Fatigue life of fibre-metal laminates in marine environment

Sai, Wei

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SINGAPORE

**FATIGUE LIFE OF FIBRE-METAL LAMINATES IN
MARINE ENVIRONMENT**

SAI WEI

Interdisciplinary Graduate School

Energy Research Institute (ERI@N)

**FATIGUE LIFE OF FIBRE-METAL LAMINATES IN
MARINE ENVIRONMENT**

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**Interdisciplinary Graduate School
Energy Research Institute (ERI@N)**

A thesis submitted to the Nanyang Technological University in partial
fulfillment of the requirement for the degree of

Doctor of Philosophy

2020

Statement of Originality

I hereby certify that the work embodied in this thesis is the result of original research, is free of plagiarised materials, and has not been submitted for a higher degree to any other University or Institution.

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Sai Wei

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I have reviewed the content and presentation style of this thesis and declare it is free of plagiarism and of sufficient grammatical clarity to be examined. To the best of my knowledge, the research and writing are those of the candidate except as acknowledged in the Author Attribution Statement. I confirm that the investigations were conducted in accord with the ethics policies and integrity standards of Nanyang Technological University and that the research data are presented honestly and without prejudice.

8 July 2020

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Date

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Chai Gin Boay

Authorship Attribution Statement

This thesis contains material from one paper published in the following peer-reviewed journal and one conference paper at the international congress where I was the first and corresponding author.

Chapters 3 and 4 One-stop model is published as Sai, W. and G.B. Chai, *Fatigue in Fiber-Metal Laminates for Small Wind Turbine Blades Application*. in MATEC Web of Conferences. May 2018. Poitiers, France: EDP Sciences.

The contributions of the co-author are as follows:

- Prof Chai suggested the initial direction of the topic.
- I prepared the draft manuscript. Prof Chai revised the draft.
- I designed and performed the laboratory work at the Structures Lab, School of Mechanical and Aerospace Engineering. I also analyzed the data.
- I performed all the modelling and calculation.

Chapters 3 and 4 RTE machine learning model is published as Sai, W., G.B. Chai, and N. Srikanth, *Fatigue Life Prediction of GLARE Composites Using Regression Tree Ensemble-Based Machine Learning Model*. Advanced Theory and Simulations: p. 2000048.

The contributions of the co-authors are as follows:

- Prof Chai suggested the materials area and edited the manuscript drafts.
- Dr. Srikanth suggested some ideas to perfect the model.
- I prepared the manuscript drafts. The manuscript was revised by Prof Chai.
- I designed and performed the laboratory work and analyzed the data.
- I performed all the modelling and calculation.

9 July 2020

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Sai Wei

Abstract

This work aims to provide a novel systematic One-stop fatigue model that could predict the fatigue life of the wind turbine blade with fiber-metal laminate (FML) as the shell skin material. Specifically, the fatigue life of FML is linked with a wind blade's lifespan with wind conditions and wind blade airfoil parameters as the inputs and fatigue cycle as the output. Firstly, the wind blade loadings were calculated based on the blade element momentum theory. The aerodynamic loads were calculated and taken as the inputs for airfoil stress analysis, which was further used for stress analysis based on the classical laminate theory. Secondly, the fatigue life was then predicted based on the fracture mechanics approach. Different types of FML, either standard grades or non-standard layups, were fabricated and tested and involved in the fatigue prediction model. The predicted S-N curves were validated with the experimental data. The comparison shows a good correlation, and the proposed One-stop model has achieved a reliable accuracy within one order of magnitude.

Further, to enhance the classical fatigue life prediction in generalization, an intermediate gray box model between the expert system and the black box system was proposed, a regression tree ensemble-based (RTE) machine learning approach. Unlike the total black box system, this grey box model provides an interpretable and extendable solution towards various FML layups. What's more, the RTE model overcomes the limitation of classical fatigue theories, i.e., lack of generalization and extensibility. Specifically, in the gray box RTE model, mechanical, geometrical properties, and fatigue loading stresses are selected as the training parameters (so-called features). FML fatigue life is predicted as the output of the model. Experimental data of 128 pieces of FML specimens with different layups were used to train and validate the machine learning model. Results show that the model can provide better fatigue life prediction accuracy and model reliability than the classical fatigue model. The most correlated, either positively or negatively, parameters to the fatigue life span are the stress

developed in the aluminum layer, S_{Al} the maximum cyclic stress, S_{max} alternating stress, S_{alt} and mean fatigue stress S_m . To exclude the influence of human errors in the whole experiment process, the RTE model was further trained based on the analyzed data obtained from the One-stop model. The model accuracy and reliability in terms of mean absolute error and the determinant of coefficient, respectively, have shown significant improvement.

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Variables

σ_{uts}	Ultimate tensile strength (MPa)
σ_y	Yield strength (KN)
σ_0	Applied stress (MPa)
F_{max}	Maximum load (KN)
t	Thickness (mm)
ρ	Density (kg/m ³)
E	Young's modulus (Gpa)
S_{max}	Maximum cyclic stress (MPa)
S_{alt}	Alternating stress (MPa)
S_m	Mean fatigue stress (MPa)
S_{Al}	Cyclic stress in aluminum layer (MPa)
n_{Al}	Number of aluminum layers
n_0	Number of 0° prepreg layers
n_{90}	Number of 90° prepreg layers
N_{Al}	Fatigue cycle determined by the failure of aluminum layers

Abbreviations

ANN	Artificial neural network
CART	Classification and regression trees
CNN	Convolutional neural network
CFRP	Carbon fiber reinforced plastic
ELM	Extreme learning machine
LR	Linear regression
NMAPE	The normalized mean absolute percentage error
ML	Machine learning
NMSE	Normalized mean squared error
R^2	Coefficient of determination
NRMSE	Normalized root mean square error
SVM	Support vector machine
SVR	Support vector regression
xgboost	Extreme gradient boosting
RTE	Regression tree ensembles

Chapter 1. Introduction

In order to maintain the continuous development and stability of various economic entities, the Intergovernmental Panel on Climate Change (IPCC) urged that humans have to reduce the carbon emission to net-zero by 2050 to avoid the non-reversible change of the atmosphere system that would occur when the accumulated CO_2 reaches to 450-600 ppm level [1, 2]. Alongside this, a number of nations and regions have set net-zero targets. The trajectory set by the Europe commission is shown in Figure 1.1.

Figure 1.1 Greenhouse gas emissions trajectory in 1.5°C scenery [3].

It has reached a consensus that renewable energy is one of the main contributions to the decarbonization in the power sector and fights against climate change [4]. From 2009 to 2018, worldwide renewable energy power capacity has increased 1220GW, and among them, wind energy occupied 33.87% [5]. To maximize the energy harvest efficiency and make economic sense, the tendency of wind turbine development is going for the supersize direction [6-8]. Up to 2019, the world's most enormous offshore wind turbine blade has reached 107-meter, and the power capacity has reached 12 MW

per unit [9]. The GE Cypress, the largest wind turbine on land, has an output capacity of 5.3MW and a rotor diameter of 158 meters [10], as shown in Figure 1.2. Why are wind turbine blades going larger and larger? One of the reasons is that a larger blade could provide more power output based on Betz's Law. This move is also driven by the quest to reduce the Levelized cost of energy (LCOE). The maximum size of a rotor blade can be limited by the strength of wind blade material, the rated power capacity, and the capability to manufacture and transport the heavy and bulk components. As wind turbine blades become larger and larger, maintenance becomes more demanding and expensive due to the size effect. This loss would be even more significant in the event of fatal damages, especially catastrophic fatigue failure.

Figure 1.2 Renewable capacity statistics from the International Renewable Energy Agency (IRENA) in 2019 (left). Giant offshore wind turbines from General Electric Co's 12MW Haliade-X with a blade length of 107 meters [6] (right).

Among all the failure types of wind turbines, rotor blade failures account for 11.86% to 16.89%, which are among the top 25% mechanical components with the most prolonged downtime as of 2019 [11, 12]. The other compendium of wind turbine accidents provided by Caithness Windfarms Information Forum (CWIF) shows that wind turbine blade accidents occupy 15.88% of total accidents in the past ten years, as shown in Figure 1.3. One of the main reasons for the failure is the fatigue loads attributed to the wind fluctuation and the turbine blade's dead weight. Thus fatigue analysis, either online or offline, plays a vital role in reducing windfarm downtime and minimizing maintenance costs in the wind energy industry [13-15]. The statistics of

failure mentioned above are mostly based on the fiber composites, the type of materials studied in the European FACT database [16, 17], and US DOE/MSU database [18, 19].

Wind Turbine Accidents Statistics (2000-2019)

Figure 1.3 Wind turbine accidents statistics (Data source: CWIF)

Other than the fatigue issue, wind blade coating erosion could happen within 1-year in service [20]. Once the protective coating is eroded, moisture and rain will seep into the laminated composite and cause debonding and delamination problems. Therefore, the life of the wind blade will be significantly reduced. Besides, the loss of protective coating will also affect the wing's aerodynamic parameters and reduce working efficiency. As depicted in Figure 1.4, noticeable erosion was found at the blade's leading edge after one to two years in service. As the time accumulated up to ten years, the coating on the leading edge almost completely eroded, leaving only the bare wooden frame. If nothing was done, the erosion can further extend and eventually cause the remaining coating layer's fragmentation or cracking. Thus, regular maintenance is essential for wind blades to meet the specified service life. Also, in a fire, the fiber

composite material can easily catch fire, which will likely cause complete loss of the wind blades.

Figure 1.4 Wind turbine blade leading edge erosion with different years of service [21].

Whether the wind turbines could fulfill the required service life or not is usually the most concern by direct end-users. From a design perspective, wind blades should be firstly designed for extreme loads; secondly, the fatigue life must be ensured the service life, i.e., 20 to 30 years [22], which is corresponding to 10^8 - 10^9 of fatigue cycles to failure. Up to now, the widely adopted regulations for wind turbines are IEC standards, e.g., IEC 61400-1, IEC 61400-2, and IEC 61400-3. Ten different load cases are defined in IEC61400-2 for safe design purposes. However, only one load case is dedicated to fatigue analysis. The fatigue analysis takes the blade root section to calculate the stress developed due to the flap-wise and edgewise bending moments. Phenomenological parameters and safety factors are applied through the equations. Though easy to understand, the regulations are lack versatility for different materials. Despite various fatigue failure phenomena observed, the dominant stress developed by the load sources is the axial stress along the wind turbine blade. Fatigue investigation of material or structure can be carried out from both aspects, i.e., size and loads. Experimental or analytical modeling can be done at the full-scale, scaled size, and specimen [23]. The real working loading conditions could be simulated by adjusting the load's complexity,

e.g., constant or variable amplitude fatigue load or on-site spectrum load [24]. Kong [25] performed full-scale static modeling and structural tests for a medium-size fiber composites wind blade and analyzed the allowable fatigue stresses by using Palmgren-Miner Rule based on the constructed Goodman diagram under sample-spectrum loads [13, 26]. Much [27-29] of the research on wind blade life was focused on modeling aerodynamic loads and then using linear damage rules to estimate fatigue life, which requires a constant life map of the same material that has already been established. Most of the models reviewed so far have analyzed and predicted the life of fiber composites wind blades from the structural level. It is more often to see that the fatigue life is predicted from the material level, which allows for the rapid investigation of various materials with different layups, load conditions and obtaining the S-N curve at much lower costs [24]. Over the past two decades, fiber metal laminates (FML) have gained popularity as an essential structural material in the aviation industry. FML was used in the upper fuselage and on the tail leading edges of the Airbus A380 due to its lightweight, high impact strength, excellent corrosion resistance, and relatively long fatigue life [30-36] compared with conventional aluminum structure. With the advances of the automation manufacturing of FML [37-39], the interest in FML is growing again as aero companies are searching for robust fuselage material adaptable to new narrowbody commercial aircraft [40]. Also, there are increasing needs in the automobile industries to exert lightweight, high stiffness material to enhance the vehicle structures' weight efficiency [41]. FML material benefits from its combined characteristics of high strength and lightweight from alternating layers and fits the gap very well. However, whether it is applied to the fuselage skin or the wind blade shell, FML is subject to periodic fatigue loads, which becomes the leading cause of material failure. Jang [42] compared different Goodman models for the fatigue life prediction of fiber-metal laminates. The S-N curve model was the most accurate way under the constant amplitude loading and spectrum loading. The fiber-metal laminate has been studied extensively from the material level in aeronautical and defense applications [31, 43, 44]. Unlike fiber composites, the fatigue life models for fiber-metal laminate -

GLARE involve the bridging effect provided by the glass fiber prepreg, which bypasses the stress in the aluminum layer and resists the crack growth [45, 46] and increases the fatigue life. Marisen [47] proposed phenomenological models to predict the crack growth rate for ARALL center notched specimens under constant amplitude loading. Guo proposed the theoretical model to calculate the bridging stress in the center cracked tension (CCT) GLARE specimens [48-50]. The improved analytical models for predicting fatigue crack growth and delamination growth rate in GLARE with one CCT and double CCT slot-cut could be seen in Chang and Alderliesten's work [45, 51-54]. Recently, Wang [55] proposed a fatigue model that predicts eccentric crack growth in GLARE. This model provides a theoretical solution to predict the crack growth rate of unsymmetrical cracks of GLARE panels under eccentric loads. It is meaningful for the arbitrary delamination shapes commonly seen in practice.

However, very few existing fatigue life models attempt to establish a direct relationship between material properties and the lifespan of GLARE wind turbine blades in the number of fatigue cycles. Comprehensive full-scale testing is very time consuming and costly, and FEA modeling provides only the study of static stress. In contrast, on-site non-destructive testing technology for giant blades has not yet been established. All of these increase the difficulty of predicting the fatigue life of wind turbines. Existing fatigue models for GLARE have not previously been linked with wind turbine blades from the structural level.

Despite the excellent performance, fatigue due to cyclic loading is one of the major issues of FML. The fatigue life prediction model of GLARE based on the elastic linear fracture mechanics method is a commonly used classical model. The fatigue life prediction by calculating the crack growth rate of notched specimens has been widely accepted [46, 52, 54-57]. Theoretical fatigue models are typically validated by the S-N plots with massive experimental data. The classical theories have limitations regarding the prediction due to the complexities in the fiber-metal laminate characteristics and

complicated fatigue failure mechanisms (fiber breakage, matrix cracking, delamination, etc.) under the varying dynamic loadings of the fatigue life in the regime of non-linear plastic deformation [58]. Once the material layup or testing conditions are changed, the theoretical models require further investigation and validation. Prediction of fatigue life for the GLARE composites could be solved by other novel methods, such as the machine learning approach.

Recently, machine learning has been making significant advancements and has been widely deployed [59] in medical, manufacturing, education, financial modeling, police force, and marketing to tackle various tasks [60]. Implementing machine learning in composite structures has begun to emerge and brings new inspiration to guide the composite materials [61-64] and structures' [65-68] development. Notably, Yang [69] proposed a stiffness degradation model to predict the graphite/epoxy composites fatigue lifespan based on the linear regression (LR) approach, allowing for accessing of residual strength at any load cycles. Loutas [70] proposed an expert system based on dynamic strain data for aerospace composite structural health monitoring. The support vector machine (SVM) was applied to distinguish the difference among multiple damage states and detect the damage's location on the composite structure. Up to now, Machine learning algorithms of either linear regression or SVM are mostly based on the optimization in Euclidean space, which could not process a large number of input features and not perform well with noisy data. Also, the penalty weights learned in LR and the hyperparameter trained in SVM could hardly be expanded to a different dataset.

On the other hand, Neural Network, as part of the heavily implemented algorithms in machine learning, appeared in many fatigue life prediction researches. Wang [71] compared multiple machine learning algorithms (MLAs) in predicting the fatigue crack growth rate of aluminum 2024-T351 and showed that the MLAs could fit the nonlinearities of the fatigue crack growth rate very well. Chakraborty [72] implemented the artificial neural network (ANN) as a learning tool to predict the embedded

delamination in graphite/epoxy plates, and good prediction results were achieved with out-of-sample data (untrained data). Vassilopoulos [73] applied ANN to predict the fatigue cycle of GFRP and constructed the constant life diagrams (CLD) by using 40%-50% of total experimental data compared to the conventional way of construction of CLDs without significant loss of accuracy. Though difficult to interpret, the artificial neural networks can somehow establish good correlations between the material characteristics and the fatigue cycles through fully connected networks. When zoom into NN's algorithm, it maps the material properties into the fatigue cycles with the weights, biases, and activation functions. To minimize the loss of the prediction, the best set of weights and biases through the training process. The only controllable variables are the weights and biases, which are not easy to extract and interpret, especially when the NN is deep. Some studies on the interpretation of deep NN [74-76] while currently are still under exploration. Thus, an algorithm with better feature interpretation is essential to develop new FML further to enhance performance.

Based on the above findings, it is necessary to establish a more accurate, interpretable model to bridge the material properties and composite structure lifespan. In particular, due to unbalanced features, existing ML algorithms that use linear or support vector machines may not accurately predict GLARE composite materials' fatigue life. Some features are so important that changes in these features will affect the weights of other features. A hierarchy arrangement of features is needed to tackle this problem. Artificial neural networks (ANN) are often described as black-box due to lack of interpretation and difficulty in knowledge extraction from hidden layers. Neural networks could not discover the importance of different input features, nor can they analyze the correlations of the features with fatigue life of GLARE composites. Among all machine learning algorithms, the regression tree ensemble xgboost algorithm was newly developed by Chen [77, 78] and initially released in the year 2014. xgboost has shown its edge in many machine learning and data mining competitions [79] due to its comparable accuracy with deep neural networks with one-third of the computation time [80]. The

adoption of a tree ensemble model, i.e., xgboost, could solve the unbalanced feature problem. Pioneer implementation of the regression tree ensembles algorithm could be found in the studies of fault detection of composites wind turbine and fatigue prediction for steel [81-83] but not yet for fiber- metal laminates.

In this thesis, the GLARE wind turbine blade the established One-stop expert model first predicted's fatigue life. The One-stop model predicts the S-N curve of GLARE wind turbine blades from the level of material specimens. Thus, rapid fatigue life analysis can be performed for different material layups and wind blade sizes under various loading conditions. In this model, the structural loads of wind blades with S809 as the airfoil were calculated based on the Euler-Bernoulli beam theory. The model derived the axial stress and inputted it into the specimen cyclic stress analysis based on classical laminate theory. The stress at each layer of the GLARE laminate can be calculated separately. The crack growth rate was predicted by assuming an elliptical delamination shape and an initial crack size. The bridging stress and stress intensity factors were analyzed according to the empirical Paris' Law type equation. Then fatigue life S-N curve was predicted and compared with experimental results. In order to enhance the accuracy of fatigue life prediction for GLARE composites at the material level, fatigue cycles are predicted by the regression tree ensemble-based (RTE) model. In the RTE model building, GLARE mechanical and geometrical properties, fatigue loading parameters, and stress distribution in the layers are selected as model parameters (or features, attributes). At the computation stage, a total dataset of 119 GLARE specimens with nine different layups is fabricated for training and validation purposes. The accuracy and reliability of the trained model are then validated with the evaluation matrix - mean absolute percentage error (MAPE), R^2 (the coefficient of determination) value, normalized mean squared error (NMSE), and normalized root mean square error (NRMSE). In order to better interpret the model parameters, the correlation between the parameters and fatigue life is established through the heat map (or correlation) diagram. To further verify the model's capability to predict new

GLARE layups, an expandability study was performed on two different GLARE layups. The results of the evaluation on the expandability show comparable accuracy and reliability with the overall model performance. Thus, the machine learning RTE model compensates well for GLARE wind blade fatigue life prediction using the classical theories. Lastly, to exclude the human errors in the experimental process, analytical fatigue data obtained from the One-stop model were trained and tested again by the RTE model. Noticeable improvement could be seen based on the results of the evaluation matrix.

To summarize, the established One-stop model using the classical fatigue theory could well bridge the gap between the fatigue life prediction of GLARE composite material and GLARE wind turbine blades. This work further proposed a machine learning RTE model to compensate for the deficiencies in the classical theories regarding the limitation of the generalization, extensibility, and massive testing time. The RTE model improved the efficiency of prediction while at the same time can maintain high accuracy, stability, and scalability of prediction results.

Chapter 2. Literature review

The approach taken for the literature review starts with structural fatigue models and material fatigue models, which majorly use the classical approaches, and lastly, the machine learning fatigue models that predict the fatigue life at both the structure and sample levels.

2.1 Structural fatigue models

From the 1950s to the 1980s, several severe aircraft accidents caused by fatigue failure have caught much attention to the study of structural fatigue life [84]. In pursuit of lighter and more fatigue-resistant aviation materials, fiber-metal laminate - GLARE was successfully developed and applied to the fuselage and leading edge of the tail surfaces of the Airbus A380. Due to constant pressurization, decompression, and gust loading of the cabin, the aircraft fuselage suffered high cyclic fatigue [85]. Under the biaxial cyclic loading, fatigue initiates at the areas where stress concentrations are high, e.g., cut-outs (aircraft windows and doors) [86] and riveted lap splice joints. The fuselage may also suffer from corrosion damage, wear defects [87], wildlife, and hailstorm strike. Similar fatigue loading conditions could be seen in wind turbine blades. Wind blades undertake the flap-wise and edgewise bending moments caused by the wind and the wind turbine blades' dead weight. In order to maximize the harvest of wind energy, the wind turbine blades' size goes larger and larger. Thus, fatigue life study would be crucial for the wind turbine to sustain the 20 to 30 years' service life requirements. A better understanding of the typical failure modes and damage types of wind turbine blades is essential for the study of fiber-metal laminates (FML) wind turbine blades. The general types of wind turbine damage types reviewed by Shohag [88] are shown in Figure 2.1

.

Type	Description
Type 1	Damage formation and growth in the adhesive layer joining skin and main spar flanges (skin/adhesive debonding and/or main spar/adhesive layer debonding)
Type 2	Damage formation and growth in the adhesive layer joining the up- and downwind skins along leading and/or trailing edges adhesive joint failure between skins)
Type 3	Damage formation and growth at the interface between face and core in sandwich panels in skins and main spar web (sandwich panel face/core debonding)
Type 4	Internal damage formation and growth in laminates in skin and/or main spar flanges, under a tensile or compression load (delamination driven by a tensional or a buckling load)
Type 5	Splitting and fracture of separate fibres in laminates of the skin and main spar (fibre failure in tension; laminate failure in compression)
Type 6	Buckling of the skin due to damage formation and growth in the bond between skin and main spar under compressive load (skin/adhesive debonding induced by buckling , a specific type 1 case)
Type 7	Formation and growth of cracks in the gel-coat; debonding of the gel-coat from the skin (gel-coat cracking and gel-coat/skin debonding)

Figure 2.1 Typical damage types of wind turbine blades reviewed in [88].

The typical fatigue mechanism in fiber composites of wind blades are debonding, delamination, and cracking. These damages are generally caused due to the cyclic loads from the wind and wind blade self-weight. Fatigue loads, manufacture defects, impact loads from hailstones, erosion from sands, degradation from UV light, salinity, and moisture induce the combined effect of laminated wind blade cracks, fracture, delamination, debonding, and buckling. Among all the damage types listed, crack and fracture caused by fatigue loads are one of the most commonly seen failure types both in fiber composite wind turbine blades and FML structures. To bridge the gap from

FML material to FML type of wind turbine blades, understanding of fatigue mechanism of FML becomes the critical point. Fatigue of FML, which includes crack initiation, crack locations, delamination, and environmental effects, are reviewed and listed in Table 2.1.

No.	Description	Reference
1	Cracks initiated as corner cracks for Al 2024-T3 or other metals at the symmetrical/unsymmetrical holes.	[89-91]
2	Cracked initiated due to the impurity inclusion and further lead to edge cracks or surface center cracks was found in Al 2024-T4.	[92, 93]
3	Longitudinal surface cracks were found over a broken frame on the FML fuselage skin panel.	[94]
4	The delamination shape of FML is in between the triangle and ellipse shapes for center notched tension-tension (CCT) fatigue tests.	[51, 53, 95]
5	Delamination extension in FML is found when an overload is applied for CCT fatigue tests.	[96, 97]
6	Delamination is more common in thick FMLs composite layers than in thin FMLs composite layers.	[98]
7	Environmental factors, e.g., temperature, moisture, and hygrothermal conditions, could degrade the FML fatigue life.	[99-102]

Table 2.1 Review of the causes of fatigue failure in fiber-metal laminates.

The airplane fuselage and wind blade are subjected to complex cyclic loads at the structural level and have similar causes of crack initiation and crack propagation. In this context, since GLARE has been successfully used as the Airbus A380 fuselage material, it may also be a potential material for wind blades' shell skin. Fatigue life prediction models of GLARE laminates for wind blade application were proposed and further discussed in the following chapters.

With all the background knowledge of FML and wind turbine blade damage modes, an investigation of the existing fatigue models for wind turbine blades follows. Most of the fatigue life prediction models for wind blades are based on the recognized approach – the Palmgren-Miner cumulative linear damage rule to predict the structure's life span under various loading conditions, as shown in equation (2.1) [103].

$$\sum_i^M \frac{n_i}{N_i} = \frac{n_1}{N_1} + \frac{n_2}{N_2} + \frac{n_3}{N_3} + \dots + \frac{n_M}{N_M} = D \quad (2.1)$$

Where n_i is the total number of cycles in the i^{th} constant stress amplitude; M is the total number of stress amplitudes; N_i is the fatigue cycle to failure under the constant stress amplitudes; D is the damage number, and $D \geq 0$ when the failure occurs.

Miner's rule is suitable for linear damage accumulation. It does not take into consideration of non-linear fatigue as well as the sequence effect. Either over conservative or non-conservative cases were discovered [104, 105]. In the natural environment, wind speeds are highly irregular, which causes cyclic loadings on the wind blade.

In order to consider the actual loadings, time-series load counting is usually performed by analyzing a short period of wind loading data recorded from the wind blade (e.g., strain gauge). The most well-known method among all the counting methods is rain flow counting (RFC). The recorded wind blade loadings are processed through the RFC and categorized into different load ranges with an accumulated number of cycles. Thus, the fatigue cycle could be predicted based on the equation (2.1). The flow chart of the prediction of wind blade fatigue life is depicted in Figure 2.2.

Figure 2.2 Rain flow counting method to predict the fatigue life of the wind blade using the Palmgren-Miner rule [106].

RFC, combined with the Palmgren-Miner rule, predicts the fatigue life span for wind turbine blades from the macrostructure level and takes little consideration of material fatigue properties. It is necessary to build up a model that bridges the existing gap by predicting the structure fatigue life from the material's fatigue properties.

