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Use of Statistical Learning in a Reliability Program for Risk Assessment of Composite Structures with Defects

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A comprehensive protocol addressing the impact of manufacture flaws on the reliability wind turbines blades has been proposed. The main points of this framework can be summarized in four disciplines: Effects of Defects, Probabilistic Structural Reliability Modeling, Criticality Analysis, and In-Field Evaluations. The majority of the work discussed herein has focused on the development statistical learning models to use as surrogate models to complicated stochastic finite element analysis. This analysis is integral to the generation of the Criticality Analysis, a risk assessment tool which can disposition a flawed composite structure.

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Nomenclature

θ	=	Off-axis fiber angle
V	=	Volume
m	=	Weibull modulus
HU	=	Hounsfield Unit
μ	=	Coefficient of linear attenuation
$\sigma_{t,c}$	=	Strength parameters of the non-flawed material (compressive and tensile)
$P_{t,c}$	=	Porosity content modifier
μ	=	Design Life (years)
λ	=	Failure rate
F	=	Combined effect of parameter
D	=	Inspection technology code
σ_f	=	Strength of flawed material
L	=	*S*tructural location parameter
t	=	Time in operation
α	=	Time to repair
I	=	Time to next inspection
R	=	Remainder of service life
S	=	Residual Strength
P_f	=	Probabilty of failure modifier
ζ	=	Predicted time to failure
$C_{1,2,3,4}$	=	Criticality modifier: Sevice Life, Inspection Interval, Failure Rate, Time to Repair

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Introduction

Improving and quantifying the reliability of composite structures can significantly impact the cost and safety in a wide variety of fields such as wind energy, military applications and aviation. (1; 2) A typical reliability program for large composites structures involves a preservice quality control assessment and in many cases, in-service inspections. Any standard reliability analysis aimed at addressing the probability of failure is typically performed and understood by only the design engineer. From this analysis threshold targets for manufacturing defects and damage sizes are regularly established in a "not to exceed" specification form. This type of control can result in large amounts of unnecessary rework or scrap.(3)

The ideal reliability program would perform an 'as-is' structural analysis for the flawed or damaged structure on a case by case or in-situ basis. However, detailed structural analysis is typically beyond the training of the manufacturing or service technician whom normally perform the inspections. Moreover, performing a comprehensive structural analysis during evaluation procedure is prohibitive from a resource, computation and monetary perspective. Discussed herein are elements of PREP (Probabilistic Risk Evaluation Protocol), a comprehensive reliability program that addresses these issues. In doing so, a detailed Stochastic Finite Element Analysis (SFEA) is embodied in a risk assessment tool developed for the technician. Computationally inexpensive algorithms developed by statistical leaning techniques are combined with other risk parameters to disposition an as-built structure.

I. Risk Assessment Protocol Framework

PREP can be divided into four interrelated components; Effects of Defects (EoD), Probabilistic Analysis, Criticality Assessment (CA) and Implementation/Feedback. The EoD effort involves the identification, characterization and analysis of defect and damage types. EoD data is fed into the Probabilistic Analysis (ie SFEA) which considers multi-scale variability and the subsequent structural response to assess the probability of failure. Statistical learning techniques are then used to build a surrogate model for the SFEA. This algorithm is incorporated into the Criticality Assessment along with other risk parameters to properly address the reliable life of a structure. The Implementation and Feedback portion make use of the CA to assess structures on the manufacturer's floor and in the field. Results from inspections as to the accuracy of the models and reliability are then fed back into the design and evaluation procedures. A conceptual diagram of these components is shown in Figure 1.

