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Stochastic modelling fatigue crack evolution and optimum maintenance strategy for composite blades of wind turbines

Hua-Peng Chen[*1], Chi Zhang[1a] and Tian-Li Huang[2b]

[1]*Department of Engineering Science, University of Greenwich, Chatham Maritime, Kent, ME4 4TB, UK*
[2]*School of Civil Engineering, Central South University, Changsha, Hunan Province, 410075, China*

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Abstract. The composite blades of offshore wind turbines accumulate structural damage such as fatigue cracking due to harsh operation environments during their service time, leading to premature structural failures. This paper investigates various fatigue crack models for reproducing crack development in composite blades and proposes a stochastic approach to predict fatigue crack evolution and to analyse failure probability for the composite blades. Three typical fatigue models for the propagation of fatigue cracks, i.e., Miner model, Paris model and Reifsnider model, are discussed to reproduce the fatigue crack evolution in composite blades subjected to cyclical loadings. The lifetime probability of fatigue failure of the composite blades is estimated by stochastic deterioration modelling such as gamma process. Based on time-dependent reliability analysis and lifecycle cost analysis, an optimised maintenance policy is determined to make the optimal decision for the composite blades during the service time. A numerical example is employed to investigate the effectiveness of predicting fatigue crack growth, estimating the probability of fatigue failure and evaluating an optimal maintenance policy. The results from the numerical study show that the stochastic gamma process together with the proper fatigue models can provide a useful tool for remaining useful life predictions and optimum maintenance strategies of the composite blades of offshore wind turbines.

Keywords: composite blade; offshore wind turbine; fatigue crack; stochastic modelling; reliability analysis; maintenance strategy

1. Introduction

Energy crisis and greenhouse effect have led to an increasing demand for clean and renewable energy. Among them, wind is the most cost-effective and feasible energy, and thus it has been a very attractive option for utilities, independent power producers and companies (Shi *et al.* 2015). Due to the shortage of space on land and the better exploit of wind energy near the sea, the development of offshore wind turbines has gained more significant attentions in recent research activities than onshore (Esteban *et al.* 2011). In the wind turbine system, the most critical component is the wind turbine blades since the manufacturing cost of the blades is approximately 15-20% of the total manufacturing cost and their maintenance cost is about 25-30% of the wind turbine production cost (Jureczko *et al.* 2005, Zhou *et al.* 2014, Florian and Sørensen 2015). In order to improve the performance of blades in offshore wind turbines, layered fibre-reinforced polymer composite materials are usually adopted for the large blades since these materials have better mechanical properties such as higher fatigue resistance and lighter weight, compared with traditional homogeneous materials such as metals (Montesano *et al.* 2016).

Fatigue damage of composite blades is often investigated by both ultimate state assessment and long-term fatigue analysis during the blade design and service stages (Hu *et al.* 2016a). For engineering structures, fatigue cracking is one of major structural damage types weakening the physical properties of the original strength of the materials by cyclical loading for long time (Liu and Shu 2015). The prediction of fatigue crack propagation needs a proper model adopting the rate of fatigue crack growth with cyclic loading in a deterministic form. For example, cyclic fatigue loading is derived by using a time-variant stochastic wind applied on a rotating rotor and based on traditional Miner model (Hu *et al.* 2013). The Paris model is used within a risk-based maintenance decision framework to optimise maintenance planning during the blade lifetime (Florian and Sørensen 2015). In order to build a reliable fatigue model, the failure mechanism of composite blades needs to be investigated firstly to understand the fatigue crack propagation of the blade within the service life. However, this is difficult due to the complexity of the mechanical properties of composite materials, limited information available on composite blade fatigue experiments (Yang *et al.* 2013a). In addition, the fatigue analysis procedure for composite blades is comprehensive, including realistic blade model generation, variable wind load calculation, random wind field simulation, aerodynamic blade analysis, and advanced fatigue damage evaluation for complex stress states (Hu *et al.* 2016b).

A deterministic mechanism may not be appropriate for

∗Corresponding author, Professor
E-mail: h.chen@gre.ac.uk
[a]Ph.D. Studnet
[b]Associate Professor

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fatigue damage assessment in composite blades. Several fatigue crack damage models with stochastic approaches were proposed to simulate the real crack propagation of composite blades in an uncertain environment. Probabilistic analysis by stochastic deterioration models is a useful tool for deteriorating structures affected by cyclic fatigue loading during the service life (Chen and Nepal 2015). By considering the nature of cumulative growth of fatigue cracks, the gamma process model is an appropriate approach for fatigue evolution modelling of the composite blades since the gamma process has been proved to be more versatile and increasingly used in stochastic deterioration modelling (Van Noortwijk 2009). It has been shown that the time to reach any given crack size in fatigue testing can be directly modelled as a stochastic process and the gamma process can represent the fatigue crack growth accurately (Guida and Penta 2015).