2.2 Material fatigue models

2.2.1 Introduction of GLARE

GLARE (Glass laminate aluminum reinforced epoxy) is a new type of fiber metal laminate developed for aerospace applications. It is composed of a thin aluminum sheet and high-strength glass fiber prepreg, and it is bonded through the epoxy adhesive in the prepreg matrix. GLARE offer advanced material properties with good fatigue resistance, high specific strength, low specific weight, excellent impact resistance, flame resistance and corrosion properties, and ease of repair [107]. The commercial standard grade of GLARE layup is listed in Table 2.2 below:

Glare grade	Sub	Metal sheet thickness [mm] & alloy	Prepreg orientation* in each fibre layer**	Main beneficial characteristics
Glare 1	-	0.3-0.4 7475-T761	0/0	fatigue, strength, yields stress
Glare 2	Glare 2A	0.2-0.5 2024-T3	0/0	fatigue, strength
	Glare 2B	0.2-0.5 2024-T3	90/90	fatigue, strength
Glare 3	-	0.2-0.5 2024-T3	0/90	fatigue, impact
Glare 4	Glare 4A	0.2-0.5 2024-T3	0/90/0	fatigue, strength in 0° direction
	Glare 4B	0.2-0.5 2024-T3	90/0/90	fatigue, strength in 90° direction
Glare 5	-	0.2-0.5 2024-T3	0/90/90/0	impact
Glare 6	Glare 6A	0.2-0.5 2024-T3	+45/-45	shear, off-axis properties
	Glare 6B	0.2-0.5 2024-T3	-45/+45	shear, off-axis properties

Table 2.2 Standard grade of GLARE laminates [108].

In order to better illustrate the definition of GLARE grades, an example of GLARE 4A - 3/2-0.4 is explained: three-layer of Al2024-T3 at the thickness of 0.4mm, two groups of prepreg layups in the alternate order, and each with the fiber orientation of 0°/90°/0°.

In order to study the fatigue life of the GLARE laminates, the fundamental material properties of GLARE laminates are to be known first. Based on the reviewed mechanical properties of various GLARE grades [107, 108], the material properties of GLARE are close to the properties of metal, rather than glass fiber composites. When it comes to fatigue prediction, most models are developed based on metal fatigue models.

Different from the metal fatigue mechanism, the fatigue of fiber metal laminates involves the interaction between the metal layer and the prepreg layer, e.g., delamination shape and size, matrix adhesive shear deformation, fiber bridging, etc. The terminology of “fiber bridging” was firstly raised by Marissen for the investigation of crack growth in ARALL. As illustrated in Figure 2.3, under the applied load σ_0 , the cyclic stress developed in the metal layer causes the crack opening. Meanwhile, the fibers in the prepreg are intact and bridging the crack opening from the aluminium layer

to restrain the crack opening. The cyclic stress formed in fibers to restrain the crack opening in the aluminum layer is bridging stress. It is one of the critical factors in determining the crack growth rate of GLARE.

Figure 2.3 Fiber bridging mechanism in FML with elliptical delamination shape formed at the interface between the prepreg layer and the aluminum layer [49].

With the aid of the fibers' bridging effect, the crack growth rate is significantly reduced in GLARE laminates compared with the monolithic aluminum 2024-T3. Though the fatigue initiation life in GLARE 3-3/2, as depicted in Figure 2.4, is shorter compared with Al2024-T3, the total fatigue life is incremented more than doubled. The underlying causes of shortened fatigue initiation life in GLARE are that the stress developed in GLARE's aluminum layer is much higher than the uniform load applied on the GLARE laminate. For example, the uniform load applied to the GLARE laminate is 180 MPa, while the stress developed in the aluminum layers is much higher than 180 MPa. Up to now, the aforementioned fiber-bridging effect is a widely accepted theory to explain the decreased crack growth rate in GLARE laminate compared with monolithic aluminum.

Figure 2.4 Crack initiation and propagation in GLARE3-3/2-0.3 and monolithic aluminum 2024-T3 [46].

It was assumed the crack initiation in GLARE is similar to that of crack initiation in monolithic aluminum under the same stress state [54]. Though the causes of stress concentrations in GLARE may not be the same with monolithic aluminium, it was assumed that the matrix cracking due to the fiber orientation does not affect the crack initiation life but the crack initiation locations. In practical scenarios, multiple crack initiation locations could expedite the crack initiation propagation process and reduce fatigue life [49]. The detail fatigue models studied to predict the fatigue life of GLARE will be depicted in detail in the following sections.

2.2.2 Fracture mechanics-based fatigue models

The fracture mechanics approach to predict fatigue assumes that all structures are flawed, and the crack growth is governed by the stress intensity factors, $K_{\max}$ and $K_{\min}$ [109]. Linear elastic fracture mechanics (LEFM) provides a quantitative relationship between stress, flaw size, and fracture toughness, K_{IC} , and thus link up the local crack-tip response with the global crack condition. The fatigue crack growth rate is defined as a power-law function by Paris and Erdogan (1963). In this equation, the range of the stress intensity factor ΔK is employed to describe the fatigue crack growth was. The general form of the Paris' law is defined as:

$$\frac{da}{dN} = C(\Delta K)^m \quad (2.2)$$

When da/dN is the crack growth rate, C and m are material constants, and ΔK is the range of the stress intensity factor. The crack growth rate versus ΔK is generally characterized in three regimes, as shown in Figure 2.5. As summarized in [109] that some factors, such as mean stress, microstructure, frequency, environment, and environment, have continuous effects throughout the crack growth process.

Figure 2.5 Schematic diagram of crack growth rate versus stress intensity ΔK [110].

The method by Guo and Wu [49] – CCT

Guo and Wu developed an analytical method based on the fracture mechanics to calculate the bridging stress provided by the fiber in GLARE and further analyzed the intensity factor of the bridging stress at the crack tip of the aluminium layer of GLARE.

Assumptions made in Guo and Wu's method:

- Linear elastic fracture mechanics apply in the aluminium layer of GLARE.
- It is questionable to assume the uniform bridging stress distribution at the crack line.
- The delamination shape between the aluminium layer and the prepreg layer is assumed to be triangular and elliptical shapes.

- The deformation of the metal in the delaminated area is negligible.

Conditions for Guo and Wu's method:

- Center cracked tension (CCT) specimen
- Unidirectional tension-tension constant fatigue loading
- Specimens are prepared with/without saw-cuts
- Stress ratio tested or analyzed at $R=0.1, 0.3$

The governing equation provided in this approach takes the form in the equation below. It assumed that the crack opening in the aluminium layer due to the applied loads is restrained by the fiber bridging effect. The combined crack opening effect is equivalent to the extension of the fibers and the adhesive in the prepreg layer.

$$\delta_{fm}(x) + \delta_{ad}(x) = u_{\infty}(x) - u_{br}(x) \quad (2.3)$$

Where δ_{fm} is the extension of the intact fiber; δ_{ad} is the adhesive shear deformation; u_{∞} is the crack opening displacement due to the applied loads, and u_{br} is the crack opening caused by the fibers.

The mechanism of the bridging stress is illustrated in Figure 2.6 and equation (2.4). Wu used bar-shaped elements to analyze the bridging stress, which interacts with the crack opening profile in the aluminium crack tip and the delamination boundary.

$$u_{br}(x_i) = 2 \sum_{j=1}^N \sigma_{br,j} g(x_i, x_j) L(x_j, y_j) \quad \text{with} \quad (2.4)$$

$$g(x_i, x_j) = G(-x_i, x_j) + G(x_i, x_j)$$

Where σ_{br} is the bridging stress in the intact fibers; $g(x_i, x_j)$ is the correction function considering the finite width of the specimen; $L(x_i, x_j)$ is the inter-link function to consider the effect of bridging stress on the crack tip in the aluminium layer.

Figure 2.6 Illustration of crack opening profile and delamination boundary [49].

In order to solve the equation above, a numerical calculation is required to perform the matrix operation for the bridging stress σ_{br} . Equation (2.3) and equation (2.4) are rearranged and further reduced into the form:

$$H_{ij}\sigma_{br,j} = Q_i \quad (2.5)$$

The relationship between the normalized bridging stress and the normalized crack size is plotted and shown in Figure 2.7 by comparing the effect of different delamination shapes with or without the saw-cut in the specimens.

Figure 2.7 Effect of delamination shape (left) and pre-cut size (right) on the bridging stress distribution.

In this approach, Guo and Wu proved that saw-cut size and shape have a noticeable impact on the bridging stress distribution. The contradictory conclusion was drawn for triangular shape delamination with the assumption of constant bridging stress distribution at the crack front. The plate width correction function $g(x_i, x_j)$ and inter-link function $L(x_i, x_j)$ added the complexities from the formula-wise. But a similar effect could also be achieved by other mathematical equations.

Guo and Wu [50] further continued the crack growth rate analysis by using a phenomenological model, and the proposed stress intensity equation takes the form:

$$\frac{da}{dN} = C((1 - R_c)^{m-1} \Delta K_{eff})^n \quad (2.6)$$

$$\Delta K_{eff} = \frac{\sqrt{l_0}}{\sqrt{(a-a_0) + \frac{l_0}{F_0^2}}} \cdot \Delta S_{eff} \sqrt{\pi a} \quad (2.7)$$

Where R_c is the effective stress ratio; l_0 is the equivalent crack length of GLARE, which needs to be calculated experimentally; a_0 is the start notch size; F_0 is the configuration parameter at the crack size $a = a_0$; ΔS_{eff} is the conditional effective applied stress.

The determination of the equivalent crack length in Guo and Wu's method provides the fundamental theory in the crack opening profile to explain FML's complicated fatigue crack mechanism. While the equation developed relies on the many factors that need to be determined experimentally, e.g., the crack shape and size, the specimens' geometry. The proposed stress intensity equation may not be able to expand to different types of GLARE layups and other types of starter notches. Either more validation tests are to be done or more generalized equations to be proposed when developing new FML. The improved fatigue model can be seen in the following reviewed Alderliesten's work.

The method by Alderliesten [111] – CCT

Alderliesten implemented the bridging stress model based on Guo and Wu's method. The improvement in the governing equation (2.8) could be seen that the 2nd term - shear deformation in the adhesive $\delta_{ad}(x)$ in equation (2.3) was modified to the shear deformation in the prepreg layer $\delta_{pp}(x)$. Alderliesten redefined the bridging stress as the crack closing stress caused by the glass fibers instead of the crack closing effect over the whole thickness of the GLARE laminate defined by Guo and Wu.

$$\delta_f(x) + \delta_{pp}(x) = v_{\infty}(x) - v_{br}(x) \quad (2.8)$$

Assumptions:

- Linear elastic fracture mechanics is applicable.
- Paris' law (equation (2.2)) applied in aluminium is applicable for the aluminium layer in GLARE.
- The deformation of the metal in the delaminated area is negligible.
- Replacement of the inter-link function to link the bridging stress in the glass fibers with the crack growth in the aluminium layer is assumed applicable.

Conditions:

- Center cracked tension (CCT) specimen
- Unidirectional tension-tension constant amplitude fatigue loading
- Stress ratio tested and analyzed at $R=0.05, 0.25$ and 0.5

Alderiliesten studied the effects of parabola and cosine delamination shapes on the bridging stress. It shows that the resulting bridging stress caused by the cosine shape delamination resembled the effect of the triangular shape. And similar bridging stress trends were found between the parabola and ellipse delamination shapes, as shown in Figure 2.8.

Figure 2.8 Bridging stress for GLARE-3 with different delamination shape functions [54].

Once the bridging stress is calculated based on equation (2.8), the stress intensity factor can be solved based on equation (2.10) to (2.12). Thus, the crack growth rate could be obtained by doing the integration of the modified Paris' law equation brought up by Alderiliesten, as shown in equation (2.9). Lastly, the fatigue cycle N could be obtained.

$$\frac{da}{dN} = C(\Delta K_{\text{eff}})^n \quad (2.9)$$

$$\Delta K_{\text{eff}} = K_{\text{farfield}} + K_{\text{bridging}} \quad (2.10)$$

$$K_{\text{farfield}} = S_{\text{AI}} \sqrt{\pi a} \quad (2.11)$$

$$K_{\text{bridging}} = 2 \sum_{i=1}^N \frac{S_{\text{br,AI}W}}{\sqrt{\pi a}} \frac{a}{\sqrt{a^2 - x_i^2 + b_i^2}} \left(1 + \frac{1}{2} (1 + \nu) \frac{b_i^2}{a^2 - x_i^2 + b_i^2} \right) \quad (2.12)$$

Similar to the bridging stress, the stress intensity factor, as shown in equation (2.12) required to be solved numerically. Different from Guo and Wu's method, the proposed way to solve the effective stress intensity is calculated analytically. Therefore, the crack growth rate analyzed here may provide more generalized applications. The author did mention the modeling of different numbers of parallel slot cuts for the comparison purpose. However, there is only one case of theoretical validation of crack growth rate with the experimental results for GLARE 3, as shown in Figure 2.9.

Figure 2.9 Predicted versus experimental crack growth rate of GLARE 3 [95].

The predicted crack growth rate decreases at the beginning and follows by an increasing linear trend. However, experiment results showed a fluctuated trend but a general slow growth rate at the later stage. The reason for the decreasing crack growth rate at the beginning could be explained due to the absence of efficient fiber bridging when the crack size is small in the aluminium layer of GLARE. On the other hand, for the pre-cut samples, the crack initiation mechanism was manipulated, which may explain the non-consistency in the crack growth plot.

The method by Chang [45] – CCT

Chang investigated the crack growth rate and fatigue cycle prediction for the round through-hole GLARE laminate based on Alderliesten's bridging stress model. All the assumptions based on Alderliesten's method are valid in Chag's model. Regarding the effective stress intensity factor, Chang proposed a revised version of the effective stress intensity factor to analyze the crack growth rate for the through-hole GLARE specimens.

$$\Delta K_{\text{eff}} = (K_{\text{re}} - K_{\text{op}})(1 - \beta) \quad \text{and} \quad \beta = \frac{K_{\text{br}}}{K_{\text{re}}} \quad (2.13)$$

$$K_{\text{re}} = \sigma_{\text{Al}} \sqrt{\pi a} \quad (2.14)$$

$$K_{\text{op}} = \sigma_{\text{op}} \sqrt{\pi a} \quad (2.15)$$

Where the fiber bridging stress intensity factor K_{br} could be calculated based on the equation (2.12); K_{re} is the stress intensity factor caused by the applied load; σ_{Al} is the stress developed in the aluminium layer of GLARE due to the cyclic applied load;

K_{op} is the stress intensity factor due to crack opening and σ_{op} is the stress in the aluminium layer due to crack opening.

Chang further superimposed the mechanism of fatigue crack initiation developed by Homan [46] in GLARE with the fatigue crack propagation to form a whole fatigue life for GLARE laminate.

$$N_{total} = N_{i,Al} + N_p \quad (2.16)$$

Where $N_{i,Al}$ is the crack initiation cycles observed experimentally [46]; N_p is crack propagation cycles obtained through the integration of the crack growth rate equation.

The predicted crack growth rate and the total fatigue life is shown in Figure 2.10. A similar decreasing trend could be observed in the da/dN plot at the beginning, while the almost constant crack growth rate was shown both experimentally and analytically.

Figure 2.10 Crack growth rate for GLARE 4A (left). Comparison of the predicted S-N curve with the experimental data for GLARE 4A (right).

Though Chang managed to obtain the full fatigue life of GLARE 4A-3/2, the experimental results were few and seemed insufficient to verify the predicted results.

What's more, the superimpose of the crack initiation fatigue life from the monolithic aluminium with the crack propagation life from GLARE may overestimate the total fatigue life since the fatigue initiation observed in GLARE is much shorter in monolithic aluminium.

The method by Wang [55] – Unsymmetrical notch

It is often found that the cracks developed globally in the structures are non-symmetrical. The eccentricity of crack development could be different from the mechanism of CCT cases. Wang proposed the unsymmetrical fatigue model to analyze the unsymmetrical fatigue behavior in GLARE.

Assumptions made in Wang's method:

- All the assumptions based on Alderliesten's method are valid.
- A non-symmetric crack can be caused either due to the non-symmetric delamination, non-symmetric crack tip, or a combination of both.
- Either the non-symmetric delamination, or crack tip, or both could lead to different total stress intensity factors at the crack tips.

Conditions for Wang's method:

- Constant amplitude tension-tension fatigue loading
- Non-symmetrical pre-cut
- Stress ratio $R=0.05$

Figure 2.11 Illustration of stress distributions for the unsymmetrical crack under equivalent loads [55].

In Wang's method, the governing equation based on the crack opening displacement developed by Guo and Wu is still valid in this model. The re-analyzed components include the crack opening displacement due to the bridging stress - $v_{br}(x)$. And the stress distribution in the crack front, σ_{br} .

$$v_{br}(x) = \sum_{-a < x_i < a} V(x, x_i) \quad \text{and} \quad (2.17)$$

$$V(x, x_i) = \frac{1}{G(1+\nu)} \text{Im} \bar{Z}_I - \frac{b(x_i)}{2G} \text{Re} Z_I$$

Where $V(x, x_i)$ is the stress function developed by Tada [58] for the crack opening due to a pair of point loads; Z_I and $\bar{Z}_I$ are Westergaad stress functions [112]; and $b(x_i)$ is the delamination shape function.

$$K_{br,1} = \sum_{-a < x_i < a} \frac{S_{br,m}(x_i)w(x_i)}{2\sqrt{\pi a}} \left[\sqrt{\frac{a+z_0}{a-z_0}} + \sqrt{\frac{a+\bar{z}_0}{a-\bar{z}_0}} - \right.$$

$$\left. \alpha b(x_i) \left(-\sqrt{\frac{a+z_0}{a-z_0}} \frac{a \cdot i}{(a+z_0)^2} + \sqrt{\frac{a+\bar{z}_0}{a-\bar{z}_0}} \frac{a \cdot i}{(a+\bar{z}_0)^2} \right) \right] \quad (2.18)$$

$$K_{br,2} = \sum_{-a < x_i < a} \frac{S_{br,m}(x_i)w(x_i)}{2\sqrt{\pi a}} \left[\sqrt{\frac{a-z_0}{a+z_0}} + \sqrt{\frac{a-\bar{z}_0}{a+\bar{z}_0}} - \right. \\ \left. \alpha b(x_i) \left(\sqrt{\frac{a-z_0}{a+z_0}} \frac{a \cdot i}{(a-z_0)^2} - \sqrt{\frac{a-\bar{z}_0}{a+\bar{z}_0}} \frac{a \cdot i}{(a-\bar{z}_0)^2} \right) \right]$$

The crack growth rate predicted by Wang, as shown in Figure 2.12, depicts an exponential growth trend. The predicted results follow the general pattern of the experimental results very well despite the wave-type experimental values. To further discover Wang's model accuracy, the mean absolute percentage error was calculated at each crack length and listed in Table 2.3.

Figure 2.12 Crack growth rates for GLARE 3A with an unsymmetrical cut [55].

	Crack size	Predicted value	Measured da/dN	MAPE
	a (mm)	da/dN (mm/cycle)	(mm/cycle)	
a1	9	0.00020	0.00013	35.00%
	10	0.00010	0.00012	20.00%

	20	0.00013	0.00017	30.76%
	30	0.00019	0.00023	21.52%
	40	0.00030	0.00034	13.33%
a2	7	0.00011	0.00015	36.36%
	10	0.00012	0.00017	41.66%
	20	0.00016	0.00018	12.50%
	30	0.00023	0.00029	26.09%
	36	0.00030	0.00035	16.67%
Mean				25.39%

Table 2.3 Mean absolute percentage error for the a1 and a2 side crack growth rate prediction.

The prediction accuracy evaluated is 25.39% by taking the sample mean value at five different crack lengths. These theoretical prediction results are considered accurate predictions. Since this model is based on the Alderliesten model, a similar trough trend was found at the beginning of crack propagation in this model, which is somewhat contrary to the experimental data model.

The method by Pearson [93] - Edge crack

Crack growth and propagation models are usually based on notched specimens, which could help localize the position of the crack and reduce the cross-sectional stress for crack initiation. However, the stress gradient at the root of the notch is very steep, so the mechanism of fatigue crack initiation is changed, which is different from the fatigue growth from a plane surface [93]. The study of crack initiation in the plain surface could represent the near to the actual fatigue mechanism since the previously reviewed CCT models are highly relied on the mechanism of fatigue initiation and crack propagation of monolithic aluminum. Thus, understanding the fatigue initiation mechanism for monolithic aluminum alloy provides the foundation for studying the fatigue model for

GLARE laminates. Pearson studied the crack initiation in aluminum alloy experimentally, and it was found that most cracks were initiated from either an edge or surface inclusions away from the edge (center crack). The stress intensity factor was obtained phonologically for short edge cracks:

$$\Delta K \cong 0.75 \Delta \sigma \pi^{1/2} a \quad (2.19)$$

Where a is crack size; $\Delta \sigma$ is the cyclic tension stress.

Figure 2.13 Propagation of very short cracks at a size of 0.006mm-0.5mm for aluminum alloy BS L65. [93].

Figure 2.13 shows similar trends in the crack growth rates for edge cracks and center cracks, while the former shows higher crack growth rates than the latter. The crack

direction was found approximately perpendicular to the direction of the applied load. The crack initiation and propagation were inspected by the in-situ microscope ($\times 130$ times). Similar research on the edge crack mechanism of FML has not been found studied extensively.

The method by Daniewicz [113] – Edge crack

Daniewicz provided an elastic-plastic model to analyze the non-linear crack propagation for edge cracks. In this model, a superposition of the two elastic models was shown in Figure 2.14. The elastic crack length is defined as $a + \rho$, and the plastic crack length is ρ at the crack tip.

Assumptions made in Daniewicz's method:

- The superposition of two elastic models could represent the non-linear elastic-plastic fatigue crack model.
- Crack propagation cycles are defined as the loading cycles when the cracks are fully open.
- Only the initial residual stress is considered in this model.

Conditions for Daniewicz's method:

- Constant amplitude mode I fatigue loading.
- Applicable for two-dimensional crack propagation.

Figure 2.14 Illustration of the superpositioned elastic-plastic fatigue model[113].

The stress intensity factor (SIF) equation could be solved by doing the integrating the weighted function. The residual stress [114] are considered pre-existing residual stress caused by the compressive stress.

$$\begin{aligned}\Delta K_{\text{eff}} &= K[S_{\text{max}}h(x) + S_r(x)] - K[S_0h(x) + S_r(x)] \\ &= K[S_{\text{max}}h(x)] - K[S_0h(x)]\end{aligned}\tag{2.20}$$

where S_0 is the scaling parameter for the crack opening stress and calculated based on weighted-function based method; S_{max} is the maximum applied load; S_r is the residual stress, and $h(x)$ is the applied stress function along the crack propagation line.

Once ΔK_{eff} is obtained, the incremental fatigue cycle could be calculated based on equation (2.21). By adding the ΔN to the previous N , the fatigue cycle versus the crack size could be plotted and shown.

$$\Delta N = \frac{\Delta a}{f(\Delta K_{eff})} \quad (2.21)$$

Where Δa is the assumed crack increment, ΔN is the result of the fatigue cycle increment corresponding to the crack size increment. The predicted crack size versus the fatigue cycle plot is shown below:

Daniewicz's method provided a simple superposition-type of elastic-plastic fatigue crack models for metals. There are some arguments about the pre-assumed hypothetical residual stress patterns. Validation of the analytical model is preferable.

The method by Chang [115] – MSD

Multiple-site damages (MSD) is one of the most dangerous scenarios in frame structures due to fatigue loading. Multiple cracks could be developed at multiple locations near the stress concentration areas, e.g., rivet joints, cut-outs. As multiple cracks are formed, the interaction in-between the fatigue cracks could increase the stress intensity factor (SIF) and thus accelerate the crack growth rate. In order to further understand the fatigue damage behavior for MSD, Chang proposed the MSD model to predict the crack growth rate for the GLARE panel with six symmetrically and centrally aligned through round holes.

Assumptions made in Chang's method:

- Linear elastic fracture mechanics (LEFM) applies to MSD.
- Guo and Wu's crack opening displacement equation are applicable to MSD.
- Mode I fatigue crack opening.

Conditions for Chang's method:

- Symmetrical and centrally located round through holes.
- Constant amplitude tension-tension fatigue loading.
- The spacing between the two notches is not far away.

Chang proposed the Guo and Wu's [116] crack opening displacement equation by adding the metal deformation term $\delta_{al}(x)$ as shown in equation (2.22). The crack opening displacement due to the bridging stress, $u_{br}(x)$, is modeled based on the function for a pair of point loads developed by Tada [58].

$$\delta_f(x) + \delta_{pp}(x) + \delta_{al}(x) = u_{\infty}(x) - u_{br}(x) \quad (2.22)$$

$$u_{\infty}(x) = 4 \frac{\sigma_{Al} S}{\pi E'_{Al}} \left[\ln \left(\cos \frac{\pi x}{2S} + \sqrt{\cos^2 \frac{\pi x}{2S} - \cos^2 \frac{\pi a}{2S}} \right) - \ln \left(\cos \frac{\pi a}{2S} \right) \right], \quad \text{for } |x| \leq a \quad (2.23)$$

$$u_{br}(x) = \int_{a_0}^a \frac{1-\nu}{G} \text{Im} \bar{Z}_I - \frac{y}{2G} \text{Re} Z_I \, dx_p, \quad \text{for } a_0 \leq |x| \leq a \quad (2.24)$$

Where $u_{br}(x, x_i)$ and $u_{\infty}(x)$ are the crack opening displacements caused by the bridging stress and the applied load, respectively; E'_{Al} is Young's modulus for aluminum under plane stress and plane strain conditions; S is the spacing between two notches; Z_I and $\bar{Z}_I$ are Westergaard stress functions [112], and y is the delamination shape function.

Compared with the CCT model developed by Chang [45] reviewed previously, in this MSD model, Chang implemented the dimensionless SIF as an extension of Wu's model [116].

$$K_{tip} = (K_{I,Al} - K_{op,Al}) f_{eff} \quad (2.25)$$

$$f_{eff} = f_0 - f_{br} \quad (2.26)$$

$$f = \int_{a_0}^a \frac{\sigma(x)}{\sigma} \frac{m(a,x)}{\sqrt{\pi a}} dx \quad (2.27)$$

Where $K_{I,Al}$ is the mode I SIF in the aluminum layer, $K_{op,Al}$ is the crack opening SIF in aluminum layer and f_{eff} is the effective dimensionless SIF, f_0 is attributed to the unit applied load, and f_{br} is the dimensionless bridging stress SIF.

Figure 2.15 Predicted versus experimental crack growth rates as a function of crack length with different applied stress at a stress ratio of 0.05 for GLARE 3.

The predicted crack growth rate for the symmetrically and centrally located MSD is shown in Figure 2.15. It is found the initial crack growth patterns from the prediction show reverse trends compared with the experimental observation. Though the mechanism of the interaction among multiple cracks may not be able to be fully disclosed by using this model, a similar linear crack growth rate was observed both in the prediction and the experimental results at the later crack development stage.

The method by Wang [117] – MSD

In Wang's multiple site damages (MSD) model, it is assumed that the fatigue mechanism in MSD includes the crack tip interaction effects and the load redistribution effects. The former is caused by the stress singularities interaction in front of two approaching cracks, which lead to accelerated crack growth and cracks link-up. The latter is caused by the reduction in stiffness when MSD cracks occur [117].

Assumptions made in Wang's MSD method:

- Linear elastic fracture mechanics applies to MSD.
- Guo and Wu's crack opening displacement equation applies to MSD.
- Mode I crack opening.

Conditions for Wang's MSD method:

- Symmetrical and centrally located round through holes.
- Constant amplitude tension-tension fatigue loading.
- The spacing between the two notches is not far away.

To artificially create the effect of stiffness reduction in the metal layer of GLARE laminate, the removal of short symmetrical strips on aluminum or fiber layers are made on both sides of the central notch. The load decomposition for the GLARE panel is illustrated in Figure 2.16. The applied load is decomposed into the load applied on the fiber layer attributed to the fiber bridging stress, and the combined load is applied on both metal and fiber layers to cause the load redistribution.

