Optimum Maintenance Strategy for Fatigue Damaged Composite Blades of Offshore Wind Turbines using Stochastic Modelling

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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 models for reproducing fatigue crack development growth, 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. On the basis of the results from fatigue model and stochastic gamma model, an optimised maintenance policy is determined to make optimal maintenance decision for the composite blades. A numerical example is employed to investigate the effectiveness of predicting fatigue crack growth and estimating probability of fatigue failure to determine an optimised maintenance policy. The results from the numerical study show that the stochastic gamma process together with the fatigue models can provide a useful tool for remaining useful life predictions and optimum maintenance strategies of the composite blades of offshore wind turbines.

1. INTRODUCTION

Energy crisis and global warming have led to increasing demand on clean and renewable energy such as wind energy. Due to the shortage of space on land and the better exploit of wind energy in the sea, offshore wind turbines have gained significant attentions in recent research and development. In the wind turbine system, the most critical component is the wind turbine blade since the manufacturing cost of the blade is about 15-20% of the wind turbine production cost (Jureczko 2005). In order to improve

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the performance of wind turbine blades, layered fibre-reinforced polymer composite materials are usually adopted for the large blades of wind turbines since these materials have better fatigue resistance and lighter weight compared with traditional materials, such as metals (Montesano 2016).

For composite blades, fatigue cracking is a major fatigue damage weakening the physical properties of the original strength of the materials by cyclical loadings in long time. The prediction of fatigue crack propagation needs a proper model adopting the rate of fatigue crack growth with cyclic loadings. 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 tough due to the complexity of the mechanical properties of composite materials and the limited information available on blade fatigue behaviour. Although a deterministic mechanism may not be appropriate for fatigue damage assessment in composite blades, several fatigue crack damage models were proposed to reproduce the crack propagation of composite blades in a deterministic form. The proper fatigue crack models should contain three stages, i.e. the initial crack length follows stochastic distribution in composite blades at the start time; fatigue crack propagation processes in accordance with some mathematic laws during the service life; and uncontrolled crack development occurs after exceeding the threshold crack length after service time (Zhou 2014).

Probabilistic analysis by stochastic deterioration models is a useful tool for deteriorating composite materials affected by cyclic fatigue loadings during the service life. The fatigue crack growth of the composite blades of offshore wind turbines can be modelled as a stochastic process with uncertainties. Considering the nature of cumulative growth of fatigue cracks, the gamma process model is an appropriate approach for fatigue evolution modelling 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 gamma process analyses the fatigue crack growth data accurately and derives the distribution of the time to reach any crack size (Guida 2015).

Maintenances for composite blades of offshore wind turbines make substantial contribution to the total life cycle costs, and are often expected to increase service lifetime with less cost in harsh marine environments. For the composite blades of offshore wind turbines, cost-effective measures for risk-based inspection and repair planning have been developed and used in many cases worldwide, e.g. Sørensen (2009) and Shafiee (2016).

This paper focuses on the stochastic modelling of fatigue crack evolution of composite blades of offshore wind turbines, where the fatigue crack growth is predicted by various models. The gamma process is then used to estimate the cumulative crack propagation 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 obtained results, an effective approach is proposed for rational and optimal planning of maintenance strategy for composite blades of offshore wind turbines. A numerical example is presented to demonstrate the gamma process is a reliable tool for stochastic modelling of fatigue cracking evolution. The failure probabilities for different fatigue crack evolutions are discussed for lifetime reliability analysis. An optimised maintenance policy is investigated to make an optimal decision for maintenance of composite blades based on the time-dependent reliability analyses. The results show that the proposed methods provide a reliable tool for predicting fatigue damage accumulation and foreseeing of fatigue failure of the composite blades of offshore wind turbines.

2. INITIAL CRACK LENGTH

The initial length and position of fatigue crack in the composite blades are often unpredictable at the start time. Thus, a stochastic initial crack state is generated in this study. The distances L_1, L_2 …. L_n from the root in composite blade follow a non-homogeneous Poisson process (Shafiee 2015), $\{N_1(L); L \geq 0\}$ with intensity function $m(L)$ and mean value function $M(L)$, i.e.

$$M(L) = \int_0^l m(y)dy, L \geq 0 \quad (1)$$

where L is the total length of the wind turbine blade. It is assumed that all described initial cracks in composite blades are independent and have equal fatigue crack growth rates. The initial size of each crack is therefore randomly generated using the gamma distribution.