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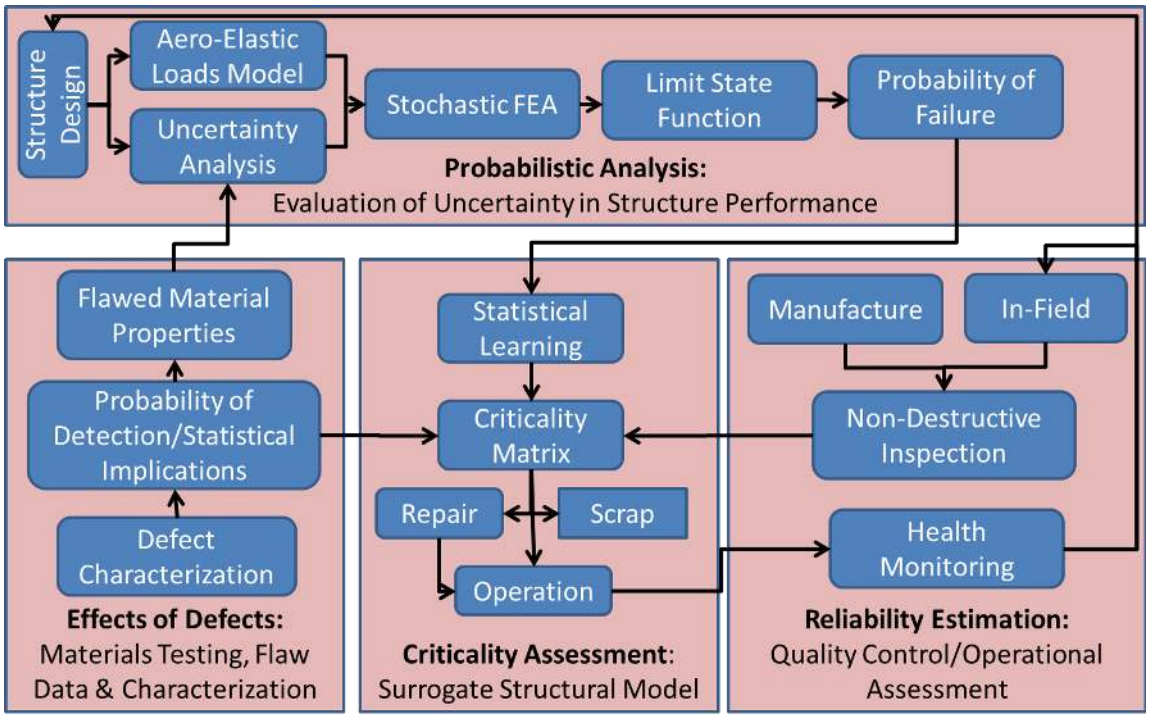


Figure 1: Framework for Defect Risk Management and Reliability Protocol

As an example for this approach, research was performed to acquire quantitative flaw data for wind turbine blades. A metric was then developed to precisely address the geometric nature of flaws based on statistical commonality in the structures of interest. The flaw types were then mechanically tested to develop empirical relationships between the flaw characterization parameters and material properties.

II. Formulation of Reliability Analysis

Uncertainties at all levels of a composite structure and in the fatigue load spectrum render standard deterministic approaches to structural response evaluations inadequate for reliability estimation. A probabilistic approach which takes into account multi-scale mechanical property variability is required for a reliability assessment to achieve an acceptable level of confidence. (4; 5; 6; 7; 8; 9) Defects have been shown to be a leading cause of composite structure failures; therefore, their inclusion in structural analysis is of critical importance. (10; 11) The standard computation used to estimate the time dependant reliability of a structure takes the form of a multi-dimensional integral evaluated over the performance function failure domain. (12; 13; 14)

$$\boldsymbol{p_f = P[G \leq 0] = \int_{g(X)\leq 0} f_x(x)dx} \quad (1)$$

Where p_f is the probability of failure, x is a vector of random input variables, $f_x(x)$ is the joint Probability Density Function (PDF) of X, and g is the limit state function. (15) Composite structures are complicated and uncertainty exists at many levels. A detailed Stochastic Finite Element Analysis (SFEA) of a composite structure can include as many as 30 material property, 10 fabrication and 10 structural uncertainty variables.

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The focus of reliability estimation is typically to calculate the probability of failure. However, the context of failure varies for each application. In a damage tolerant design, one might be interested in the probability of failure between the current evaluation and the next inspection interval, as embodied in the aviation industry by Barely Visible Impact Damage and damage threat assessment levels. This type of analysis has worked well for the aviation industry where an aircraft can be pulled into a hanger and inspected quite easily. (16; 17) However, not all composite structures are as accessible or used in such regulated industries.

Many composite structures are subject to variable amplitude loading. Application of these loading scenarios to design and testing is often unreasonable. Therefore, rainflow counting is typically used to convert a spectrum of loads into a set of "equivalent" constant amplitude reversals. The fatigue life can then be used in conjunction with Palmgren-Miner's rule for linear damage accumulation to construct the compact limit state function shown below in Equation 2. (18)

$$g(\boldsymbol{X}) = 1 - D(\boldsymbol{X}) = 1 - \sum_{i=1}^{k} \frac{\Delta n(S_i)}{N(S_i)} \tag{2}$$

Where D is the cumulative damage index, n is the number of load cycles at the applied stress S_i and N is the number of cycles to failure at the applied stress S_i. Fatigue failure is defined to occur when D exceeds a value of 1. The resulting stress (S_i) is a function of the uncertainty parameter vector X and is found from a structural analysis. Previous work has shown that composites are sensitive to the variations in loading rehearsal and therefore accurate modeling of fatigue damage accumulation requires usage of fatigue life estimations for a specific the R-ratios. Constant Life Diagrams (CLD) are used for this purpose, such as the example shown in Figure 2.(19)