Figure 2.16 Illustration of the decomposition of load in the fiber metal laminate with a discrete notch on aluminum layers [117].

The governing equation for the calculation of the SIF takes the form:

$$K_{\text{total}} = K_{\text{redis}} + K_{\text{br}} \quad (2.28)$$

$$K_{\text{redis}} = \sigma_m \sqrt{\pi a} \quad (2.29)$$

Where K_{redis} is the SIF attributed to the stress redistribution; K_{br} is the SIF caused by the bridging stress from the glass fibers, and it could be calculated based on Alderliesten's CCT model [54]. σ_m is the stress developed in the aluminum layer, and it can be calculated based on the classical laminate theory [46] with the pre-required applied stress on the GLARE laminate.

As illustrated in Figure 2.16, the applied load is decomposed into three constituents.

The applied stress σ_{applied} could be calculated with the known applied load P_{applied} .

$$P_{\text{applied}} = P_{f,1} + P_m + P_{f,2} \quad \text{and} \quad (2.30)$$

$$P_{f,1} = \sigma_{f,\text{applied}} n_f t_f a$$

$$P_m = \sigma_{m,\text{applied}} n_m t_m W$$

$$P_{f,2} = \sigma_{f,\text{applied}} n_f t_f (W - a)$$

To compute the amount of load transferred to the metal layer, and fiber due to the load redistribution, Westergaard stress function is implemented:

$$\sigma_{\text{westergaard}} = \frac{P_m + P_{f,2}}{\int_a^{x_l} \frac{t_{\text{FML}}}{\sqrt{1 - (a/x)^2}} dx + \int_{x_l}^{x_r} \frac{E_{\text{notch}}}{E_{\text{FML}}} \frac{t_{\text{notch}}}{\sqrt{1 - (a/x)^2}} dx + \int_{x_r}^W \frac{t_{\text{FML}}}{\sqrt{1 - (a/x)^2}} dx} \quad (2.31)$$

Since $\sigma_{\text{westergaard}}$ is the combined redistributed stress from both the aluminum and fiber, the redistributed stress developed in the aluminum layer σ_m could be again calculated by the classical laminate theory.

Figure 2.17 Predicted versus experimental crack growth rate for GLARE 3 with notches and $\sigma_{\max}$ 140 MPa.

Wang's MSD crack growth prediction model well captured the crack growth acceleration due to the notched layers in the GLARE laminate. This model is developed based on the principle of superposition and the crack growth displacement model. Specifically, the crack growth was assumed to be contributed by the bridging stress and the stress redistribution. And the latter concept was described with the Westergaard stress distribution to represent the stress distribution ahead of the crack tips. However, artificial strips either in aluminum or fiber layers may not sufficiently describe the actual stiffness reduction in the real case of multiple-site damage scenarios. Overall, this model does provide an alternative way to model fatigue behavior for MSD.

2.2.3 S-N curve approach

S-N curve is a widely adopted approach to determine the number of load cycles-to-failure and other relevant fatigue properties for materials experimentally, e.g., fatigue endurance limit and fatigue yield strength. The S-N curve can be derived based on the fracture mechanics approach reviewed in the previous chapter. In this part, the experimental approach [118] to obtain the S-N curve is reviewed for FML with an aluminum core and carbon fiber reinforced polymer (CFRP).

Stoll [118] applied Coffin-Manson's approach to calculating the fatigue cycle for the aluminum layer in the FML. The relationship between material plastic strain and fatigue cycles are quantified by the equation below:

$$\frac{\Delta\epsilon_{pl}}{2} = \epsilon'_f (N_B)^c \quad (2.32)$$

Where ϵ'_f is the failure strain; $\Delta\epsilon_{pl}/2$ is the amplitude of plastic strain; N_B is the fatigue cycles to failure; c is the fatigue ductility coefficient.

The stiffness-based phenomenological equation for CFRP to determine the S-N curve was provided by Ogin [119]. Herein, the fatigue failure was defined as a 20% reduction of the stiffness of CFRP. It was also found that the dominant cause of the stiffness reduction is the cracking of 90° carbon fiber and the fracture of the middle aluminum layer. The modified Paris' law type equation is shown:

$$-\frac{1}{E_0} \frac{dE}{dN} = A \left[\frac{\sigma_{max}^2}{E_0^2 (1 - E/E_0)} \right]^n \quad (2.33)$$

where E_0 is the initial Young's modulus for the FML; dE/dN is the change of Young's modulus per fatigue cycle; $\sigma_{\max}$ is the maximum applied fatigue stress; A and n are material constants obtained from fatigue tests.

Figure 2.18 S-N plot for the aluminum layer in the FML(left). S-N curve predicted and measure for the FML at stress ratio of 0.1 and frequency of 5Hz.

High-contrast Post-Mortem CT thermal imaging for the FML sample is shown in Figure 2.19. The thermal image was taken at 100,000 cycles, where the fatigue failure criteria were met.

Figure 2.19 Post-Mortem CT thermal imaging for the fatigue tested specimens.

The method provides an intuitive way to locate the high internal stress caused by friction. While the method of determination of the aluminum layer fracture using the thermal image may not be exact. As shown in Figure 2.19, the thermal image was taken when there is a fracture in the aluminum. There may have cracking of 90° carbon fiber

or both situations, as well as the delamination, etc. The rest of the damage modes are not detectable in this method.

2.3 Machine learning fatigue models

The classical fatigue models reviewed in the previous sections are mostly based on the linear elastic fracture mechanics theory (LEFM). The classical models could not sufficiently represent the non-linear plastic crack phenomenon. The correlation of multi-variable with the FML fatigue life is not yet discovered thoroughly. No explicit and generalized function was built between the multi-variable and fatigue cycle. In order to counter the shortcomings of classical models, machine learning assisted expert models could be seen in various interdisciplinary research areas [120-130].

Machine Learning is an enlargement of the intersection of Computer Science and Statistics [131]. Machine learning techniques could be classified into four categories by the nature of the data they acquire [132]:

- Supervised learning (concerned with classified or labeled data)
- Semi-Supervised learning (concerned with unclassified or unlabeled data)
- Unsupervised learning (concerned with a mixture of classified and unclassified data)
- Reinforcement learning (no data required)

The machine learning algorithms are summarized into a mindmap in Figure 2.20 based on the various related sources [133-136] and the latest packages developed in the open-source Python coding platform. This mindmap tree may not exhaust all the machine learning technique, while it could provide a general guide regarding the selection of the algorithm or method based on the functionality.

Figure 2.20 Mind map of machine learning algorithms

For the purpose of fulfilling the target of the prediction of FML fatigue life, regression targeted algorithms were reviewed. The most commonly used efficient prediction-based machine learning algorithms: regularized linear regression (Ridge, Lasso), decision tree, support vector regression (SVR), ensemble methods, and neural networks. With a number of options available, consideration must be given as to how to select the optimum algorithm to train the fatigue mode. A simplified guideline provided by scikit learn is shown in Figure 2.21. Up to now, machine learning algorithms have not been widely applied in FML's fatigue life study. The literature review of machine learning algorithms related to it includes but is not limited to FML materials. In order to provide a broader view of current work that has been done, reviewed materials also include metals and fiber composites.

Figure 2.21 General guideline of the selection of estimators.

2.31 Regularized linear regression

Regularized linear regression though not often used separately, is the most fundamental loss function frequently embedded with many other machine learning algorithms. Therein, two types of regularized linear regression methods are introduced: Ridge and Lasso. Ridge regression (Tikhonov regularization) imposes an L2-norm regularization into the least square cost function. Compared with the ordinary least square (OLS), L2-regularization, $\lambda_2 \|\theta\|^2$, could shrink the norm of the coefficients and decreases the model complexity. The cost function, to measure the model performance and quantifies the error between the predicted value and the expected values, is written below:

$$L(\theta, \lambda) = \sum_{n=1}^N (y_n - \theta^T x_n)^2 + \lambda_2 \|\theta\|^2 \quad (2.34)$$

$\|\cdot\|$ stands for the Euclidean norm of a vector, λ_2 is the regularization penalty (or tuning parameter), which controls the trade-off between the bias and variance. When λ_2 approaches to 0, more penalties on the bias; when λ_2 approaches to ∞ more

penalties on variance. Thus, Ridge better minimizes the errors between the predicted value and actual value and obtains the optimum model complexity in analyzing multiple regression data that suffer from collinearity.

Lasso regression (least absolute shrinkage and selection operator) incorporates L1-norm regularization, $\lambda_1 \|\theta\|$, which penalizes the non-zero coefficients for the sum of the absolute values into the OLS cost function.

$$L(\theta, \lambda) = \sum_{n=1}^N (y_n - \theta^T x_n)^2 + \lambda_1 \|\theta\| \quad (2.35)$$

As with Ridge, Lasso regularization parameter λ_1 controls the trade-off between errors and bias and reduces over-fitting issues. It also has the advantage of the estimation of the sparse model with the feature selection. It allows some of the coefficients to be zero $\hat{\theta}_j(\lambda_1) = 0$ while Ridge regression only allows for the coefficients close to being zero but not equal to zero. A zero coefficient means there is no relation with the predicted object and thus could be excluded from the model.

2.32 Support vector machine (SVM)

The support vector machine algorithm was first developed by Vapnik and further developed up to date and had a sound orientation towards real-world applications [137]. Excellent performance was obtained both in the appliance of classification (SVM) and prediction (SVR) [138-140] in the late 20th century. In this context, SVR was often implemented as a benchmark prediction model and based on comparing the model accuracy and stability with the newly developed machine learning algorithms. The basic idea is to find the boundary $\pm \varepsilon$ deviation from the hyperplane, where the errors could be minimized. This boundary is called the margin of tolerance (black dash lines), within which the dataset is used for the model training, as shown in Figure 2.22.

Figure 2.22 The tolerance margin setting corresponds to a linear SVM [141].

Unlike the regularized linear models based on the classical least squares regression, which calculates the loss based on the difference between the predicted value $f(x)$ and the target value y , the loss is zero only when $f(x)=y$. SVM allows for a margin of tolerance ϵ , which is predefined, and only when the bias is higher than ϵ , a loss is recognized. The cost function is termed as ϵ -insensitive loss, and the objective is to minimize the error and to define the hyperplane that maximizes the margin formed by $f(x) + \epsilon$ and $f(x) - \epsilon$. The prediction function of the SVM model is:

$$y_i = \langle w, x_i \rangle + b \quad \text{with } \omega \in \chi, b \in \mathbb{R} \quad (2.36)$$

Where w is the weight for the corresponding feature; x_i is the value of the input feature; $\langle ., . \rangle$ represents the dot product operation.

The basic principle of SVR is based on the minimization of the Euclidian distance:

$$\text{obj} = C \sum_{i=1}^l (\xi_i + \xi_i^*) + \frac{1}{2} \|w\|^2 \quad (2.37)$$

$$\text{Subject to } \begin{cases} y_i - \langle w, w_i \rangle - b \leq \varepsilon + \xi_i \\ \langle w, w_i \rangle + b - y_i \leq \varepsilon + \xi_i \\ \xi_i, \xi_i^* \geq 0, i = 1, \dots, n \end{cases}$$

where ξ_i and ξ_i^* are the relaxation factor that measures the distance between the boundary and predicts the fatigue cycles outside the boundary; $C > 0$, and the penalty imposed on observations of the outliers and helps prevent overfitting. With the fundamental knowledge of SVR, models proposed based on this method are reviewed in the following session.

The method by Nair [142] – MLPs and SVM for damage classification

Nair [142] proposed the support vector machine (SVM) model to classify the acoustic emission (AE) signals obtained from a new type of GFRP, i.e., fiber-reinforced polymer (FRP) – balsa wood composite. As a comparison, Nair also implemented a multilayer perceptron (MLPs) algorithm for the FRP-balsa damage classification. Before the diagnose of the damage types, the AE signals are pre-processed with k-means clustering. Different clusters are recognized by each kind of damage, which is fiber breakage, matrix cracking, debonding, and delamination.

The number of clusters is first estimated based on the Davies-Bouldin (DB) index [143] and validated based on the S_i value, which takes the form:

$$\begin{aligned} DB &= \frac{1}{k} \sum_{i=1}^k \max_{i \neq j} R_{ij} \quad \text{and} \\ R_{ij} &= \frac{S_i + S_j}{M_{ij}} \end{aligned} \tag{2.38}$$

The DB index is the average similarity between each cluster C_i for $i = 1, \dots, k$ and its most similar one C_j . Herein, k denotes the features of the data; S_i and S_j are the

average distances between each point of cluster i and cluster j and the corresponding centroid of that cluster; $M_{i,j}$ is the distance between cluster centroids C_i and C_j .

$$S_i = \left(\frac{1}{T_i} \sum_{j=1}^{T_i} |X_j - A_i|^p \right)^{1/p} \quad (2.39)$$

$$M_{i,j} = \|A_i - A_j\|_p = \left(\sum_{k=1}^n |a_{k,i} - a_{k,j}|^p \right)^{1/p} \quad (2.40)$$

Where A_i is the centroid of cluster i ; T_i is the number of vectors in cluster i ; $a_{k,i}$ is the k^{th} element of A_i , and n represents the number of elements in A .

The results of the clustering based on the AE signal are shown in Figure 2.23. Cluster overlapping and sparse distribution could be found.

Figure 2.23 Clustering of AE signal based on duration (a) and rise time (b) for the FRP-Balsa wood composite panel damage due to fiber breakage [142].

Figure 2.24 Compare the SVM model on the classification of the GFRP panel damage mode with experimental.

Nair employed the SVM model to classify the failure modes of GFRP coupons by using the AE signals-related parameters. However, before the classification, AE signals clustering and the results could be seen in Figure 2.24, (a) and (c) are the load schedule, and the corresponding identified three clusters, as is the case for (b) and (d). The so-called damage modes were determined using scanning electron microscopy (SEM) after the fatigue tests. While the AE signals were collected along with the tests, fiber breaking, or matrix cracking, or delamination may happen individually or simultaneously. The identified patterns in the AE signals may represent the overlapped damage modes instead of a single one.

The method by Widodo [144] –SVM and RVM

Widodo implemented SVM and Relevance Vector Machine (RVM) for the incipient fault diagnosis of machine bearings. The data is collected from the AE, and vibration signal, as shown in Figure 2.25. They are collected from the accelerometer and AE sensor fixed on the bearing housing, respectively. Artificial cracks and splits are made on the various locations of the bearings.

Figure 2.25 Signals collected from AE sensor in (a) and accelerometer in (b) [144].

The model proposed by Widodo starts from the feature collection. A total of 26 feature parameters are collected and analyzed from the statistical analysis and enveloping. The purpose of the enveloping study is to show the characteristics of bearing in frequencies by filter out unimportant signals using band-pass filtering (BPF). In the pursuit of the model convergence and accuracy, feature reduction was performed by component

analysis by calculating the eigenvalue of the covariance matrix, which incorporates independent component analysis (ICA), principal component analysis (PCA), and their kernel, E.G., KICA, KPCA. The results of the PCA are shown in Figure 2.26. It indicates that ICA and PCA perform better than KICA and KPCA regarding the clustering of features for the bearings under various conditions.

Figure 2.26 Component analysis for selected components of the AE signal at 80 rpm.

The introduction of SVM could be found in equation (2.36) and (2.37). The relevance vector machine (RVM) algorithm adopts Bayesian inference for either regression or classification. The Bayesian method provides a method for defining constraints, overcomes the problem of overfitting by treating parameters as random variables, and introduces a suitable prior distribution to them. In RVM, a hierarchical prior is usually defined on the weight parameter in the first level, i.e., Gaussian prior, while the variance parameter in the second level uses an independent Gamma super prior [145]. In

Widodo's RVM model, the second level adopted Laplace's method proposed by MacKay [146]. The prior distribution takes the form:

$$P(t|w) = \prod_{n=1}^N \prod_{k=1}^K \sigma(y_k; y_1, y_2, \dots y_K)^{t_{nk}} \quad (2.41)$$

Where t_{nk} is the indicator variable for observation n in class k ; y_k is the predictor for class k . Since RVM transforms the K multi-class problem to a series on n classification problem, each y_k is coupled in the multinomial logic function:

$$\sigma(y_k; y_1, y_2, \dots y_K) = \frac{e^{y_k}}{e^{y_1} + e^{y_2} + \dots + e^{y_K}} \quad (2.42)$$

Widodo has compared the model classification accuracy with and without component analysis. In the former, SVM average classification error is 85.7% to 86.6%; and 42.85% for RVM. With the ICA, SVM, and RVM average classification errors are 8.9% and 26.0%, respectively.

In Widodo's model, component analysis plays a vital role in the feature reduction and minimization of model classification error. The comparison results among different component analyses show that ICA could achieve a much lower error percentage. It worth noticing that the error percentage range for other groups of signal data is wide. The proposed model has achieved a small error for a specific group of data, it was not well generalized for the whole dataset. Regarding the classification algorithm, RVM achieves good prediction results for a particular group of data compared with SVM, but a high average error in general.

2.33 Ensembled decision trees (EDT)

Ensembled decision trees compose a bunch of decision trees. Different from the algorithms mentioned above, the decision tree has a layered structure, which is similar to flowcharts. It includes nodes to represent features, branches to render a decision rule, and leaves to present the outcome. This algorithm could both used for classification and regression problems. In classification analysis, the Gini value and Gini index [147] are adopted to measure the purity of the input dataset and the splitting nodes. In regression prediction, MSE is usually applied as the criteria to measure the quality of tree splitting.

$$\text{Gini}(D) = 1 - \sum_{k=1}^{|y|} p_k^2 \quad (2.43)$$

$$\text{Gini_index}(D, a) = \sum_{v=1}^V \frac{|D^v|}{|D|} \text{Gini}(D^v) \quad (2.44)$$

Where $p_k (k = 1, 2, \dots, |y|)$ represents the ratio of k-type specimens in the dataset D; a is the discrete attribute that has the possible value $(a^1, a^1, \dots, a^V)$ and there are V-nodes to classify the dataset D. This model is very straightforward and easy to understand, but more processes are required to prune the branches to solve the over-fitting issues.

The method by Marani [148] – ensembled decision trees (EDT)

Marani proposed a decision forest model made up of 30 decision trees to classify the defects in CFRP by using the thermal NDT, which analyzes the CFRP's thermal behavior during a short thermal pulse. Since the data obtained is in thermography, the most related parameters in this model are temperature, time, and thermal images. In order to eliminate the effect of material properties during the experiments, the temperature contract between the defective and non-defective areas was derived below:

$$\Delta T_{\text{approx}}(0, T) = Q \sqrt{\frac{t_\delta}{t}} \frac{\sum_t (Q - T_0 \varepsilon \sqrt{\pi t_\delta}) - \sum_{t_\delta} (Q - T_0 \varepsilon \sqrt{\pi t})}{(Q - T_0 \varepsilon \sqrt{\pi t_\delta})(Q(1 + \sum_{t_\delta}) - T_0 \varepsilon \sqrt{\pi t_\delta})} \quad (2.45)$$

where $\sum_t = 2 \sum_{n=1}^{\infty} R^n \exp(-n^2 \frac{d^2}{\alpha t})$ and $\sum_{t_\delta} = 2 \sum_{n=1}^{\infty} R^n \exp(-n^2 \frac{d^2}{\alpha t_\delta})$; the term α [m²/s] is the thermal diffusivity; Q [J/m²] is the amount of source energy transferred to the surface of the specimen; t_δ is the time when the maximum temperature achieved on the specimen's top surface.

To reduce the parameters to be trained in the machine learning algorithms, equation (2.45) is approximated by least-square fitting:

$$\Delta T_{\text{approx}}(0, T) = (a_1 t^2 + a_2 t) e^{-a_3 t} \quad (2.46)$$

Herein, a_1 , a_2 and a_3 are the only features and based on which the machine learning models were learned and trained. Equation (2.45) and equation (2.46) versus time is shown in Figure 2.27. Though the defect contrast plots at the shortest time of the pulse are different in the quantity level, the approximated model is good enough to classify the thermal contrast behavior under different source pulses.

Figure 2.27 Comparison of normalized and approximated thermal contrast behavior as a function of d^2/α [148].

The three features mentioned in the approximation model are obtained through the thermal camera images measured on the top surface of the specimens. The thermal videos are processed through the feature maps, which extracts the feature vector for each pixel. The general structure of the feature extraction takes the form in Figure 2.28.

Figure 2.28 Arrangement of feature vectors in the model based on the feature maps [148].

The model is trained based on the referenced feature vectors. Marani implemented the classifiers of the decision tree, ensembled decision trees and k – Nearest Neighbor, and evaluated the accuracy of each classifier with the confusion matrix:

$$\begin{cases} \text{BACC} = \frac{\frac{TP}{TP+FN} + \frac{TN}{TN+FP}}{2} \\ \text{PPV} = \frac{TP}{TP+FP} \\ \text{TPR} = \frac{TP}{TP+FN} \end{cases} \quad (2.47)$$

BACC is the balanced accuracy, which is used for unbalanced training or testing dataset; PPV, also called precision, refers to the positive predictive value, TPR (true positive rate), or sensitivity or recall. The detailed terms about the confusion matrix could be seen in Figure 2.29.

	Actual = Yes	Actual = No
Predicted = Yes	True Positive (TP)	False Positive (FP)
Predicted = No	False Negative (FN)	True Negative (TN)

Figure 2.29 Terminology of the confusion matrix for classification.

The highest classification accuracy was achieved by using the algorithm of ensembled decision trees. The mean average rate achieved is around 85%. In general, the model proposed by Marani included three stages: first, simplify the temperature contrast function with fewer features; second, built up the link between the features and the temperature coordinates from the thermal images; lastly, classify the defects in CFRP

samples with the vectorized data. The curve-fitting kind of temperature function plays an essential role in facilitating the final classification. The model trained only limits to the CFRP samples within the thickness of 3mm and the flaw size of a few millimeters, making the model application to limited composite materials.

The method by Li [149] – the ensemble of AR and RBF

Li proposed a boosted machine learning model composed of an autoregressive (AR) model and radial basis function (RBF) as the base predictors to predict the aluminum material fatigue properties. The fatigue parameters obtained from experiments are crack dimensions measured by calipers and relative voltage.

The Autoregressive (AR) model is a standard technique for processing time-series signals. It returns output values in a time series and recurs linearly with previous values in the same time series but a stochastic term. The linear AR model applied in this rBoost model as one of the base predictors takes the form:

$$Y = X\Theta \quad (2.48)$$

Where

$$X = \begin{bmatrix} z(1) & z(2) & \cdots & z(r) \\ z(2) & z(3) & \cdots & z(r+1) \\ \vdots & \vdots & \cdots & \vdots \\ z(N_t - r - s + 1) & z(N_t - r - s + 2) & \ddots & z(N_t - s) \end{bmatrix} \quad (2.49)$$

and

$$\Theta = (X^T W X)^{-1} X^T W Y \quad (2.50)$$

with

$$W = \begin{bmatrix} L_t(1) & 0 & \cdots & 0 \\ 0 & L_t(2) & \cdots & 0 \\ \vdots & \vdots & \cdots & \vdots \\ 0 & 0 & \ddots & L_t(N_t) \end{bmatrix} \quad (2.51)$$

Herein, X and Θ are the matrixes of features and weights respectively; N_t is the number of training dataset; r is the dimension of the input vector; $L_t(i)$ is the distribution of training dataset at time t .

The second base predictor, radial basis function (RBF), is a three-layer feed-forward neural network. The activation function used in the hidden layer is the Gaussian membership function, as shown in equation (2.52).

$$G_j = \exp \left(-\frac{1}{2} \frac{\|I - \Pi_j\|^2}{\sigma_j^2} \right), \quad j = 1, 2, \dots, n \quad (2.52)$$

Where n is the number of nodes in the second hidden layer; $I = [z(i-1), z(i-2), \dots, z(i-r)]$ are the features in the input layer of RBF; $\Pi_j = [\mu_{j,1}, \mu_{j,2}, \dots, \mu_{j,r}]$ and σ_j , are the center and the spread of the Gaussian MF.

Figure 2.30 Structure of RBF predictor [149].

The structure of the RBF is shown in Figure 2.30. The model parameters are trained through the gradient method. At each epoch, the parameters are updated with:

$$\nabla G_j = -L_t(i)\alpha \frac{\partial Y}{\partial G_j} \quad (2.53)$$

$$\nabla O_j = -L_t(i)\alpha \frac{\partial Y}{\partial O_j} \quad (2.54)$$

Where α is the learning rate; L_t is the distribution of the training data at step t ; G_j is the Gaussian membership function; and O_j is the weights function.

Figure 2.31 Structure of the rBoost model [149].

The ensembled boosted model developed by Li is shown in Figure 2.31. The model starts from an initial data distribution $L_1(i) = \frac{1}{N}, i = 1, 2, \dots, N$, the data classification at step t is trained through the base predictors, h_t and the weights are updated accordingly as β_t , the prediction result at each iteration is modeled as p_t .

The rBoost is evaluated at MSE and RMSE and compared with AdaBoost and AdaBoost.RT. rBoost shows advantages in the prediction accuracy compared with the other two boosted methods. The forecasted trends of the relative voltage compared with the measured time series data are displayed in Figure 2.32. Though the predicted trends

show a tight fit with the measured data, the prediction results are not directly linked to any material fatigue properties, e.g., crack length, fatigue cycle, fatigue loads, etc.

Figure 2.32 Predicted performance of the rBoost using AR model as base predictors for material fatigue prognosis.

2.34 Neural Networks models

Neural networks consist of neural, and inter-connected with the weighted links. In the aspect of architecture, neural networks could generally be classified into feedforward and feedback neural networks. In feed-forward neural networks (FFNN), similar to the open-loop system, information flows from the input layer to the output layer without feedbacks, e.g., multi-layer perceptron (MLPs). On the other hand, feedback networks,

also called backpropagation, are trained by recycling the outputs' errors to the previous hidden layer. A single layer of FFNN is shown in Figure 2.33.

Figure 2.33 A single hidden layer neural network.

The method by Wang [71] - FFNN with ELM to predict crack growth rate

Wang provided the FFNN models with different embedded algorithms to predict the fatigue crack growth rate for Al2024-T351. Wu compared three types of algorithms: backpropagation (BP) with the genetic optimizer, radial basis function network, and extreme learning machine (ELM). It was found that ELM has superior performance over the other two algorithms. ELM is an emerging machine learning algorithm created by Huang [150], and it can be embedded into a single layer perceptron or multi-layer perceptron (MLPs). The pseudocode for the standard ELM algorithm is shown in Figure 2.34.

<p>Algorithm ELM: Given a training set $\aleph = \{(\mathbf{x}_i, \mathbf{t}_i) \mathbf{x}_i \in \mathbf{R}^n, \mathbf{t}_i \in \mathbf{R}^m, i = 1, \dots, N\}$, activation function $g(x)$, and hidden node number $\tilde{N}$,</p> <p>Step 1: Randomly assign input weight $\mathbf{w}_i$ and bias b_i, $i = 1, \dots, \tilde{N}$.</p> <p>Step 2: Calculate the hidden layer output matrix $\mathbf{H}$.</p> <p>Step 3: Calculate the output weight β</p> <p>$\beta = \mathbf{H}^\dagger \mathbf{T}$,</p> <p>where $\mathbf{T} = [\mathbf{t}_1, \dots, \mathbf{t}_N]^T$.</p>
--

Figure 2.34 Pseudocode for the standard ELM algorithms [150].