The cracks in composite blades can be detected through various structural health monitoring systems, e.g., SCADM (Yang 2013), optical fibre (Sierra-Pérez 2016) or modal analysis (Di Lorenzo 2016). These techniques have the capability of detecting quantity, location, and length of fatigue cracks in a reasonably short period of time after crack initiation. From these techniques detections, the average number of cracks is set at 0.3 per meter length of the blade, by assuming Poisson initial cracks to be evenly distributed along the length of the whole blade. This may not be realistic, but other models with cracks concentrated in certain areas of the composite blade can easily be implemented.

3. CRACK PROPAGATION MODELS

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, including linear methods or non-linear methods.

3.1 Miner model

Miner's rule is one of the most widely used linear cumulative fatigue damage models and is probably the simplest model for failures caused by fatigue (Miner 1945), as shown in Fig. 1.

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

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

where n_i is the number of cycles at time i; N is the average number of cycles to failure when the fatigue crack reaches threshold crack length a_N.

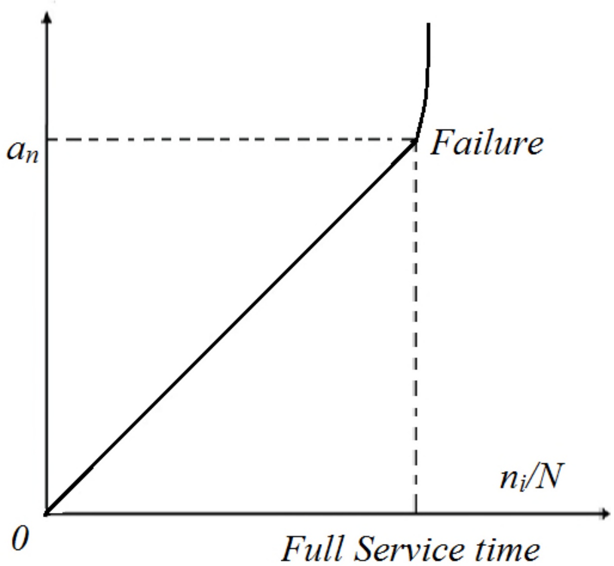

Fig. 1 A schematic of typical Miner's rule for fatigue crack evolution

3.2 Paris model

Various exponential models of composite materials for fatigue damage are reviewed by Degrieck (2001) gives. A widely used model for constructing the relationship between the fatigue crack growth and the cycles of stress is based on a powerful equation known as Paris model (Pugno 2006).

The fatigue crack propagation in Paris law can be divided into three stages, crack initiation stage, subcritical crack propagation stage and critical crack propagation stage, as shown in Fig. 2. With fatigue crack propagation under repeated loading, the structure quickly reaches the first stage of the failure process. Stage 1 covers the initial crack following Poisson process. Stage 2 is linear increasing growth part following Paris equation. Finally, the rate of crack propagation becomes unstable and uncontrolled, leading to structural failure. Therefore, the total life of a structure with fatigue damage can be predicted by using the Paris model.

Based on the simple Paris–Erdogan crack growth model (Paris 1963), the following linear elastic fracture mechanics model is used to describe crack propagation

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

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.

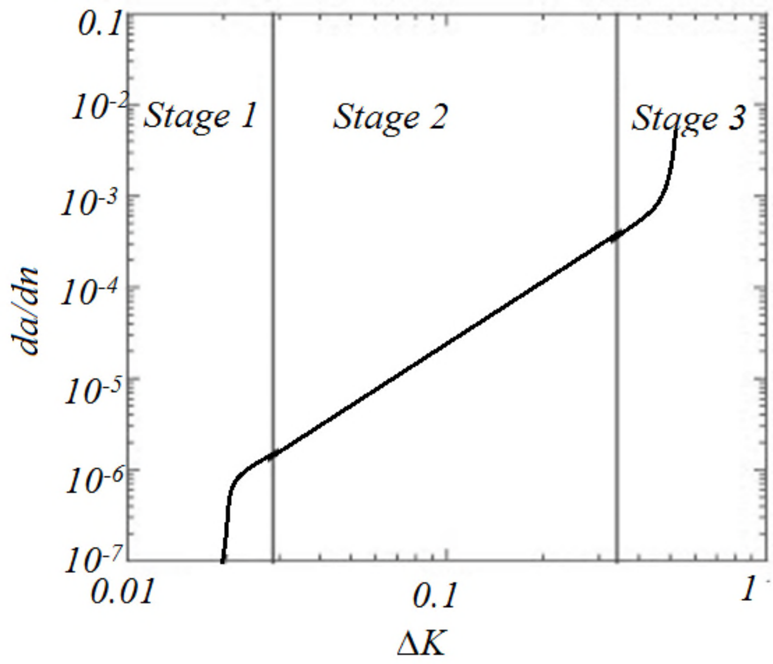

Fig. 2 A schematic of the typical Paris model for fatigue crack evolution

Then the fatigue crack length at i time a_i is calculated from

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

where n_i is the cycles at i time. The fatigue crack length reaches the value a_N, when failure occurs (Kim 2013).