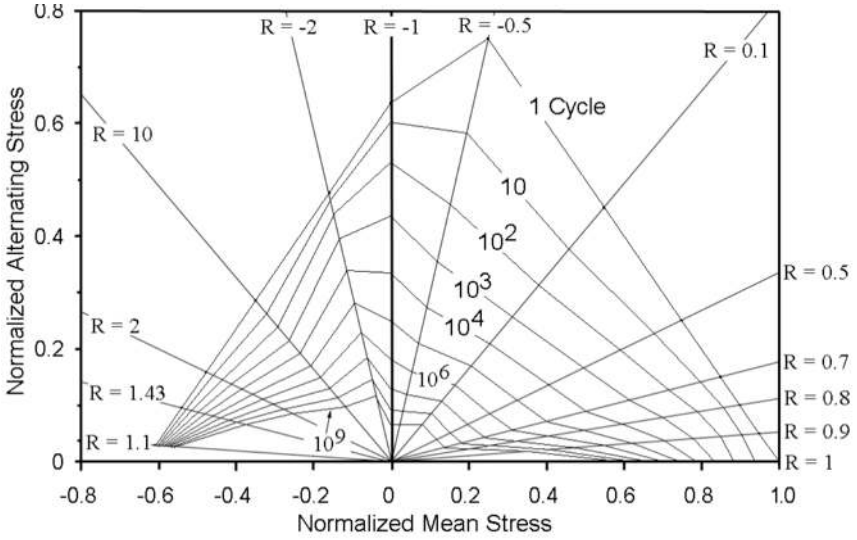


Figure 2: Example GFRP Constant Life Diagram

The amount of data necessary to generate a CLD is often prohibited by cost and time constraints. Therefore a number of predictive algorithms have been developed in lieu of copious amounts of testing. The Piecewise Linear methodology (Figure 3) has shown good accuracy with limited amount of test data, therefore it was used in this analysis. (20)

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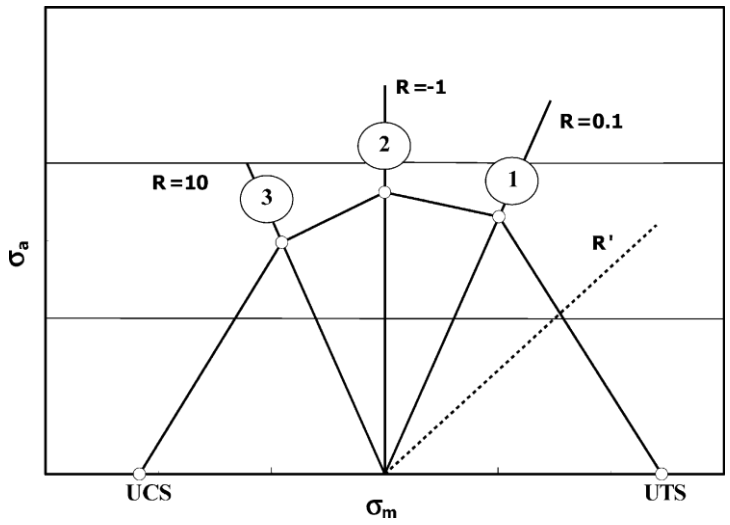


Figure 3: Approximation of CLD with a Piecewise Linear Representation

The wind loading spectrum utilized for this analysis was derived from the well known WISPER load reversal probability distributions.(20) A Probability Mass Function (PMF) was developed from the WISPER data to generated probability values for 100 load reversal bins. The Probability Mass Distribution and complimentary Cumulative Distribution are displayed in Figure 4.

