Multiscale Damage Modelling of Composite Materials Using Bayesian Network

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Abstract. Fibre reinforced polymers or as they widely are known composite materials, have made it possible to develop and manufacture large wind turbine and tidal blades central to competitiveness of wind and tidal turbines against other energy sources. Composite materials are light, corrosion free and easy to manufacture into complex aerodynamic/hydrodynamic profiles of wind and tidal blades. Even though polymer-based materials like composites used in wind and tidal blades do not corrode the same way as metals do, they undergo environmental degradation. One of the main mechanisms triggering degradation of polymers is their material structure which is not as "tight" as metals with significant free space between the polymeric chains. Due to these characteristics, unlike metals, polymers tend to absorb elements of their surrounding environment such as liquids, gas and humidity. For glass reinforced epoxy which the wind and tidal blades are typically manufactured of, absorption of water and humidity causes change in both epoxy matrix and glass Fibres, consequently leading to degradation of the material properties. Due to multi-parameter complex and rather uncertain nature of the environmental degradation of composites, typically full-scale aging tests are done which are limited, costly and time consuming. The limited number of possible full-scale tests fail to generate enough data points for statistical evaluation of uncertainties. In this paper a methodology for evaluation of environmental degradation of composites in a probabilistic scheme using Bayesian Networks is presented. The developed scheme is used to develop a digital integrity assessment tools for blades in wind and tidal industries. An illustrative case study is performed to demonstrate the application of the developed tool.

Keywords: Composite material, Multiscale Damage Modelling, Bayesian Network

1 Introduction

Polymers and polymer-based composites are generally known for their low reactivity with their environments. They are widely used where corrosion has been a big problem with metals such as pipes used to transfer water. However, polymers and composites have their own environmental degradations. The structure of polymer-based materials is not as "tight" as metals and have significant free space between the polymeric chains. When polymers are exposed to a liquid or gas components from the environment, depending on their affinity to the polymer type and structure diffuse into the polymer. The diffusion mechanism is schematically shown in Figure 1. Absorption of elements from the environment can potentially have two effects on the properties of the polymer:

- 1. **Swelling:** Depending on the type of polymer and its affinity to the environment, polymers may absorb different amount of the elements in their environment. For example, polyethylene at high temperature may absorb up to 15% of its weight if it is exposed to aromatic oil. For epoxy and water, up to 1.5% of the weight of epoxy water can be absorbed. The absorption of liquids and gases cause polymer to swell i.e. to expand and as a result of swelling polymers become soft and plasticized.
- **2. Chemical degradation and brittleness**: The elements of the environment which have diffused into a polymer over time may react with polymer chains and cause chemical degradation and brittleness.

For Fibre reinforced polymers or composites the environmental degradation is more complex due to multi-material structure of composite materials. The process of diffusion into composite is similar to non-reinforced polymers, however the diffusion is anisotropic i.e. the diffusion rates is different in different directions. In Fibre reinforced polymers the effect of exposure to the environmental elements which diffuse into the material should be assessed for the three constituents of composite materials i.e. for the matrix, Fibre and Fibre/matrix interface as shown in Figure 2, which makes the assessment much more complex.

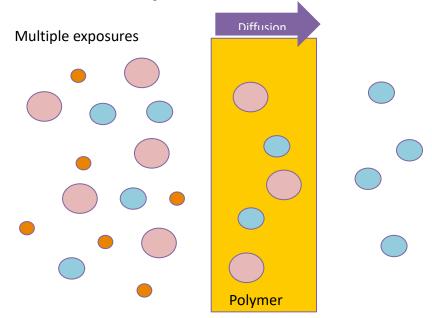


Fig. 1. Diffusion of environmental components into a polymer

In Figure 3 the process of environmental degradation for composite materials is shown. After exposure to an environment, the process of diffusion starts, resulting in a concentration of environmental elements in the material and exposure of Fibre, matrix and their interface. Over time and depending on the temperature, chemical reactions may start in one of the three constituents of the material system, changing its properties including resistance to short-term and long-term static loads and cyclic loads. The process shown in Figure 3 depends on characteristics such as different constituents of the material, the exposure environment, temperature, time, stress state and damage in the material and include various degradation mechanisms and strong anisotropy the material. Modelling such a complex process in a probabilistic framework (which is central for integrity assessment of structures made of composite materials for offshore application where significant environmental exposure is expected), has been a big challenge, thereby requiring methods other than traditional structural reliability analysis (SRA).