Wang proposed a simplified crack length equation. The crack length is calculated by using the summation of the incremental crack length, as shown in equation (2.55).

$$a_N = a_0 + \sum_{i=1}^N da_i \quad (2.55)$$

$$a_N = a_0 + \sum_{i=1}^N f_{MLA}(\Delta K_i, R) \quad (2.56)$$

$$\begin{aligned} \Delta K_i &= \gamma \Delta \sigma \sqrt{\pi a_i} \quad \text{and} \\ \gamma &= g\left(\frac{a_i}{w}\right) \end{aligned} \quad (2.57)$$

Where a_N is the crack length at N^{th} cycle; a_0 is the initial crack size; da_i is the incremental crack length at i^{th} cycle obtained from MLA; ΔK_i is the range of stress intensity factor; R is stress ratio; γ is a geometric factor, g is the function for different sample types, and w is sample width.

The predicted crack growth curve using ELM is shown in Figure 2.35. The model provides generalized nonlinear prediction capabilities towards different types of aluminum alloys. In the aspect of the machine learning algorithm, ELM is not investigated for the sparse high-dimensional application. Given the dataset of fiber metal laminates with different categories of layup, this ELM may not be able to achieve as same prediction accuracy as this metal fatigue model.

Figure 2.35 The predicted crack growth for Al 2024-T351 (left) and Al 7050-T7451 (right).

Wang directed correlate the stress intensity range ΔK_i and stress ratio R with crack growth length a_N by using the machine learning models. The multi-variable fatigue model is a two-variable crack growth model instead. The function g is related to different types of materials but not indicated clearly in this model, giving the space for artificial manipulation of the regression lines towards the experimental data.

The method by Filho [151] - BP to detect fatigue damages

Back-propagation (BP) is one of the most used algorithms in a neural network. It can fine-tune the weight of neural networks based on the error rate obtained in the previous iteration. However, BP requires to adjust the weight appropriately to ensure a lower error rate and improve its generalization.

The procedure of the BP-based neural network is shown in Figure 2.36. Firstly, forward propagation is applied to obtain the output of the hypothesis with the given input dataset (step 1-2). The outputs obtained through the trained model are compared with the actual outputs, and the loss function calculates the error rates. In order to minimize the error rates, differentiation of the loss function is performed. The errors are computed from

the output layer to the 2nd layer. The input layers have no errors. The process of looking for the minimum gradient of the loss function is called gradient descent. At each layer, the error could be traced back and minimized through gradient descent. Accordingly, the weights could be adjusted.

Figure 2.36 Schematic diagram for backward propagation neural network [152].

In order to explain the backward propagation in the aspect of the formula, the pseudocode is shown in Figure 2.37.

Algorithm BP: Given the training set $\{(x^{(1)}, y^{(1)}), \dots, (x^{(m)}, y^{(m)})\}$
Set $\Delta_{ij}^{(l)} = 0$ (for all l, i, j)
For $i = 1$ to m
 Set $a^{(1)} = x^{(1)}$
 Perform forward propagation to compute $a^{(l)}$ for $l = 2, 3, \dots, L$
 Using $y^{(i)}$, compute $\delta^{(L)} = a^{(L)} - y^{(i)}$
 Compute $\delta^{(L-1)}, \delta^{(L-2)}, \dots, \delta^{(2)}$
 $\Delta_{ij}^{(l)} := \Delta_{ij}^{(l)} + a_j^{(l)} \delta_i^{(l+1)}$
 $D_{ij}^{(l)} := \frac{1}{m} \Delta_{ij}^{(l)} + \lambda \theta_{ij}^{(l)} \quad \text{if } j \neq 0$
 $D_{ij}^{(l)} := \frac{1}{m} \Delta_{ij}^{(l)} \quad \text{if } j = 0$

Figure 2.37 Pseudocode for the standard backpropagation algorithm.

where $a^{(l)}$ is the hypothesis outputs (predicted value); $\delta^{(l)}$ is the node error in the layer l ; $\Delta_{ij}^{(l)}$ is the accumulator for the computation of the partial derivatives for the loss function; $\lambda\theta_{ij}^{(l)}$ is the regularization term; $D_{ij}^{(l)}$ is the partial derivative of the cost function respecting each parameter (or feature, attribute).

Filho [151] proposed a Back-propagation neural network model to detect the FML failure modes based on the ultrasonic signal data. Two failure modes: aluminum fracture and delamination, were investigated. The FML specimens with pre-treated fracture and delamination are shown in Figure 2.38. There are 80 and 100 signal data points taken on the samples for fracture and delamination testing purposes.

Figure 2.38 Defective regions of the tested FML panel. The fracture region is shown on the left (10mm X 20mm), and the delamination region is shown on the right (20mm X 20mm)

To better indicate the material characteristics, the ultrasonic signals were firstly processed from time series to the frequency domain using the Discrete Fourier Transform (DFT) [153]. The transformation equation takes the form:

$$X\left(e^{j\frac{2\pi}{N}k}\right) = \sum_{n=0}^{N-1} x[n]e^{-j\frac{2\pi}{N}kn} \quad \text{for } 0 \leq k \leq N-1 \quad (2.58)$$

Filho used PCA and ICA for the frequency-domain data preprocessing. PCA and ICA have been widely used for feature elimination and feature extraction in neural network

models for multiple feature problems. PCA [154] represents the linear transformation of original data to statistically linearly independent data, and thus, the signal correlation can be removed. ICA [155] continues to produce independent higher-order information after the process of PCA. The PCA and ICA analyzed frequency-domain data of no defect, delamination, and fractured FML panel are shown in Figure 2.39.

Figure 2.39 Average Fourier transformed signals for different classes of failure mode detection (left). Frequency-domain data projected into Principle Components (right).

As shown in the above figure of ICA, the difference of the load curves between the data points of no defect and delamination is barely recognized. The second spike in the PCA load curve plot for the no-defect-data is not indicated clearly, whether it is repeatable at different detection points or not. Otherwise, the profile of no defect and fracture are highly coincident in the trend. The pre-processed frequency-domain data was treated as the input data set for the single-hidden-layer neural network, as illustrated in Figure 2.33. The classification output function is declared as:

$$y = \phi(\sum_{i=1}^n w_i x_i + w_0) \quad (2.59)$$

where $\phi(\cdot)$ is the activation function; x_i stands for the input signal and w_i are the weights.

Based on the pre-processing of the time-serious data with DFT, PCA, and ICA algorithms, the classification signal data was evaluated based on the normalized efficiencies product $EP = Ef_1 \times Ef_2 \times Ef_3$ and confusion matrix C , where the diagonal (true positive and true negative) represents the correct classification. High promising accuracy results were revealed in this model based on the EP value and confusion matrix score for the situation of “true positive”. Typically, to evaluate the accuracy of classification models, evaluation of model accuracy, precision, and recall are required. Purely investigate the standalone percentage value for “true positive” classification could not ensure the model’s reliability.

The method by Artymiak [156] - BP to predict S-N

P. Artymiak proposed a combined ANN model to predict the S-N curve for different categories of steel fatigue data. Instead of taking in multiple input parameters, P. P. Artymiak built a two-stage ANN model, as shown in Figure 2.40. In stage I, input parameters –tensile strength, yield strength, and notch factor, are fed into the three networks (network 1,2,3) and trained with the individual outputs, which are the weights (WW), bias (b), and the fatigue limit (S_{aD}). The outputs from the stage I, the relationship between the stress amplitude (S_{ai}) and fatigue limit (S_{aD}) are trained through the stage II network 4. The final output of the neural networks is the slope and the fatigue limit of the S-N curve.

Figure 2.40 Structure of the ANN network employed for the S–N curves prediction [156].

A total of 109 fatigue data with six categories was obtained from the database in German. 70% of data of each type were used for model training, and the rest of the data for model testing.

Figure 2.41 Prediction results in different categories using two-stage NN [156].

The model accuracy was evaluated based on the relative number of load cycles and the corresponding relative fatigue limit. The scatter of the prediction data was represented using the standard division. The equations are formulated:

$$n_{rel} = \frac{N_{exp}}{N_{calc}} \quad (2.60)$$

$$T = \frac{n_{rel,90\%}}{n_{rel,10\%}} = 10^{2.56 \cdot s} \quad (2.61)$$

$$S_{aD,rel} = \frac{S_{aD,exp}}{S_{aD,calc}} \quad (2.62)$$

$$T = \frac{S_{aD,rel,90\%}}{S_{aD,rel,10\%}} = 10^{2.56 \cdot s} \quad (2.63)$$

Based on equation (2.60) to equation (2.62), the results of the evaluation are shown in Table 2.4. To present the evaluation results directly, the MAPE is further included.

Network No.	n_{rel}	$MAPE_{n_{rel}}$	T_n	$S_{aD,rel}$	$MAPE_{S_{aD,rel}}$	T_S
1	1.53	34.64%	5.3	0.98	2.04%	1.3
2	1.65	39.39%	3.5	0.99	1.01%	1.1
3	0.83	20.48%	5.4	0.94	6.38%	1.4
4	1.17	14.53%	3.8	1.02	1.96%	1.4
5	2.98	66.44%	6.7	1.12	10.71%	1.4
6	0.88	13.63%	3.1	0.95	5.26%	-
Average	-	31.52%	4.6	-	4.56%	1.3

Table 2.4 Evaluation results of ANN compared with the Synthetic results.

The mean absolute percentage error calculated for P. Artymiak's model: the fatigue cycle and the fatigue limit are 31.52% and 4.56%; the average scatter is 4.6 and 1.3,

respectively. The two-stage ANN model essentially is two ANN models; one is the prediction of the fatigue limit; the other is the prediction of the fatigue cycle based on the prediction results of the previous stage. It could be concluded that the ANN model's prediction towards the fatigue cycle and fatigue limit is within an order of magnitude. But due to the limited fatigue data, the ANN model does not show the generalized predictability for the different fatigue data categories.

The method by Choi [157] - BP to predict the crack length

Choi proposed a backpropagation neural network to predict the split length in the center-notched graphite/epoxy laminates. The fatigue test loads were obtained from the TWIST spectrum's modified load sequence to simulate the commercial flights' load. The modified fatigue loads include ten levels of loads, with various stress ratios and frequencies. The damage on the center-notched specimen, as shown in Figure 2.42, was monitored by the image obtained from the X-ray radiography. A single parameter, the length of the longitudinal crack, was measured to characterize the damage matrix.

Figure 2.42 (a) Specimen geometry and (b) Modified TWIST fatigue loads [157].

In Choi's BP model, $\log_{10}N$ and $\sigma_{\max}$ are the input parameters, and the split length of the round center notch is the output. The object function of the neural network is defined as:

$$L = g_{\text{linear}} \left[\sum_{k=1}^2 w_k^3 g_{\text{sigmoid}} \left(\sum_{j=1}^3 w_{k,j}^2 g_{\text{sigmoid}} \left(\sum_{i=1}^2 w_{j,i}^1 p_i + b_j^1 \right) + b_k^2 \right) + b^3 \right] \quad (2.64)$$

$$[p_i] = \begin{bmatrix} \log_{10}N \\ \sigma_{\max} \end{bmatrix} \quad (2.65)$$

Where w_n and b_n denote the n^{th} layer weight and bias, respectively; p_i is the matrix of the input parameters.

The neural network is trained in a feed-forward manner with the sigmoid function applied for the hidden layers and linear activation function for the output layer. The weights and biases are trained and learned backward from the output layer to the first hidden layer. The backpropagation in this model is based on the Levenberg–Marquardt algorithm, which denotes:

$$\Delta \vec{x} = -[\nabla^2 V(\vec{x})]^{-1} \nabla V(\vec{x}) \quad (2.66)$$

$$\begin{aligned} V(\vec{x}) &= \frac{1}{2} \sum_{i=1}^M e_i^2(\vec{x}) = \frac{1}{2} \sum_{i=1}^M (L_i - L_i^*)^2 \quad \text{and} \\ \nabla V(\vec{x}) &= J^T(\vec{x}) e(\vec{x}) \\ \nabla^2 V(\vec{x}) &= J^T(\vec{x}) J(\vec{x}) + S(\vec{x}) \end{aligned} \quad (2.67)$$

$$S(\vec{x}) = \frac{1}{2} \sum_{i=1}^M e_i^2(\vec{x}) \nabla^2 e_i(\vec{x}) \quad (2.68)$$

Where $V(\vec{x})$ is the performance index to be minimized; M is the number of input data; J is the Jacobian matrix which calculates the 1st order derivative for the errors corresponding to the weights and bias; L_i and L_i^* are the experimental and the predicted value of split length, respectively.

To investigate the effect of the number of neurons, Choi conducted three different combinations of neurons in the hidden layers, that is 2-2, 3-2, and 4-2. The model is evaluated based on the MSE, and it turns out the combination of 3-2 gives the lowest MSE value. The predicted split length is first compared with the prediction results from simple power-law: $L = L_0 N^D$. The MSE of the power law is around three times higher than the 3-2 backpropagation neural network model. Due to the high nonlinearity in the split growth, simple power-law could not fit the input parameters well a single weight from curve fitting. Backpropagated neural networks could train and learn the weights from multiple neutrons and rectify the model with minimum error. From the perspective of model integrity, the measured fatigue cycle is the output of the experiment and is at the same level as the split length. The model is trained with the outputs from the experiments as the input parameters in this BP model. Though this model achieved good accuracy results, the model's expandability will be limited in a new material layup.

In summary, the reviewed structural fatigue models enable the understanding of fatigue failure and fatigue damages at the structure level for wind turbine blade application. To further study the fatigue mechanism, the review is brought down at the material level. The most recent theoretical fatigue model based on classical laminate theory and fracture mechanics' approach is reviewed. These models are typically validated by massive experimental tests. Due to the complexities in the fiber-metal laminate characteristics and complicated fatigue failure mechanisms, the classical theories have limitations regarding predicting fatigue life in the regime of non-linear plastic deformation. Once the material layup or testing conditions are changed, the theoretical models require further investigation and validation. Prediction of fatigue life for the

GLARE composites could be solved by other novel methods, such as the machine learning approach.

On the other hand, machine learning models learn the input data's underlying patterns and build linear or non-linear correlations with the desired output. This learning process mostly relies on large data, e.g., sensor signals, as shown in the reviewed SVM, EDT, and NN models. However, those models mainly provide approaches to classify fatigue damages for metals or fiber composites. No existing work has been done on the prediction of FML fatigue life using the machine learning models. In the following chapter, an expert system assisted tree-ensembled based ML fatigue model is proposed to compensate with the classical fatigue model.

Chapter 3. Methodology

In this section, the One-stop classical fatigue model and the machine learning RTE model are introduced to predict the fatigue life for a constant chord untwisted S809 airfoil wind turbine blade using GLARE as the shell skin material. With the aim of better predicting the fatigue life as yet, at this point, no similar work has not been done. The One-stop model comprises three steps: firstly, calculate the aerodynamic load of wind blades under both flap-wise and edgewise bending moments at different wind speeds. Secondly, bridge the axial stress from the structure level to the material level using the global one-directional stress to local stress analysis. Lastly, predict the fatigue cycle and construct a constant life diagram. To compensate for the limitations in the classical theories, i.e., lack of generalization, extensibility, and massive testing time in fatigue prediction towards various GLARE types, the RTE model was proposed and validated with the experimental data. In order to exclude human errors in the experiments, the data set was obtained from the classical model and then passed to the RTE model for training and prediction. The model accuracy was evaluated by the Mean squared error (MSE), Mean absolute percentage error (MAPE), and the coefficient of the determinant (R^2 value). Key parameters in the fatigue model were further discussed in the sensitivity study.

3.1 One-stop fatigue model to predict the fatigue life of the wind turbine blade

The One-stop model aims to establish a direct relationship between material properties and fatigue life of composite structures. A couple of theories and empirical equations are integrated to achieve the purpose. In summary, the proposed methodology to predict GLARE samples' fatigue life for small wind turbine blade application is shown in Figure 3.1. The software used for the numerical analysis is MATLAB.

Figure 3.1 Procedure for the theoretical prediction of GLARE fiber-metal laminate in wind turbine blade application.

3.1.1 Aerodynamic modeling

The aerodynamic modeling is to calculate the thrust and torque for constant chord and untwisted airfoil S809 caused by the average wind speed from wind class IV(6m/s) to wind class I(10m/s) based on IEC 61400–2 [158] using the blade element momentum (BEM) theory. Followed by the calculation of flap-wise and edgewise bending moments at the root section of the blade. The maximum bending moments were used

as airfoil structural stress analysis. The differential equations for the calculation of thrust and torque are listed below [159]:

$$dT = \sigma' \pi \rho \frac{U^2(1-a)^2}{\sin^2 \varphi} (C_L \cos \varphi + C_D \sin \varphi) r dr \quad (3.1)$$

$$dQ = \sigma' \pi \rho \frac{U^2(1-a)^2}{\sin^2 \varphi} (C_L \sin \varphi - C_D \cos \varphi) r^2 dr \quad (3.2)$$

$$\sigma' = \frac{Bc}{2\pi r} \quad (3.3)$$

where dT and dQ are the differential thrust and torque; σ' is the local solidity; 'a' is the induction factor; C_L and C_D are lift and drag coefficients; φ is the flow angle, which is the sum of pitch angle θ and angle of attack ∂ , and 'r' is the wind blade radius. The detail aerodynamic forces and bending moments are explained in Figure 3.2.

Figure 3.2 Load analysis for wind turbine blade airfoil.

In Figure 3.2, F_{wind} is the resultant air force due to the lift and the drag. Because of the pressure difference on the pressure side and suction side of the blade, tip loss correction factor F_{tip} was applied for the computation of thrust and torque [159].

The detailed design parameters of the 20kW wind turbine are listed in Table 3.1, which are aligned with the experimental tested airfoil S809 data by NREL [160]. The GLARE with a layup of Al/0₄/Al is designed as the wind blade shell skin.

Items	Symbol	Value	Unit
Average wind speed	U	6, 7.5, 8.5, 10	m/s
Rated power	P _r	20	kW
Radius of blade	R	5.05	m
Design tip speed ratio	λ _d	6	
Number of blades		3	
Design angle of attack	α	6	°
Airfoil		S809	
Chord length	c	0.457	m
Shell skin thickness	t	1.86	mm
Air density	ρ _{air}	1.225	kg/m ³
GLARE 2 density	ρ _{g2}	2084.91	kg/m ³

Table 3.1 The design parameters for the 20kW wind turbine.

3.1.2 Structural load calculation

The main wind turbine blade loadings include the flap-wise and edgewise bending moments. The differential equation (3.1) and (3.2) were analyzed based on the distributed load along the wind turbine blade, as shown in equation (3.4) and (3.5).

$$M_x = \frac{1}{4} F_{\text{tip}} c \rho_{\text{air}} U_{\text{rel}}^2 (C_L \cos \varphi + C_D \sin \varphi) (R - x)^2 \quad (3.4)$$

$$M_y = \frac{1}{2} F_{\text{tip}} \left(\frac{1}{4} c R \rho_{\text{air}} U_{\text{rel}}^2 (C_L \sin \varphi - C_D \cos \varphi) + \rho_{g2} A g \right) (R - x)^2 \quad (3.5)$$

where M_x and M_y are the flap-wise and edgewise bending moments, respectively; U_{rel} is the relative wind speed, and it can be calculated at $U_{rel} = U(1 - a)/\sin\phi$. The design standard for small wind turbines, IEC61400-2, provides only the empirical equations of bending moments at the blade root. With the equations above, the bending moments could be calculated at different sections of the blade, which enables the analysis of axial stress along the wind blade length [161], as shown in equation (3.6).

$$\sigma_z = E_{z,i} \left(\left(\frac{M_y I'_{xx} - M_x I'_{xy}}{I'_{xx} I'_{yy} - (I'_{xy})^2} \right) x + \left(\frac{M_x I'_{yy} - M_y I'_{xy}}{I'_{xx} I'_{yy} - (I'_{xy})^2} \right) y \right) \quad (3.6)$$

where σ_z and $E_{z,i}$ are the stress and Young's modulus in the axial direction of the blade. To calculate the discrete stress distribution at each local element, a transformation of the laminate material is required. I'_{xx} , I'_{yy} and I'_{xy} are the moments of inertia calculated based on the parallel theorem assuming uniform thickness throughout the airfoil baseline. The centroid of S809 was firstly located, as shown in Figure 3.3, “x” and “y” are the distance between each local coordinate and the airfoil centroid.

Figure 3.3 Illustration of local and global centroids for airfoil S809.

Transformation of the adhesive and prepreg layers were performed by taking the Al2024-T3 as the reference material. Moments of inertia about the centroid of the airfoil was then calculated by summing up the value of the discrete points.

$$\begin{aligned}
 I'_{xx} &= \sum_{j=1}^N E_{Z,i} (I_x(j) + n_i A(j) \times y(j)^2) \\
 I'_{yy} &= \sum_{j=1}^N E_{Z,i} (I_y(j) + n_i A(j) \times x(j)^2) \\
 I'_{xy} &= \sum_{j=1}^N E_{Z,i} n_i A(j) x(j) y(j)
 \end{aligned} \tag{3.7}$$

Where i represents the different types of material in the FML, j represents the local centroids along the airfoil baseline, and N is the number of local elements. Material properties of the shell skin GLARE-2 involved in the structural load and axial stress calculation are listed below [46, 54].

Parameters	Unit	Al 2024-T3	S2 glass fiber/epoxy	Adhesive
E_x	[GPa]	72.4	48.9	2.0
E_y	[GPa]		5.5	
E_{xy}	[GPa]	27.6	5.55	1.0
ν_{xy}		0.33	0.33	0.3
ν_{yx}		0.33	0.0371	
α	[1/°C]	22×10^{-6}	6.1×10^{-6}	

Table 3.2 Material properties for GLARE composites

3.1.3 Fatigue life prediction

The fatigue life of GLARE laminate is defined as the total fracture of the aluminum layers in the laminate. The prediction model includes stress analysis based on the

classical laminate theory and fatigue life prediction based on the linear fracture mechanics approach. The modified crack opening mechanism based on Alderliesten's and Chang's models is shown in Figure 3.4. The improvements are: the crack opening profile is narrowed considering the natural crack growth without artificial pre-cuts; the bridging stress was calculated based on the effects of both the fiber and adhesive film instead of fiber alone.

Figure 3.4 Illustration of crack opening profile and delamination profile.

In order to predict the fatigue life of GLARE, the stress developed in the aluminum layer under cyclic loads must be known first. The stress developed at each layer of GLARE-2 could be calculated from equation (3.8), and the detailed derivation could be found from [46].

$$\bar{\sigma}_p = S_p [S_{lam}^{-1}(\bar{\sigma}_{lam}) + \Delta T(\alpha_{lam} - \alpha_p)] \quad (3.8)$$

where S_p represents the stiffness for the specific layer in the FML; S_{lam} is the stiffness for the laminate composite; $\bar{\sigma}_{lam}$ is the applied stress on the laminate; ΔT is

the temperature difference between the environment (25°C) and the curing temperature (125°C); α_{lam} and α_p are the thermal expansion coefficients.

The fatigue model aims to predict the fatigue cycle at specific constant tension-tension fatigue loads compared with the experimental data. The fatigue damage is under the mode I fatigue opening, as shown in Figure 3.5. With the known stress intensity factor and crack growth rate, the fatigue cycle could be obtained by the integration of the Paris' law typed equation, i.e., $\frac{da}{dN} = C(\Delta K)^m$.

Figure 3.5 Crack growth rate for mode I fatigue opening [162].

The crack growth rate for GLARE laminate is calculated below based on the Paris' law equation [163]. By doing trapezoidal integration of equation (3.9), the fatigue life cycle N could be calculated.

$$\frac{da}{dN} = C(\Delta K_{eff})^n \quad (3.9)$$

where $C=2.17 \times 10^{-12}$ and $n=2.94$ are the material constants for Al2024-T3 [52]; ΔK_{eff} is the effective stress intensity factor with the unit of $\text{MPa}\sqrt{\text{mm}}$. The equation of the effective stress intensity factor was listed [45]:

$$\Delta K_{\text{eff}} = (K_{\text{re}} - K_{\text{op}}) \left(1 - \frac{K_{\text{br}}}{K_{\text{re}}}\right) \quad (3.10)$$

where K_{re} is the stress intensity factor of the aluminum layer of the GLARE laminate; K_{op} is the crack opening stress intensity factor; and K_{br} is the intensity factor due to bridging stress. The equations for SIF take the form below:

$$K_{\text{re}} = F_{\text{re}} \sigma_{\text{Al}} \sqrt{\pi a} \quad (3.11)$$

$$K_{\text{op}} = \sigma_{\text{op}} \sqrt{\pi a} \quad (3.12)$$

$$K_{\text{br}} = 2 \sum_{i=1}^N \frac{\sigma_{\text{br,Al}}(x_i) w}{\sqrt{\pi a}} \frac{a}{\sqrt{a^2 - x_i^2 + b_i^2}} \left(1 + \frac{1}{2} (1 + \nu) \frac{b_i^2}{a^2 - x_i^2 + b_i^2}\right) \quad (3.13)$$

$$\sigma_{\text{br,Al}} = \frac{n_{\text{fm}} t_{\text{fm}}}{n_{\text{Al}} t_{\text{Al}}} \sigma_{\text{br}} \quad (3.14)$$

where $F_{\text{re}} = \sqrt{\sec(\pi a/W)}$ is the shape correction factor; ‘a’ is the half crack size and ‘w’ is the discrete element width; σ_{Al} is the stress developed in the aluminum layer; σ_{op} is the crack opening stress in the aluminum layer, which could be found at [164]; $\sigma_{\text{br,Al}}$ is the bridging stress; σ_{br} is the crack closing stress in the glass fiber layers in the laminate [54]; n_{fm} and n_{Al} are the numbers of layers; t_{fm} and t_{Al} are the layer thickness.

The model for the calculation of the bridging stress was studied by Marisen [165] and improved by Alderliesten [52] for the fiber metal laminates. The equations for bridging stress are based on [52, 54, 57]:

$$\begin{aligned}
\sigma_{br} &= H^{-1}Q \\
H &= \sum_{j=1}^N \frac{v(x_j, x_j)}{\sigma_{br}(x_j)} - \frac{b(i)}{E_f} \delta(i, j) \\
Q &= v_{\infty}(i) - \delta_{pp}(i) - \frac{\sigma_f}{E_f} b(i)
\end{aligned} \tag{3.15}$$

and

$$\begin{aligned}
v_{\infty} &= 2 \frac{\sigma_{Al}}{E_{Al}} \sqrt{a^2 - x^2} \\
\delta_{pp} &= C \sigma_{Al} t_{Al} \sqrt{\frac{t_f}{G_f} \left(\frac{1}{F_{Al}} + \frac{1}{F_f} \right)}
\end{aligned} \tag{3.16}$$

where v_{∞} represents the crack opening in the aluminum layer due to the applied stress; δ_{pp} is the crack opening due to the prepreg shear deformation; σ_{Al} and σ_f are the stress in the aluminum layer and prepreg layer; F_{Al} , F_f and F_{ad} are stiffness; and C is the correction parameter.