3.3 Reifsnider model

Besides linear and exponential fatigue crack propagation models, various non-linear crack propagation models are also investigated. According to Reifsnider (2012), the fatigue damage evolution is non-linear in composite materials and the development of fatigue process is shown in Fig. 3.

Reifsnider fatigue crack model for composite has been widely investigated theoretically and experimentally, and they can predict the fatigue crack damage process within the period of the fatigue life. The crack evolution equation by Zhang (2016c) can be written as

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

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

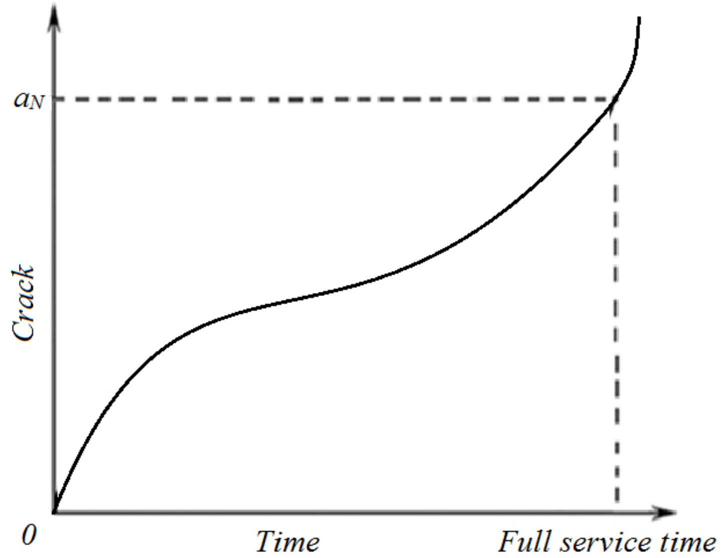

Fig. 3 A schematic of the typical Reifsnider model for fatigue crack evolution

4. STOCHASTIC GAMMA MODEL

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 2012). A proper model by Abdel-Hameed (1975) called gamma wear process for deterioration occurring random in time was the first study for the application of gamma process in stochastic deterioration modelling. The advantage of this stochastic process is that the required mathematical calculations are relatively straightforward and the results are trustful. Gamma process with uncertainties is a stochastic process, and has been proved to be an effective tool for simulating the deterioration process.

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 length for composite blades of offshore wind turbines. A failure can occur even under the stress resistance of the materials because of long time fatigue loading. 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: (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 $t>s \geq 0$. (Chen 2013)

The probability density function $Ga(x | v,u)$ is expressed 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 *Γ(v)* and incomplete gamma function *Γ(v,x)* is defined, respectively, as

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

$$\Gamma(v,x) = \int_x^\infty x^{v-1} e^{-x} dv \tag{10}$$

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

According to the crack length growth, the probability density function can be written as:

$$F(a) = Ga(a|v,u) = \frac{u^v}{\Gamma(v)} x^{v-1} e^{-ua} \tag{11}$$

For the composite wind turbine blades, the fatigue failure is defined as experiencing *N* times loading at *T* time, where fatigue crack length reaches the threshold crack length a_N. The critical crack length a_{cr}, *chosen by the threshold value and factor of safety,* depends on the construction design requirement, environmental conditions and the safety factor of the structures. The service life of the wind turbine blades can be predicted by accumulating the growth in each individual time before reaching critical crack length. According to the relationship between stress and cycles called S-N curves, the bearing capacity of structures decreases when the number of loading increases. Therefore, the fatigue failure probability of the structure also increases as the resistance of blades reduces. Repairing for the structure therefore should be undertaken in time to prevent structural failure.

The failure probability can be calculated (Zhang 2016b) by

$$F(t) = Pr\{t \geq t_{cr}\} = Pr\{a \geq a_{cr}\} = \int_{a_{cr}}^\infty f(a) da = \frac{\Gamma(v(t), ua_{cr}))}{\Gamma(v(t))} \tag{12}$$

where a_{cr} is critical crack length; *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* by fatigue crack models.