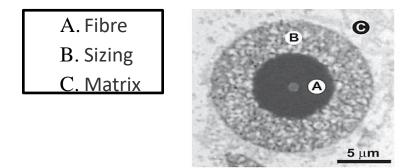


Fig. 2. A unit cell in composite materials

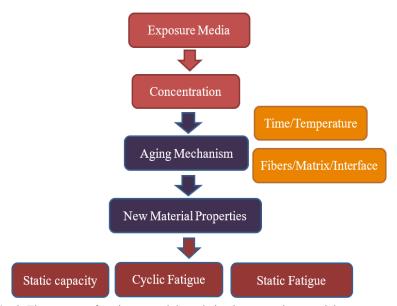


Fig. 3. The process of environmental degradation in composite materials

2 Probabilistic Graphical Models

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As discussed previously, modeling the progression of damage in composites materials is a challenging task mainly due to the uncertainty in the multi-scale physics of the damage process and the large variability in behavior that is observed, even for the tests of nominally identical specimens. As a result, there is much uncertainty related to the choice of the class of models among a set of possible candidates for predicting damage behavior. One tool for assessing risk and reliability for engineering structures is through structural reliability analysis (SRA). Let us first recall the basic principles of SRA.

In SRA, the Probability of Failure (PoF) is defined through a multidimensional integral [1]:

$$PoF = \int_{D_f} f_X(x) \, dx$$

where \mathbf{x} is the vector containing all the basic random variables, i.e., all uncertain variables making up the system. The integrand $f_{\mathbf{X}}(\mathbf{x})$ is the joint probability density function of all the variables \mathbf{x} , and the domain of integration is the failure domain $D_f = \{\mathbf{x} : g(\mathbf{x}) \leq 0\}$ which is given by the sign of the limit state function $g(\mathbf{x})$. The limit state function returns a negative value under system failure conditions, and a positive value under acceptable conditions. This function can be hard to formulate for complex problems, and it also depends on \mathbf{x} , that is, it depends on the integration variable. The fact that the domain of integration depends on the integration variable is a challenge in SRA.

To solve the aforementioned challenge, one may rely on Monte Carlo methods, i.e., sampling-based methods, to numerically approximate the integral. However, this is in practice is not applicable for real-life problems involving for example finite element models (due to the huge number of samples needed and the cost of running finite element models). Moreover, there are approximate methods such as first-order and second-order reliability methods (commonly abbreviated FORM or SORM, respectively), which have been very successfully applied in the industry. They are fast and efficient, but do not provide any guarantee in terms of the accuracy of the result. However, in order to use these methods, we have to formulate a limit state function and we must also assume that this function satisfies certain differentiability properties.

The above paragraph highlights some limitations of traditional SRA. Is there a different approach for assessing risk and reliability in complicated structural systems? In this manuscript, we have relied on the concept of Probabilistic Graphical Models (PGM). PGMs are diagrammatic representations of probability distributions where each node represents a random variable, and edges express probabilistic relationships between random variables [2]. One may say that PGM is in a way a marriage between

probability theory and graph theory: Probabilistic because they deal with chances and graphical because they express dependencies between variables on a graph. One can separate between two types of PGM, directed PGM and undirected PGM as shown in Figure 4.