Optimum maintenance strategies for composite blades make substantial contributions to reducing the total lifecycle cost of offshore wind turbines. The strategies are also expected to extend longer service lifetime with less cost in harsh marine environments. Since maintenance actions follow inspections, the integrated inspection and maintenance schedule is required to make the informed decisions (Chen and Huang 2012, Kim *et al.* 2013). Considering the uncertainties in the fatigue crack development in the manufacturing process, in the operation environment, and in the actions of maintenance, the probabilistic approaches for the optimal management for deteriorating offshore wind turbines were developed to minimise the lifecycle cost (Márquez-Domínguez and Sørensen 2012). In addition, probabilistic analysis with consideration of the dynamic wind load uncertainty can be applied to reliability analysis and design optimisation process to obtain reliable lifecycle cost analysis for wind turbine blades (Hu *et al.* 2016a). The optimisation of maintenance measures for risk-based or condition-based inspection and the repair plans for the composite blades of offshore wind turbines have been developed and used in some practical cases worldwide (Sørensen 2009, Nielsen and Sørensen 2011, McMillan and Ault 2007, Li and Liu 2015 and Shafiee *et al.* 2016). However, limited research is available on optimum inspection and maintenance strategy based on the stochastic models for predicting the fatigue crack propagation of the composite blades.

This paper focuses on the stochastic modelling of fatigue crack evolution of the composite blades of offshore wind turbines, where the growth of fatigue crack is predicted by various models. The gamma process is then used to estimate the cumulative crack evolution and to determine the probability of fatigue failure since the modelling of the deterioration process considers uncertainties over the service life. On the basis of stochastic deterioration modelling, a cost-effective approach is proposed for the rational and optimal planning of maintenance actions for composite blades of offshore wind turbines. A numerical example is presented to demonstrate the stochastic gamma process is a reliable tool for modelling fatigue cracking evolution and determining the failure probability. The failure probabilities for different fatigue crack evolutions of composite blades are discussed in lifetime reliability analysis. An optimised maintenance policy is then investigated to make an optimal decision for maintenance of composite blades based on the time-dependent reliability analysis and lifecycle cost analysis. The results show that the proposed approach provides a reliable tool for predicting fatigue damage accumulation and foreseeing of fatigue failure of the composite blades of offshore wind turbines.

2. Fatigue crack models for composite blade

According to the study of Shafiee *et al.* (2015), the proper fatigue crack model for composite blades of offshore wind turbines should contain three stages, i.e. initial crack stage, crack propagation stage, and crack fracture stage. With fatigue crack propagation under repeated loading, the initial crack in structure quickly reaches the first stage following stochastic process at an uncertain start time. After the initial crack stage, the fatigue crack propagation develops by some mathematic laws in this stage. Finally, the fatigue crack becomes unstable and uncontrolled after exceeding the critical crack length at the crack fracture stage, leading to fracture in the structure.

2.1 Initial crack stage

The initial time and position of fatigue cracks in the composite blades are often unpredictable since the differences in mechanical properties and uncertainties in various environments. Thus, a stochastic initial crack state is generated in this study. It is assumed that the starting time point t_s in the composite blade follows a non-homogeneous Poisson process (Shafiee *et al.* 2015). The probability of the *k*th fatigue crack occurrence is here expressed as

$$P_k = \frac{\lambda^k e^{-\lambda}}{k!} \tag{1}$$

where λ is the average start time of cracks in the structure.

It is assumed that all described initial cracks in composite blades are independent and have the same fatigue crack growth rates. The start time t_s is therefore randomly generated by using a Poisson distribution when initial crack happens.

The cracks in composite blades can be detected through various structural damage detection techniques (Zhang *et al.* 2016b), e.g., System Controller Administration (SCADM) system (Yang *et al.* 2013b), optical fibres (Sierra-Pérez *et al.* 2016), fuzzy c-means (FCM) clustering techniques (Yu and Zhu 2015) or modal analysis (Di Lorenzo *et al.* 2016). These techniques have the capability of detecting quantity, location, initial time, and length of fatigue cracks in a reasonably short period after crack initiation. From these techniques, the average start time of cracks is estimated as 0.3 year for the composite blade of offshore wind turbines (Florian and Sørensen 2015), by assuming that Poisson initial cracks are evenly distributed along the whole service time, as shown in Fig 1.

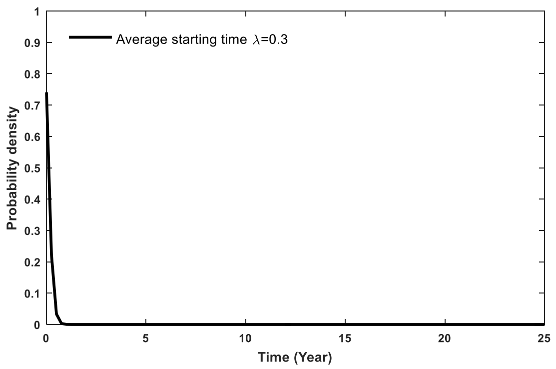

Fig. 1 Probability density of crack started point time by Poisson process

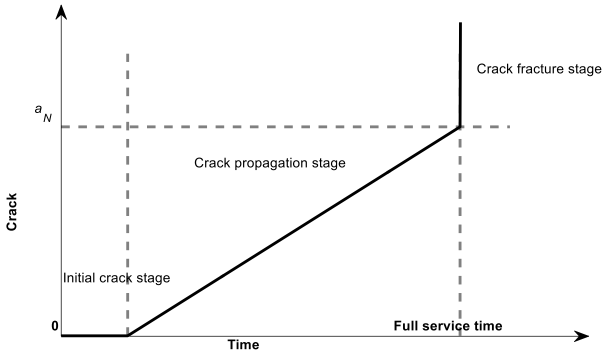

Fig. 2 A schematic of typical Miner's rule for fatigue crack evolution

After initial cracks occur, the cracks quickly progress into the propagation stage.