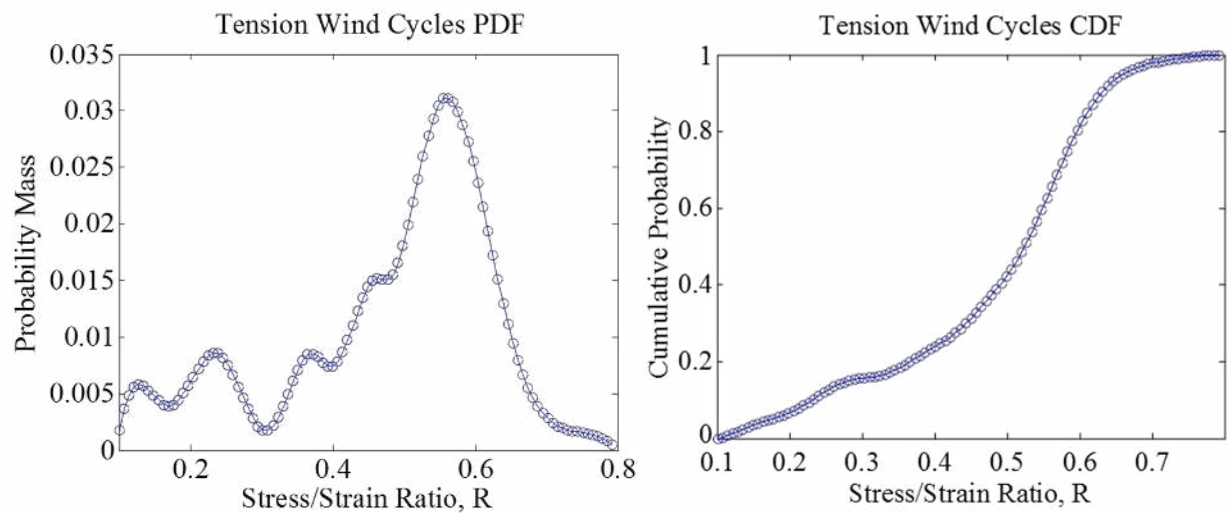


Figure 4: Wind Cycle Distributions

One cannot properly assess the integrity of any portion of a complex composite structure without considering the global response and load share tendencies. It is well known that 2D shell elements used in 3D Finite Element models are required to capture information such as three-dimension distortions, stress concentrations and buckling strengths. (21) A full scale blade model (Figure 5, top) was used in this analysis. The majority of the material uncertainty parameters (E, G, ν, etc.) variations have been implemented as system wide global properties. The occurrence of flaws has been captured by analyzing a local region of the mesh (Figure 5, bottom).

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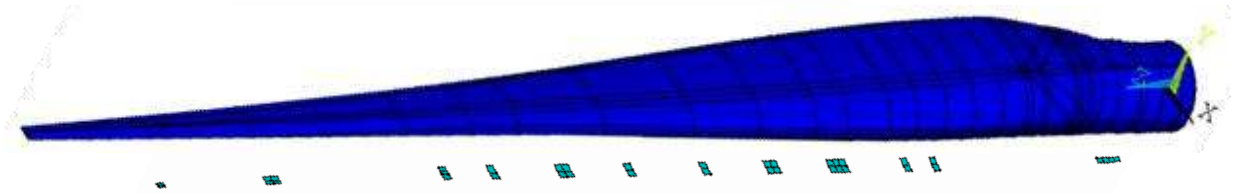


Figure 5: Full blade FEA model (top), elements with flaws down the length of the spar cap (bottom)

Flaw locations and magnitude parameters were treated as stochastic variables. First the probability of a flaw occurring in a specific location was described by a novel spline fit, spatially derived Probability Mass Function capable of updating without the use of traditional inference techniques. A user, such as a quality control technician performing inspections on the composite structure records the frequency and location of observed flaws. These points are treated as delta functions in the subsequent PMF fitting procedure which utilizes piecewise polynomials. Frequencies can easily be updated as more events are recorded enabling the regeneration of distributions used in the SFEA. This data is hard to come by therefore a fictitious set of frequencies was selected by the author. The chosen frequencies and corresponding PMF is displayed in Figure 6.