3.2 Experimental methods

In this part, the fabrication of GLARE specimens is introduced in detail and followed by material characterization tests, including tensile tests, fatigue tests, and hygrothermal tests.

3.2.1 Panel fabrication

GLARE panels were fabricated at a curing temperature of 125°C, a pressure of 80psi, and the vacuum pressure of -22 psi. The total autoclave curing time is 218 minutes. The error percentage of temperature is controlled within 5% during the heat up and curing stages. The glass fiber prepreg used is Hexcel 913. Redux film adhesive 609 (300g/m²) was applied between the Al2024-T3 layer and the prepreg layer to promote the bonding. The detailed layup for GLARE panel fabrication is displayed in Figure 3.6. The sequence of the fabric plies starting from the steel support base plate is arranged in the

order of non-porous-release material – bleeder cloth – porous-release fabric. The non-porous-release fabric is woven fiberglass with polytetrafluoroethylene coating, and it is designed for resin restriction. The bleeder cloth is a non-woven polyester fabric that allows airflow throughout the vacuum bagging process and bleeds out the excess resin in the FML panel. The porous-release-fabric directly contacts the FML panel, and it enables excess resin, volatiles, and trapped air to escape into the breather during the curing process. Symmetric fabric plies are laid on top of the FML panel to comprehend the functions. The vacuum bag is then sealed and connected to the autoclave pump through the connection head.

Figure 3.6 Layup sequence of GLARE panel for autoclave curing

After the GLARE panel is cured, it is sent for waterjet cutting, and samples of the same size, 210 mm long and 25 mm wide, are cut out. In order to ensure the curing quality, an electron microscope (4 to 16 times) is used to check the curing quality. The first curing cycle was shown in Figure 3.7, labeled as ‘old cycle’. After several rounds of improvement, the curing cycle was finalized by checking the bonding quality of the GLARE specimens.

Figure 3.7 Improvements on the autoclave curing cycle for the fabrication of GLARE laminates.

It could be seen from Figure 3.7 that under the old curing cycle, different sizes of cavities could be observed at the interface of the aluminum layers and the prepreg layers. Improvements in the new curing cycle are mainly by extending the stage I curing at 90°C and slightly increasing time at stage III and decreased stage IV time. Thus, the entire curing process's time is almost the same between the improved cycle and the old cycle. However, the bonding quality in the former is very uniform with merely unobservable cavities. The detailed curing parameters could be found in Table 3.3 below:

Cycle	Modifications
Stage I: heat up rate	From 1.55°C/min to 2.06 °C/min
Stage II: low T curing	From 30mins to 40mins

Stage III: heat up rate	From 2.33°C/min to 1 °C/min
Stage IV: high T curing	From 90mins to 40mins
Stage V: cooling rate	From 2.4°C/min to 2 °C/min

Table 3.3 Improvement of the curing cycle for the fabrication of GLARE panels.

Two different layups of fabricated GLARE panels are shown in Figure 3.8. The bleeder cloth absorbed the excess blue color adhesive. It was observed in Figure 3.8(b) that the four corners of the cured GLARE panels are slightly bending downwards due to the pressure and vacuum force. It is assumed that the cut-out specimens are flat without any curvature since the samples are cut one centimeter away from the edges.

Figure 3.8 Fabricated GLARE - 2 and GLARE - 3 panels (size: 30cm by 30cm) by using the autoclave machine at a curing temperature of 125°C, the pressure of 80psi, the vacuum pressure of -22 psi, and the total autoclave cycle time of 218 minutes.

3.2.2 Hygrothermal tests

In order to test the effect of moisture and temperature on the fatigue life of GLARE, part of the samples were hygrothermal tested at 80°C, 95% relative humidity, and a total accumulation time of 1000 hours. The machine used for the hygrothermal tests is the Thermotron chamber.

The tested samples include three-layer aluminum GLARE-3 and four-layer aluminum GLARE-4. The hygrothermal tests' detailed process is listed as follows: first, obtain the initial sample weight by using a weighing scale with at least four decimal places, then remove the samples from the Thermotron chamber approximately every 100 hours and weigh. Thus, the weight gain of the specimens due to the hygrothermal condition can be obtained.

3.2.3 Fatigue test

Tension-tension constant amplitude fatigue tests were performed using the MTS810 servo-hydraulic testing machine based on the standard of ASTM D3479. The maximum cyclic load applied varies from 100MPa to 259MPa, at the frequency of 5Hz, and the stress ratio of 0.05. The gripping pressure applied to the specimens was calculated based on the equation (3.17). The fatigue cycle was recorded when the aluminum layers of the GLARE specimens reached a total fracture.

$$P_{\text{grip}} = 0.9 \times \frac{12F_{\text{max}}}{66.45} \quad (3.17)$$

where P_{grip} is the gripping pressure, F_{max} is the failure load obtained from the material characterization tests. The ratio of 12/66.45 is generally suggested for monolithic material; a further reduction ratio of 0.9 is applied to avoid too much stress induced at the clamp area of the laminate specimens.

3.3 Expert system assisted tree-ensembled based ML fatigue model

With the advancement of machine learning in leading technologies, it is perceived that machine learning (ML) is a new and effective alternative for the classic fatigue life prediction. In this part, a regression tree ensembled based (RTE) model was proposed to predict the fatigue life of GLARE composites, and the prediction results were evaluated and compared with the benchmark algorithm - support vector regression (SVR). In this model, mechanical, geometrical properties and fatigue loading stresses are selected as the training parameters (so-called features), and the GLARE fatigue life is predicted as the output of the model. Experimental data of a total of 98 GLARE-2, GLARE-3 specimens with ten different layups are used for the training and validation of the ML model. Results show that the ML model can provide good life prediction accuracy. Specifically, with the average results of 1000 iterations, the MAPE of 25.57%, the R^2 value of 0.82, the NMSE of 0.01, and the NRMSE of 0.08 are obtained. The results show that the most correlated, either positively or negatively, parameters to the fatigue life span are S_{Al} , S_{max} , S_{alt} and S_m .

The proposed methodology to predict the fatigue life of GLARE samples using the RTE model is illustrated in Figure 3.9. Briefly, the ML prediction model starts with data collection of GLARE laminate properties as input variables (geometric properties, mechanical properties, and fatigue load levels) and fatigue cycles as the output. The preprocessed dataset is then loaded to the model program for training. After running for 1000 times to exclude the randomness, the model is evaluated with the four matrices – MAPE, R^2 , NMSE, and NRMSE. The model is implemented with the xgboost package and svr package using Python.

Figure 3.9 The procedure for the prediction of GLARE fatigue life by using the regression tree ensembled based (RTE) approach [166].

3.3.1 Data collection and preprocessing

The fatigue data for the GLARE samples were obtained from the fatigue tests over 119 samples. A total of 13 features (Table 3.4) were selected for the prediction GLARE fatigue cycle. Due to the thickness difference between GLARE-2, GLARE-3, and GLARE-4, an individualized model was trained separately for two groups: one group for GLARE-2 and GLARE-3 (total 98 specimens) and the other for GLARE-4 (21 samples).

Number	Variable	Units
1	σ_{uts}	MPa
2	σ_y	MPa
3	F_{max}	KN
4	t	mm
5	d	kg/m ³

6	E	MPa
7	$S_{\max}$	MPa
8	S_{alt}	MPa
9	S_m	MPa
10	S_{Al}^*	MPa
11	n_{Al}	
12	n_0	
13	n_{90}	

Table 3.4 Features selected for the training of the fatigue life prediction model.

Note: S_{Al}^* is the cyclic stress developed in the aluminum layer of GLARE caused by external loads and the curing stress [46]. S_{Al} is calculated based on the classical laminate theory, as shown in equation (3.8).

The recorded data was then processed with data cleaning, by which obvious error or blank data at the head or tail was trimmed off. The dataset was normalized with logistic transformation for better convergence, as shown in Figure 3.10.

Figure 3.10 (a)Raw dataset for GLARE-2, GLARE-3 (b) Logistic transformed GLARE-2, GLARE-3 data (c) Raw data for GLARE-4 (d) Logistic transformed GLARE-4 data.

Red-blue colors in Figure 3.10 are assigned to the data bubbles according to the different fatigue life spans. In order to show the fatigue data more explicitly, the bubble size was adjusted based on the measured fatigue cycle.

3.3.2 Machine learning RTE models

Up to now, many algorithms have been developed, among which only a few choices may suit well for the dataset. Choosing the correct estimator (or algorithm) could save time regarding the frequent switching between multiple estimators. General guidelines of estimator's selection provided by scikit-learn are shown in Figure 2.21.

Based on the guide from scikit-learn, support vector regression (SVR) and ensemble regression estimators are suggested for prediction. In practice, building up the model based on each estimator requires a full understanding of the mechanism of fatigue development behind the dataset.

3.3.2.2 Regression tree ensembles model

Machine learning algorithms are mathematical models that learn patterns from data and build generalizable models to make predictive analysis [167]. The regression tree ensembles (RTE) model is based on the newly developed xgboost algorithm. Compared with traditional boosted algorithms, xgboost further incorporates the Newton boosting. Briefly, Newton boosting is a higher-order approximation matrix to determine the tree structure, which starts from weak learners (also called base learners) with performance slightly better than random chance [168], e.g., decision tree, neural network [169]. By iteratively focusing on the errors resulting at each step until a suitable strong learner (an estimator, well-defined correlation with the actual results) is obtained as a sum of the successive weak ones. The enhanced RTE model consists of a weighted combination of multiple regression trees to minimize an overall loss. The objective functions are minimized by iteratively applying individualized penalization terms on each new tree. In the t^{th} round of training, the model function with the sum of t learners and K -additive functions, that is:

$$\hat{y}_i^t = \sum_{k=1}^t f_k(x_i) = \hat{y}_i^{(t-1)} + \epsilon f_t(x_i), \quad f_k \in F, \quad (3.18)$$

where $F = \{f(x) = w_{q(x)}\} (q: \mathbb{R}^m \rightarrow T, w \in \mathbb{R}^T)$ is the space of regression trees; q is the independent structure for each tree with corresponding weights w ; T is the number of leaves in the tree. $f_t(x_i)$ is the new function at time t ; $\hat{y}_i^t$ and $\hat{y}_i^{(t-1)}$ are the model

at time t and time $t - 1$; x_i is the input variable, and ϵ is the shrinkage factor to avoid overfitting.

The objective function consists of the loss function l and the regularization term Ω . The former represents the error between the predicted value and measured value, and the latter Ω consists of the penalization on the number of terminal nodes, the leaf weights, and the tree depth. The target is to minimize the squared loss of the objective function:

$$\begin{aligned} \text{Obj}^{(t)} &= \sum_{i=1}^n l(y_i, \hat{y}_i^{(t)}) + \sum_{i=1}^t \Omega(f_i) \\ \text{where } \Omega(f_t) &= \gamma T + \frac{1}{2} \lambda \sum_{j=1}^T w_j^2 \end{aligned} \quad (3.19)$$

Where w_j are the leaf scores; λ is the regularization penalty or tuning parameter which controls the trade-off between the bias and variance.

In the individual tree, weighted quantile-splitting [170, 171] approach (e.g., for 100-split points, 10-quantile split is $(x_{10}, x_{20}, \dots, x_{100})$) is adopted by calculating the information gain for candidate splits on the features, and the best split of nodes is selected based on the maximum information gain [172]. The objective function developed by Chen [77] to maximize the information gain at each split takes the form:

$$\text{Gain} = \frac{1}{2} \left[\frac{(\sum_{i \in I_L} g_i)^2}{\sum_{i \in I_L} h_i + \lambda} + \frac{(\sum_{i \in I_R} g_i)^2}{\sum_{i \in I_R} h_i + \lambda} - \frac{(\sum_{i \in I} g_i)^2}{\sum_{i \in I} h_i + \lambda} \right] - \gamma \quad (3.20)$$

Where $I = I_L \cup I_R$ is the complete set of left and right nodes after the split; λ and γ are penalization terms. g_i and h_i are the 1st order and 2nd order gradient equations of the objective function after the Taylor expansion.

3.3.3 RTE model parameters

There is a total of 13 input features to the RTE model, as indicated in Table 3.4. To illustrate how the individual boosted tree grows and predicts the fatigue cycle of GLARE composites, a randomly picked tree structure is shown in Figure 3.11.

Figure 3.11 Plot of a randomly picked boosted tree with three nodes, four leaves, the learning rate of 0.2, maximum depth of a tree is 2, the number of trees planted (iterations) of 1000. L2 regularization term on weights of 0.5 and L1 regularization term on weights of 0.01.

The plotted randomly picked boosted tree structure starts from the root node - S_{Al} which is chosen with the highest information gain from the total training data. The value of S_{Al} represents the condition and base on which the tree splits into branches. The algorithm has found that among all the possible splits, the split at $E(\text{MPa})$ as internal nodes (child nodes) gives the maximum information gain. The optimized tree structure is 2-layer in-depth, and the split ends at the leaf (decision). The leaf weights are the average residuals (the difference between the measured value and the predicted value) learned at each leaf of the tree, and they are added to the predicted fatigue cycle of, e.g., $\hat{y}^n$. New residuals are learned from the n^{th} tree and suppressed in the $(n+1)^{\text{st}}$ tree. Thus, each tree is boosted based on the residuals from the previous tree and achieves high accuracy in prediction through the additive training. The ultimate number of 134 trees (iterations) was found by using 3-fold cross-validation.

3.3.4 Evaluation methods

The performance of machine learning RTE models is assessed by model accuracy and model reliability [173]. The model accuracy is evaluated by the three standard regression metrics, which are mean absolute percentage error (MAPE), normalized mean squared error (NMSE), normalized root mean squared error (NRMSE). Whereas the model reliability is evaluated by the coefficient of the determinant (R^2 value) and standardized residuals. To eliminate the random error and systematic bias, shuffling of the dataset was performed before each prediction.

Mean absolute percentage error

MAPE is one of the most useful statistical measures for model evaluation. It takes the average prediction accuracy and gives a direct view of the prediction error in percentage.

$$\text{MAPE}(y_i, \hat{y}_i) = \frac{1}{N} \sum_{i=1}^N \left| \frac{y_i - \hat{y}_i}{y_i} \right| \quad (3.21)$$

Normalized Mean squared error

NMSE measures the average of the squared difference between the measured fatigue life and the predicted value and normalized by the maximum and minimum of the measured fatigue cycles. MSE is usually the default evaluation matrix for most of the regression algorithms.

$$\text{NMSE}(y, \hat{y}) = \frac{\frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2}{(y_{i,max} - y_{i,min})^2} \quad (3.22)$$

Normalized Root mean squared error

Like the concept of MSE, RMSE also measures the average magnitude of errors and reduces the order of MSE, which makes it sensitive to the outlier data. When the outlier data has a substantial base value, the error could be magnified through RMSE. NRMSE is normalized RMSE.

$$\text{NRMSE}(y, \hat{y}) = \frac{\sqrt{\frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2}}{y_{i,\max} - y_{i,\min}} \quad (3.23)$$

The coefficient of determination (R^2)

R^2 measures how well the predicted fatigue cycles approximate the measured fatigue cycle. The range of the R^2 scores lie between 0 to 1. The higher the R^2 value, the less unexplained variance, and the better the prediction. It happens that R^2 scores lie outside the range of [0,1] when the wrong model is chosen or wrong coefficients are applied.

$$R^2(y_i, \hat{y}) = 1 - \frac{\sum_{i=1}^N (y_i - \hat{y}_i)^2}{\sum_{i=1}^N (y_i - \bar{y})^2} \quad (3.24)$$

where y_i is the measured fatigue cycle; $\hat{y}$ is the predicted fatigue cycle; and N is the total number of specimens tested.

Standardized residuals

Standardized residuals usually are plotted against the fitted values (predicted values) to discover the underlying error patterns. As a rule, a random pattern with residual points dispersed around the horizontal axis suggests the errors are consistent with the stochastic errors, and the appropriate model is selected for the regression analysis.

$$e_i^* = \frac{e_i}{\sigma_e} = \frac{e_i}{\sqrt{\frac{1}{N} \sum_{i=1}^N (e_i - \bar{e})^2}} \quad (3.25)$$

Where e_i are the residuals between the observed fatigue cycle and the predicted ones; σ_e is the standard deviation for the residuals.

In summary, the methodology of two fatigue models are introduced in this chapter, i.e., the One-stop classical fatigue model and the RTE machine learning model. The methods of fabrication and preparation of specimens for room temperature and hygrothermal fatigue tests are also described. The predicted fatigue cycles from both the One-stop and the RTE models are compared and discussed in the next chapter. Experimental statistics and test results will also be displayed in the next chapter accordingly.

Chapter 4. Evaluation of results

The methodology results are depicted and explained in the order: results of the One-stop expert model, results of experiments, and the results of the RTE machine learning model.

4.1 Results of One-stop fatigue model

4.1.1 Predicted load and stress distribution for the airfoil

The edgewise and flap-wise bending moments are calculated and shown in Figure 4.1 based on equation (3.4) and (3.5). The highest bending moments occur at the blade root section and lowest at the blade tip.

Figure 4.1 (a) Edgewise bending moments for the 3-meter wind blade and (b) flap-wise bending moments at different wind speeds.

The maximum bending moments at the wind speed of 10m/s is calculated as 2473Nm at flap-wise and 1492Nm at edgewise. The normal stress at the wind blade root section for the airfoil S809 was calculated based on equation (3.6). Color codes are assigned to

the corresponding stress range to show the stress distribution along the airfoil and assist in identifying the stress concentration areas of the airfoil, as shown in Figure 4.2.

Stress (Mpa)	Color Code
[0,10]
(10,20]
(20,30]
(30,40]
(40,45]
(45,50]
>50

Figure 4.2 Color codes for the indication of stress levels at the airfoil shell skin.

The loads involved in the stress analysis are the flap-wise distributed load w_y due to the aerodynamic loads and edgewise distributed load w_x caused by the weight of the wind blade and the gravity. Thus, the axial stress along the airfoil was calculated at different wind speeds, as shown in Figure 4.3. It is found that the most upper and lower surfaces of the blade experience the highest stress, as the wind speed increases, the stress increases accordingly.

Figure 4.3 Stress distribution at the root section of the wind blade (note that the x and y-axis is exaggerated in ratios) for the shell skin GLARE-2 at average wind speeds of (a) 6m/s, (b) 7.5m/s, (c) 8.5m/s and (d) 10m/s under the edgewise distributed load w_x and flap-wise distributed load w_y .

The maximum axial stress calculated for the airfoil S809 is 41.8MPa at the average wind speed of 10m/s. With a safety factor of 2.87 applied to the axial stress, a starting fatigue load of 120MPa was thus obtained and used for specimen stress analysis and fatigue life prediction.

4.1.2 Predicted stress in GLARE sample

Based on the classical laminate theory, the stresses at each layer of fiber-metal laminates were computed. In the GLARE-2 laminate, due to the highest stiffness in Al 2024-T3, the highest load developed. It is shown in Figure 4.4 that the stress in the aluminum layer is around 1.8 times the maximum applied stress at the laminate.

Figure 4.4 Stress at different layers of GLARE-2 at the maximum applied stress of 180MPa under tension-tension fatigue test with a stress ratio of 0.05 and frequency of 5Hz.

In order to evaluate the performance of individual GLARE laminates, six different layups were assessed, and the bridging stress, the remote stress intensity factor (SIF), bridging SIF, and crack growth rate were plotted, shown in Figure 4.5 to Figure 4.10. For each type of GLARE, the expert One-stop fatigue model was evaluated based on MAPE, NMSE, NRMSE and R^2 value by comparing the predicted fatigue cycle with the experimental value.

Figure 4.5 (a) Bridging stress calculated for the aluminum layer of GLARE-2 - 0_4° at the maximum applied load of 140MPa, 160MPa, and 180MPa by assuming of elliptical delamination shape. (b) SIF caused by remote stress. (c) SIF caused by bridging stress. (d) crack growth rate at different applied loads. MAPE: 35.30%, NMSE: 0.01, NRMSE: 0.11, R^2 : 0.99.

The bridging stress in the aluminum layer of the GLARE-2- 0_4° laminate was analyzed by assuming the prepreg layers are intact during the crack propagates from 0.01mm to 12.5mm at different applied loads. As the crack size increased, small trenches were observed in the bridging stress diagram. The reason may be that the near-zero crack size requires higher bridging stress to grow initially, followed by a short period of stress

relaxation. As the cracks begin to propagate, the bridging stress gradually and stably decreases.

Figure 4.6 (a) Bridging stress calculated for the aluminum layer of GLARE-2 - 0°_2 at the maximum applied load of 140MPa, 160MPa, and 180MPa by assuming of elliptical delamination shape. (b) SIF caused by remote stress. (c) SIF caused by bridging stress. (d) crack growth rate at different applied loads. MAPE:43.10%, NMSE: 0.05, NRMSE: 0.22 and R^2 of 0.52.

Compared with GLARE-2- 0°_4 , the performance of GLARE-2- 0°_2 shows lower SIF value, decreasing trends of bridging stress, and higher crack growth rates. The reason for the above findings are possibly caused by fewer layers of 0° glass fiber prepreg in

GLARE-2-0₂^o. Higher error percentage in terms of MAPE and R² value is observed as well. The reason may be due to the discontinuity of samples manufactured in different batches.

Figure 4.7 (a) Bridging stress calculated for the aluminum layer of GLARE-3- 0₃^o-0.4 at the maximum applied load of 140MPa, 160MPa, and 180MPa by assuming of elliptical delamination shape. (b) SIF caused by remote stress. (c) SIF caused by bridging stress. (d) crack growth rate at different applied loads. MAPE: 32.56%, NMSE: 0.06, NRMSE: 0.24, R²: 0.29.

In the aspect of layup, GLARE-3-0₃^o-0.4 has more layers of aluminum and 0^o glass fiber prepreg. More stress is developed in the aluminum layers, which accelerates the crack growth. The bridging stress and SIF are higher in value compared with GLARE-

2. Though lower MAPE value, the R^2 value is lower compared with GLARE-2 specimens.

Figure 4.8 (a) Bridging stress for the aluminum layer of GLARE-3- 0° - 90°-0.4 at the maximum applied load of 140MPa, 160MPa, and 180MPa by assuming elliptical delamination shape. (b) SIF caused by remote stress. (c) SIF caused by bridging stress. (d) crack growth rate at different applied loads. MAPE: 40.25%, NMSE: 0.08, NRMSE: 0.29, R^2 : -0.12.

Similar trends in the plot of Figure 4.8 could be found in Figure 4.7. The difference in value was caused by the prepreg layup between GLARE-3-0° and GLARE-3-0°-90°. A negative value of R^2 indicates a large amount of unexplained variance. In short,

although an acceptable MAPE value was obtained for GLARE-3-0°-90°, the significant variance in the experimental data did not provide a reliable comparison between the one-stop model and the experimental results.

Figure 4.9 (a) Bridging stress calculated for the aluminum layer of GLARE-4 - 0°₃ at the maximum applied load of 140MPa, 160MPa, and 180MPa by assuming of elliptical delamination shape. (b) SIF caused by remote stress. (c) SIF caused by bridging stress. (d) crack growth rate at different applied loads. MAPE: 29.21%, NMES: 0.01, NRMSE: 0.24, R^2 : 0.45.

It could be seen from Figure 4.9 that the plot of bridging stress and SIF of GLARE-4-0°₃ show similar value compared with GLARE-3-0°₃ but the lower value in the crack

growth rate. Both two laminates have more 0° prepreg layers, more aluminum layers compared with GLARE-2 laminates.

Figure 4.10 (a) Bridging stress for the aluminum layer of GLARE-4 -0°-90°-0° at the maximum applied load of 140MPa, 160MPa, and 180MPa by assuming of elliptical delamination shape. (b) SIF caused by remote stress. (c) SIF caused by bridging stress. (d) crack growth rate at different applied loads. MAPE: 28.1%, NMES: 0.12, NRMSE: 0.35, R^2 : 0.41.

In GLARE-4 -0°-90°-0°, there is only one layer of prepreg layup difference compared with GLARE-4-0°. All the values, i.e., bridging stress, SIF, and da/dN are lower. It could be explained that negative stress is developed in the 90° layer offsets part of the

positive stress developed in the 0° layer and thus lowered the value of the bridging stress and, therefore, lower SIF and da/dN .

In order to study the effect of the stress ratio, stress ratios of $R=0.05$, 0.1 , and 0.3 were applied in both the expert prediction model and experiments for $G-2-0_4^\circ$. The results are shown in Figure 4.11. As the stress ratio increases, the fatigue stress decreases, and thus the fatigue cycle predicted and tested both extended.

Figure 4.11 Compared to the expert model prediction with the benchmark test results for GLARE-2 $-0_4^\circ-0.4$.

4.1.3 Predicted fatigue life

The fatigue cycles for the six types of aforementioned GLARE laminates were predicted and compared with the experimental results, as shown in Figure 4.12. It could be found that the experimental data disperse around the trends of the predicted data.

However, at the low fatigue cycle and the high fatigue cycle, discrepancies are more prominent. This issue is mainly caused by the limitation of the linear classic fatigue theories, which could not well fit the so-called two-stage S-N curve.

Figure 4.12 Predicted versus the experimental S-N curve results for (a) $G-2-0^\circ_4$, MAPE: 35.30%, NMSE: 0.01, NRMSE: 0.11, R^2 : 0.99. (b) $G-2-0^\circ_2$, MAPE: 43.10%, NMSE: 0.05, NRMSE: 0.22 and R^2 of 0.52. (c) $G-3-0^\circ_3$, MAPE: 32.56%, NMSE: 0.06, NRMSE: 0.11 and R^2 of 0.92. (d) $G-3-0^\circ_2$, MAPE: 32.56%, NMSE: 0.06, NRMSE: 0.11 and R^2 of 0.92. (e) $G-3-0^\circ_1$, MAPE: 32.56%, NMSE: 0.06, NRMSE: 0.11 and R^2 of 0.92. (f) $G-3-0^\circ_0$, MAPE: 32.56%, NMSE: 0.06, NRMSE: 0.11 and R^2 of 0.92.

NRMSE: 0.24, R^2 : 0.29. (d) G-3-0°-90°, MAPE: 40.25%, NMSE: 0.08, NRMSE: 0.29, R^2 : -0.12. (e) G-4-0°₃, MAPE: 29.21%, NMES: 0.01, NRMSE: 0.24, R^2 : 0.45. (f) G-4-0°-90°-0°, MAPE: 28.1%, NMES: 0.12, NRMSE: 0.35, R^2 : 0.41.

Comparison was made between the fatigue life at the same maximum stress of 120MPa for the GLARE types shown in the S-N plot in Figure 4.12 with the fatigue life of Al 2024-T3 [46]. It was found that G-3-0°-90° shows comparable fatigue life with Al 2024-T3 but 27.5% lower density. For G-2-0°₂ and G-2-0°₄ show two times and three times longer fatigue lifespan compared with Al 2024-T3 but around 25% of lower density.

The predicted S-N plot could be further analyzed for safe fatigue design. A case study was performed for GLARE-2-0°₄ as follows: the prediction matches the trend of the experimental results well. The fatigue constants were calculated at $\alpha = -0.237$ and $\beta = 2337.657$ for the bi-linear S-N curve computed in Figure 4.13 based on the Basquin equation [174].

$$S_{\max} = \alpha(N_f)^\beta \quad (4.1)$$

The endurance limit S_e at the fatigue cycle of 10^6 was obtained at the alternating stress S_a of 47.5MPa, which included the safety factor of 2.87 for the structural load analysis. Further correction factors for the surface finish and 95% reliability are 0.9 and 0.868, respectively [175]. The new endurance limit S'_e was calculated at $S_a = 37$ MPa with an accumulated safety factor of 3.67.