2.2 Crack propagation stage

In order to study crack onset and crack growth process, various methods were proposed for constructing the relationship between the fatigue crack growth and the cycles of stress at crack propagation stage, including linear, exponential or other non-linear methods.

2.2.1 Miner model

Miner's rule is one of the most widely used linear cumulative fatigue damage models and is probably the simplest model for describing failure caused by fatigue (Miner 1945), as shown in Fig. 2.

From Miner model, the fatigue crack length a_i at time i is express as

$$a_i = a_N \sum_{i=1}^{k} \frac{n_i}{N} \tag{2}$$

where n_i is the number of cycles at time i; N is the total number of cycles when the fatigue crack reaches critical crack length a_N, which is assumed as a deterministic value in this study. In practice, fatigue life N is exactly reflected in the number of load cycles to failure, so it is necessary that the damage criterion is deterministically consistent

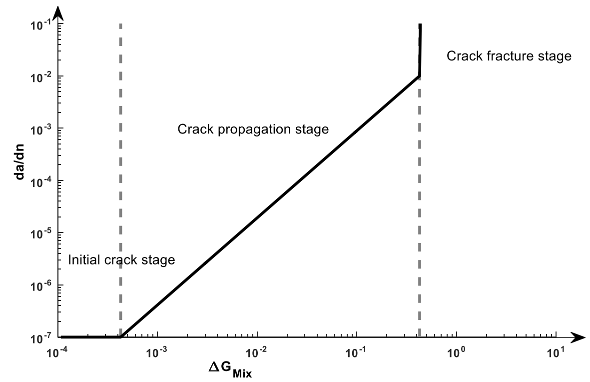

Fig. 3 A schematic of the typical Paris model for fatigue crack evolution

(Sun *et al.* 2014).

2.2.2 Paris model

Various exponential models for fatigue damage of composite materials are reviewed by Degrieck and Van Paepegem (2001). One of widely used exponential models for constructing the relationship between the fatigue crack growth and the cycles of stress is based on a powerful equation, known as Paris model (Paris and Erdogan 1963). The generalised Paris law for composite materials is then proposed by Pugno *et al.* (2006). Therefore, the crack propagation of composite blades with fatigue damage, especially for delamination, can be predicted by using the Paris model in crack propagation stage (Blanco *et al.* 2006).

Based on the theory of Paris law, the following linear elastic fracture mechanics model is used to describe crack propagation

$$\frac{da}{dn} = C(\Delta K(a))^m, \qquad a(0) = a_0 \tag{3}$$

where a is the crack length; a_0 is the initial fatigue crack length; n is the number of load cycles; C and m are parameters related to material constants; ΔK is stress energy release rate, defined as

$$\Delta K = S \cdot Y\sqrt{\pi a} \tag{4}$$

where S is the amplitude of stress; Y represents the symmetry function which varies with the location of the crack. Then the fatigue crack length at the ith cycle a_i is calculated from

$$a_i = \left[a_0^{\frac{(2-m)}{2}} + \left(\frac{2-m}{2}\right) C \cdot S^m Y^m \pi^{\frac{m}{2}} n_i \right]^{\left(\frac{2}{2-m}\right)} \tag{5}$$

When the fatigue crack length reaches the value a_N, failure of the structure occurs.

2.2.3 Reifsnider model

Apart from linear and exponential fatigue crack propagation models, various other non-linear crack propagation models are also proposed. The fatigue damage in composites contains both microscopic and macroscopic mechanisms at all stages during the fatigue process. During the initial period of the lifetime of composite blades, small

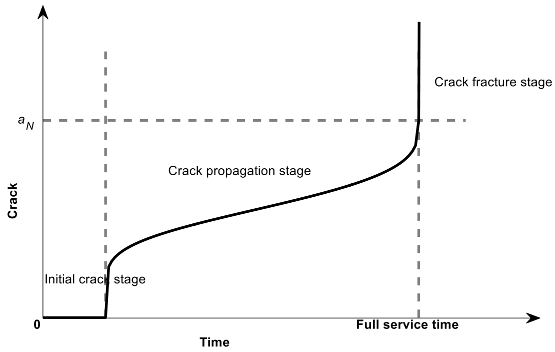

Fig. 4 A schematic of the typical Reifsnider model for fatigue crack evolution

non-interactive cracks occur in the matrix, and some broken fibres begin to appear. With the matrix cracking density reaching saturation and fibre breaking continuously, some cracks are coupling, and interfacial debonding occurs in the composites. At the later stage, delamination between layers occurs after crack intersecting each other. Delamination and localised fibre breaking develop rapidly and the material fractures during the end period of fatigue life (Wu and Yao 2010).

According to Reifsnider (2012), the fatigue damage evolution follows a non-linear mathematic law in composite materials and the development of fatigue process is shown in Fig. 4.

Reifsnider fatigue crack model for composites has been widely investigated theoretically and experimentally, and it can be used to predict the fatigue crack damage growth within the period of the fatigue lifetime. The crack evolution equation for composite blades can be written as

$$a_i = a_N - a_N(1 - \left(\frac{n_i}{N}\right)^B)^A \tag{6}$$

where *A*, *B* are model parameters, respectively. The fatigue crack length a_i is 0 when n_i=0 and reaches the critical crack length a_N when $n_i=N$.