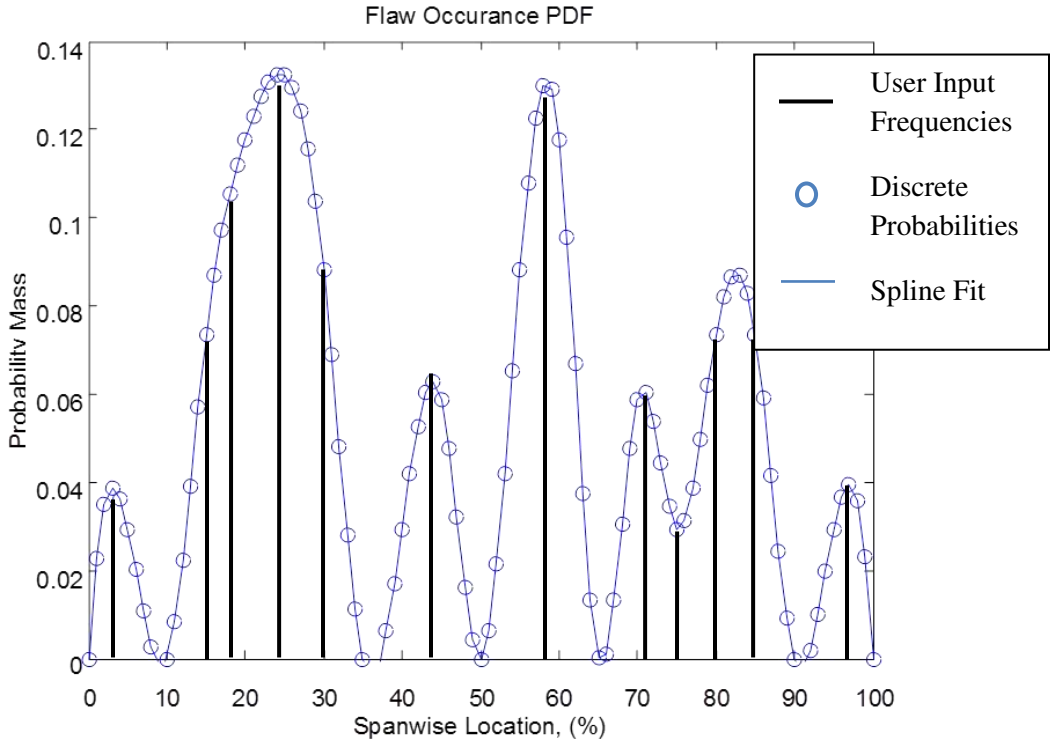


Figure 6: Spatial Distribution for the Probability of Flaw Occurrence

The previous discussion is used in the stochastic analysis to ascertain the probability of a flaw occurring in a specific location. When the sampling algorithm identifies the existence of a flaw, a second distribution describes the probability of the flaw's magnitude. Figure 7 displays the treatment of an example flaw magnitude as an uncertainty parameter used in this analysis. It was found that off-axis fiber angle for the case of out-of-plane waves found in a survey of wind turbine blades follow typical distributions such as Normal and Weibull. Further information on the acquisition and generation of the

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various flaw distributions and the mechanical response correlating to the characteristic parameter (e.g. wave off-axis fiber angle) can be found in (22) and (23).

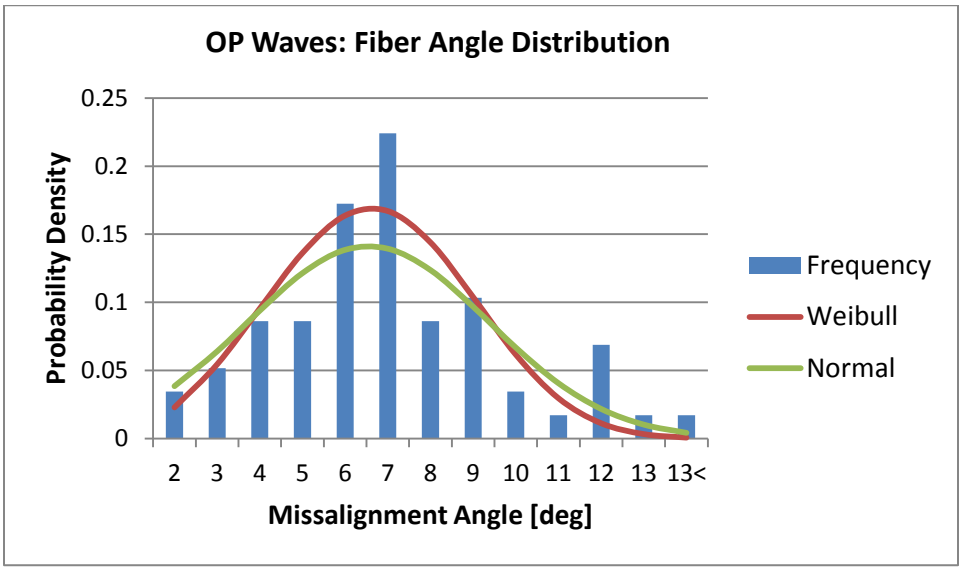


Figure 7: Collected Out-of-Plane Wave off axis fiber angles (24)

The evaluation of Equation 1 in the proposed form, either directly or through analytical approximation methods such as the First Order Reliability Method (FORM) is not practical considering the dependence of the limit state equation on detailed finite element analysis. Several methods, such as Sensitivity Based Reliability Analysis which utilizes perturbation techniques and the Response Surface Method which uses 2nd order polynomial regression, have shown success in solving implicit performance functions. Both techniques were evaluated for this body of work, however, using the Monte Carlo Method (MCM) numerical sampling procedure to solve the equation is particularly well suited for SFEA and providing training data for a Statistical Learning (SL) algorithm. A more in depth discussion of this analysis can be found in Ref (25)

