Abstract

Composite materials are widely adopted in aerospace and other high-performance applications due to their lightweight characteristics and excellent mechanical properties. Currently, adhesive bonding has become the preferred alternative to traditional riveted joints for assembling composite structures. However, the complexity of manufacturing processes, combined with varying operational conditions, often leads to internal defects such as disbonds and voids, which significantly increase the risk of structural failure. As a result, despite its advantages in maintaining load transfer continuity and preserving fibre integrity, adhesive bonding still faces acceptance challenges compared to conventional mechanical fastening methods.

Currently, various non-destructive testing and structural health monitoring-based techniques are employed to inspect composite structures and assess their remaining service life, with the aim of enhancing detection accuracy and extending operational longevity. However, due to the extreme sensitivity of traditional elastic wave methods to the microstructure of the actually bonded region and noise interference, achieving effective detection remains a significant challenge. In recent years, the emergence of multi-model ensemble techniques has helped overcome these issues. Hybrid models based on digital twins integrate signal processing techniques with deep learning, addressing the challenges associated with fault feature extraction in traditional methods while providing a neural network-based approach for predicting remaining useful life.

The primary objective of this dissertation is to develop a model for damage diagnosis and remaining useful life prediction of bonded composite materials. It also highlights the feasibility of using guided waves for experimental measurements and assessing the crack length within adhesion. Compared to single neural network structures, this study adopts a multi-model collaborative approach to address the issues associated with classic neural network-based remaining useful life prediction, such as single-value outputs and the reliance on Bayesian networks for uncertainty quantification. Adopting the ensemble fracture mechanics model effectively simulates the nonlinear characteristics of crack propagation, which is not constrained by limitations related to the insufficient initial sample size or a short prediction horizon. Furthermore, a dropout-based approximation of the Bayesian approach is used, eliminating the need to assign probability distributions to hidden layer nodes within

the neural network, thereby reducing model complexity. The prediction output consists of confidence intervals, improving the reliability of the results. Compared with traditional Bayesian networks, repeated experimental trials demonstrate an accuracy improvement of 16.43%. Additionally, a data augmentation and segmentation method is proposed to address the initial-stage deviation problem in remaining useful life prediction. Experimental results show that initial-stage prediction errors can be effectively reduced after data adjustments. Chapter 5 presents the results of all models developed in this dissertation, alongside a comparative analysis with currently established mainstream approaches.

The integration of multi-model digital twin technology aims to resolve the issues of Bayesian dependence in prediction processes and the single-value nature of remaining useful life predictions. This research further provides technical support for the broader application of adhesively bonded composite materials across different fields.