2.3 Crack fracture stage

The crack fractures stage occurs when the crack has developed to the final stage under cyclic loading. Then, cracking becomes unstable and the release of strain energy is sufficient to make the cracks self-propagate until complete disruption and failure occurrence. Once crack fracture stage is reached, failure will occur whether or not the stress is increased. This stage starts after the uncontrolled crack development exceeds the critical crack length a_N and reflects in an overall expansion of the structure, as shown in Figs. 2-4. When it occurs, the crack length will rapidly increase, and the whole structure could not resist any further stress, leading to the structural failure.

3. Failure probability of gamma process for composite blade

The Gamma process is a stochastic process with an independent non-negative gamma distribution increment with identical scale parameter monotonically accumulating over time in one direction, which is suitable to model gradual damage such as wear, fatigue, corrosion, erosion (Chen and Alani 2012, 2013). Gamma process with uncertainties has been proved to be an effective tool for simulating the deterioration process (Van Noortwijk 2009, Chen and Nepal 2015, Chen and Xiao 2015). The advantage of modelling the above deterioration processes by Gamma process is that the required mathematical calculations are relatively straightforward and the results are trustful (Van Noortwijk and Frangopol 2004, Van Noortwijk *et al.* 2007, Van Noortwijk 2009).

The relationships between the fatigue crack growth and the cycles of stress expressed in above three models can be used for reproducing the fatigue crack growth for composite blades. Fatigue crack growth is a process under uncertain conditions such as wind speed, wave loads and humidity. Thus, it can be considered as a time-dependent stochastic process $\{X(t), t\geq 0\}$, where $X(t)$ is a random quantity for all $t\geq 0$.

The gamma process is a continuous stochastic process $\{X(t), t\geq 0\}$ with the following three properties (Van Noortwijk 2009, Chen and Alani 2013, Huang *et al.* 2016): (1) $X(t)=0$ with probability one; (2) $X(t)$ has independent increments; (3) $X(t)-X(s)\sim Ga(v(t-s),u)$ for all $t>s\geq 0$. The probability density function *Ga(xav,u)* is expressed here as

$$Ga(x|v,u) = \frac{u^v}{\Gamma(v)} x^{v-1} e^{-ux} I_{(0,\infty)}(x) \tag{7}$$

where *v* is shape parameter; *u* is scale parameter; and $I_{(0,\infty)}(x)$ is defined as

$$I_{(0,\infty)}(x) = \begin{cases} 1 & if\ x \in (0,\infty) \\ 0 & if\ x \notin (0,\infty) \end{cases} \tag{8}$$

The complete gamma function $\Gamma(v)$ and incomplete gamma function $\Gamma(v,x)$ is defined, respectively, as

$$\Gamma(v) = \int_0^\infty x^{v-1} e^{-x} dx\ ;\ \Gamma(v,x) = \int_x^\infty x^{v-1} e^{-x} dv \tag{9}$$

where $v\geq 0$ and $x>0$.

According to the crack length growth, the probability density function in terms of fatigue crack *a* can be written as

$$f(a) = Ga(a|v,u) = \frac{u^v}{\Gamma(v)} x^{v-1} e^{-ua} \tag{10}$$

For the composite blades, the fatigue failure is defined as experiencing *N* times loading at full-service time *T* for offshore wind turbines depending on the design requirement and environmental conditions, where fatigue crack length *a* reaches the critical crack length a_N. According to the relationship between resistant stress and loading cycles, the bearing capacity of the structure decreases when the number of loading cycles increases. Therefore, the fatigue failure probability of the structure also increases the resistance of the composite blades reduces. Maintenance, repair, and operations for the structure, therefore, should be undertaken in time to prevent structural failure.

The probability of the fatigue affected composite blades to fail during their lifetime is given as

$$F(t) = Pr\{t \geq t_{cr}\} = Pr\{a \geq a_{cr}\} = \int_{a_{cr}}^{\infty} f(a)da = \frac{\Gamma(v(t), ua_{cr}))}{\Gamma(v(t))} \quad (11)$$

where a_{cr} is the critical crack length at time t_{cr}, depending on the maintenance requirements; $v(t)$ is shape function and can be obtained from the expected crack growth discussed in the previous section, by assuming that $v(t)$ equals the crack length a obtained from fatigue crack models.

The probability of failure per unit time at t_j is thus computed from

$$p_j = F(t_j) - F(t_{j-1}), \qquad for\ j = 1,2,3 \ldots \quad (12)$$

When the fatigue crack length a reaches the critical value a_{cr}, the probability of failure becomes unity, and the composite blade fails. As fatigue crack length approaches the critical value, the requirement for maintenance becomes necessary to reduce the risk of structural failure and to prevent the unacceptable possible failure loss. The service time of composite blades can be extended by proper maintenance policy based on the probability of failure.

In general, there are two main approaches for simulating gamma jumping process, namely Increment Sampling of Gamma (ISG) and Bridge Sampling of Gamma (BSG) (Van Noortwijk and Frangopol 2004). When simulating gamma jumping process, there are three key points need to be taken into consideration (Avramidis and L'Ecuyer 2006): (1) This process should correspond to the time; (2) It is a continuous process during the whole time; (3) The process is summed by a set of various random jumping values. The details of two jumping methods of the gamma process are discussed in Avramidis and L'Ecuyer (2006).