III. FEA Model Validation

The structural analysis discussed in the preceding section has been validated on a full scale structural test. As part of the Blade Reliability Collaborative efforts a subscale (9m) version of a multi-megawatt wind turbine blade was manufactured with intentional defects. The article was fatigue tested at the National Wind Technology Center. Forced hydraulic actuation was used at three locations (Figure 8, Figure 9 left) allowing for the assessment of multiple flaw and regional considerations. The test was in essence comparable to three discrete Monte Carlo simulations wherein the uncertainty variables were known. This test gave significant insight into the scaling factors for transitioning from laboratory coupons to full structures and indications that for this type of structure a local failure constitutes a global structural failure. One failure location at an out-of-plane flaw which was consistent with numerical predictions is displayed in Figure 9 (right).

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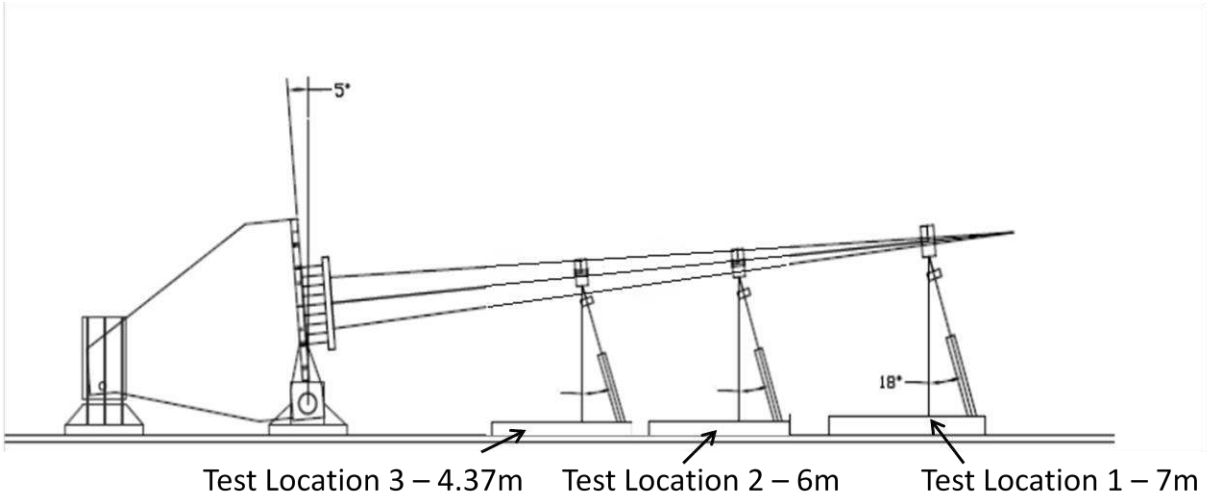


Figure 8: Blade test layout & progression



Figure 9: Blade test (left), Failure at flaw location (right)

IV. Development of a Machine Learning Surrogate SFEA Model

There are many elements that play a role in failure, some global or macro and some local or micro most all of which can be captured in a SFEA. While this type of analysis will provide the designing engineer with significant insight, the complexity and computational costs render it unusable for case by case in-situ reliability estimation. There exists a need to evaluate the reliability of a structure quickly on the manufacturers' floor as a quality control effort or in the field by technicians that captures more information than a 'not to exceed' specification. This type of an assessment needs to be fast, accurate and interfaced as a 'black box'.

One approach that has been taken in recent years has been to use SL techniques to produce a surrogate model of the finite element solver that provides the value of the performance function g(x). These applications generally follow a regression approach. However, the reliability problem can be regarded as a classification task. Defining the safe and failure classes as $g(x)>0$ and $g(x)<0$ respectively, a classification function can be used for the disposition of new samples in the training data based solely on sign (Equation 3). (26) Both techniques were assessed in this body of work.