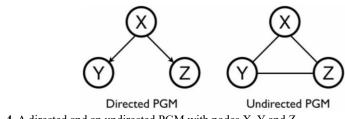


Fig. 4. A directed and an undirected PGM with nodes X, Y and Z

We will focus on a variant of directed PGM which is called Bayesian Network (BN). The Bayesian interpretation of probability represents probability as a degree or quantification of a personal belief or state of knowledge. Your initial (prior) belief changes in light of new information or evidence. Given an observation or measurement in an experiment, a revised probability of the desired outcome might change, i.e., we think in a conditional way. A BN is a tool to represent this Bayesian and conditional way of thinking via a Directed Acyclic Graph (DAG). BNs are therefore directed and contain no cycles. More information about BNs is discussed by the author in [3].

3 Bayesian network modelling of composite materials

To start building the Bayesian network of environmental degradation of composite materials, the degradation process must be broken down into its various mechanisms including the causal relationship between each mechanism. Once the problem is broken down, various nodes and edges for the BNs are identified. The environmental degradation of glass/epoxy composites which is the main material used in wind and tidal blades are shown in Figure 5. Assume that the location of interest for us in the structure has the coordinates of x and y. When the structure is exposed to an environment (here water) it will diffuse into the material. Six parameters that control the amount and rate of absorption are maximum uptake in equilibrium condition M_{eq} , anisotropic diffusivity parameters D_{11} , D_{22} and D_{33} , matrix crack density and temperature. If these parameters are known, a diffusion analysis can be done using finite element method to determine the concentration of the exposure medium in the desired location at time t.

Once the concentration is known, the effect of concentration on matrix, fibres and interface is required to be evaluated. The primary effect of water on epoxy is softening and plasticization. However, exposure of glass fibres to water leads to reduction of their diameter, as components from fibres get dissolved in water causing reduction in both stiffness and strength in fibre direction in the composite material. Furthermore, a coating-like layer on the surface of fibres, bonding them to matrix may undergo chemical degradation, cracking and depending from fibres. These three effects when combined change the mechanical properties in fibre and transverse to fibre direction. The degraded mechanical properties can then be used in the structure analysis to evaluate the possibility of failure in fibres, matrix and between the composite material's layers.

If the combined effect of degradation of mechanical properties and the applied loads is matrix cracking, it will accelerate the diffusion process (although this failure mechanisms is not considered to be critical to the structural integrity) that needs to be included in updating the diffusivity parameters.

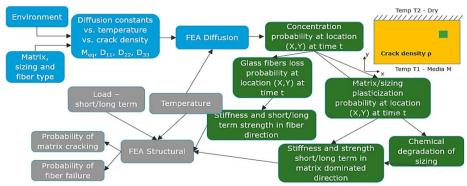


Fig. 5. Schematic representation of environmental aging process in glass/epoxy composite material

4 Illustrative case study

4.1 Problem description

The configuration of tidal turbine blade have many designs due to the existence of many competing technologies. For example, in addition to the shell and web structure similar to wind industry (Figure 6 left), some devices have solid composite blade, such as OpenHydro turbine (Figure 6 right). These blades are made of composite material (mainly glass fibre reinforced epoxy composite) due to its superior performance in corrosion resistance and weight saving. Tidal blades are often fully submerged in seawater condition. Hence, the environmental degradation due to moisture is the main challenge for the industry for ensuring long term integrity of the component. For this case study, OpenHydro's blade is chosen due to its simplicity in design and configuration.

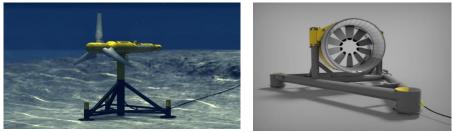


Fig. 6. Configuration of tidal turbine blade

4.2 Diffusion data and modeling

A diffusion model was created in Abaqus to resemble the OpenHydro blade. The aim of this model is to analyze the moisture content of the whole blade. The blade is modelled as a flat rectangle plate of 5000 mm x 2400 mm x 200mm in length, width and thickness respectively. It is made up of 5 layers of Biax (+/-45°), 0° UD and 90° UD with the thickness depicted in Table 1. For the diffusion analysis, the critical parameters are the diffusivity constants: D_{ii} , where ii are 11, 22 and 33 which represent Fibre, transverse to Fibre and out of plane directions respectively, see Figure 7.