Figure 4.13 Comparison of experimental fatigue life for GLARE-2-0 $^{\circ}$ -0.4 with the theoretical prediction.

In order to investigate the interaction of mean stress and alternating stresses on the S-N curve of GLARE-2, the constant life diagrams were constructed. The minimum load ratio $r = S_a/S_m$ was found to be at least 0.14 to avoid the yield failure when $S_e = 47.5$ MPa, and $r = 0.1$ when $S'_e = 37$ MPa. The safe fatigue design zone at the safety factor of 2.87 and 3.67 is highlighted in Figure 4.14.

Figure 4.14 Constant life diagram at $N=1090000$, endurance limits S_e (with $SF=2.87$) and S'_e (with $SF=3.67$).

Sensitivity studies were performed to evaluate the effect of the critical variables involved in the fatigue equations, which are the maximum applied load (S_{max}), Young's modulus (E), the thickness of the aluminum layer (t_{al}) and the number of prepreg layers (n_{pp}), pre-cut size (a_s) and the stress ratio (R). The sensitivity study was conducted by varying the five parameters in the range of $\pm 50\%$ of the actual value as independent variables to examine the effects on the generated fatigue cycle (N). A broader comparison range was given to the stress ratio to see the impact on the fatigue cycle. The reference applied load is defined at 216MPa, which was selected by taking the average of all the experimental loads. The results of the sensitivity study are shown in Figure 4.15.

Figure 4.15 Sensitivity study of the parameters- S_{max} , E , t_{al} , n_{pp} , as and R are involved in the prediction model.

Among all the six parameters, S_{max} shows the most prominent negatively log relation with N . When S_{max} reduces 50%, N could be prolonged more than one thousand times while an increase of 50% causes an 85.86% reduction in N . Since the safety factor is directly linked to S_{max} , thus we can conclude from the finding from Figure 1.4(a) that

a higher safety factor in the design is positively correlated to the wind blade's fatigue life. The stress ratio R shows a high positive exponential correlation with N . As the stress ratio increases, the stress amplitude applied to the laminates becomes smaller, and a positive correlation is inferred. t_{al} shows less effect and correlated positively with N in the range of $[-57.11\%, 63.93\%]$. Due to the highest stiffness of the aluminum, the most elevated stress developed, thus t_{al} relates to fatigue life positively. However, there is a tradeoff between the specific weight and fatigue life. The effect of E and n_{pp} are minor and negatively correlated with N , which shows the sensitivity ranges of $[-26.13\%, 37.39\%]$ and $[-18.11\%, 35.29\%]$, respectively. It implies a moderate quantity of prepreg shall be applied. The initial crack size shows the least effect, which is around $[-2\%, 2\%]$.

The One-stop model could be further expanded to the load with various stress ratios. It is time-consuming to test numerous fiber metal laminate layups while maintaining the multiple stress ratios. With the help of the One-stop model, the effect of stress ratios could be analyzed analytically with good accuracy and reliability.

Figure 4.16 Data augmentation for GLARE-2-0₄° at different stress ratios.

As shown in Figure 4.16, the fatigue life of GLARE-2-0₄° is predicted at various stress ratios. As R increases, the stress amplitude decreases, which prolongs the fatigue cycle. This kind of analysis could save ample testing time and reinforce the data augmentation.

4.2 Results of experiments

This section mainly introduces the GLARE specimen statistics and material characterization results from tensile tests, fatigue tests, and hygrothermal tests. The total number of specimens tested for fatigue was 128.

4.2.1 Specimen statistics

In order to train the machine learning model to predict various layups of GLARE-2, GLARE-3, and GLARE-4 laminates, twelve different layups were fabricated, and fatigue testing with a total of 128 specimens. All the samples were prepared at the same

size of 250mm (length) × 25mm (width). Specimen thickness varies from 1.58mm to 4.82mm. The detailed specimen statistics are shown in Figure 4.17.

Figure 4.17 Quantity distribution for different categories of GLARE layup (four types of GLARE-2, five types of GLARE-3 layups, and three kinds of GLARE-4). The total number of specimens tested is 128.

4.2.2 Tensile tests

GLARE laminates were characterized through the tensile tests. Tensile tests were performed based on the ASTM D3039 [176]. The mechanical test properties and geometrical properties for GLARE-2, GLARE-3, and GLARE-4 specimens with different stacking sequences are shown in Table 4.1.

Types	σ_{uts}	F_{max}	t	ρ	E	σ_y
Units	MPa	KN	mm	kg/m ³	GPa	MPa
G2(0-0)	332.8	12.99	1.58	2113.5	43.7	198.4
G2(0-0-0-0)	508.3	23.22	1.85	2084.7	50.3	229.8
G2-(0-90-0)	371.1	15.50	1.73	2079.7	46.7	206.9
G2-(0-90-0-90-0)	370.9	18.31	2.02	1893.0	43.3	223.1
G3(0-90)	305.8	20.18	2.76	2014.9	43.9	192.5
G3(0-0)	394.4	24.98	2.69	2044.8	43.8	206.0
G3(0-0-0)	407.2	34.09	3.34	1864.1	44.4	177.6
G3(0-90-90-0)	319.8	26.08	3.31	1999.1	41.9	188.5
G3(0-90-0)	358.9	27.37	3.04	2007.7	43.1	198.0
G4 (0-90-0)	374.5	41.13	4.35	1960.2	34.2	194.7
G4(0-0-0)	403.4	43.23	4.34	1956.4	29.8	211.6
G4(0-90-90-0)	328.5	40.34	4.82	1936.4	32.6	182.3

Table 4.1 Material characterization of a total of twelve types of GLARE layups with four types of GLARE-2, six types of GLARE-3, and three types of GLARE-4.

Based on the material characterization results, general findings are listed:

- As the increase of the 0° prepreg, the ultimate tensile strength (σ_{uts}), failure load (F_{max}), and yield strength (σ_y) increases.
- As the increase in the number of prepreg layups, the density of GLARE laminates decreases.
- Compared with the groups of GLARE-3 and GLARE-4, Young's modulus of the GLARE-2 group shows the comparative advantage.

- The density of the fabricated GLARE specimens varies from 1936.4 kg/m³ to 2113.5 kg/m³. Compared with Al 2024-T3, with a density of 2780 kg/m³, GLARE can provide a specific weight saving of 24% to 30%.

Critical reflections on material characterization results:

- Certain grades of GLARE samples are manufactured in limited quantities. These samples may not provide enough information for the RTE model to learn the data's underlying patterns.
- When the samples were manufactured in different batches, the mechanical properties were found to be discontinuous.

4.2.3 Hygrothermal tests

The results of GLARE-3 and GLARE-4 specimen weight increase are shown in Figure 4.18 and Figure 4.19. In total, four GLARE-3 specimens and ten GLARE-4 specimens were tested.

Figure 4.18 Hygrothermal tests for GLARE-3 at 80 °C, 95% humidity, and total accumulated time of 1000 hours. ‘G-3B’ represents the inverse layup sequence (90°-0°) compared with ‘G-3’ (0°-90°).

Figure 4.19 Hygrothermal tests for GLARE-4 at 80 °C, 95% humidity, and total accumulated time of 1000 hours. ‘G-4B’ represents the inverse layup sequence (90°-0°-90°) compared with ‘G-4’ (0°-90°-0°).

It could be seen that GLARE-3 shows a lower weight increase rate compared with GLARE-4. The reason could be due to more moisture absorber, i.e., glass fiber prepreg and adhesive layers, are shown in GLARE-4. Though the trends of weight gain due to moisture for GLARE-3 and GLARE-4 show differently, the final average weight gain at 1000 hours is 0.9% for both. Some studies [101, 177, 178] have shown that under the hygrothermal condition, moisture equilibrium state for fiber-metal laminates could be reached around accumulated time of 1000-1300 hours with less than 0.2% weight increase. In the above reference work, either the GLARE composite material sample has fewer prepreg layers, or the sample's side surface is sealed with silicone. This explains why the moisture gain in this article shows a higher percentage than the reference, as well as more time may need to reach the equilibrium of moisture absorption.

Figure 4.20 S-N plot for hygrothermal conditioned GLARE-4 specimens.

The fatigue life of hygrothermal-condition tested GLARE-4 specimens are compared with room conditioned samples, as shown in Figure 4.20. The hygrothermal samples are 56.3% lower on average compared with room conditioned specimens.

4.2.4 Fatigue tests

The detailed fatigue test data and setup could be seen in the appendix Table C. 1, Table C. 2. The fractured specimens were classified into brittle failure and non-brittle failure. Stiffness-fatigue cycle (K-N) plots with transition necks, and transition slopes were observed from the non-brittle failure specimens. Conversely, they were perceived as a brittle failure.

Figure 4.21 Stiffness – fatigue cycle (K-N) plots for (a) G-2 at 224.2MPa, (b) G3-2 at 139.4MPa, (c) G-4 at 240MPa and (d) G3-2 at 200MPa.

As shown in Figure 4.21, the short and abrupt transition neck was found in the Stiffness – fatigue cycle (K-N) plot for GLARE-2. Whereas, a long and gentle transition slope, is found in GLARE-4's K-N plot. The K-N plots for the GLARE-3 exhibit both short-gentle change and abrupt failure slope.

Based on the K-N plot, all the fatigue tested specimens are classified into these three categories: transition neck, transition slope, and brittle failure, as shown in Table 4.2.

Type	Fatigue failure types
G2(0-0)	transition slope; brittle failure
G2(0-0-0-0)	transition neck; transition slope
G2-(0-90-0)	transition slope; brittle failure
G2-(0-90-0-90-0)	transition neck; transition slope
G3(0-90)	brittle failure
G3(0-0)	transition neck; transition slope
G3(0-0-0)	transition neck; transition slope
G3(0-90-90-0)	transition neck; transition slope
G3(0-90-0)	transition neck; transition slope
G4 (0-90-0)	brittle failure
G4(0-0-0)	transition neck; transition slope
G4(0-90-90-0)	transition slope

Table 4.2 Classification of the fatigue tested specimens based on the K-N plot.

It is observed in Table 4.2 that most of the GLARE layups exhibit multiple fatigue failure types. Specimens show transition necks in their K-N plot at lower maximum cyclic loads, while at higher maximum cyclic loads, only transition slopes were discovered. Layups that dominate with brittle failure may or may not encounter the transition slope. The interlink between the failure types and the number of prepregs and aluminum layers will be further discussed in chapter 4.3.

4.3 Results of expert system assisted tree ensembled machine learning fatigue model

4.3.1 Results of RTE prediction

The RTE model was trained by 80% of the data set and validated by the remaining 20% of the data. Since the model shuffles the training data during each run, which causes randomness to occur. When the predicted value deviates more from the experimental ones, large errors will be reflected in the evaluation results. Similarly, small deviations correspond to good results. Neither of them represents the model's general performance. Thus, the RTE model was run 1000 times, and the evaluation results are averaged to avoid extreme evaluation results from either too large or too small deviations. For the justification of chosen 1000 runs, it has been tested that the averaged result is not fluctuating when training times reach 1000 and above. Overall, the performance of the model is good with the MAPE of 25.57%, the R^2 value of 0.82, the NMSE of 0.01, and the NRMSE of 0.08.

To diagnose the prediction accuracy, residual patterns and outlier data, predicted fatigue cycles versus measured fatigue cycles, and the corresponding residual plots were represented in four random results, as shown in Figure 4.22. The prediction model shows the mean absolute error percentage (MAPE) range of 15.04%-38.88%, R^2 value range of 0.67-0.96 and average standardized residuals (μ_e) range of -0.24 to 0.34. The x-axis and y-axis represent the predicted fatigue cycle and the measured fatigue cycle, respectively. The red solid regression lines were plotted based on the least-squares polynomial fit of degree one to the data points (x =predicted fatigue cycles, y =measured fatigue cycle). The dotted identity line (slope =1) was employed as a reference for the deviation of the regression line.

Figure 4.22 Comparison of four random groups of measured fatigue cycles (y-axis) with predicted fatigue cycles (x-axis) and the corresponding standard residuals for GLARE-2 and GLARE-3.

By comparing the regression line (solid red line) formulated based on the data bubbles, the prediction is approximately consistent with good accuracy, as referenced by the dotted line of identity (slope = 1) in Figure 4.22. But prediction bias was observed at the long fatigue life span, i.e., the diverging (the blue-color bubbles) residual-fitted value plots of Figure 4.22(b) and Figure 4.22(d) show that the model underestimates the value in long fatigue life spans ($N > 2,000,000$). This phenomenon may occur due to the much lower cyclic load than the yield strength σ_y was applied, which caused low induced localized strain and approximate infinite fatigue life. Outlier data could be detected at several rounds of random testing. The same outlier data point is found in Figure 4.22(e) and Figure 4.22(g), which could be solved by either neglecting the obvious outliers during the data preprocessing stage or adding in more repetitive specimens at the same fatigue loads.

For the purpose of better model convergence, GLARE-4 specimens were trained and predicted separately due to the apparent thickness difference between GLARE-2 and GLARE-3. In total, 20 GLARE-4 samples with three types of layups are involved in the prediction. The measured versus the predicted fatigue cycle with the corresponding standardized residuals were plotted and shown in Figure 4.23. Compared with the random forecast with GLARE-2 and GLARE-3, the accuracy and reliability presented in GLARE-4 are less uniform. As shown in Figure 4.23, extremely high accuracy (MAPE: 3.85%) and high reliability (0.99) could be found. A pair of high accuracy with low reliability or a pair of low accuracy with high reliability is more commonly seen.

Figure 4.23 Comparison of four random groups of measured fatigue cycles (y-axis) with predicted fatigue cycles (x-axis) and the corresponding standard residuals for GLARE-4.

4.3.2 RTE Model accuracy and reliability

The accuracy of the model was assessed by the MAPE, NMSE, and NRMSE. The smaller the error, the higher the accuracy of the model. The R^2 value ranges from 0 to 1, indicates the proportion of the variance in the dependent variable (fatigue cycle N) that is predictable from the independent variables (the 13 features). The closer the R^2 value approaches 1, the better the experimental results were predicted by the machine learning model, and the higher the model reliability.

Figure 4.24 Evaluation of MAPE, NMSE, NRMSE and R^2 for the RTE model at the average value of 10, 100,1000, and 10000 runs of prediction. Best prediction results at 1000-run with MAPE: 25.57%, R^2 :0.82, NMSE:0.01 and NRMSE: 0.08 for GLARE-2 and GLARE-3.

The evaluation results of the RTE model are compared with the Support Vector Machine (SVM). The algorithm of SVM is described in the literature review section. The detailed parameters settings of SVM are selected based on the exhaustive way of searching over the specified range of the parameter values, i.e., the function of grid search cross-validation. The key hyperparameters in SVM are regularization parameter – C (0.1, 1, 100, 1000), epsilon (0.02,0.03,0.05,0.06,0.07,0.08,0.09,1,2,3,4) for the width of SVM epsilon-tube, and kernel coefficient – gamma (0.0001, 0.001, 0.005, 0.1, 1, 3, 5). The ultimate parameter set is defined based on the customized evaluation score matrix – mean squared error. This evaluation result is then passed to the cross-validation function, which performs 3-fold cross-validation and returns the MSE, RMSE, MAPE and R^2 scores for the SVM model.

Due to the randomness in data shuffle, 10 and 100 iterations in Figure 4.24 deviate from the rest of the runs. As the prediction goes to 1000-run and 10000-runs, the results are stabilized and repeatable. The model achieves the lowest MAPE of 25.57% and R^2 value of 0.82 at 1000-run of prediction. The NMSE and NRMSE are stabilized at the value of 0.01 and 0.08. The computational cost also plays a part in the model efficiency. Compared with the average result of 1000-run, the average iteration of 10,000-run has no significant improvement in accuracy and reliability, but it takes ten times longer computation time. Thus, 1000-run is suggested for the dataset size of a hundred-scale. The prediction process for GLARE-4 is the same as GLARE-2 and GLARE-3, and the evaluation results are compared with the analytical fatigue cycle in Table 4.3.

Model expandability is defined as whether the trained machine learning model can predict new GLARE layups' fatigue life that the model has not seen (or trained). GLARE-3-0°-90° and GLARE-3-0°-90°-90°-0° are selected as the objects and studied separately. The standard of the selection of the GLARE for the expandability study is based on the partial similarity in the layups of the training dataset. The individual MAPE, R^2 value, NMSE, and NRMSE for the study objects are compared with the

overall model performance obtained at the average results of 1000-run, as shown in Figure 4.25.

Figure 4.25 Expandability study of G3-0°-90°, G3-0°-90°-90°-0° and comparison of the MAPE, R^2 value, NMSE, and NRMSE with the overall model performance.

It is found that G3-0°-90°-90°-0° has the lowest MAPE value of 13.79%, while moderate R^2 and higher NMSE and NRMSE compared with the overall model performance. It indicates small bias and low variance for the model to expand to the prediction of G3-0°-90°-90°-0°. The reason for high NMSE and NRMSE may cause by the large base value from the outliers. Bias with the large base value can be magnified through NMSE and NRMSE. The expandability study of G3-0°-90° shows moderate MAPE, NMSE, and NRMSE but lower R^2 value, which indicates a high percentage of variance is unpredictable. The accuracy and reliability of the expandability object's

assessment depend to a large extent on the total number of samples, the dispersion of the cyclic loads, and the number of repeated tests for each fatigue load.

4.4.3 RTE Model features

In order to discover the most correlated feature and the corresponding effects on the fatigue life of GLARE specimens, the Pearson correlation coefficients between each input feature and the fatigue cycle were calculated and shown in the heatmap of Figure 4.26. Pearson correlation values range from -1 to 1. The higher the correlation between the parameter and the fatigue cycle, the higher the value, while 0 means no correlation. Warm colors (red, orange, light orange) indicate higher absolute Pearson correlations, while cool colors (dark blue, light blue) indicate lower absolute Pearson correlation values. The number of layers for aluminum and prepreg are transformed into categorical variables “0” or “1”. Thus, a total of 22 features are inputted to the model training.

Figure 4.26 Correlation study of the 13 features (with additional eight categorical features) to fatigue life (N_{al}) of GLARE-2 and GLARE-3 specimens by using the heatmap approach. Warm colors indicate a high absolute Pearson correlation between

features and fatigue cycles, while cool colors indicate a low absolute Pearson correlation.

The highest correlated feature to the fatigue cycle is the S_{Al} , which is the cyclic stress developed in the aluminum layer in the GLARE sample. The correlation coefficient of -0.76 shows a highly negative correlation between S_{Al} and N . Followed by S_{max} , S_{alt} , and S_m which are the cyclic fatigue loadings and show the same correlation coefficient of -0.7 with N due to the inter-relationship of $S_m = (S_{max} + S_{min})/2$ and $S_{alt} = (S_{max} - S_{min})/2$. The feature of density ρ shows a positive correlation of 0.38 with fatigue cycle N . The top three highest densities among the nine different layups are G2-Al-0°-Al (2113kg/m³), G2-Al-0°-Al(2084 kg/m³) and G3-Al-0°-Al-0°-Al (2045kg/m³). It implies that specimens with more prepreg layers, generally higher failure loads, and higher cyclic loading were applied during the fatigue tests, which do not reflect prolonged fatigue cycles. The feature n_0 and n_{90} transformed into categorical variables '0' or '1' shows GLARE layup with six layers of 0° prepreg (G3-Al-0°-Al-0°-Al) and six layers of 90° prepreg (G3-Al-90°-Al-90°-Al) is a negative correlate with fatigue life at -0.39 and -0.4. The rest of the features with $|\text{Pearson correlation}| < 0.3$ are kept in the model, considering the complementary information provided are not substitutable. The correlogram, which depicts the correlation statistics between each feature, is plotted at a Pearson correlation greater than 0.5 and shown in the appendix Figure A. 1. The equation for the Pearson correlation takes the form:

$$r_{xy} = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2} \sqrt{\sum_{i=1}^n (y_i - \bar{y})^2}} \quad (4.2)$$

Where n is the sample size; (x_i, y_i) are the sample points; $\bar{x}$ and $\bar{y}$ are the sample mean.

4.3.4 RTE model prediction based on analytical data

During the experimental tests among all the processes, there are unavoidable human errors, i.e., the fabrication of FML panel, waterjet cutting of specimens, material characterization, and fatigue tests. Difficulties arise when new materials are developed, and no standard benchmark test data is available for comparison. Possible ways to minimize human errors are:

1. Establishing standard protocols for the manufacture, preparation, and testing of the specimens.
2. Provide formal training for the related personnel who participates in the experiment process.
3. Build up the industrial quality control systems, e.g., six sigma methodology.
4. The nature of the human error, namely randomness, can also be described by a probability model.

However, at the preliminary stage of material design and fatigue life prediction, the theoretical analysis plays an important and dominant role. Once several material types are selected for batch sample testing, the procedures mentioned above can be adopted. But in this thesis, these procedures are not in the range of study.

In this part, the fatigue life of four types of GLARE-2 and GLARE-3 laminates are predicted using the One-stop model. The RTE model is trained based on the predicted data from the One-stop model. The data set of a total of 80 specimens is shown in Figure 4.27.

Figure 4.27 (a) One-stop model predicted the S-N plot for GLARE-2 and GLARE-3. (b) Logistic transformation of the GLARE 2 and GLARE 3 data to normalized data. Red-blue colors are assigned to the data bubbles according to the different fatigue life spans. In order to show the fatigue data more explicitly, the bubble size was adjusted based on the measured fatigue cycle.

Less number of analyzed data was shown in the S-N plot compared with the previous experimental data set. The reason is that the repeating tests were involved at the same fatigue loading during the tests, while not the analytical model. The predicted fatigue cycles versus the analyzed fatigue cycles were compared with the prediction accuracy, residual patterns. The corresponding residual plots were represented in four random results, as shown in Figure 4.28.

Figure 4.28 Comparison of four random groups of measured (One-stop analyzed data) fatigue cycles (y-axis) with the RTE model predicted fatigue cycles (x-axis) for GLARE-2 and GLARE-3.

More generalized patterns could be found in the analytical dataset. The analytical model could avoid outlier data and abnormal data, increasing model accuracy and reliability. The evaluated results based on the analytical data are compared with the experimental data in Figure 4.29.

Figure 4.29 Evaluation of MAPE, NMSE, NRMSE and R^2 for the RTE model at the average value of 10, 100,1000, and 10000 runs of prediction. The prediction results at 1000-run with MAPE: 18.34%, R^2 : 0.89, NMSE: 0.0039 and NRMSE: 0.0485.

The overall evaluation results for the RTE model's prediction based on the analyzed data outputted from the classical model are compared with the prediction using experimental data for GLARE-2, GLARE-3, and GLARE-4. The improvement for the RTE model using the analytical data is shown in Table 4.3. Due to the apparent

difference in thickness, GLARE-4 fatigue life is separately trained and predicted from GLARE-2 and GLARE-3.

Evaluation matrix	G2, G3	Improvement	G4	Improvement
MAPE	18.34%	-28.29%	17.87%	-59.59%
R ²	0.89	+8.12%	0.36	+25.41%
NMSE	0.0039	-42.74%	0.0203	+12.26%
NRMSE	0.0485	-54.45%	0.0997	-18.13%

Table 4.3 Comparison of the RTE model evaluation results on the One-stop analyzed data and the experimental data.

Prediction results based on the analyzed data largely reduced the MAPE and NRMSE values for all the GLARE layups. The model reliability also has been increased tremendously for GLARE-4. The reason behind the improvement in RTE model accuracy and reliability could be the elimination of outlier data, which is caused either by human errors or equipment errors. On the other hand, analytical data could not 100% represent the fatigue mechanism in the fiber-metal laminates. The analytical model itself carries a certain percentage of bias, so as the case for the machine learning RTE model. By comparing the RTE model towards the different sources of data, i.e., analytical data and experimental data, the range of the accuracy of the RTE model could be generally defined. The range of MAPE for GLARE-2 and GLARE-3 is [18.34%, 25.57%], and GLARE-4 is [17.87%, 44.23%]. The model's reliability range is [0.82, 0.89] and [0.22, 0.36] for GLARE-2, 3 and GLARE-4 respectively.

In summary, the proposed One-stop fatigue model could predict the fatigue life of various GLARE layups as the shell skin material of the S809 airfoil wind turbine blade. The predicted S-N curves are compared with the experimental value. The MAPE value has been achieved in the range of 28.1% to 40.25%. To validate the classical One-stop model and train the machine learning RTE model, a total of 128 samples were fabricated

and fatigue tested. Overall, the performance of the RTE model has achieved better prediction accuracy with the MAPE of 25.57%, the R^2 value of 0.82, the NMSE of 0.01, and the NRMSE of 0.08. The reliability of the RTE model in terms of the model's expandability is also studied. The new GLARE types are selected based on the partial similarity in the trained layups. It is found that the lowest MAPE value of 13.79%, while moderate R^2 and higher NMSE and NRMSE compared with the overall model performance. In order to exclude human errors in the experiments, analytical outputs from the One-stop model are fed into the RTE model, and the prediction accuracy and reliability are shown primarily improved.

Chapter 5. Conclusion

5.1 Summary of expert One-stop model

This study shows a novel One-stop methodology that establishes a direct relationship between the blade material's properties and its actual fatigue cycle. No similar model has been proposed for GLARE as the wind blade shell skin material. The prediction of blade fatigue life is essential for wind blade maintenance and cost reduction. It would further reduce the Levelised Cost of Electricity of the wind energy produced. The predicted fatigue life for GLARE specimens shows a good correlation with the data obtained from the experiments with evaluated accuracy of 67.98% and R^2 value of 0.84, which is considered an accurate prediction model in the same order of magnitude. Safety factors were applied to the S-N curve and Constant Life diagrams at the endurance limit. In order to avoid yield failure, the safe fatigue design area is obtained, and the minimum fatigue load ratio is 0.14 and 0.1 under the safety factors of 2.87 and 3.67, respectively. The most correlated factors found from the sensitivity study to affect fatigue life are the stress developed in the aluminum layer and the aluminum layer thickness. Young's modulus of the laminate and the number of prepreg layers show minor effects. This sensitivity study could be used as a reference guide for GLARE composites design optimization. This expert methodology could save a significant amount of time on fatigue tests on various material layups and combinations. It helps to improve the efficiency of the selection of the optimum material for structure application.

This One-stop model can help quickly predict the fatigue life of wind turbine blades and early fatigue detection from a single wind turbine to a large wind farm. It can significantly reduce the chance of wind turbine blade failure due to fatigue, thereby reducing maintenance costs. Thus, wind farms could provide a more stable and clean energy supply. Excess wind energy can even be stored through multiple energy storage

methods, which helps to gradually achieve energy self-sufficiency in energy importing countries and reduce dependence on fossil fuels. Furthermore, it can effectively reduce greenhouse gas emissions and work as a possible way to reverse the sea-level rise in the future, which will be a tremendous contribution to stable economic growth and continued global development.

This proposed One-stop model is applicable for constant chord and untwisted wind turbine blades with GLARE as the shell material under the average wind speed conditions.

