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# Online remaining fatigue life prognosis for composite materials based on strain data and stochastic modeling

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**Abstract.** The present study utilizes a state-of-the-art stochastic modeling with structural health monitoring (SHM) data derived from strain measurements, in order to assess the remaining useful life (RUL) online in composite materials under fatigue loading. Non-Homogenous Hidden Semi Markov model (NHHSMM) is a suitable candidate with a rich mathematical structure capable of describing the composite's multi-state damage evolution in time. The proposed model uses as input SHM data in the form of strain measurements obtained from the Digital Image Correlation (DIC) technique to a coupon-level constant amplitude fatigue test campaign. The obtained from the stochastic model RUL estimations are compared with the actual RUL and the effectiveness of the prognosis is discussed.

## Introduction

Towards a condition based health monitoring and decision making for composite structures, the need for diagnostic and prognostic capabilities based on structural health monitoring (SHM) data rises continuously and draws increasing attention the last few years. Stochastic modeling and more specifically Markov chains have been employed for damage modeling in composites as early as the 1980s by Bogdanoff and Kozin [1] and later Rowatt and Spanos [2]. An extension of the classic Markov chains i.e. the Hidden Markov Models (HMMs) proved useful in several applications since they describe adequately the unobserved (hidden) degradation state of a system through a sequence of observations. They assume though, a geometrically distributed state duration which is not always a realistic assumption. A natural generalization of the HMMs is the Hidden Semi-Markov Models (HSMMs), introduced by Ferguson [3], which relax the assumption of geometric state duration distribution allowing any distribution for the sojourn times in the different states of the hidden process, in order to achieve a better description of a real problem dataset.

Moghadass and Zuo [4,5] extended the HSMM framework developing a more general model i.e. the Non-Homogenous Continuous Time Hidden Semi Markov Model (NHCTHSMM) that introduces a dependence of state transitions on the age of the engineering component as well as the sojourn time in the various states. Eleftheroglou et. al [6,7] applied this model in acoustic emission data from the fatigue of a series of open hole CFRP composites to successfully predict the RUL in any moment during the lifetime. This 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 as well as 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.

This article is organized as follows: section ‘Testing campaign and experimental set-up’ introduces the experimental set-up and the test campaign, section ‘Stochastic modeling of damage accumulation and Prognostic measures’ presents the proposed model and defines the prognostic measures. Finally, section ‘Conclusions’ highlights concluding remarks are about the RUL estimations.

## Testing campaign and experimental set-up

Seven open-hole Carbon Fibre Reinforced Polymer (CFRP) specimens with a $[0/\pm45/90]_{2s}$ lay-up were subjected to fatigue loading with maximum amplitude 90% of the static tensile strength, R=0 and f=10 Hz. The tests were executed in a MTS 100 kN universal test machine and they run up to final failure.

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 entire fatigue test. The strain degradation histories of the seven open-hole specimens are presented in Fig. 1. To obtain the strain distribution in a periodic fashion, the following steps executed: every 500 cycles the tests were interrupted, the specimens were loaded quasi statically up to the maximum load within 1 sec where the load was kept constant for 2 sec so as to take a picture, then the specimens were unloaded within 1 sec and the fatigue tests continued. Fig. 2 presents the loading process. The reader can refer to Eleftheroglou et al. [8] for a more detailed description regarding the extracted strain data.

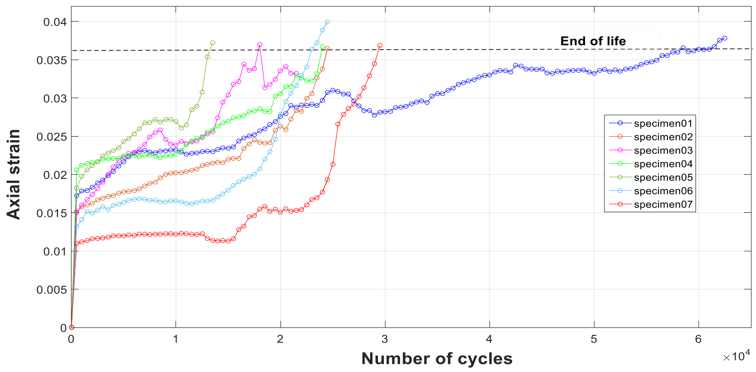


Fig.1. Axial strain degradation histories of seven open-hole specimens

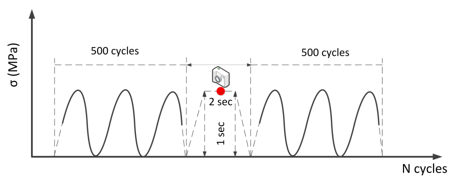


Fig. 2. A schematic of the loading procedure and the acquisition of pictures using the stereovision system.

The six strain maps of Fig.3 highlight the axial strain evolution in the loading direction for specimen07 where the last snapshot was manually taken when the specimen failed.

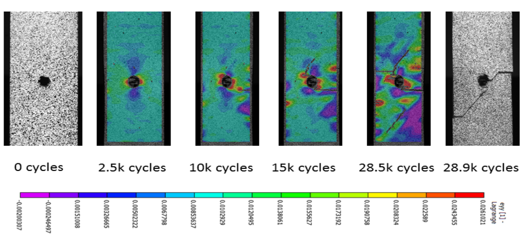


Fig.3. The axial strain evolution in the loading direction.

## Stochastic modeling of damage accumulation and Prognostic measures

The procedure of damage accumulation in composite materials under fatigue loading is modeled via NHCTHSMM. A short introduction to the mathematical model follows. The reader can refer to Moghadass and Zuo [4,5], Eleftheroglou and Loutas [6] and Eleftheroglou et al. [7] for a more detailed description. The model is characterized by an initialization and training procedure.