Parameter	Ply thickness (mm)
Biax (+/-45°)	25
0° UD	65
90° UD	20
0° UD	65
Biax (+/-45°)	25

Table 1. Fibre orientation and thickness in the model

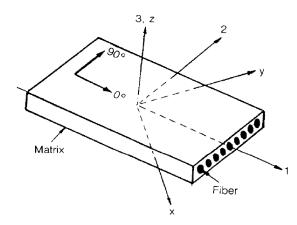


Fig. 7. Composite coordinate system (from DNV-DS-J102)

The diffusion coefficients are obtained from the experimental results from Norwegian University of Science and Technology (NTNU) [4] as part of the Joint Industry Project (JIP) affordable composite. The parameters used for the diffusion analysis are shown in Table 2. The diffusivity constants are artificially increased by 10 times the values in order to exaggerate the speed of diffusion for the demonstrator. In the model, it is assumed that the blade is exposed to water on all external surface except the root of the plate, which is assumed to be connected to blade root connection with limited exposure to water. Figure 8 shows the moisture content (concentration) distribution in the blade subjected to 20,000hrs of exposure to water. Figure 9 shows the changes of concentration of moisture over time at different locations (nodes) along the thickness of the blade. The nodes nearer to the surface show the concentration reaching saturation quicker.

Parameter	Value
$D_{11} (mm^2/h)$	0.1598
$D_{22} (mm^2/h)$	0.036
D ₃₃ (mm ² /h)	0.036
Solubility ¹ (g/cm ³)	0.01795

Table 2.	Parameters	for	diffusion	analysis

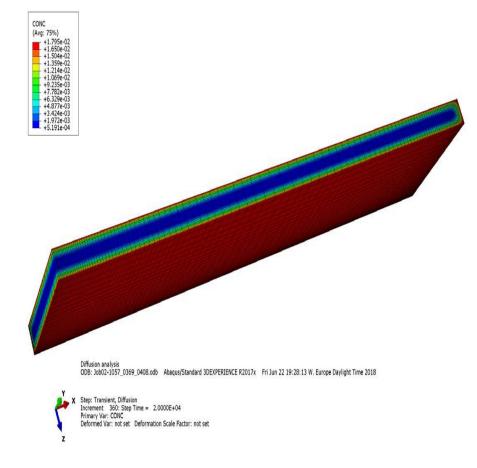


Fig. 8. Concentration of water in the blade subjected to 20,000 hours of exposure

¹ water mass solubility in Table 3 (0.93% = 0.0093) needs to be converted to volumetric by multiplying it for the composite density (1.93 g/cm3). Hence, 0.01795 (=0.0093 x 1.93) is used.

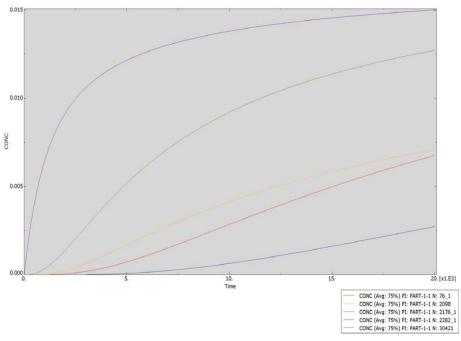


Fig. 9. Changes of concentration of moisture at different locations along the thickness of the blade

4.3 Loss of Glass Fibres

One of the main degradation mechanisms is the loss of glass fibres due to corrosion (leeching of alkali metallic ions in the presence of water around the fibre). Due to the loss of glass fibre, the radius of the glass fibre will be reduced. As it is a chemically driven process, the following relationship was used to calculate the reduction in radius of the fibre follows the following relationship in:

$$\begin{cases} t \leq t_{st}: \quad r = r_0 - \frac{K_0^I}{\rho_{glass}} t \\ t > t_{st}: \quad r = r_{t_{st}} - \frac{K_0^{II}}{\rho_{glass}} (t - t_{st}) \end{cases}$$

and the following parameters (given in Table 3) are used to estimate the fibre radius after a certain period of exposure to the [5].