Critical reflections of this study are listed as the following: Human errors are found can significantly affect the model's accuracy and reliability, which can be either reduced or quantified as a parameter in the prediction model. Due to the limitation of time and testing facility, finite specimens are fabricated for each material type. However, more characteristic information of the materials could produce a better-converged expert fatigue model. In addition, based on the experimentally measured density for the various kinds of GLARE, it can provide 24% to 30% of specific weight saving compared with aluminum 2024-T3 while much slower crack propagation rate, i.e., one to three times pronged fatigue life. Among all the GLARE types fabricated, it was found that G-3-0°-90° shows comparable fatigue life with Al 2024-T3 but 27.5% lower density. For G-2-0°₂ shows two times and G-2-0°₄ of three times prolonged fatigue lifespan compared with Al 2024-T3 but around 25% of lower density. Other than the wind blade shell skin, GLARE can also be used as other load-bearing components in the structures, e.g., wind turbine spar.

5.2 Summary of machine learning RTE model

The established grey box - regression tree ensembles (RTE) model predicts the fatigue life of GLARE from the machine learning approach. In comparison with experimental

data, the RTE model shows the overall good mean absolute accuracy at 74.43% and R^2 value of 0.82 for the total dataset of 98 GLARE specimens and nine layups by taking the average results of 1000-runs. A total of 13 features were selected as the input variables for the model training, among which the cyclic stress S_{Al} developed in the aluminum layer, cyclic fatigue loadings - S_{max} , S_{alt} , and S_m are found to be the most prominent features of the output fatigue cycle. The density of GLARE shows a positive correlation coefficient of 0.38, indicating that more prepreg layers do not contribute to prolong the fatigue life. This correlation study gives good advice for the material developers to enhance the fatigue life of FML by controlling the level of stress developed in the aluminum layers and limiting the maximum number of layups in the FML laminates. To study the model expandability, two GLARE layups - G3-0°-90° and G3-0°-90°-90°-0° were evaluated and compared with the overall model performance. Lowest bias (MAPE: 13.79%) and low variance (R^2 value:0.70) were discovered in G3-0°-90°-90°-0°. Prediction results of G3-0°-90° show moderate bias (MAPE:31.24%) but relatively high variance (R^2 value:0.47). Expandability studies showed that the machine learning RTE model's implementation results were encouraging, and provided a constructive method to predict fatigue life in the preliminary and design stages of new FML material development.

This RTE model is further enhanced with the One-stop expert model. In this model, the data set is obtained from the expert model, which excludes human errors in the experimental process. The expert model enhanced the RTE model shows that improvement in MAPE is 28.29% and 59.86% for GLARE-2, 3, and G4, respectively. Improvement in R^2 is 8.12% for GLARE-2 and GLARE-3, and 64.9% for GLARE-4.

5.3 Future work

For the continued development of the One-stop model, different material layups, and various designs of fatigue stress ratios could be conducted and validated with the experimental results. Thus, with the broad range of FML materials and increased

variabilities of the fatigue stress states, the expandability of the One-stop could be significantly improved. For the continuing study of the RTE model, this prediction model could be further developed in accuracy, reliability, and expandability by increasing the number of repetitive tests on the aspect of data set enhancement and reducing the dataset's noise, and adding more varieties in the GLARE layups. High-frequency fatigue testing could be used to tackle the experiment's time-consuming issues. More data in the same layup category can be useful for reducing the bias of certain features and getting more accurate weights for that feature. Bias caused by human error can also be reduced through established manufacturing protocols, i.e., six-sigma methodology, and quantified by probabilistic modeling. In terms of algorithm improvement, the predictive model can also be extended to various input features, for instance, providing feedback from timely on-site sensor signals from composite structures (such as aircraft, wind turbine blades, automobiles, etc.). The early crack growth and fatigue damage phenomena can be captured and correlated with the structures' fatigue life. The on-site, time-dependent features may reduce the operational downtime and prevent catastrophic failure of the composite structures.

For future research, the RTE model can be combined with deep learning neural networks. Large-scale fatigue data can be obtained and input the hybrid machine learning model to predict fatigue life more accurately from the material level and further advance the early fatigue damage detection and fatigue life prediction for composite structures. Generally, expert systems combined with interpretable and hierarchical machine learning algorithms may become increasingly common in laminate material design and development, field damage monitoring and detection, fatigue life prediction, and catastrophic failure control. In a broader context, with the advancement of automated composite material production, the application of laminated composite materials could gain status in various industries and provide high throughput material screening capabilities.

References

1. Solomon, S., et al., *Irreversible climate change due to carbon dioxide emissions*. Proceedings of the national academy of sciences, 2009. **106**(6): p. 1704-1709.
2. Marchal, V., et al., *OECD environmental outlook to 2050*. Organization for Economic Co-operation and Development, 2011. **8**: p. 397-413.
3. Commission, E., *Communication from the commission to the European parliament, the European Council, the Council, the European economic and social committee, the committee of the regions and the European investment bank*. A Clean Planet for all. A European strategic long-term vision for a prosperous, modern, competitive and climate neutral economy. Brussels, 2018. **28**: p. 2018.
4. *Sustainable Energy for All*, at <<https://www.seforall.org/>>, in *Regulatory Indicators for Sustainable Energy (RISE)* 2018.
5. *Renewable Energy Statistics 2018*, I.R.E.A. (IRENA), Editor. 2018.
6. Mathis, W., *Utility Company Wants Turbines Bigger Than Jumbo Jets for U.S. Wind Farm*, in *Bloomberg*. December 9, 2019: Markets.
7. Johnson, N., et al., *Investigation of Innovative Rotor Concepts for the Big Adaptive Rotor Project*. 2019, National Renewable Energy Lab.(NREL), Golden, CO (United States).
8. Thomsen, O.T., *Sandwich materials for wind turbine blades—present and future*. Journal of Sandwich Structures & Materials, 2009. **11**(1): p. 7-26.
9. Kellner, T., *Extreme Measures: At 107 Meters, The World's Largest Wind Turbine Blade Is Longer Than A Football Field. Here's What It Looks Like*, in *GE Renewables*. Apr 18, 2019
10. Brown, T., *GE's Largest Onshore Wind Turbine Prototype Installed and Operating in the Netherlands*, in *GE Report*. Mar 13, 2019.

11. *Wind turbine accident and incident compliation*. 2019: Caithness Windfarm Information Forum 2019.
12. Hahn, B., M. Durstewitz, and K. Rohrig. *Reliability of wind turbines, experiences of 15 years with 1,500 WTs*, in *'Wind Energy. in Proceedings of the Euromech Colloquium*. 2007. Springer-Verlag Berlin Heidelberg.
13. Kong, C., et al., *Investigation of fatigue life for a medium scale composite wind turbine blade*. International Journal of Fatigue, 2006. **28**(10): p. 1382-1388.
14. Spera, D.A., *Wind turbine technology: fundamental concepts of wind turbine engineering*. Vol. 3. 1994: ASME press New York.
15. Marin, J., et al., *Study of damage and repair of blades of a 300 kW wind turbine*. Energy, 2008. **33**(7): p. 1068-1083.
16. De Smet, B. and P.W. Bach, *Database FACT: Fatigue of composites for wind turbines*. 1994: Netherlands Energy Research Foundation ECN.
17. Kensche, C.W. and S. Andersen, *Fatigue of materials and components for wind turbine rotor blades*. 1996: Office for Official Publ. of the Europ. Communities.
18. Mandell, J.F. and D.D. Samborsky, *DOE/MSU composite material fatigue database: test methods, materials, and analysis*. 1997: Sandia National Laboratories Albuquerque.
19. Mandell, J.F., et al., *New fatigue data for wind turbine blade materials*. J. Sol. Energy Eng., 2003. **125**(4): p. 506-514.
20. Keegan, M.H., D. Nash, and M. Stack, *On erosion issues associated with the leading edge of wind turbine blades*. Journal of Physics D: Applied Physics, 2013. **46**(38): p. 383001.
21. Powell, S., *3M wind blade protection coating W4600*. Industrial Marketing Presentation, 2011.
22. Hau, E., *Wind Turbines Fundamentals, Technologies, Application, Economics*. 2013: Springer.
23. Brøndsted, P. and R.P. Nijssen, *Advances in wind turbine blade design and materials*. 2013: Elsevier.

24. Mayer, R.M., *Design of composite structures against fatigue: applications to wind turbine blades*. 1996: MEP.
25. Mandell, J.F., R.M. Reed, and D.D. Samborsky, *Fatigue of fiberglass wind turbine blade materials*. 1992: Sandia National Laboratories Contractor Report SAND92-7005. Albuquerque, NM.
26. Kong, C., J. Bang, and Y. Sugiyama, *Structural investigation of composite wind turbine blade considering various load cases and fatigue life*. Energy, 2005. **30**(11-12): p. 2101-2114.
27. Loza, B., et al., *Comparative Fatigue Life Assessment of Wind Turbine Blades Operating with Different Regulation Schemes*. Applied Sciences, 2019. **9**(21): p. 4632.
28. Kulkarni, P.A., et al., *Statistical wind prediction and fatigue analysis for horizontal-axis wind turbine composite material blade under dynamic loads*. Advances in Mechanical Engineering, 2017. **9**(9): p. 1687814017724088.
29. Veers, P., *Fatigue loading of wind turbines*, in *Wind Energy Systems*. 2011, Elsevier. p. 130-158.
30. Lankford, J., *The growth of small fatigue cracks in 7075-T6 aluminum*. Fatigue & Fracture of Engineering Materials & Structures, 1982. **5**(3): p. 233-248.
31. Chai, G.B. and P. Manikandan, *Low velocity impact response of fibre-metal laminates—A review*. Composite Structures, 2014. **107**: p. 363-381.
32. Chang, P.-Y., P.-C. Yeh, and J.-M. Yang, *Fatigue crack initiation in hybrid boron/glass/aluminum fiber metal laminates*. Materials Science and Engineering: A, 2008. **496**(1-2): p. 273-280.
33. Takamatsu, T., et al., *Fatigue crack growth properties of a GLARE3-5/4 fiber/metal laminate*. Engineering Fracture Mechanics, 1999. **63**(3): p. 253-272.
34. Roebroeks, G., *Fibre-metal laminates: recent developments and applications*. International journal of fatigue, 1994. **16**(1): p. 33-42.

35. Ishak, N.M., S.D. Malingam, and M.R. Mansor, *Selection of natural fibre reinforced composites using fuzzy VIKOR for car front hood*. International Journal of Materials and Product Technology, 2016. **53**(3-4): p. 267-285.
36. Sadighi, M., R. Alderliesten, and R. Benedictus, *Impact resistance of fiber-metal laminates: A review*. International Journal of Impact Engineering, 2012. **49**: p. 77-90.
37. Apmann, H., et al., *Automated manufacture of fibre metal laminates to achieve high rate of production*. Lightweight Design worldwide, 2017. **10**(4): p. 28-33.
38. Sherkatghanad, E., et al., *Innovative approach to mass production of fiber metal laminate sheets*. Materials and Manufacturing Processes, 2018. **33**(5): p. 552-563.
39. Apmann, H., *Automated FML manufacturing for aircraft fuselages*. SAE International Journal of Aerospace, 2016. **9**(2016-01-2112): p. 214-216.
40. Black, S., *Fiber-metal laminates in the spotlight*, in *CompositesWorld*. 2017.
41. Muflikhun, M.A., T. Yokozeki, and T. Aoki, *The strain performance of thin CFRP-SPCC hybrid laminates for automobile structures*. Composite Structures, 2019. **220**: p. 11-18.
42. Jang, Y.J., et al., *Development of fatigue life prediction method and effect of 10-minute mean wind speed distribution on fatigue life of small wind turbine composite blade*. Renewable energy, 2015. **79**: p. 187-198.
43. Ghasemi, A.R. and M. Mohandes, *Free vibration analysis of rotating fiber-metal laminate circular cylindrical shells*. Journal of Sandwich Structures & Materials, 2019. **21**(3): p. 1009-1031.
44. Fatt, M.S.H., et al., *Ballistic impact of GLARE™ fiber-metal laminates*. Composite structures, 2003. **61**(1-2): p. 73-88.
45. Chang, P.-Y. and J.-M. Yang, *Modeling of fatigue crack growth in notched fiber metal laminates*. International Journal of Fatigue, 2008. **30**(12): p. 2165-2174.
46. Homan, J.J., *Fatigue initiation in fibre metal laminates*. International Journal of Fatigue, 2006. **28**(4): p. 366-374.

47. Marisen, R., *Fatigue crack growth in ARALL, a hybrid aluminium-aramid composite material: Crack growth mechanisms and quantitative predictions of the crack growth rates*, PhD Thesis. 1990, Delft University of Technology.
48. Guo, Y. and X. Wu, *A theoretical model for predicting fatigue crack growth rates in fibre-reinforced metal laminates*. Fatigue & Fracture of Engineering Materials & Structures, 1998. **21**(9): p. 1133-1145.
49. Guo, Y.-J. and X.-R. Wu, *Bridging stress distribution in center-cracked fiber reinforced metal laminates: modeling and experiment*. Engineering Fracture Mechanics, 1999. **63**(2): p. 147-163.
50. Guo, Y.-J. and X.-R. Wu, *A phenomenological model for predicting crack growth in fiber-reinforced metal laminates under constant-amplitude loading*. Composites Science and Technology, 1999. **59**(12): p. 1825-1831.
51. Alderliesten, R. and J. Homan, *Fatigue and damage tolerance issues of Glare in aircraft structures*. International Journal of Fatigue, 2006. **28**(10): p. 1116-1123.
52. Alderliesten, R., *Analytical prediction model for fatigue crack propagation and delamination growth in Glare*. International Journal of Fatigue, 2007. **29**(4): p. 628-646.
53. Alderliesten, R., et al., *Fatigue and damage tolerance of glare*. Applied Composite Materials, 2003. **10**(4): p. 223-242.
54. Alderliesten, R.C., *Fatigue crack propagation and delamination growth in Glare*. 2005.
55. Wang, W., C. Rans, and R. Benedictus, *Analytical prediction model for non-symmetric fatigue crack growth in Fibre Metal Laminates*. International Journal of Fatigue, 2017. **103**: p. 546-556.
56. Wu, G. and J.-M. Yang, *Analytical modelling and numerical simulation of the nonlinear deformation of hybrid fibre-metal laminates*. Modelling and Simulation in Materials Science and Engineering, 2005. **13**(3): p. 413.

57. Sai, W. and G.B. Chai. *Fatigue in Fiber-Metal Laminates for Small Wind Turbine Blades Application*. in *MATEC Web of Conferences*. May 2018. Poitiers, France: EDP Sciences.
58. Tada, H., et al., *The stress analysis of cracks handbook*. Vol. 130. 2000: ASME press New York.
59. Mitchell, R., J. Michalski, and T. Carbonell, *An artificial intelligence approach*. 2013: Springer.
60. Jordan, M.I. and T.M. Mitchell, *Machine learning: Trends, perspectives, and prospects*. Science, 2015. **349**(6245): p. 255-260.
61. Liu, H., et al. *Prognostics of damage growth in composite materials using machine learning techniques*. in *2017 IEEE International Conference on Industrial Technology (ICIT)*. 2017. IEEE.
62. Li, J., et al., *Fiberglass-reinforced polyester composites fatigue prediction using novel data-intelligence model*. Arabian Journal for Science and Engineering, 2019. **44**(4): p. 3343-3356.
63. Loutas, T., N. Eleftheroglou, and D. Zarouchas, *A data-driven probabilistic framework towards the in-situ prognostics of fatigue life of composites based on acoustic emission data*. Composite Structures, 2017. **161**: p. 522-529.
64. Al-Assaf, Y. and H. El Kadi, *Fatigue life prediction of unidirectional glass fiber/epoxy composite laminae using neural networks*. Composite Structures, 2001. **53**(1): p. 65-71.
65. Dervilis, N., et al. *Machine learning applications for a wind turbine blade under continuous fatigue loading*. in *Key Engineering Materials*. March 2014. Bali,Indonesia: Trans Tech Publ.
66. Younis, H.B., et al. *Prediction of fatigue crack growth rate in aircraft aluminum alloys using radial basis function neural network*. in *2018 Tenth International Conference on Advanced Computational Intelligence (ICACI)*. March 2018. Xiamen, China: IEEE.

67. Roy, S., et al., *A novel machine-learning approach for structural state identification using ultrasonic guided waves*. Safety, Reliability, Risk and Life-Cycle Performance of Structures and Infrastructures; CRC Press: Boca Raton, FL, USA, 2013: p. 321-328.
68. Neerukatti, R.K., et al., *Fatigue life prediction using hybrid prognosis for structural health monitoring*. Journal of Aerospace Information Systems, 2014. **11**(4): p. 211-232.
69. Yang, J., et al., *A stiffness degradation model for graphite/epoxy laminates*. Journal of Composite materials, 1990. **24**(7): p. 753-769.
70. Loutas, T.H., et al., *Intelligent health monitoring of aerospace composite structures based on dynamic strain measurements*. Expert Systems with Applications, 2012. **39**(9): p. 8412-8422.
71. Wang, H., et al., *A comparison study of machine learning based algorithms for fatigue crack growth calculation*. Materials, 2017. **10**(5): p. 543.
72. Chakraborty, D., *Artificial neural network based delamination prediction in laminated composites*. Materials & Design, 2005. **26**(1): p. 1-7.
73. Vassilopoulos, A.P., E.F. Georgopoulos, and V. Dionysopoulos, *Artificial neural networks in spectrum fatigue life prediction of composite materials*. International Journal of Fatigue, 2007. **29**(1): p. 20-29.
74. Montavon, G., W. Samek, and K.-R. Müller, *Methods for interpreting and understanding deep neural networks*. Digital Signal Processing, 2018. **73**: p. 1-15.
75. Ghorbani, A., A. Abid, and J. Zou. *Interpretation of neural networks is fragile*. in *Proceedings of the AAAI Conference on Artificial Intelligence*. 2019.
76. Noh, H., et al. *Regularizing deep neural networks by noise: Its interpretation and optimization*. in *Advances in Neural Information Processing Systems*. 2017.
77. Chen, T. and C. Guestrin. *Xgboost: A scalable tree boosting system*. in *Proceedings of the 22nd acm sigkdd international conference on knowledge discovery and data mining*. 2016. ACM.

78. Chen, T., et al., *Xgboost: extreme gradient boosting*. R package version 0.4-2, 2015: p. 1-4.
79. Nielsen, D., *Tree Boosting With XGBoost-Why Does XGBoost Win" Every" Machine Learning Competition?* 2016, Norwegian University of Science and Technology.
80. Sheridan, R.P., et al., *Extreme gradient boosting as a method for quantitative structure–activity relationships*. Journal of Chemical Information and Modeling, 2016. **56**(12): p. 2353-2360.
81. Zhang, D., et al., *A data-driven design for fault detection of wind turbines using random forests and XGboost*. IEEE Access, 2018. **6**: p. 21020-21031.
82. Choi, D.-K., *Data-Driven Materials Modeling with XGBoost Algorithm and Statistical Inference Analysis for Prediction of Fatigue Strength of Steels*. International Journal of Precision Engineering and Manufacturing, 2019. **20**(1): p. 129-138.
83. Song, K., et al., *A steel property optimization model based on the XGBoost algorithm and improved PSO*. Computational Materials Science, 2020. **174**: p. 109472.
84. Schijve, J., *Fatigue of aircraft materials and structures*. International Journal of Fatigue, 1994. **16**(1): p. 21-32.
85. Sunder, R. and B. Ilchenko, *Fatigue crack growth under flight spectrum loading with superposed biaxial loading due to fuselage cabin pressure*. International Journal of Fatigue, 2011. **33**(8): p. 1101-1110.
86. Schijve, J., *Fatigue of structures and materials*. 2001: Springer Science & Business Media.
87. Al-Mukhtar, A. *Case Studies of Aircraft Fuselage Cracking*. in *Advanced Engineering Forum*. 2019. Trans Tech Publ.
88. Shohag, M.A.S., et al., *Damage mitigation techniques in wind turbine blades: A review*. Wind Engineering, 2017. **41**(3): p. 185-210.

89. Schijve, J. and F. Jacobs, *Fatigue Crack Propagation in Unnotched and Notched Aluminum Alloy Specimens*. NLR-TR M. 2128, Nat. Aero-Astronaut. Res. Inst.(Amsterdam), 1964.
90. Lin, X. and R. Smith, *Fatigue shape analysis for corner cracks at fastener holes*. Engineering Fracture Mechanics, 1998. **59**(1): p. 73-87.
91. Fawaz, S. and B. Andersson, *Accurate stress intensity factor solutions for corner cracks at a hole*. Engineering Fracture Mechanics, 2004. **71**(9-10): p. 1235-1254.
92. Grosskreutz, J. *Critical mechanisms in the development of fatigue cracks in 2024-T4 aluminum*. in *ICF2, Brighton (UK) 1969*. 1969.
93. Pearson, S., *Initiation of fatigue cracks in commercial aluminium alloys and the subsequent propagation of very short cracks*. Engineering Fracture Mechanics, 1975. **7**(2): p. 235-247.
94. Khan, S., O. Kintzel, and J. Mosler, *Experimental and numerical lifetime assessment of Al 2024 sheet*. International Journal of Fatigue, 2012. **37**: p. 112-122.
95. Alderliesten, R.C., *Fatigue crack propagation and delamination growth in Glare*. 2005.
96. Huang, Y., et al., *Delamination and fatigue crack growth behavior in Fiber Metal Laminates (Glare) under single overloads*. International Journal of Fatigue, 2015. **78**: p. 53-60.
97. Khan, S., R. Alderliesten, and R. Benedictus, *Delamination in Fiber Metal Laminates (GLARE) during fatigue crack growth under variable amplitude loading*. International Journal of Fatigue, 2011. **33**(9): p. 1292-1303.
98. Cortes, P. and W. Cantwell, *The tensile and fatigue properties of carbon fiber-reinforced PEEK-titanium fiber-metal laminates*. Journal of Reinforced Plastics and Composites, 2004. **23**(15): p. 1615-1623.

99. Botelho, E., L. Pardini, and M. Rezende, *Evaluation of hygrothermal effects on the shear properties of Carall composites*. Materials Science and Engineering: A, 2007. **452**: p. 292-301.
100. Browning, C., G. Husman, and J. Whitney. *Moisture effects in epoxy matrix composites*. in *Composite Materials: Testing and Design (Fourth Conference)*. 1977. ASTM International.
101. Da Silva, D., E.C. Botelho, and M. Rezende, *Hygrothermal aging effect on fatigue behavior of GLARE*. Journal of Reinforced Plastics and Composites, 2009. **28**(20): p. 2487-2499.
102. Hu, Y., et al., *The effects of temperature variation on mechanical behaviors of polyetheretherketone-based fiber metal laminates*. Polymer Composites, 2018. **39**(5): p. 1447-1454.
103. Lee, Y.-L. and H.-T. Kang, *Vibration Fatigue Testing and Analysis*. Metal Fatigue Analysis Handbook: Practical Problem-Solving Techniques for Computer-Aided Engineering, 2011: p. 333-382.
104. Wahl, N.K., *Spectrum fatigue lifetime and residual strength for fiberglass laminates*. 2001, Montana State University-Bozeman, College of Engineering.
105. Nussen, R. and D. Van Delft, *Alternative fatigue formulations for variable amplitude loading of fibre composites for wind turbine rotor blades*, in *European Structural Integrity Society*. 2003, Elsevier. p. 563-574.
106. Barradas-Berglind, J. and R. Wisniewski, *Representation of fatigue for wind turbine control*. Wind Energy, 2016. **19**(12): p. 2189-2203.
107. Wu, G. and J.-M. Yang, *The mechanical behavior of GLARE laminates for aircraft structures*. JOM Journal of the Minerals, Metals and Materials Society, 2005. **57**(1): p. 72-79.
108. Vlot, A. and J.W. Gunnink, *Fibre metal laminates: an introduction*. 2011: Springer Science & Business Media.
109. Parker, G., *Encyclopedia of materials: science and technology*. 2001.

110. Ambriz, R.R. and D. Jaramillo, *Mechanical behavior of precipitation hardened aluminum alloys welds*. Light Metal Alloys Applications, 2014: p. 35-59.
111. Alderliesten, R., *Fatigue Crack Propagation and Delamination Growth in Glare, PhD Thesis*. 2005, Delft University of Technology.
112. Westergaard, H.M., *Bearing pressures and cracks*. Trans AIME, J. Appl. Mech., 1939. **6**: p. 49-53.
113. Daniewicz, S., J. Collins, and D. Houser, *An elastic-plastic analytical model for predicting fatigue crack growth in arbitrary edge-cracked two-dimensional geometries with residual stress*. International Journal of Fatigue, 1994. **16**(2): p. 123-133.
114. Heaton, M., *On the calculation of stress intensity factors due to thermal and residual stress fields*. CEGB Research Report NW/SSD/RR/158, 1976.
115. CHANG, P.Y., P.C. YEH, and J.M. YANG, *Fatigue crack growth in fibre metal laminates with multiple open holes*. Fatigue & Fracture of Engineering Materials & Structures, 2012. **35**(2): p. 93-107.
116. Wu, X. and A. Carlsson, *Weight Functions and Stress Intensity Factor Solutions, 1991*. Pergamon Press, Oxford, UK.
117. Wang, W., et al., *Predicting the influence of discretely notched layers on fatigue crack growth in fibre metal laminates*. Engineering Fracture Mechanics, 2015. **145**: p. 1-14.
118. Stoll, M.M. and K.A. Weidenmann, *Fatigue of fiber-metal-laminates with aluminum core, CFRP face sheets and elastomer interlayers (FMEL)*. International Journal of Fatigue, 2018. **107**: p. 110-118.
119. Ogin, S., P. Smith, and P. Beaumont, *Matrix cracking and stiffness reduction during the fatigue of a (0/90) s GFRP laminate*. Composites Science and Technology, 1985. **22**(1): p. 23-31.
120. Lee, J., D. Almond, and B. Harris, *The use of neural networks for the prediction of fatigue lives of composite materials*. Composites Part A: Applied Science and Manufacturing, 1999. **30**(10): p. 1159-1169.