4. Optimum maintenance strategy

4.1 Maintenance in service life

During service time, significant uncertainties may exist in the length of the fatigue cracks in composite blades of offshore wind turbine due to the limitations of the testing facilities, operational experience and offshore environments. Here, the reliability of the composite blades could be quantitatively represented by the probability of failure curves over the time. On the basis of the probability of failure, the maintenance actions may be required to restore the capacity of the composite blades. In order to optimise maintenance strategies, the cost of maintenance and the estimation of the remaining service life of composite blades should be investigated. Typical maintenance strategies can be classified as preventive maintenance, which is performed before the composite blades are out of service, and corrective maintenance, which is undertaken by replacing the damaged structural members to maintain the serviceability of the structural system.

In this study, the effectiveness of different types of maintenance strategy is assumed as the reduction of fatigue

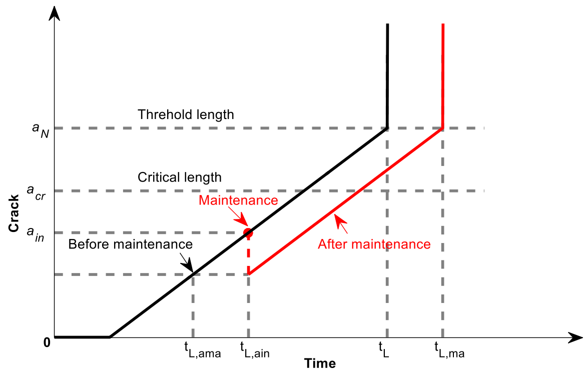

Fig. 5 Influence of maintenance strategy on the service life of composite blades

crack length. It is assumed here that repairs may not be possible to recover the fatigue crack length to zero, and the fatigue crack propagation rate remains the same after the maintenance. When the fatigue crack length becomes the predetermined critical length by inspection, the structure is considered to reach its service lifetime t_L. In the case of maintenance at time t_{in}, the maintenance takes place to reduce the fatigue crack length from a_{in} to a_{ma}, namely

$$a_{ma} = ka_{in} \quad (13)$$

where a_{in} and a_{ma} are the current fatigue crack length before maintenance and the reduced fatigue crack length after maintenance, respectively; k is the maintenance coefficient representing the effectiveness of maintenance, ranging from 0 to 1 with a larger value of k indicating less effectiveness in repair.

After the maintenance, the fatigue crack continues increasing until reaching the predetermined critical length associated with the structural service lifetime $t_{L,ma}$, as shown in Fig. 5.

The service life after maintenance $t_{L,ma}$ can be estimated from

$$t_{L,ma} = t_L + t_{L,ain} - t_{L,ama} \quad (14)$$

where t_L is the service lifetime without maintenance; $t_{L,ain}$ is the service lifetime when the crack length reaches a_{in}; and $t_{L,ama}$ is the service lifetime when the crack length reaches a_{ma}.

4.2 Lifecycle cost analysis

In this study, the lifecycle cost C_t for the management of composite blades during service time includes the inspection cost C_{in}, the maintenance cost C_{ma} and the failure risk cost C_{fa} (Chen 2015), defined as

$$C_t = C_{in} + C_{ma} + C_{fa} \quad (15)$$

Here, the detection technique is considered to inspect the fatigue crack length, and its inspection cost is assumed to be a constant value C_{in}. The maintenance cost is usually affected largely by the effectiveness of the specific maintenance methods, e.g., more effective maintenance methods may require more resources and cost more obviously. Since the maintenance is normally performed after the inspection, the influence of inspection uncertainties on the maintenance cost should be considered. The maintenance cost C_{ma} is calculated from

$$C_{ma} = C_m \cdot (1 - 0.7k)^r \quad (16)$$

where C_m is a constant; and r is a positive integer (Kim *et al.* 2013). The failure risk cost is generally related to the probability of failure and the replacement cost C_{re} for composite blades, given as

$$C_{fa} = [F(t_i)]^q \cdot C_{re} \quad (17)$$

where q is an adjustment parameter.

Consequently, the total lifecycle cost C_t for the composite blades of offshore wind turbines in service can be given as

$$C_t = C_{in} + C_m \cdot (1 - 0.7k)^r + [F(t_i)]^q \cdot C_{re} \quad (18)$$

During the lifecycle of composite blades affected by fatigue cracking, a series of inspection and maintenance may be needed, which requires the planned maintenance strategy to be scheduled and optimised. Different maintenance strategies may require a different amount of resources and cost, and then improve the condition of the blade to different levels.

In this study, one optimal maintenance during the service life is considered to find the optimised inspection and maintenance time for composite blades of offshore wind turbines. The objectives of the optimisation problem are to maximise the service life after maintenance $t_{L,ma}$ and to minimise the total cost of maintenance C_t with different maintenance coefficients. Since it is difficult to compare the total cost C_t for different the service life after maintenance $t_{L,ma}$, the optimisation problem can be expressed as finding the maximum cost efficiency factor C_e to determine optimal maintenance strategy, namely

$$C_e = \frac{t_{L,ma}}{C_t} \quad (19)$$

Finally, after comparing the cost efficiency under different maintenance coefficients, the optimal maintenance strategy represented by the maintenance coefficient can be determined.