Table 3. Parameters for estimation of Fibre radius subjected to moisture content

$K_0^I \left(g/m^2 \cdot s \right)$	K_0^{II} (g/m ² ·s)	t _{st} (h)	R^2 (t \leq t _{st})	R^2 (t > t _{st})
3.00.10-9	6.68·10 ⁻¹⁰	166	0.8069	0.9653

From the diffusion model, it is possible to estimate the average moisture content over the whole blade. Using the averaged moisture content in the blade, the new fibre radius due to degradation (by moisture) can be estimated using the following relationship:

Moisture
content
$$\chi \quad r = r_{t_{st}} - \frac{K_0^{II}}{\rho_{glass}}(t - t_{st}) =$$
 New radius

In DNVGL-ST-C501, section 4.6.6, for UD plies, it can be assumed that:

$$E_1 = E_1^0 \cdot \frac{V_f}{V_f^0}$$

Hence, we can assume:

$$E_1(t) = \left[\frac{FVF_{new}(t)}{FVF_0}\right] = E_0 \Delta FVF(t)$$
(1)

where $E_1(t)$ is the young modulus after water exposure time t, $FVF_{new}(t)$ is the new fibre volume fraction at time t, with radius loss $r_0 - r(t)$. If we assume:

$$V_f \sim fibre\ cross\ section = \pi r^2$$

Then

$$\Delta FVF(t) = \frac{FVF_{new}(t)}{FVF_0} \approx \frac{\pi [r(t)]^2}{\pi r_0^2}$$
$$= \left(\left(r_0 - \frac{\kappa_0^I}{\rho_{fibre}} t_{tst} - \frac{\kappa_0^{II}}{\rho_{fibre}} (t - t_{tst}) \right) / r_0 \right)^2 \qquad (2)$$

Hence, the degraded stiffness due to fibre loss can be estimated using equation (1) and (2). Furthermore, due to the presence of moisture, matrix in the composite experiences plasticization. The impact of the aforementioned phenomenon is to cause reduction in the young modulus in the direction transverse to the fibre and in the out of plane direction. From the data provided by NTNU in [6] it was estimated that a reduction of approximately 11% in the matrix young modulus was seen, when the matrix is saturated in the moisture. Hence, in the finite element model, the matrix properties can be degraded by 11% to account for the plasticization.

4.4 Structural Finite Element Model

A structural finite element model was created to model the strain distribution in the blade under loading. For the sake of simplicity, the mechanical properties given in the DNVGL-ST-C501 are used in the finite element model for UD 0° and 90° and for Biax 45° stated in Table 4. In Table 4, E is the young modulus; v is the Poisson's ratio; G is the shear modulus and subscripts of these properties indicate the direction following the coordinate in Figure 7. For the loading, a uniformly distributed pressure loads of 0.164 MPa is applied on one main surface to represent the current loads, see Figure 10.

Property	Value (UD 0° & 90°)	Value (Biax 45°)
E ₁₁	26700 MPa	26700 MPa
E ₂₂ *	7132 MPa	26700 MPa
E ₃₃ *	7132 MPa	7132 MPa
<i>v</i> ₁₂	0.26	0.26
<i>v</i> ₁₃	0.26	0.26
V ₂₃	0.26	0.26
G ₁₂	3500 MPa	3500 MPa
G ₁₃	2800 MPa	2800 MPa
G ₂₃	2800 MPa	2800 MPa

