Composite Structures xxx (2016) xxx–xxx

Contents lists available at ScienceDirect

Composite Structures

journal homepage: www.elsevier.com/locate/compstruct

# A data-driven probabilistic framework towards the in-situ prognostics of fatigue life of composites based on acoustic emission data

Theodoros Loutas [a,*], Nick Eleftheroglou [a,b], Dimitrios Zarouchas [b]

[a] Dpt of Mechanical Engineering & Aeronautics, University of Patras, Greece
[b] Faculty of Aerospace Engineering, TU Delft, The Netherlands

ARTICLE INFO

*Article history:*
Received 25 August 2016
Revised 19 October 2016
Accepted 25 October 2016
Available online xxxx

*Keywords:*
SHM
Remaining useful life
Machine learning techniques
Condition-based reliability
Acoustic emission
Composite materials

ABSTRACT

An innovative prognostic data-driven framework is proposed to deal with the real-time estimation of the remaining useful life of composite materials under fatigue loading based on acoustic emission data and a sophisticated multi-state degradation Non Homogeneous Hidden Semi Markov Model (NHHSMM). The acoustic emission data pre-processing to extract damage sensitive health indicators and the maximum likelihood estimation of the model parameters from the training set are discussed in detail. In parallel, a Bayesian version of a well-established machine learning technique i.e. neural networks, is utilized to approach the remaining useful life estimation as a non-linear regression task. A comparison between the two algorithms training, operation, input-output and performance, highlights their ability to offer reliable remaining useful life estimates conditional on health monitoring data from composite structures under service loading. Both approaches result in very good estimations of the mean remaining useful life of unseen data. NHHSMM is concluded as the preferable option as it provides much less volatile predictions and more importantly is characterized by confidence intervals which shorten as more data come into play, an essential trait of a robust prognostic algorithm.



## 1. Introduction

Prognostics of the remaining useful life of composite structures based on SHM measurements is a new dynamically rising field towards a condition-based maintenance framework. After extensive work the past two decades in the field of diagnostics with a concurrent increase of the Technology Readiness Level of several structural health monitoring (SHM) technologies, the next step is prognostics as clearly stated in [1]. Of central importance in prognostics is the remaining useful life (RUL) estimation of a component/asset preferably in real-time during fatigue service loading. The procedure of damage accumulation in composite structures, especially during fatigue loading, is a complex phenomenon of stochastic nature which depends on a number of parameters such as type and frequency of loading, stacking sequence, material properties etc. For example, the fatigue life of a specific composite material has a quite significant scatter that deterministic models cannot a priori accurately predict. This is obviously due to the complex multiphase nature of composites, the variation of inherent defects (fiber misalignment, voids, and resin-rich and resin-poor areas) that cannot be absolutely controlled during the manufacturing process, the randomness of loads, the stochastic activation of different damage mechanisms and an incomplete knowledge about the physics behind the evolution and interaction of damage mechanisms. The result is that coupons from the same composite material batch, being manufactured under the very same process, tested under the same machine in alike conditions can fail in totally different number of cycles. Very limited work has been documented in the structural damage prognostics field, especially concerning composite materials and structures. In Liu et al. [2] a data driven prognostic methodology was presented. A framework relying on Gaussian Processes used SHM data, i.e. acoustic emission (AE) data and Lamb wave signals, to predict the RUL of composite beams subjected to constant amplitude fatigue loading. In the feature extraction process wavelet transform and principal component analysis (PCA) were applied to determine effective damage indices. By comparing the RUL estimations from Lamb wave signals and AE features, it can be seen that Lamb's RUL predictions provided better estimations than AE's RUL predictions.

The same research team in [3] proposed a condition based structural health monitoring and prognosis approach to estimate the RUL of notched CFRPs composite specimens with $[0/90]_s$

* Corresponding author.
*E-mail addresses:* loutas@mech.upatras.gr (T. Loutas), N.Eleftheroglou@tudelft.nl (N. Eleftheroglou).

http://dx.doi.org/10.1016/j.compstruct.2016.10.109
0263-8223/

Please cite this article in press as: Loutas T et al. A data-driven probabilistic framework towards the in-situ prognostics of fatigue life of composites based on acoustic emission data. Compos Struct (2016), http://dx.doi.org/10.1016/j.compstruct.2016.10.109

stacking sequence under uniaxial and biaxial fatigue loading. The RUL predictions were based on real time sensor signals from electrical strain gages placed at different locations on the composite coupons. In addition, a flash thermography system was used in order to monitor the damage states of the composite specimen. The proposed RUL prediction methodology consists of the online diagnostics process i.e. direct cross-correlation analysis on strain measurements and the offline prognostics process via Gaussian Processes. The work of Peng et al. [4,5] proposed a real-time composites fatigue life prognosis framework. They combine Bayesian inference, Lamb waves and a mechanical stiffness degradation model for in-situ fatigue life prediction. A modified Paris law described the relationship between the stiffness degradation rate, the stress range and current stiffness. The studied material system was carbon-epoxy open-hole specimens with layup $[90_3/0_3]_s$ under constant amplitude fatigue loading.