5. Numerical example

5.1 Fatigue crack propagation and gamma jumping process

With the fatigue models described above, a numerical example is adopted to investigate the applicability of these three fatigue crack models to the composite blades of wind turbines. The existing studies of fatigue cracking in composite blades show that superficial cracks are the most common form of damage. It is possible that more than one crack can propagate at the same time. However, the crack with the largest length is the one that ultimately causes the composite blade failure.

The measurement of deterioration in this study is based on the length of the longest crack simulated by the three fatigue models with gamma jumping process. When the crack exceeds a given critical length, the crack growth propagation unstably accelerates in short time, and the composite blade loses its mechanical properties. Once this situation happens, the blade structure can be treated as failed and a corrective replacement will be necessary.

The start time of initial crack follows Poisson process with average start time point setting at 0.3 year when crack happens in the blade. The random value is obtained by MATLAB tool, and the tool gives a value of 0.25 year for the start time t_s of the first crack occurrence. It is assumed the critical crack length a_N is 100mm for the composite blades of offshore wind turbines. When the crack length reaches this threshold, the crack becomes uncontrollable, and the blade fails.

For offshore wind turbines, the typical service life is 20 to 30 years, and the service lifetime of 25 years is used here. Miner model simply assumes that cracks grow linearly and eventually reach the critical length a_N when the service lifetime ends. In Paris model, the parameters m and C are assumed as 2.5 and 3.5e-13, respectively (Zhang *et al.* 2016a). The parameters A and B in Reifsnider model are taken as 0.1 and 0.3, respectively (Zhang and Chen 2016b).

Fig. 6 shows crack predictions by the three different models for the fatigue crack evolution of composite blades during the service life. The differences between these predictions are significant for different fatigue models.

Miner model is simple linear crack development model during the service time, and obviously, it is the simplest way to describe the crack propagation. For Paris model, the crack lengths grow slowly and gradually until reaching 5 mm, and it takes about 20 years for this growth. When the service time is near the end of the lifetime, crack length becomes unstable and develops rapidly from 5 mm to the critical length. The crack evolution by Reifsnider model grows shapely and unstably at the beginning and reaches nearly 30 mm within two years. After this, fatigue crack increases slowly and gradually as the service time increases between 3 and 22 years. When the fatigue damage reaches around 70 mm, the fatigue crack becomes unstable again and increases quickly to the crack length threshold.

In this paper, the fatigue crack length is assumed as a random quantity following the gamma jumping process based on three typical fatigue crack models since the uncertainties exist in the fatigue crack propagation and the operation environments. The prediction for the propagation of fatigue cracks of the composite blade from these models with gamma jumping process is also plotted in Fig. 6.

The results show that jumping gamma process matches well the fatigue crack growth generally under different fatigue crack evolution models. Although some values from gamma process have discrepancy, the trends of the fatigue crack development are almost the same, compared with predictions by the deterministic models. In gamma jumping process, the crack length development is accumulated by jumping values for these intervals as time increases. These random values between two close time points can reflect the uncertainties affected by the loading and environments.

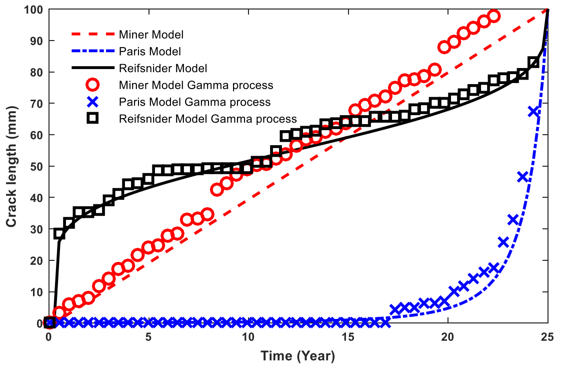

Fig. 6 Propagation of fatigue crack of composite blades under three fatigue models with gamma jumping process

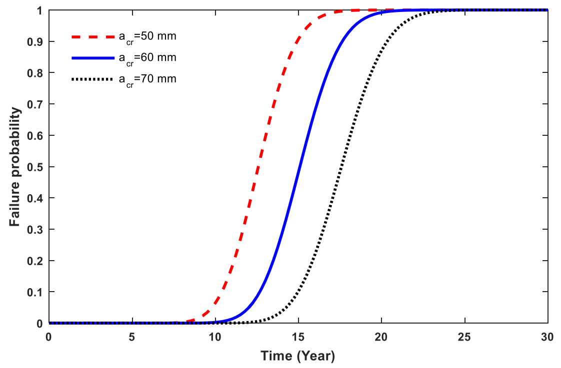

Fig. 7 Failure probability over time by Miner model for various critical fatigue crack lengths, i.e., a_{cr}= 50 mm, 60 mm and 70 mm

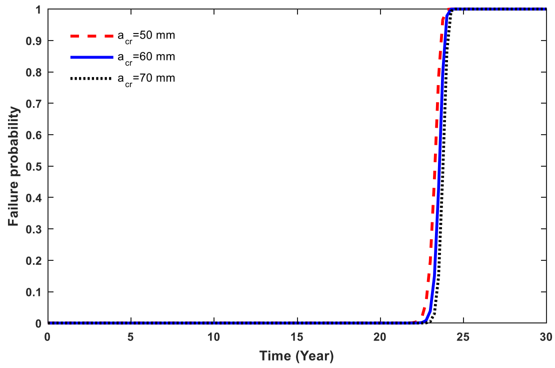

Fig. 8 Failure probability over time by Paris model for various critical fatigue crack lengths, i.e. a_{cr}=50 mm, 60 mm and 70 mm