Table 4. Mechanical properties of UD 0° and 90° and Biax 45°

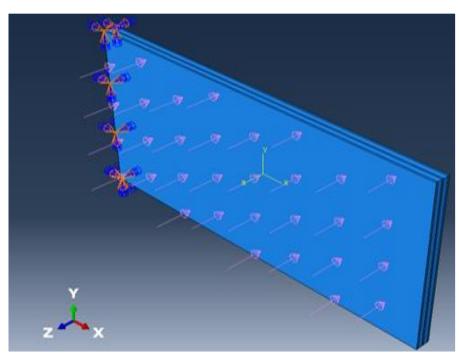
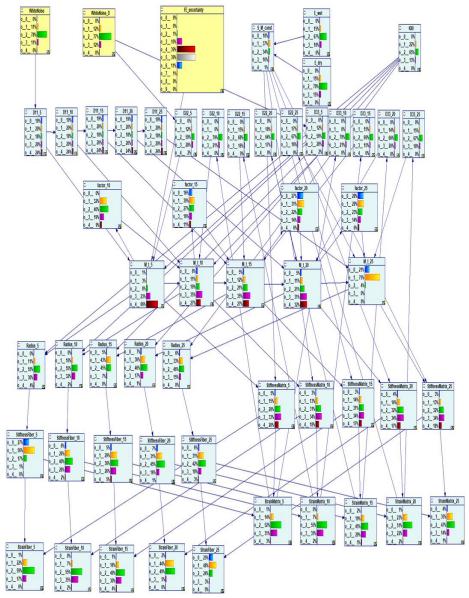
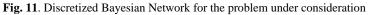


Fig. 10. Uniformly distributed pressure applied on the blade

124.5 Bayesian model of blade and results

The discretized BN for the problem under consideration is shown in Figure 11. A software program GeNIe [7] was used to build the BN.





Two vital steps of building a BN model of the tidal blade are to identify the nodes of the BN and to define various nodes and establish the relationships (between parent and child nodes). The former is done by using the expert judgement, while the

latter is achieved either by experimental data or by obtaining a parametric fit to the FEA data (as shown in Figure 12). In order to cater for the uncertainty in the experiments and FEA, nodes representing white noise (characterized by standard Gaussian distribution having mean of zero and some standard deviation) is added to the BN. These nodes are represented by the yellow color in Figure 11. The uncertainty quantified in the first step of the BN is propagated through the next steps of the BN, as will be seen in the results.

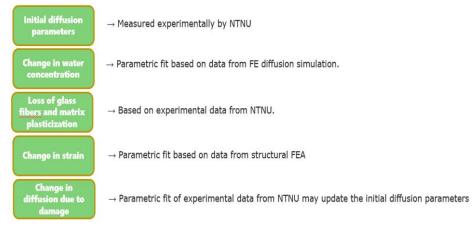


Fig. 12. Methods used to establish relationship between various nodes in the BN

Once the BN is established, it can be used in the forward direction to obtain the evolution of the probability density function (PDFs) with time for the parameter of interest i.e. moisture content, stiffness in the Fibre direction and strain in the Fibre direction. The PDFs of the parameters are shown in Figures 13, 14 and 15 respectively, and the trend of PDFs (i.e. shifting of mean and increasing of the standard deviation as the time progresses) is as expected.

