

WG4: Prognosis of the structural integrity of bonded joints

Advantages and Disadvantages of Methodologies for Prognosis of the Structural Integrity of Bonded Joints under Environmental and Operational Conditions (within the Context of a Roadmap to Certification)

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References: CA18120_WG4_D02

Date: October 23, October 2023

N. of pages: 8

Keywords: prognosis, bonding

From the beginning

Monitored physical phenomenon (depending on the damage)

- integrity monitoring system | diagnostics
 - sensors multiplexing and networking | diagnostics
 - monitoring of usage condition | usage monitoring
- diagnostics + usage monitoring → data cumulative recording
data cumulative recording → health management of structure

Initial system information

Initial system information (design, test, maintenance, operator experience)

Operational and environmental measurement system | future loading model

Structural health monitoring measurement system | structural health model

Initial physical model | updated physical model

All of them → **prognosis model** → estimate remaining service life, time to failure or time to maintenance.

Monitoring schemes resulting from

- Monitoring schemes resulting from design philosophies
- Load exceedance | loads monitoring
- Damage monitoring | multi-site damage design | damage tolerant design

Loads and overloads

- The significance of loads
- Loads and loads characterization
- Service load characterization
- Load cycle counting
- Load spectrum generation
- Load monitoring (i. e. sensors)

Some basics on fatigue and fracture

- Fatigue life evaluation
- Estimation of damage critical location in structures
- The damage tolerance principle
- Stress concentration factors
- Fatigue damage growth
- Enhancing damage tolerance
- Damage propagation calculation
- Fatigue Life Curves
- Fatigue life evaluation
- Damage mapping
- Estimation of damage accumulation
- Critical design parameters

Some basics on damage tolerance

- Safety margins, that tolerate the existence of micro-damage
- Safety margins, that tolerate the damage propagation without failing
- Damage-tolerant concept for composite components
- Efficient and economically viable process of monitoring micro-damage
- Efficient and economically viable process of monitoring damage propagation in real-time
- Sensitivity in the localisation of defects and the evaluation of their severity
- Prediction accuracy of the residual life of damaged composites
- Estimate the stiffness degradation of composites for the prediction of the residual life

Technical report on “**Advantages and disadvantages of methodologies for prognosis of the structural integrity of bonded joints under environmental and operational conditions**”

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Central importance is the term *Remaining Useful Life (RUL)* which is actually at the epicenter of every prognostic task.

The term comes from the ancient Greek word prognosis which literally means to have prior/early knowledge.

The prognostic methodologies can be roughly classified into two major categories.

First, there are model-based prognostics, where a mathematical model describing the physics of the joint or structure is required and used to predict the degradation up to a certain point i.e.

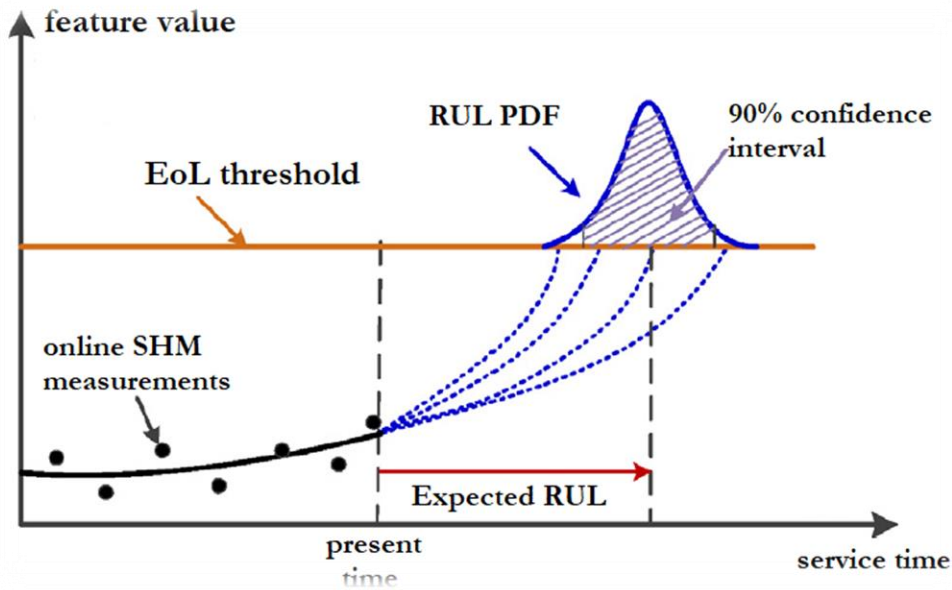
End-of-Life threshold.

Secondly, there are data-driven prognostic approaches which rely on stochastic mathematical models or ***Machine Learning*** algorithms and the existence of historical data.

Data driven **RUL** prediction is more commonly utilized in the field of structures due to the difficulty of accurately describing the materials degradation relying only in physical models.

Prognosis

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In the Figure the concept of SHM-based prognostics is highlighted.

The SHM measurements obtained during service are supposed to feed mathematical models and algorithms which have been trained on historical data to provide with mean estimations of RUL.

Data driven prognostics

Even though there are several studies dealing with **RUL** prediction of composites using physical models, data-driven methods are more popular, since, as mentioned in the introduction, the physics governing the failure of materials and structures are complex and not perfectly understood.

