Prognostic and Health Management (PHM) and Artificial Intelligence in order to estimate the remaining useful lifetime of CMC composite materials

Nathalie Godin[1], Pascal Reynaud[1], Claudio Fusco[1], Gilbert Fantozzi[1]

[1]MATEIS, INSA of Lyon, France

Damage of composite materials is a key factor for the durability in service. It is therefore essential to define the most suitable damage indicators and to develop models to estimate the Remaining Useful Lifetime (RUL) from analysis of precursor events resulting from damage. Acoustic emission is relevant to the development of the PHM because it allows knowing the state of damage of a composite structure in real time. This approach is based on two phases: diagnostic and prognostic. The diagnosis phase must be able to detect, locate, identify the damage and assess its severity. The prognosis phase, based on the results of the diagnosis and on models, makes it possible to evaluate the residual lifetime. This work is dedicated to lifetime prediction using AE for long-term tests on CMC during static and cyclic fatigue tests at high temperatures. New indicators of damage have been defined, based mainly on acoustic energy analyses. These indicators highlight critical times (around 20 % for the cyclic fatigue tests and 50 % of the composite lifetime for the static fatigue tests) allowing an evaluation of the remaining lifetime. Moreover, the identification of damage, using a supervised classification method based on random forest approach, makes possible to get a real-time detection of each damage phenomena and to identify the mechanism responsible for this critical time. This technique requires a database of labelled signals: the training set. This training set is created by merging data collected during tensile test at 450°C and 500°C and cyclic fatigue tests. This analysis pointed out different damage mechanisms generated by cyclic loading, which are mainly debonding and friction at matrix/fibre and matrix/matrix interfaces. Furthermore, a link is established between characteristic time at 20 % for the cyclic fatigue and the beginning of the matrix cracking. For the static fatigue test, the critical time around 50 % corresponds to the delayed failure of thermally aged fibres (slow crack growth, oxidation). To perform RUL prognostics, the results obtained with these new indicators can be used to propose new predictive laws of lifetimes complementary to the classical Benioff's law. Nevertheless, the determination of the acoustic signatures and characteristic times are linked to testing conditions and specimen geometries. The specific values of the AE parameters are very sensitive to the experimental set up. Actually, in addition of type of failures, the AE signals depend on other parameters like type of sensor, geometry of the sample and the distance between source and sensor. The majority of the studies are based on the assumption that the feature measurements and the identified classes for the library are error-free. However, one cannot exclude that the library may contain uncertainty. The performance of the classifier depends on both the number of the available training signals as well as the specific values of the signals. However, certainly, in the dataset, some learning data have wrong labels. In this study, we also investigate the influence of sensors, thickness, and position of the fibre by finite element simulations. In this context, merging the simulated and the experimental data enables to enlarge the library for machine learning algorithms. In addition, modelling AE signals allows us to enlarge of the training while avoiding the high costs required by extensive experimental campaigns. The results underline the interest to use the data obtained with the modelling work, in order to increase the robustness of the supervised classification of AE signals.