the past several decades, the development of reliable prognostic systems to accurately analyze and estimate the crack propagation in an equipment has attracted the attention of industrial practitioners and researchers.

Some prognostic models have been developed using historical degradation data from a population of similar equipment, whereas the real-time condition monitoring data of the specific equipment were not considered [16–19]. These historical information, however, may not be always available in practical industrial systems, especially for newly produced equipment or expensive components where the data acquisition costs too much [20]. More importantly, different practical operational conditions, such as load, temperature, and speed, could significantly impact on the rate of the degradation processes, which makes each specific system present a particular degradation trajectory [21]. Therefore, it is important to include the condition monitoring data of the targeted equipment. To address this issue, Cadini et al. [14] introduced a failure prognostic method for fatigue crack growth prediction using a stochastic crack growth model and a Bayesian technique to dynamically update the degradation state from a sequence of monitored measurements. In this sense, recursive Bayesian algorithms are potentially suitable for model-based prognostic frameworks. Indeed,

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Nomenclature

Abbreviations

ASCE	American Society of Civil Engineers
FDI	Fault Detection and Isolation
IMMPF	Interacting Multiple Model Particle Filter
MSE	Mean Square Error
MLE	Maximum Likelihood Estimation
PDF	Probability Density Function
PHM	Prognostics and Health Management
SIF	Stress Intensity Factor

Latin symbols

C	material constant
f	state transition function
F	augmented state transition function
g	measurement function
G	augmented measurement function
h(x)	geometric factor
m	material constant
N	number of fatigue load cycles (cycle)
N_M	number of degradation models
p	constant of polynomial crack growth model
R	stress ratio of the crack growth process
t	time (cycle)
T	prediction time (cycle)
w	weight of individual degradation model in the ensemble
x	degradation state (mm)
$\hat{x}$	estimated degradation state of individual degradation model (mm)
$\tilde{x}$	estimated degradation state of the ensemble (mm)
y	augmented degradation state
z	measurement (mm)

Greek symbols

δ	time horizon for error coefficient estimation (cycles)
ΔK	stress intensity factor (MPa $\sqrt{m}$)
$\Delta\sigma$	cyclic stress amplitude (MPa)
Δt	time interval (cycle)
θ	degradation model parameter
σ_ω^2	state noise variance
σ_υ^2	measurement noise variance
τ	prediction interval (cycle)
υ	measurement noise
φ	estimation error coefficient of individual degradation model
ω	state noise

the *prior* distribution of the degradation states can be combined with the likelihood of the monitored measurements for updating the *posterior* distribution of the states adaptively when new measurements are available. In [22], Boris et al. presented a prognostic method based on a Bayesian technique to dynamically update the stress intensive range of the physical degradation model at each load cycle until failure, using the condition monitoring measurements. In another study, a comprehensive architecture for both fault detection and isolation (FDI), and failure prognosis for a UH-60 planetary carrier plate was carried out by exploiting a non-linear degradation model and a Bayesian variant, to effectively detect abnormal conditions and predict online the crack depth evolution of the equipment [23].

In practice, the performance of online prognostic models for fatigue crack growth heavily depends on the adopted physics-of-failure model and it is very important to figure out an appropriate modelling framework for a specific degradation process under time-varying operation conditions. To address this issue, numerous fatigue crack growth models have been extensively studied [24–30]. In [31], a comparison of stochastic fatigue crack growth models including the Markov chain model, the Yang's power law model, and a polynomial model were carried out. The results showed that each degradation model has its own range of applicability, and only fits a certain particular degradation process. To the knowledge of the authors, there is no general consensus on a comprehensive prognostic model for fatigue crack growth under different degradation processes. Recently, in the applications of Lithium-ion battery prognostics, hybrid and multi-degradation model ensembles have gained interest because of higher accuracy and better generalization capability than individual degradation models [32,33]. The basic idea behind these empirical frameworks is to find a set of diverse degradation models which cover different situations so that they complement each other. In [33], an interacting multiple model particle filter (IMMPF) was introduced to combine the estimations from three battery capacity degradation models. The study concluded that the interacting multiple model can achieve higher robustness in terms of smaller estimation errors and more stable performance than a single model.

In this paper, a prognostic framework for fatigue crack growth is proposed by integrating a recursive Bayesian technique and a dynamic ensemble. The degradation state of the component is estimated based on the condition monitoring data collected until the current load cycle, and short-term degradation state prediction is performed to anticipate and proactively prevent sudden breakdowns of the component in a near future. The key contribution of the work is the dynamic ensemble which combines different crack evolution models with dynamic weights. The dynamic weights are computed based on the historical estimation error for a predefined number of the latest load cycles. To the authors' knowledge, this ensemble framework has been here developed and applied for the first time for a prognostic problem of fatigue crack growth. To validate the performance of the proposed framework, a case study concerning fatigue crack growth with evolving operation conditions is carried out and the results are compared with those obtained by applying single degradation models.

The rest of this paper is organized as follows. Section 2 introduces the degradation models for fatigue crack growth and details the proposed prognostic framework. Section 3 describes the illustrative case study of fatigue crack growth with different load conditions. Finally, Section 4 concludes the study.