$$c(x) = sgn(g(x)) \quad (3)$$

The fundamental approach to supervised statistical leaning consists of 3 elements: a random vector generator function, a supervisor, and a learning machine. The vector generator produces random vectors x, consisting of the uncertainty variables sampled from the joint distributions. The supervisor yields the correct class label (c) which corresponds to a vector of sampled variables, x. The supervisor in this case is the SFEA. There are many classical and modern classification methods which can be used for the learning machine. Methods evaluated for this analysis include Fisher Discrimination, Bayesian Classification, Classification Trees, Probabilistic Neural Networks, Multi- Layer Perceptrons and Support Vector Machines. Models that have shown the most success for these types of problems and were therefore compared in this investigation are; Multi- Layer Perceptrons (MLP) and Support Vector Machines (SVM). In classification analysis, the MLP models is a as follows: (27)

$$g(x) = \bar{h}(\sum_{k=0}^{m} w_k h(\sum_{j=0}^{d} w_{kj} x_j)) \quad (4)$$

Where a problem has number of dimensions d and m number of hidden layer neurons. Sigmoid functions are typically used for the h functions. The weights, w, can be optimized by minimization of the square error function sum (Equation 5). (27)

$$R_c = \frac{1}{2}\sum_{j=1}^{l}(c_j(x) - \hat{c_j}(x))^2 \quad (5)$$

The SVM has model of form show by Equation 6 where α_i are Langragian multipliers, b is a threshold and s the number of support vectors.. Particular emphasis is placed on the kernel function, K. Several functions were evaluated: polynomial, Fourier, sigmoidal, and inverse multiquadric. The Radial Basis Function (Equation 7), was chosen for this analysis. (26)

$$g(x) = \sum_{i=1}^{s} \alpha_i c(x_i)(K(x_i, x) + b) \quad (6)$$

$$K(x, y) = \exp\left(-\zeta \|x - y\|^2\right) \quad (7)$$

Data on flaw location, magnitude, strain response and probability of failure was generated in the Monte Carlo simulations and used for training the SL algorithms. Both techniques, regression and classification were successful at predicting the SFEA response given an input set of data. The regression technique was used to generate localized strain and damage accumulation response which can be of use to the designer assessing sensitivities and performing optimization on a structure. The classification approach was successful in predicting the probability of failure given a 'known unknown' flaw set (assumed flaw existence beneath inspection thresholds, described similarly to Figure 6) and data from a fictitious inspection interval.

V. Risk Assessment

Use of these models have yielded success as a surrogate model for predicting the probability of failure and detailed structural response. However, this information is inadequate to perform an acceptable risk analysis concerned with disposition of flawed composite structures. The next step is to incorporate the SL models into a Criticality Assessment (CA).

The proposed CA is an efficient procedure for evaluating the reliable operation (or risk) of an as-built composite structure with known defects. The procedure has adopted two parameters from a technique

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developed by the military to evaluate the reliability of a system: Failure Modes and Effects and Criticality Analysis (FMECA). This analysis uses two generalized parameters that define a space in which reliability issues are evaluated; Criticality and Severity (28; 29). These definitions have been modified for evaluations of composites structures as follows:

Criticality: A measure of the propensity for a flaw to cause a failure. Predominantly focused on probability of failure; incorporates damage progression, statistical variations, probability of flaw detection and combined effects of known/unknown proximity flaws. (Probabilistic/Numerical)

Severity: Similar to consequence estimation used in traditional rick assessment. Developed from specific user parameters assessing monetary ($), health/safety (H) and time (T) implications. (Heuristic/Deterministic/Probabilistic)

The CA input parameters and algorithms are specific to each structure, material, and flaw type under investigation. Most of these parameters are used in the probabilistic analysis described earlier. They are broken into two basic groups: Global and Inspection Specific parameters. The global parameters generally pertain to the entire fleet (or manufacturing batch) of a particular blade model. Some global parameters may be cataloged for use in a fashion similar to airworthiness directives used in the aviation industry (24). Flaw specific parameters are recorded by the investigator for each particular evaluation. The input parameters are detailed in Table 1.

Table 1: Criticality Analysis Input Parameters

	Input Parameter Description	**Symbol**	**Description**
Global Inputs (G_i)	Strength parameters of the non-flawed material (compressive and tensile)	$\sigma_{t,c}$	Based on database of material properties and test results
	Assumed global porosity content (% by matrix volume)	Pt,c	Strength reduction factors based on test results for tension and compression
	Design Life (typically 20 years)	μ	Variable unit is hours
	Failure rate specific to model	λ	Typically 10-4 to 10-3 for wind turbine blades
	Combined effect of another flaw in close proximity (based on Cumulative Distribution Functions)	F	Probability of failure modifier based on probabilistic evaluation
	Inspection technology code	D	Probability of detecting another flaw, based on probability of detection (POD)
Evaluation Specific Inputs (E_i)	Flaw Characteristic Parameter; e.g. Fiber angle, % porosity, crack length	σ_f	Failure strength parameter specific to flaw
	Location Parameter: High or Low pressure side	$\sigma_{t,c}$	Specifies material properties to be used i.e. high pressure side => tension
	Generic structural location description; e.g. Root, Flap spar, Root transition etc.	L	Weighted function based on region specific strain concentrators
	Time in operation	t	Can be used to estimate cumulative operational loading.
	(Mean) Time to repair (TTR)	α	Compared with predicted time to failure
	Time to next inspection	I	Compared with predicted time to failure