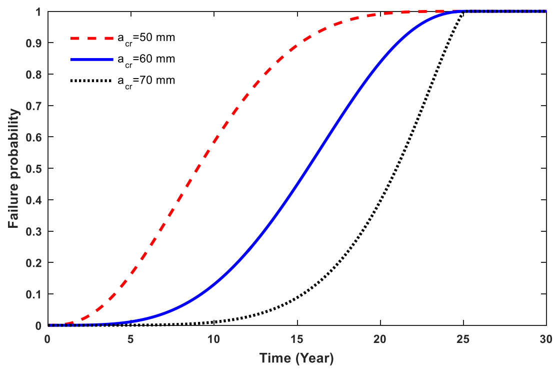

Fig. 9 Failure probability over time by Reifsnider model for various critical fatigue crack lengths, i.e., a_{cr}=50 mm, 60 mm and 70 mm

5.2 Failure probability of composite blades

By combining fatigue crack evolution models with stochastic gamma process, the performance deterioration of the composite blades during service life can be modelled. The results of failure probabilities for different predefined critical crack lengths for these three fatigue models, i.e., a_{cr}=50 mm, 60 mm, and 70 mm, are shown in Figs. 7-9, respectively.

The trends of the probability of failure curves for different critical lengths appear similar. At first, the probability of fatigue failure grows slowly, which indicates the structure behaves normally. As the service time increases, the failure probability increases gradually until reaching a certain point, and then the curve has a rapid rise when the fatigue crack reaches the predefined critical length. Finally, the failure probability reaches to a value of very close to unity, and the composite blade fails. The probability of failure associated with the fatigue crack evolution depends on the given acceptable limit, with a higher probability of failure for a lower acceptable level at any given time. The probability of failure increases dramatically over time and reaches approximately 50% at the time when the expected fatigue crack exceeds the given acceptable limit.

For Miner model, the predefined critical length has a significant impact on failure probability, as shown in Fig. 7. The time when failure probability becomes unstable is around ten years for three cases. With lower critical crack length, the unstable time is slightly earlier and vice versa. The shapes of failure probability curves for different critical crack length are similar. The time of failure probability reaching close to unity for these three predefined critical crack lengths is about 20 year where the blade needs to be repaired or replaced.

From the failure probability results by Paris model shown in Fig. 8, it is obvious that all three curves of failure probability are very close. The time when failure probability becomes unstable is approximately 23 year. With different critical crack length, the unstable time point roughly remains unchanged. The rapid increase in failure probability occurs between 21 and 23 year, which rises from 10% to unity in 2 years, where the structure fails. The reason for this situation is that this model has a rapid crack growth at around 20 year after the long time stable crack growth.

In Reifsnider model, the time when failure probability becomes unstable is obviously different, as shown in Fig. 9. The smaller critical crack length gives the unstable time point much earlier, compared with other two models. With increase in critical crack length, the unstable time points are delayed significantly. The times of failure probability reaching a value close to unity are also different, depending

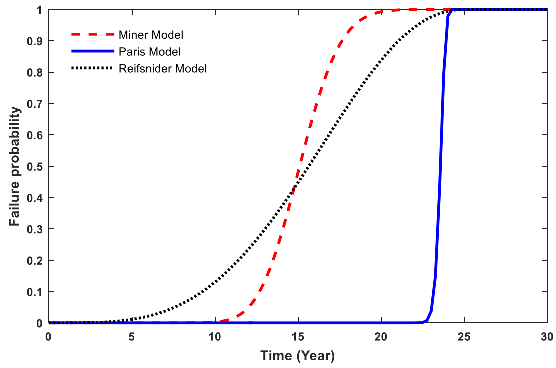

Fig. 10 Comparisons of failure probability over time for critical fatigue crack length of 60mm by three fatigue crack growth models

on the given limited values, where the structures can be treated as failure.

Fig. 10 compares these three fatigue crack growth models with the critical crack limit of 60 mm. The linear model has problems to reproduce the feature of composite crack growth. Paris model could not give significant distinctions on different critical lengths, and the results of failure probability are nearly same. Reifsnider model gives more reasonable fatigue crack propagation results under gamma stochastic process, as discussed in Fig. 6. The failure probability by Reifsnider model gives reliable results as the assumed critical length significantly influences the probability of failure.

5.3 Maintenance strategy for composite blades

Based on previous results, the Reifsnider model is selected to reproduce the fatigue crack growth for the composite blades during the service life, which is typical 25 years for offshore wind turbines. The detection technique is adopted for fatigue crack inspection in this numerical example. It is assumed that the critical value of the fatigue crack length a_{cr} is 60 mm. In addition, it is assumed that the inspection cost C_{in} is £5 million, the maintenance cost factors C_m is £10 million, and the failure risk cost C_{re} is £100 million in this example. The coefficient factors r is 10 and the adjustment factor q is 2, respectively. The maintenance coefficient k is set as 0.2, 0.5 and 0.8 in this case for comparisons, respectively.

The optimum maintenance strategies for the fatigue crack in composite blades are shown in Fig. 11, and every point in Fig. 11 represents a specific maintenance strategy, where both the maintenance time and the cost efficiency are given. As expected, the cost-efficiency curves increase in the beginning time until seven years, and then they decline quickly after reaching the peak.