The initial topology is obtained by defining the following elements;

- the number of possible hidden or discrete degradation states (N),
- the transition diagram that defines the allowed transitions between the hidden states,
- the probability density function which characterizes the sojourn time at each hidden state,
- the degradation histories (observations) and
- the observation SHM data quantization since the data´s domain is continuous.

The Bayesian Information Criterion (BIC) and Akaike Information Criterion (AIC) (Danfeng et al. [9]) were employed to estimate the optimum number of hidden states which was found at N=4. Furthermore, the transition diagram allowed soft-neighbourhood transitions and hard, direct transition from any hidden state to failure state. The Weibull distribution was selected for the sojourn time since it is widely used for modelling degradation phenomena. In addition, the degradation histories were obtained from the DIC technique in form of strain measurements ($\mathbf{y_{1:L}}$). The strain data quantization was achieved through clustering via a k-means algorithm and under a monotonicity objective function, which can be utilized using the Mann-Kendal criterion. As a result, the number of clusters was found equal to V=24.

After the initialization the training procedure followed and it is characterized by the observation and degradation process. The observation process correlates the observations with the hidden states via the estimation of observation matrix ($\boldsymbol{B}$) and the degradation process determines the sojourn time at each hidden state via the estimations of the scale and shape Weibull parameters ($\boldsymbol{\Gamma}$). In order to estimate the characteristic parameters $\boldsymbol{\theta}=\{\boldsymbol{B},\boldsymbol{\Gamma}\}$, the Maximum Likelihood Estimation (MLE) procedure is utilized.

$$L\left(\boldsymbol{\theta},\boldsymbol{y}^{(1:K)}\right) = \prod_{k=1}^{K} Pr\left(\boldsymbol{y}^{(k)}\middle|\boldsymbol{\theta}\right) \xRightarrow{L'=\log(L)} L'\left(\boldsymbol{\theta},\boldsymbol{y}^{(1:K)}\right) = \sum_{k=1}^{K} \log\left(Pr(\boldsymbol{y}^{(k)}|\boldsymbol{\theta})\right)$$

$$\boldsymbol{\theta}^* = arg\max_{\theta}\left(\sum_{k=1}^{K} log\left(Pr\left(\boldsymbol{y}^{(k)}|\boldsymbol{\theta}\right)\right)\right) \tag{1}$$

where K is the available number of training degradation histories i.e. K=6.

Based on the estimation of $\boldsymbol{B}$ and $\boldsymbol{\Gamma}$ parameters the prognostic measures can be defined. In this study the mean, median and confidence intervals of RUL are proposed as a prognostic measures. These measures were calculated via the cumulative distribution function (CDF) of RUL. The definition of the RUL CDF is :

$$Pr\left(RUL_{t_p} \leq t\middle|\boldsymbol{y}_{1:t_p},\boldsymbol{M}\right) = 1 - R(t+t_p\,|\,\boldsymbol{y}_{1:t_p},\boldsymbol{M}) \tag{2}$$

where **M** denotes a specific model topology that includes the initial topology and $\boldsymbol{\theta}$ parameters, $R\left(t\middle|\boldsymbol{y}_{1:t_p},L>t_p,\boldsymbol{M}\right) = Pr\left(L>t\middle|\boldsymbol{y}_{1:t_p},L>t_p,\boldsymbol{M}\right)$ is the conditional reliability function i.e. the probability that the system continues operating until a time t, given that the system has not failed and the observation sequence (strain data) is known until the current time $t_p$. The time domain of $t_p$ is [1, L], where L is the structure's life-time.

The RUL measures were estimated via Eq. 2. Fig. 4a and 4b present not only the estimations for the mean, median RUL but also provide a 90% confidence interval of RUL for the specimen03 and specimen06. The choice of these specimens was random, similar results were obtained for the rest specimens.

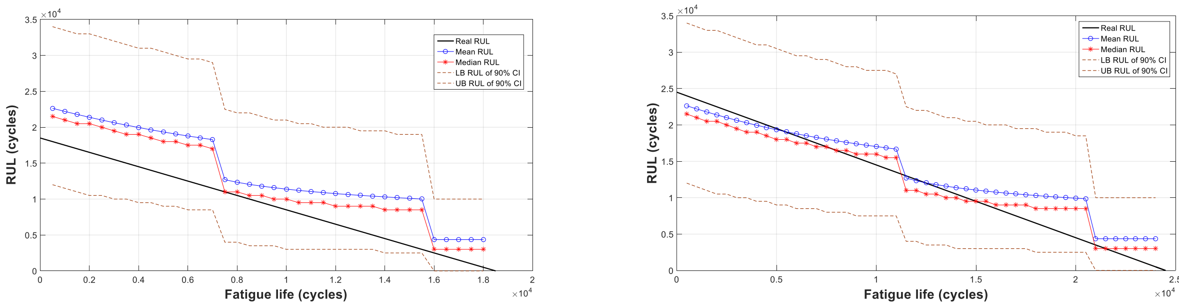


Fig. 4. Mean and median estimations of RUL with 90% confidence intervals for a) specimen03 b) specimen06

## Conclusions

A prognostic methodology based on the NHCTHSMM and DIC/strain measurements was proposed in order to obtain estimations and confidence intervals for the real-time remaining useful life of open-hole composite specimens during fatigue loading. The initialization and training of the NHCTHSMM was analytically discussed. The presented RUL estimations confirm that this stochastic framework can potentially model the damage accumulation process in composite materials under fatigue loading using strain data since the RUL estimations converge quite satisfactorily with the actual RUL values.

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