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The severity designation describes how severe a failure in terms of consequences. The current revision of Severity Number has the form described by $f(\$, \mathbf{H}, \mathbf{T})$. The required parameters \$, H and T are to be designated by decision and policy makers whereas the Criticality Number is predominantly an engineering formulation. The Criticality Number $[f(\mathbf{G_i E_i})]$ for an in-situ reliability estimation is calculated using the statistical algorithms described earlier. The algorithms are computationally inexpensive and can be performed by a handheld processing unit such as a cell phone or tablet.

An example of the current revision criticality analysis has been performed on the flaws placed into the blade test article. The graphical results of this analysis are shown in Figure 10. This example illustrates how criticality and severity are mapped and quadrants are established describing the risk of a specific flawed structure instance. At present, the risk quadrants and severity designations are place holders. Further analysis and input from manufacturers will help define the quadrant space. This example illustrates how a very severe flaw may not be critical at the evaluation time. However, a less severe flaw considering other parameters has a high risk. For instance, flaws 101 and 104 have almost identical characterization parameters and, therefore, have significant structural implication to the local region. However, flaw 101 is not located in a high strain region and therefore can be consider non-critical.

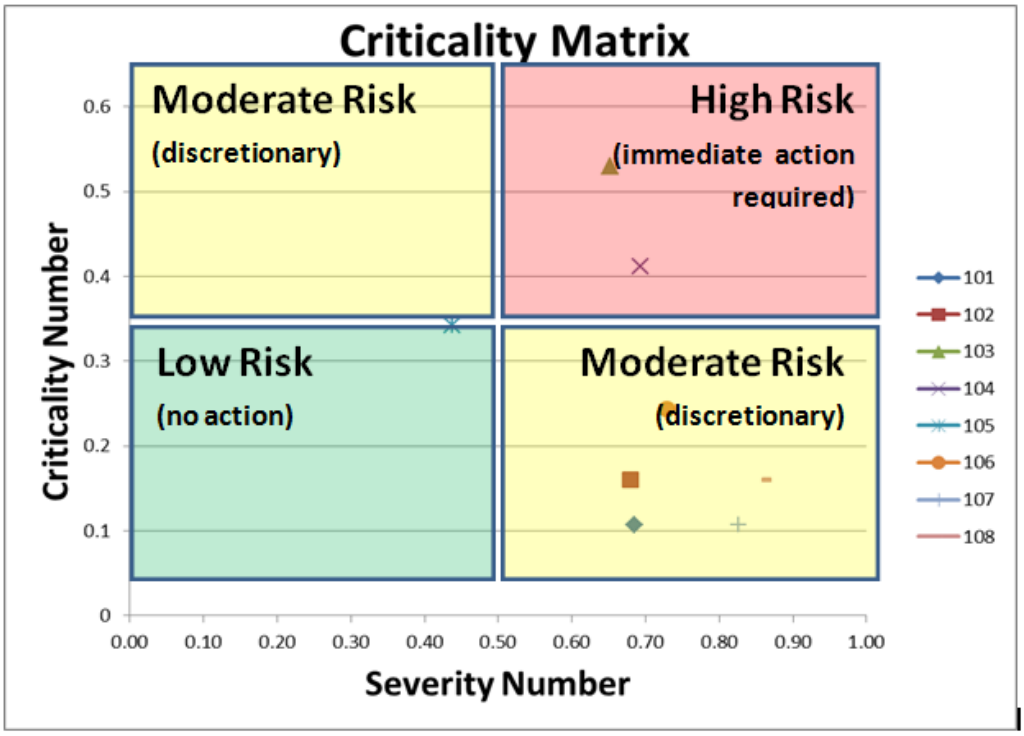


Figure 10: Graphical Criticality matrix example

VI. Conclusions and Future Work

A comprehensive protocol addressing the impact of defects on the reliability wind turbines has been proposed. The main points of this framework can be summarized in four disciplines: Effects of Defects, Probabilistic Structural Reliability Modeling, Criticality Analysis, and In-Field Evaluations. The majority of the work discussed herein has focused on the development statistical learning models to use as surrogate models to complicated stochastic finite element analysis. This analysis is integral to the

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generation of the Criticality Analysis, a risk assessment tool which can disposition a flawed composite structure. A natural extension to this work is assessment of existing fleets.

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