The minimum total cost values and extended service year values after the maintenance can be found with different maintenance coefficients, as listed in Table 1. The results in Fig. 11 and Table 1 show the maintenance strategies with various maintenance coefficients, i.e., k= 0.2, 0.5, and 0.8 of composite blades during the service life.

For the case with maintenance coefficient 0.2, the blade

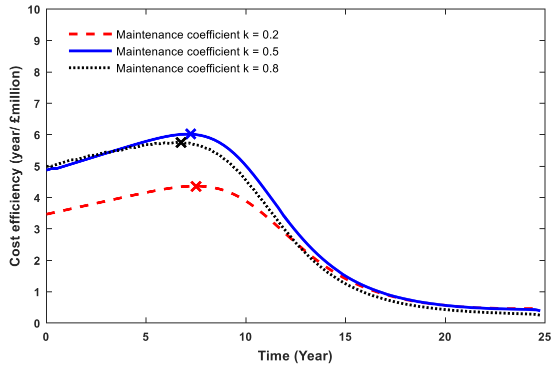

Fig. 11 The optimum maintenance cost efficiency over service time for the composite blade with various maintenance coefficients, i.e., k=0.2, 0.5, and 0.8

Table 1 The minimum total cost and extended service time for different maintenance coefficients

Maintenance coefficient k	Optimal maintenance time (year)	Cost efficiency (year/ £million)	Extended service time (year)	Lifetime total cost (£million)
0.2	7.50	4.3636	32.5	7.448
0.5	7.25	6.0157	32.0	5.319
0.8	6.75	5.7687	29.5	5.114

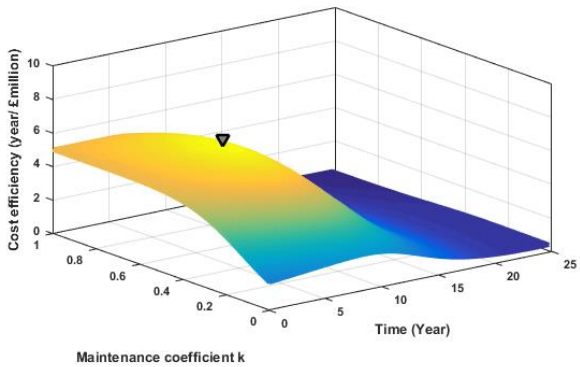

Fig. 12 The global optimum maintenance cost efficiency over service time for the composite blades under varying maintenance coefficients

has an extended service life of 32.5 year when the maintenance is taken at 7.50 year. However, the cost efficiency is lower for this case, which indicates this strategy is not cost-effective. For the case with maintenance coefficient 0.8, the intervention takes place at 6.75 year, and then the extended service life of the composite blade is extended to 29.5 year, while the total cost for this strategy is decreased to £5.114 million. Although this strategy does not cost more, the extended service time is also less. The value of cost efficiency shows that this strategy is not cost-effective as well. In the case with maintenance coefficient 0.5, the final extended service life of the composite blade is 32.0 year, and the total cost for this strategy is £5.319 million. The cost efficiency of this strategy is the highest among all three strategies, which means this is the most cost-effective strategy among these three different maintenance coefficients.

In order to find the most cost-effective maintenance, the cost efficiency is plotted both maintenance coefficient and service time again. The results in Fig. 12 show the cost efficiency with maintenance coefficient between 0 and 1 over the lifetime of the composite blade. The global maximum cost efficiency value is found to be 6.1058 when k equals 0.578 and the maintenance time is 7.00 year. The total cost is £5.200 million and the service time after maintenance will be extended to 31.8 year.

6. Conclusions

This study uses a stochastic method to analyse fatigue damage evolution processes for the composite blades of offshore wind turbines. A numerical case study is presented to investigate the effectiveness of the stochastic deterioration modelling with different fatigue crack development models. The results show that stochastic fatigue damage modelling gives reliable results and can be used for analysing the failure probabilities of composite blades. On the basis of the obtained results, the following conclusions can be drawn.

By using the gamma jumping process associated with the fatigue damage models during the service time, the proposed methods give excellent simulations on fatigue crack evolution of wind turbine composite blades. The proposed stochastic modelling methods evaluate reasonably the lifetime distribution of probability of failure for composite blades and can be used to assist in the inspection and maintenance of composite blades in operation.

Three different crack propagation models are discussed in this study according to the gamma process. Depending on the assumed critical lengths, Reifsnider model gives more reliable results, comparing with linear Miner model and exponential Paris model. The linear Miner’s law has problems to reproduce the feature of composite crack growth since the crack propagation of the composite material is not linear according to various material experiments. The Paris law is typically used to describe the crack propagation of metals material, so it may also be an inappropriate model for composite wind turbine blade. The Reifsnider model can better simulate the crack growth of composite blades under the practical situations. The failure probability under different predefined critical crack lengths can be further used to estimate the failure time of composite blades for inspection and maintenance in various situations.

The proposed optimum maintenance strategy based on the reliability analysis and lifecycle cost analysis can give a balance between the extended service life and the total cost for maintenance of the composite blades. The proposed methods will be more cost-effective for repairing the composite blades experienced fatigue when the interventions are conducted at the early stage of the fatigue crack propagation.

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