Chiachio et al. [6–9] realized remaining fatigue life estimations in composite materials under constant amplitude fatigue loading utilizing monitoring data and some empirical or phenomenological damage mechanics models, i.e. shear-lag, variational and crack opening displacement, in order to correlate the macro-scale stiffness reduction and the micro-scale damage. Furthermore, a Bayesian inference of the modified Paris law was used to model the evolution of matrix-cracks density. A set of 12 piezoelectric sensors were used to monitor the effects of matrix micro-cracks density and delamination, but also a set of triaxial strain gauges to measure the normalized effective stiffness. Also, X-rays were periodically used to visualize and evaluate the micro-crack density. This information was used in order to develop a mapping between the Lamb wave signals and micro-crack density. Utilizing the estimated micro-crack density and one of the aforementioned damage mechanics models the current stiffness was assessed. Taking into consideration this assessment and the Bayesian modified Paris law, the RUL was predicted. In this study notched dog-bone carbon-epoxy specimens with stacking sequence $[0_2/90_4]_s$ were used. A key finding from this study is that the shear-lag model is the best option regarding this specific case study.

Eleftheroglou and Loutas [10] and Eleftheroglou et al. [11] proposed a novel purely data-driven framework for the in-situ health state assessment and prognosis of the RUL in open hole carbon/epoxy specimens with $[0/45/-45/90]_{2s}$ stacking sequence under constant amplitude fatigue loading. This approach was based on stochastic multi-state degradation modeling utilizing Non-Homogeneous Hidden Semi Markov Model (NHHSMM) and AE [10] or strain measurements [11]. Regarding the first case, windowed cumulative RA (rise time/amplitude) data were used as damage sensitive feature. In the second case a stereovision system was used to perform 3D full field DIC measurements in order to monitor the strain distribution on the coupon surface during the fatigue test.

The aforementioned studies represent some of the most important prognostic approaches that can be found in the literature with application to composite structures. The majority of them use empirical models. These models suffer from the fact that there is no widely accepted theory for the progressive failure of composites and the works that adopt such approaches model specific damage mechanisms (e.g. delamination and matrix cracking) without accounting for their interactions making a series of assumptions. The proposed framework of condition-based reliability assessment is driven by the increased usage of composite materials in high-end applications in industries such as the aerospace, automotive and wind energy among others and the need to enhance our understanding of the damage process and the health assessment of a subcomponent or a structure during service life has become more pressing than ever.

In the present paper, we propose data-driven methodologies that are independent of the material's layup and do not make any assumption regarding the damage mechanics. The present work extends the recent findings of the authors in [10] where Non Homogeneous Hidden Semi Markov Models were used, making an attempt to benchmark with a Bayesian version of the well-established in the machine learning field feed-forward artificial neural network. Both models are dependent on a training process necessary to estimate in a probabilistic fashion their parameters. In NHHSMM we follow a maximum likelihood approach for parameter estimation whereas the Bayesian Feedforward Neural Network has a purely Bayesian approach considering the networks weight and biases as random variables. Various prognostic performance metrics are employed for the comparison. The superior behavior and robustness of the NHHSMM model is highlighted and concluded mainly in terms of a decrease in error bounds as more SHM data come into play.

## 2. Fatigue damage accumulation in composites

It is from the very early ages in composites research that researchers attempted to understand the way damage evolves and accumulates in a composite material. Case and Reifsnider in [12] explained in a qualitative manner how damage and failure mechanisms may commence, interact and lead to the final failure. Fig. 1 summarizes this process in a generic high-level description of damage accumulation in composites under any type of service loading.

Apparently, it is a multi-state degradation process which initiates with transverse matrix cracking in the most highly stressed/strained layers. Matrix cracks form, saturate at the Characteristic Damage State (CDS), propagate and coalesce to form early debondings and in very tough matrices lead to early fiber failures locally. Debondings and matrix cracks propagate to form delaminations in the interfaces between the layers whilst fiber bundles begin to fail more frequently accelerating the induced damage in the final stage of the material's service life up to the final macroscopic failure. This is a damage process as described in a generic way. The precise damage accumulation sequence is dependent on the exact layup, the material properties of the composite's constituents, the defects induced during manufacturing, the loading profile, environmental conditions etc.

## 3. Machine learning algorithms

### 3.1. Non-Homogeneous Hidden Semi Markov Models (NHHSMM)

The damage process in composite materials can be considered as a stochastic hidden process which manifests itself only indirectly through for instance SHM or NDT data. Multi-state degradation modeling is an appropriate framework to model damage in composites which gradually accumulates and increases during service loading. To this direction the most interesting and mathematically rich stochastic models are Hidden Semi Markov Models. These models were extended in [13] to take into account non-homogeneity i.e. age dependence during state transitions. To fully describe a NHHSMM the definition of a series of elements is required. The number of possible discrete degradation health states ($N$), the transition diagram which defines the connectivity between the states and the allowed transitions, the transition rate's statistical function ($\lambda$), the observations i.e. the SHM damage-sensitive feature(s) $y_{1:t}$ and the number of discrete feature values ($m$) after the observations quantization. The number of hidden states obviously refers to the number of discrete levels of degradation. In a Maximum Likelihood Estimation (MLE) approach,