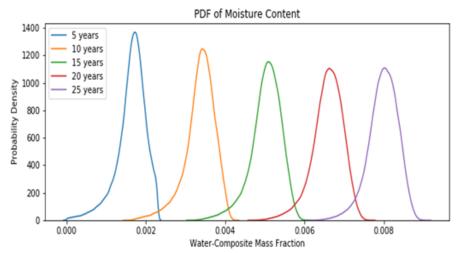


Fig. 13. PDF of moisture content for 5 to 25 years' time period

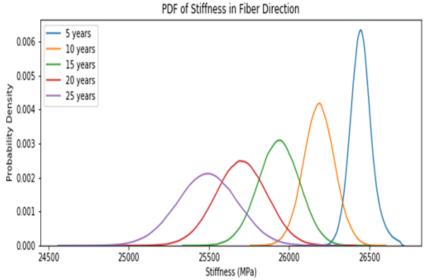


Fig. 14. PDF of stiffness for 5 to 25 years' time period

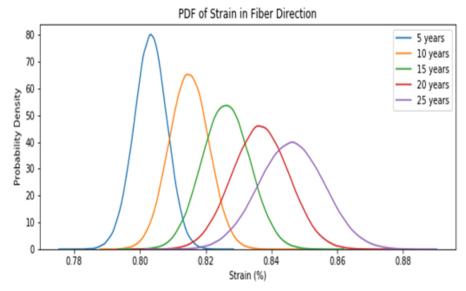


Fig. 15. PDF of strain for 5 to 25 years' time period

Up until now, we demonstrated the use of the BN in the forward direction (i.e. causal reasoning) to predict the evolution of the output parameters (or parameters of interest), for a given set of input parameters. An added advantage of BN is that besides causal reasoning, it can also be used for inferential reasoning, i.e. given an evidence in one of the parameters, the probability distribution of the other parameters can be obtained. For e.g. Figure 16 indicates the probability distribution of Strain in Fibre direction, before and after evidence setting in Stiffness in the Fibre direction.

	StrainFiber_5 (%)		StrainFiber_10 (%)		StrainFiber_15 (%)		StrainFiber_20 (%)		StrainFiber_25 (%)	
	From	То	From	То	From	To	From	То	From	To
0_0	0.78	0.79	0.78	0.793	0.79	0.804	0.795	0.816	0.82	0.838
1	0.79	0.8	0.793	0.806	0.804	0.818	0.816	0.837	0.838	0.856
2	0.8	0.81	0.806	0.819	0.818	0.832	0.837	0.858	0.856	0.874
3	0.81	0.82	0.819	0.832	0.832	0.846	0.858	0.879	0.874	0.892
4	0.82	0.83	0.832	0.845	/ 0.846	0.86	0.879	0.9	0.892	0.91

Results Before Evidence

 StrainFiber_5 	StrainFiber_10	 StrainFiber_15 	 StrainFiber_20 	StrainFiber_25
o_0_ 1%	0_0_ 0%	0_0_ /%	o_0_ 2%	o_0_ 25%
o_1_ 22%	o_1_ 7%	o_1_/16%	o_1_ 44%	o_1_ 48%
o_2_ 59%	o2 55%	o_2_/ 49%	o_2_ 49%	o_2_ 24%
o3 17% <mark></mark>	o3 35%	o_3/_ 30%	o_3_ 5%	o_3_ 3%
0_4_ 0%	o_4_ 2%	o_A_ 4%	o_4_ 0%	o_4_ 0%

Results After Evidence (Stiffness Fiber = 25500)

StrainFiber_5	5 O StrainFiber_10	/ 🔿 StrainFiber_15	StrainFiber_20	StrainFiber_25
o0 0%	o_0_ 0%	o_0_ 0%	o_0_ 0%	o_0_ 15%
o_1_ 3%	o_1_ 3%	o_1_ 9%	o_1_ 32%	o_1_ 47%
o_2_ 54%	o_2_ 45%	o_2_ 44%	o_2_ 59%	o_2_ 32%
o_3_ 42%	o_3_ 47%	o_3_ 40%	o3 9%	o_3_ 5%
o_4_ 1%	o_4_ 4% / p	o_4_ 7%	o_4_ 0%	o_4_ 0%

Assume threshold strain = 0.85%

Fig. 16. PDF of strain in the Fibre direction for 5 to 25 years' time period

5 Conclusion

The main conclusion of the paper is as follows:

- Complex multi-parameter problems such as environmental aging are difficult to assess in the traditional SRA due to difficulty in determination of limit state function.
- To crack such problems Probabilistic Graphical Modelling (PGM) such as Bayesian Networks (BNs) can be utilized.
- Bayesian Networks (BN) provides the possibility of adaption of real-time data and field measurements to update the models.
- BNs can be built in a transparent manner by a combination of deterministic physical models, expert knowledge and empirical data.
- The PDFs of the parameters (moisture content, stiffness and strain) and the trend of PDFs (i.e. shifting of mean and increasing of the standard deviation as the time progresses) is as expected.
- BN has also been used to demonstrate evidential reasoning by putting evidence of strain 0.85%. The PDFs of parameters (moisture content, stiffness and strain) thus obtained can be used for inspection planning of the tidal blades.

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