121. Yu, W., et al., *Towards statistical modeling and machine learning based energy usage forecasting in smart grid*. ACM SIGAPP Applied Computing Review, 2015. **15**(1): p. 6-16.
122. Buczak, A.L. and E. Guven, *A survey of data mining and machine learning methods for cyber security intrusion detection*. IEEE Communications Surveys & Tutorials, 2015. **18**(2): p. 1153-1176.
123. Farrar, C.R. and K. Worden, *Structural Health Monitoring.: A Machine Learning Perspective*. 2012: John Wiley & Sons.
124. Zheng, H., J. Yuan, and L. Chen, *Short-term load forecasting using EMD-LSTM neural networks with a Xgboost algorithm for feature importance evaluation*. Energies, 2017. **10**(8): p. 1168.
125. Stulp, F. and O. Sigaud, *Many regression algorithms, one unified model: A review*. Neural Networks, 2015. **69**: p. 60-79.
126. Raccuglia, P., et al., *Machine-learning-assisted materials discovery using failed experiments*. Nature, 2016. **533**(7601): p. 73.
127. Perera, K.S., Z. Aung, and W.L. Woon. *Machine learning techniques for supporting renewable energy generation and integration: a survey*. in *International Workshop on Data Analytics for Renewable Energy Integration*. 2014. Springer.
128. Peters, J., *Machine learning for motor skills in robotics*. KI-Künstliche Intelligenz, 2008. **2008**(4): p. 41-43.
129. Libbrecht, M.W. and W.S. Noble, *Machine learning applications in genetics and genomics*. Nature Reviews Genetics, 2015. **16**(6): p. 321.
130. Kourou, K., et al., *Machine learning applications in cancer prognosis and prediction*. Computational and structural biotechnology journal, 2015. **13**: p. 8-17.
131. Mitchell, T.M., *The discipline of machine learning*. Vol. 9. 2006: Carnegie Mellon University, School of Computer Science, Machine Learning

132. Mohammed, M., M.B. Khan, and E.B.M. Bashier, *Machine learning: algorithms and applications*. 2016: Crc Press.
133. Marsland, S., *Machine learning: an algorithmic perspective*. 2015: CRC press.
134. Zhou, Z.-H., *Ensemble methods: foundations and algorithms*. 2012: CRC press.
135. Zhu, X. and A.B. Goldberg, *Introduction to semi-supervised learning*. Synthesis lectures on artificial intelligence and machine learning, 2009. **3**(1): p. 1-130.
136. Sugiyama, M., *Statistical reinforcement learning: modern machine learning approaches*. 2015: CRC Press.
137. Drucker, H., et al. *Support vector regression machines*. in *Advances in neural information processing systems*. 1997.
138. Burges, C.J., *A tutorial on support vector machines for pattern recognition*. Data mining and knowledge discovery, 1998. **2**(2): p. 121-167.
139. Cherkassky, V. and Y. Ma, *Practical selection of SVM parameters and noise estimation for SVM regression*. Neural networks, 2004. **17**(1): p. 113-126.
140. Weston, J., et al., *Support vector density estimation*. Advances in Kernel Methods—Support Vector Learning, 1999: p. 293-306.
141. Kleynhans, T., et al., *Predicting top-of-atmosphere thermal radiance using merra-2 atmospheric data with deep learning*. Remote Sensing, 2017. **9**(11): p. 1133.
142. Nair, A., C. Cai, and X. Kong, *Studying Failure Modes of GFRP Laminate Coupons Using AE Pattern-Recognition Method*. Journal of Aerospace Engineering, 2019. **32**(4): p. 04019031.
143. Davies, D.L. and D.W. Bouldin, *A cluster separation measure*. IEEE transactions on pattern analysis and machine intelligence, 1979(2): p. 224-227.
144. Widodo, A., et al., *Fault diagnosis of low speed bearing based on relevance vector machine and support vector machine*. Expert systems with applications, 2009. **36**(3): p. 7252-7261.
145. Tzikas, D.G., et al., *A tutorial on relevance vector machines for regression and classification with applications*. EURASIP News Letter, 2006. **17**(2): p. 4.

146. MacKay, D.J., *The evidence framework applied to classification networks*. Neural computation, 1992. **4**(5): p. 720-736.
147. Breiman, L. and R. Ihaka, *Nonlinear discriminant analysis via scaling and ACE*. 1984: Department of Statistics, University of California.
148. Marani, R., et al., *Modeling and classification of defects in CFRP laminates by thermal non-destructive testing*. Composites Part B: Engineering, 2018. **135**: p. 129-141.
149. Li, D.Z., W. Wang, and F. Ismail, *A regulated boosting technique for material fatigue property prognostics*. Engineering Applications of Artificial Intelligence, 2017. **57**: p. 153-159.
150. Huang, G.-B., Q.-Y. Zhu, and C.-K. Siew, *Extreme learning machine: theory and applications*. Neurocomputing, 2006. **70**(1-3): p. 489-501.
151. Simas Filho, E.F., et al., *Decision support system for ultrasound inspection of fiber metal laminates using statistical signal processing and neural networks*. Ultrasonics, 2013. **53**(6): p. 1104-1111.
152. MOAWAD, A., *Neural networks and back-propagation explained in a simple way*, in *Medium*. 2018.
153. Diniz, P.S., E.A. Da Silva, and S.L. Netto, *Digital signal processing: system analysis and design*. 2010: Cambridge University Press.
154. Jolliffe, I.T. and J. Cadima, *Principal component analysis: a review and recent developments*. Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences, 2016. **374**(2065): p. 20150202.
155. Hyvärinen, A. and E. Oja, *Independent component analysis: algorithms and applications*. Neural networks, 2000. **13**(4-5): p. 411-430.
156. Artymiak, P., et al., *Determination of S-N curves with the application of artificial neural networks*. Fatigue & Fracture of Engineering Materials & Structures, 1999. **22**(8): p. 723-728.

157. Choi, S.W., E.-J. Song, and H.T. Hahn, *Prediction of fatigue damage growth in notched composite laminates using an artificial neural network*. Composites Science and technology, 2003. **63**(5): p. 661-675.
158. Commission, I.E., *IEC 61400–2: Wind turbines—part 2: small wind turbines*. 2013, IEC, Geneva.
159. Manwell, J.F., J.G. McGowan, and A.L. Rogers, *Wind energy explained: theory, design and application*. 2010: John Wiley & Sons.
160. Butterfield, C., W. Musial, and D. Simms, *Combined experiment phase I. Final report*. 1992, National Renewable Energy Lab., Golden, CO (United States).
161. Megson, T.H.G., *Aircraft structures for engineering students*. 2013: Elsevier.
162. Ritchie, R.O. and M.E. Launey, *Crack Growth in Brittle and Ductile Solids*, in *Encyclopedia of Tribology*, Q.J. Wang and Y.-W. Chung, Editors. 2013, Springer US: Boston, MA. p. 596-605.
163. Paris, P.C. and F. Erdogan. *A critical analysis of crack propagation laws*. 1963. ASME.
164. Newman Jr, J., *A crack opening stress equation for fatigue crack growth*. International Journal of Fracture, 1984.
165. Marisen, R., *Fatigue crack growth in ARALL, a hybrid aluminium-aramid composite material: Crack growth mechanisms and quantitative predictions of the crack growth rates*. 1990.
166. Sai, W., G.B. Chai, and N. Srikanth, *Fatigue Life Prediction of GLARE Composites Using Regression Tree Ensemble-Based Machine Learning Model*. Advanced Theory and Simulations, 2020. **3**(6): p. 2000048.
167. Bishop, C.M., *Pattern recognition and machine learning*. 2006: Springer.
168. Kearns, M., *Thoughts on hypothesis boosting*. Unpublished manuscript, 1988. **45**: p. 105.
169. Zhou, Z.-H., *Ensemble learning*, *Encyclopedia of Biometrics*. 2009, Springer Berlin.

170. Greenwald, M. and S. Khanna, *Space-efficient online computation of quantile summaries*. ACM SIGMOD Record, 2001. **30**(2): p. 58-66.
171. Zhang, Q. and W. Wang. *A fast algorithm for approximate quantiles in high speed data streams*. in *19th International Conference on Scientific and Statistical Database Management (SSDBM 2007)*. 2007. IEEE.
172. Kullback, S. and R.A. Leibler, *On information and sufficiency*. The annals of mathematical statistics, 1951. **22**(1): p. 79-86.
173. Palmer, P.B. and D.G. O'Connell, *Regression analysis for prediction: understanding the process*. Cardiopulmonary physical therapy journal, 2009. **20**(3): p. 23.
174. Basquin, O. *The exponential law of endurance tests*. in *Proc Am Soc Test Mater*. 1910.
175. Gwet, K.L., *Handbook of inter-rater reliability: The definitive guide to measuring the extent of agreement among raters*. 2014: Advanced Analytics, LLC.
176. Materials, A.C.D.-o.C., *Standard test method for tensile properties of polymer matrix composite materials*. 2008: ASTM International.
177. Poodts, E., et al., *Experimental characterization of a fiber metal laminate for underwater applications*. Composite Structures, 2015. **129**: p. 36-46.
178. Botelho, E., L. Pardini, and M. Rezende, *Hygrothermal effects on damping behavior of metal/glass fiber/epoxy hybrid composites*. Materials Science and Engineering: A, 2005. **399**(1-2): p. 190-198.
179. Synced, *Tree Boosting With XGBoost — Why Does XGBoost Win “Every” Machine Learning Competition?*, in *Synced AI TECHNOLOGY & INDUSTRY REVIEW*. 2017.

Appendix A. Correlograms

Figure A. 1 Correlogram for the features of G-2 and G-3 with the Pearson correlation value greater than 0.5.

Figure A. 2 Correlogram for the features of G-4 with the Pearson correlation value greater than 0.5.

Appendix B. Heatmap

Figure B. 1 Heatmap for GLARE-4 specimens.

Appendix C. Fatigue Tests

Sample	UTS(MPa)	Failure L(N)	(μm)	Density	E(MPa)	Yield(MPa)	MaxCyclic	AlterStres	MeanStres	Stress_al(N	N_al	Layers	Layers	Layers	Layers	
P2-G2A-6	223	9042	1605	2114	40620	175	134	64	70	216	54076	54076	2	2	0	2
P2-G2A-9	223	9042	1605	2114	40620	175	123	58	64	201	143186	143186	2	2	0	2
P2-G2A-8	223	9042	1605	2114	40620	175	112	53	59	184	119770	119770	2	2	0	2
P2-G2A-7	223	9042	1605	2114	40620	175	100	48	53	167	157073	157073	2	2	0	2
P7-G2A-5	381	15012	1569	2117	39850	223	259	123	136	391	32445	32445	2	2	0	2
P7-G2A-7	381	15012	1569	2117	39850	223	222	106	117	339	12186	12186	2	2	0	2
P7-G2A-6	381	15012	1569	2117	39850	223	204	97	107	314	14872	14872	2	2	0	2
P7-G2A-9	381	15012	1569	2117	39850	223	167	79	87	262	59341	57348	2	2	0	2
P7-G2A-3	381	15012	1569	2117	39850	223	156	74	82	246	108937	98000	2	2	0	2
P16-G2A-	394	14907	1574	2110	50600	197	167	79	87	262	68550	63888	2	2	0	2
P16-G2A-	394	14907	1574	2110	50600	197	156	74	82	246	97036	96153	2	2	0	2
P16-G2A-	394	14907	1574	2110	50600	197	134	64	70	215	260698	159677	2	2	0	2
P16-G2A-	394	14907	1574	2110	50600	197	134	64	70	215	163380	157692	2	2	0	2
P8-G2-7	545	24233	1831	2101	50252	236	251	119	132	400	67938	11296	2	4	0	2
P8-G2-6	545	24233	1831	2101	50252	236	237	113	125	380	158080	10648	2	4	0	2
P8-G2-5	545	24233	1831	2101	50252	236	224	107	118	362	97381	13684	2	4	0	2
P8-G2-8	545	24233	1831	2101	50252	236	224	107	118	362	86098	12500	2	4	0	2
P8-G2-9	545	24233	1831	2101	50252	236	224	107	118	362	148871	12698	2	4	0	2
P8-G2-4	545	24233	1831	2101	50252	236	211	100	111	343	199041	14666	2	4	0	2
P8-G2-2	545	24233	1831	2101	50252	236	158	75	83	268	523917	78723	2	4	0	2
P10-G2-2	498	23801	1863	2085	49820	234	254	121	133	404	45481	13298	2	4	0	2
P10-G2-3	498	23801	1863	2085	49820	234	242	115	127	387	40468	13444	2	4	0	2
P10-G2-5	498	23801	1863	2085	49820	234	203	97	107	332	1125208	84800	2	4	0	2
P10-G2-9	498	23801	1863	2085	49820	234	150	71	79	257	NaN	118909	2	4	0	2
P10-G2-8	498	23801	1863	2085	49820	234	140	67	74	242	NaN	138554	2	4	0	2
P10-G2-7	498	23801	1863	2085	49820	234	120	57	63	214	NaN	270238	2	4	0	2
P18-G2-2	481	21622	1866	2068	50947	219	250	119	131	399	108838	16666	2	4	0	2
P18-G2-3	481	21622	1866	2068	50947	219	250	119	131	399	NaN	17545	2	4	0	2
P18-G2-4	481	21622	1866	2068	50947	219	250	119	131	399	90935	19897	2	4	0	2
P18-G2-6	481	21622	1866	2068	50947	219	245	116	129	392	67134	20178	2	4	0	2
P18-G2-14	481	21622	1866	2068	50947	219	235	112	123	377	117131	21153	2	4	0	2
P18-G2-15	481	21622	1866	2068	50947	219	235	112	123	377	36206	24489	2	4	0	2
P18-G2-16	481	21622	1866	2068	50947	219	235	112	123	377	412801	23076	2	4	0	2
P18-G2-17	481	21622	1866	2068	50947	219	235	112	123	377	320145	27857	2	4	0	2
P11-G2-2	371	18309	2017	1893	43250	223	200	95	105	432	21559	21111	2	3	2	2
P11-G2-3	371	18309	2017	1893	43250	223	200	95	105	432	23113	22698	2	3	2	2
P11-G2-4	371	18309	2017	1893	43250	223	180	86	95	395	42505	40634	2	3	2	2
P11-G2-5	371	18309	2017	1893	43250	223	180	86	95	395	31606	30128	2	3	2	2
P11-G2-6	371	18309	2017	1893	43250	223	180	86	95	395	67107	41904	2	3	2	2
P11-G2-7	371	18309	2017	1893	43250	223	160	76	84	358	149159	72115	2	3	2	2
P11-G2-8	371	18309	2017	1893	43250	223	160	76	84	358	99984	68589	2	3	2	2
P11-G2-9	371	18309	2017	1893	43250	223	160	76	84	358	130914	62500	2	3	2	2
P3-G3A-8	289	18845	2783	2012	45230	181	195	93	102	401	11914	11914	3	2	2	4
P3-G3A-1	289	18845	2783	2012	45230	181	195	93	102	401	6200	6200	3	2	2	4
P3-G3A-1	289	18845	2783	2012	45230	181	167	79	88	349	10615	10615	3	2	2	4
P3-G3A-1	289	18845	2783	2012	45230	181	153	73	81	323	21241	21241	3	2	2	4
P3-G3A-1	289	18845	2783	2012	45230	181	153	73	81	323	37853	37853	3	2	2	4
P3-G3A-9	289	18845	2783	2012	45230	181	139	66	73	297	32420	32420	3	2	2	4
P3-G3A-1	289	18845	2783	2012	45230	181	139	66	73	297	31340	31340	3	2	2	4
P3-G3A-1	289	18845	2783	2012	45230	181	125	60	66	272	58595	58595	3	2	2	4
P3-G3A-1	289	18845	2783	2012	45230	181	125	60	66	272	49028	49028	3	2	2	4
P17-G3A-	323	21511	2732	2017	42527	204	153	73	81	323	43287	43287	3	2	2	4
P17-G3A-	323	21511	2732	2017	42527	204	153	73	81	323	47479	47479	3	2	2	4
P17-G3A-	323	21511	2732	2017	42527	204	153	73	81	323	54393	54393	3	2	2	4
P17-G3A-	323	21511	2732	2017	42527	204	139	66	73	297	84044	84044	3	2	2	4
P17-G3A-	323	21511	2732	2017	42527	204	139	66	73	297	80100	80100	3	2	2	4
P17-G3A-	323	21511	2732	2017	42527	204	139	66	73	297	95285	95285	3	2	2	4
P17-G3A-	323	21511	2732	2017	42527	204	126	60	66	273	160312	160312	3	2	2	4
P17-G3A-	323	21511	2732	2017	42527	204	126	60	66	273	119144	119144	3	2	2	4

Table C. 1 Statistics for a total of 119 specimens, part I.

Sample	UTS(MPa)	FailureL(N)	t(μm)	Density	E(MPa)	Yield(MPa)	MaxCyclic	AlterStres	MeanStre	Stress_sl	N	N_al	Layers	Layers	Layers	Layers
P9-G3-2	394	24979	2687	2045	43840	206	200	95	105	334	37545	36666	3	4	0	4
P9-G3-3	394	24979	2687	2045	43840	206	200	95	105	334	34944	34944	3	4	0	4
P9-G3-4	394	24979	2687	2045	43840	206	180	86	95	304	92685	67948	3	4	0	4
P9-G3-6	394	24979	2687	2045	43840	206	180	86	95	304	110441	75793	3	4	0	4
P9-G3-7	394	24979	2687	2045	43840	206	180	86	95	304	67363	67363	3	4	0	4
P9-G3-5	394	24979	2687	2045	43840	206	160	76	84	274	613727	149038	3	4	0	4
P9-G3-8	394	24979	2687	2045	43840	206	160	76	84	274	231332	126984	3	4	0	4
P9-G3-9	394	24979	2687	2045	43840	206	160	76	84	274	282164	140384	3	4	0	4
P22-G3-2	407	34091	3340	1864	44399	178	240	114	126	403	12393	11269	3	6	0	4
P22-G3-5	407	34091	3340	1864	44399	178	240	114	126	403	11375	10079	3	6	0	4
P22-G3-6	407	34091	3340	1864	44399	178	240	114	126	403	20888	12063	3	6	0	4
P22-G3-3	407	34091	3340	1864	44399	178	230	109	121	388	14870	11442	3	6	0	4
P22-G3-4	407	34091	3340	1864	44399	178	230	109	121	388	7939	9102	3	6	0	4
P22-G3-7	407	34091	3340	1864	44399	178	230	109	121	388	15105	11923	3	6	0	4
P22-G3-8	407	34091	3340	1864	44399	178	230	109	121	388	15721	12948	3	6	0	4
P22-G3-9	407	34091	3340	1864	44399	178	220	105	116	373	16797	NaN	3	6	0	4
P22-G3-10	407	34091	3340	1864	44399	178	220	105	116	373	37618	15555	3	6	0	4
P22-G3-11	407	34091	3340	1864	44399	178	220	105	116	373	15881	15384	3	6	0	4
P22-G3-12	407	34091	3340	1864	44399	178	220	105	116	373	27448	13934	3	6	0	4
P22-G3-13	407	34091	3340	1864	44399	178	210	100	110	358	37238	18444	3	6	0	4
P22-G3-14	407	34091	3340	1864	44399	178	210	100	110	358	44288	19452	3	6	0	4
P22-G3-15	407	34091	3340	1864	44399	178	210	100	110	358	48791	18493	3	6	0	4
P22-G3-18	407	34091	3340	1864	44399	178	200	95	105	343	121346	24603	3	6	0	4
P22-G3-19	407	34091	3340	1864	44399	178	200	95	105	343	52551	21846	3	6	0	4
P22-G3-16	407	34091	3340	1864	44399	178	200	95	105	343	83010	24489	3	6	0	4
P22-G3-20	407	34091	3340	1864	44399	178	200	95	105	343	71449	24045	3	6	0	4
P22-G3-24	165	13716	3340	1864	33350	137	150	71	79	545	1823	1823	3	0	6	4
P22-G3-25	165	13716	3340	1864	33350	137	130	62	68	484	3128	3128	3	0	6	4
P12-G3-3	320	26083	3315	1999	41890	189	160	76	84	412	62703	62703	3	4	4	4
P12-G3-5	320	26083	3315	1999	41890	189	150	71	79	391	77186	76086	3	4	4	4
P12-G3-6	320	26083	3315	1999	41890	189	140	67	74	369	232399	232399	3	4	4	4
P13-G3-2	359	27372	3038	2008	43050	198	160	76	84	338	62703	62703	3	4	2	4
P13-G3-9	359	27372	3038	2008	43050	198	160	76	84	338	64835	64835	3	4	2	4
P13-G3-3	359	27372	3038	2008	43050	198	150	71	79	320	74786	74786	3	4	2	4
P13-G3-7	359	27372	3038	2008	43050	198	150	71	79	320	165027	109722	3	4	2	4
P13-G3-6	359	27372	3038	2008	43050	198	140	67	74	303	232399	138666	3	4	2	4
P13-G3-5	359	27372	3038	2008	43050	198	130	62	68	285	280358	198412	3	4	2	4
P13-G3-4	359	27372	3038	2008	43050	198	120	57	63	267	493611	270666	3	4	2	4
P13-G3-8	359	27372	3038	2008	43050	198	120	57	63	267	513400	263492	3	4	2	4
P4-G4A-7	374	41130	4354	1960	34160	195	337	160	177	684	165	165	4	6	3	6
P4-G4A-8	374	41130	4354	1960	34160	195	262	125	138	544	3168	3168	4	6	3	6
P4-G4A-1	374	41130	4354	1960	34160	195	225	107	118	475	5350	5350	4	6	3	6
P4-G4A-1	374	41130	4354	1960	34160	195	206	98	108	440	11336	11336	4	3	6	6
P4-G4A-9	374	41130	4354	1960	34160	195	187	89	98	405	25877	25877	4	6	3	6
P4-G4A-1	374	41130	4354	1960	34160	195	169	80	88	371	31094	31094	4	6	3	6
P14-G4-4	403	43232	4343	1956	29800	212	240	114	126	415	99250	27380	4	9	0	6
P14-G4-8	403	43232	4343	1956	29800	212	240	114	126	415	82770	23717	4	9	0	6
P14-G4-9	403	43232	4343	1956	29800	212	240	114	126	415	106908	25000	4	9	0	6
P14-G4-5	403	43232	4343	1956	29800	212	220	105	116	385	199514	36538	4	9	0	6
P14-G4-7	403	43232	4343	1956	29800	212	220	105	116	385	937218	44444	4	9	0	6
P14-G4-6	403	43232	4343	1956	29800	212	200	95	105	354	NaN	67021	4	9	0	6
P14-G4-3	403	43232	4343	1956	29800	212	160	76	84	292	5422162	106382	4	9	0	6
P14-G4-2	403	43232	4343	1956	29800	212	120	57	63	231	NaN	369680	4	9	0	6
P15-G4-2	329	40340	4817	1936	32550	182	200	95	105	525	21720	21720	4	6	6	6
P15-G4-3	329	40340	4817	1936	32550	182	200	95	105	525	23645	23645	4	6	6	6
P15-G4-4	329	40340	4817	1936	32550	182	180	86	95	481	43664	43664	4	6	6	6
P15-G4-5	329	40340	4817	1936	32550	182	180	86	95	481	41795	41795	4	6	6	6
P15-G4-6	329	40340	4817	1936	32550	182	180	86	95	481	37179	37179	4	6	6	6
P15-G4-7	329	40340	4817	1936	32550	182	160	76	84	436	66458	66458	4	6	6	6
P15-G4-8	329	40340	4817	1936	32550	182	160	76	84	436	79078	79078	4	6	6	6
P15-G4-9	329	40340	4817	1936	32550	182	160	76	84	436	55100	55100	4	6	6	6

Table C. 2 Statistics for a total of 119 specimens, part II.

Figure C.1 Fatigue test setup and the post-fatigue test specimens

Appendix D.Pseudocode

Algorithm: Newton Tree Boosting

Input : Data set $\mathcal{D}$.
A loss function L .
The number of iterations M .
The learning rate η .
The number of terminal nodes T_n

- 1 Initialize $\hat{f}^{(0)}(x) = \hat{f}_0(x) = \hat{\theta}_0 = \arg \min_{\theta} \sum_{i=1}^n L(y_i, \theta)$;
- 2 **for** $m = 1, 2, \dots, M$ **do**
 - 3 $\hat{g}_m(x_i) = \left[\frac{\partial L(y_i, f(x_i))}{\partial f(x_i)} \right]_{f(x)=\hat{f}^{(m-1)}(x)}$;
 - 4 $\hat{h}_m(x_i) = \left[\frac{\partial^2 L(y_i, f(x_i))}{\partial f(x_i)^2} \right]_{f(x)=\hat{f}^{(m-1)}(x)}$;
 - 5 Determine the structure $\{\hat{R}_{jm}\}_{j=1}^T$ by selecting splits which maximize $Gain = \frac{1}{2} \left[\frac{G_L^2}{H_L} + \frac{G_R^2}{H_R} - \frac{G_{jm}^2}{H_{jm}} \right]$;
 - 6 Determine the leaf weights $\{\hat{w}_{jm}\}_{j=1}^T$ for the learnt structure by $\hat{w}_{jm} = -\frac{G_{jm}}{H_{jm}}$;
 - 7 $\hat{f}_m(x) = \eta \sum_{j=1}^T \hat{w}_{jm} \mathbf{I}(x \in \hat{R}_{jm})$;
 - 8 $\hat{f}^{(m)}(x) = \hat{f}^{(m-1)}(x) + \hat{f}_m(x)$;
- 9 **end**

Output: $\hat{f}(x) \equiv \hat{f}^{(M)}(x) = \sum_{m=0}^M \hat{f}_m(x)$

Figure D. 1 Pseudocode for Newton tree boosting[179]

Algorithm: Gradient Tree Boosting

Input : Data set $\mathcal{D}$.
A loss function L .
The number of iterations M .
The learning rate η .
The number of terminal nodes T_n

1 Initialize $\hat{f}^{(0)}(x) = \hat{f}_0(x) = \hat{\theta}_0 = \arg \min_{\theta} \sum_{i=1}^n L(y_i, \theta)$;

2 **for** $m = 1, 2, \dots, M$ **do**

3 $\hat{g}_m(x_i) = \left[\frac{\partial L(y_i, f(x_i))}{\partial f(x_i)} \right]_{f(x) = \hat{f}^{(m-1)}(x)}$;

4 Determine the structure $\{\hat{R}_{jm}\}_{j=1}^T$ by selecting splits which maximize
 $Gain = \frac{1}{2} \left[\frac{G_L^2}{n_L} + \frac{G_R^2}{n_R} - \frac{G_{jm}^2}{n_{jm}} \right]$;

5 Determine the leaf weights $\{\hat{w}_{jm}\}_{j=1}^T$ for the learnt structure by
 $\hat{w}_{jm} = \arg \min_{w_j} \sum_{i \in \hat{I}_{jm}} L(y_i, \hat{f}^{(m-1)}(x_i) + w_j)$;

6 $\hat{f}_m(x) = \eta \sum_{j=1}^T \hat{w}_{jm} \mathbf{I}(x_i \in \hat{R}_{jm})$;

7 $\hat{f}^{(m)}(x) = \hat{f}^{(m-1)}(x) + \hat{f}_m(x)$;

8 **end**

Output: $\hat{f}(x) \equiv \hat{f}^{(M)}(x) = \sum_{m=0}^M \hat{f}_m(x)$

Figure D. 2 Pseudocode for Gradient tree boosting[179]

List of Publication

Journal Paper

Sai, W., G.B. Chai, and N. Srikanth, *Fatigue Life Prediction of GLARE Composites Using Regression Tree Ensemble-Based Machine Learning Model*. Advanced Theory and Simulations: p. 2000048.

Sai, W., G.B. Chai, and N. Srikanth, *Deep learning in the fundamental material characterization* (under preparation)

Conference Paper

Sai, W. and G.B. Chai, *Fatigue in Fiber-Metal Laminates for Small Wind Turbine Blades Application*. in MATEC Web of Conferences. May 2018. Poitiers, France: EDP Sciences.

Conference Oral Presentation

Sai, W., G.B. Chai, *Fatigue in Fiber-Metal Laminates for Small Wind Turbine Blades Application*, presented in The 12th International Fatigue Congress 2018, Poitiers, France.

Sai, W., G.B. Chai, and N. Srikanth, *Load analysis of small wind turbine blades with fiber-metal laminate skin*, presented in 22nd International Conference on Composite Materials 2019, Melbourne, Australia.