Data-driven prognostics is a recent approach that relies on the existence of historical degradation SHM data and mathematical/machine learning (ML) models to associate the latent degradation process of the structure with direct sensor measurements, rather than trying to create complex physical (and usually empirical) models to describe the different damage and failure mechanisms.

Prognostic performance metrics

To assess the performance of different prognostic models, specific prognostic performance metrics are usually employed.

Precision, Mean Square Error (MSE), Mean Absolute Percentage Error (MAPE), Cumulative Relative Accuracy (CRA), Convergence and Confidence Intervals Convergence (CIC) are frequently used as prognostic performance criteria.

Five out of these seven criteria compare the mean predicted **RUL** versus the actual RUL [2] whereas CIC was introduced recently in [1] to assess the confidence intervals performance as well besides the mean RUL estimates.

The metrics definitions are provided in the publications:

Eleftheroglou, N., et al., *Structural health monitoring data fusion for in-situ life prognosis of composite structures*. Reliability Engineering & System Safety, 2018. **178**: p. 40-54.

Saxena, A., et al., *Metrics for offline evaluation of prognostic performance*. International Journal of Prognostics and health management, 2010. **1**(1): p. 4-23.

Remarks

It can be seen from this short review that there is limited literature on composite adhesive joints.

There is however significantly more literature on fatigue prognostics of composite materials in general.

Two major prognostics categories were discussed, i.e. model based and data-driven prognostics.

Due to the nature of composite materials; inhomogeneity, complex failure mechanisms, as well as different properties depending on stacking sequence;

it is extremely difficult to create a physical model able to capture this complex degradation, and, also able to be generalized.

Data-driven methods on the other hand rely on **SHM** measurements which can be correlated to the degradation of a component, and this is why they have gained increased popularity recently.

With a carefully designed sensor network it is possible to monitor the component's health and obtain useful information on the degradation process.

Health Indicators (HIs), extracted from the raw sensor data, can then be integrated in a prognostic framework for damage and/or **RUL** prognosis.

A major advantage of data driven prognostics is that they are not dataset specific frameworks and can be implemented regardless of the structure/system as long as a proper training process has been implemented.

A database with historical data up to failure in similar material/structure is required though which is not always easy.

Apparently, the more the historical information regarding the degradation process are available, the better the training and the efficiency of the prognostic algorithms.

Tables (next pages) summarize the advantages and disadvantages of the two approaches that were discussed.

Model based prognosis

Advantages	Disadvantages
<ul style="list-style-type: none"> - Gives insight in the physics of the problem under study - No need for historical information 	<ul style="list-style-type: none"> - Hard to create a general physical model for degradation of materials or joints - Empirical models rely on several assumptions not always realistic in real life applications - Application specific (dependent on material properties and stacking sequence) - Hard to gene

Data-driven prognostics

Advantages	Disadvantages
<ul style="list-style-type: none"> - Easy to implement - Application independent as long as historical data exist - A plethora of ML algorithms and stochastic mathematical models potentially interesting to implement 	<ul style="list-style-type: none"> - Usually black box methods (no correlation to the physics of the problem under study) - Dependent on historical data for training - HIs need to be constructed to from raw sensor measurements to capture the degradation <p style="text-align: right;"><i>HI – Health Indicator</i></p>

General remarks ...

- Historically, the Miner’s rule inspired by M. A. Miner in 1945, was the first attempt in engineering to predict the remaining lifetime in terms of loading cycles of a structure.
- It is one of the most widely used (linear) cumulative damage models for failures caused by fatigue.
- In the late 90s Philippidis and Vassilopoulos [2] proposed a quadratic tensor polynomial failure criterion for fatigue behavior prediction of GFRP materials subjected to uniaxial and multi-axial loading. The criterion was validated using an extensive experimental campaign, concluding that lifetime is associated to thickness when constant amplitude loading is introduces, while in irregular loading conditions a Miner coefficient for multiaxial stress states can be introduced to iteratively do the dimensioning.
- In [3] a composite stiffness degradation model is proposed. The model contains two material parameters and is proportional to the fatigue life and inversely proportional to the fatigue load level. The model proved capable of describing the fatigue damage evolution, and able to predict the RUL of the tested specimens.
- A different attempt was followed in [4]. A prognostic framework was proposed which considered strain energy release rate from different damage modes in order to establish a failure threshold for prognostics. The model was based on a modified Paris’ Law, as the model for damage evolution. The model was validated on experimental data on tension-tension fatigue.
- Chiachio et al. [5], proposed another model for composite RUL prediction. A Bayesian filtering framework considering multiple failure models and mechanisms was proposed. The validation of the model was performed on tension- tension fatigue experiments on CFRP panels.
- A hybrid model is proposed in [6]. First a stiffness degradation model is presented which is then integrated to a Bayesian inference model alongside PZT measurements for RUL prediction. The stiffness is calculated from measurements from Lamb waves. The validity of the method was investigated on open-hole specimens subjected to constant amplitude fatigue loading.
- In [7], a model to predict, residual stiffness and strength as well as fatigue life of UD composites subjected to tension-tension fatigue is proposed. Strains measured via extensometer and DIC were used as model inputs to predict the residual strength. By

forcing the failure to occur at a constant ultimate strain, the stress and stiffness are known throughout the entire lifetime. Hence S-N curves are used to predict the specimen's RUL.

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