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

$$p_j = F(t_j) - F(t_{j-1}), for\ j = 1,2,3 \ldots \tag{13}$$

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

5. GAMMA JUMPING PROCESS

In general, there are two main approaches for simulating gamma process, namely Increment Sampling of Gamma (ISG) and Bridge Sampling of Gamma (BSG) (Van Noortwijk, 2004). The gamma process is the Lévy process according to the gamma distribution (Avramidis 2006). When simulating this random process, there are three key points i.e. this process should be corresponding to the time; it is a continuous process during the whole time; the process is summed by a set of various random jumping values.

5.1 Increment Sampling of Gamma process

When fatigue crack evolution of the blades is modelled as gamma process, the increment of fatigue crack length at each jumping point is required. A path of the gamma process is sampled by these time point: t_0, t_1, t_2, t_3…… t_{n-1}, t_n, which means n times per units are the same and the increment in each time interval can be presented by:

$$\Delta a_i = a(t_i) - a(t_{i-1}), \quad \Delta t_i = t_i - t_{i-1} \tag{14}$$

Considering the gamma process, the fatigue crack length at t_i can be represented as:

$$\Delta a_i \sim Ga(a|v(t_i) - v(t_{i-1}), u) \tag{15}$$

Therefore, the probability density function of Δa_i is

$$f(\Delta a_i) = \frac{u^{v(t_i)-v(t_{i-1})}}{\Gamma(v(t_i)-v(t_{i-1}))} \Delta a_i^{v(t_i)-v(t_{i-1})-1} e^{-u\Delta a_i} \tag{16}$$

The fatigue crack length can be accumulated by summing the sampled length in each time points, that is

$$a_i = \sum_0^i \Delta a_i \tag{17}$$

5.2 Bridge Sampling of Gamma process

According to the study by Avramidis (2006), the propagation of the fatigue crack length can be calculated by the Gamma Bridge Sampling. The BSG is one of simulation method for this process based on the representation of the process as a subordinated Brownian motion (Pandey 2004). The main parts of the bridge sampling can be summarised as follows.

Selecting any three time points during the whole life i.e. T $0 \le t_i < t_j < t_k \le T$, and therefore the values of these three points are $Ga(t_i|v,u)$, $Ga(t_j|v,u)$, $Ga(t_k|v,u)$, respectively. Assuming $Y_1 = Ga(t_j|v,u) - Ga(t_i|v,u)$ and $Y_2 = Ga(t_k|v,u) - Ga(t_j|v,u)$,

Y_1 and Y_2 are mutually independent. According to the property of gamma process, $Y_1 \sim Ga(g_1, u), Y_2 \sim Ga(g_2, u)$ where $g_1 = (t_j - t_i)v$ and $g_2 = (t_k - t_j)v$. Also, let $Y_3 = Y_1 + Y_2 = Ga(t_k|v, u) - Ga(t_i|v, u)$ is $Y_3 \sim Ga(g_3, u)$ where $g_3 = (t_k - t_i)v$. From incomplete gamma distribution density of Y_1 is:

$$f_{Y_1|Y_3}(y_1|y_3) = \frac{1}{B(g_1,g_2)} \left(\frac{y_1}{y_3}\right)^{g_1-1} (1 - \frac{y_1}{y_3})^{g_2-1} {y_3}^{-1} \tag{18}$$

This indicates

$$Ga(t_j|v, u) = Ga(t_i|v, u) + b_{t_j} y_3 \tag{19}$$

where $b_{t_j} \sim Beta(g_1, g_2)$ and $Beta(v, u)$ is the beta function.

In order to simplify the simulation process, the whole life [0, T] divided into 2^m steps time points, which are *T; T/2; T/4, 3T/4; ...; $2^{-m}T$, $3x2^{-m}T$, ..., $(1\text{-}2^{-m})T$* points during the process. The steps of simulating gamma process can be summarised

(1) Calculating the whole crack width from 0 to T:

$$a_0 = a_0, a_T = a_{cr} \tag{20}$$

(2) Dividing this period into two equal time periods, i.e. [0, T/2] and [T/2, T], the crack length at T/2 is

$$a_{T/2} = a_0 + (a_T - a_0) * Y \quad Y \sim Beta\left(\frac{v}{2}, \frac{v}{2}\right) \tag{21}$$

(3) Continuously dividing these two periods in to equal two parts and calculating the crack width

$$\begin{cases} a_{T/4} = a_0 + (a_{T/2} - a_0) * Y \quad Y \sim Beta\left(\frac{v}{4}, \frac{v}{4}\right) \\ a_{3T/4} = a_{T/2} + (a_{T/2} - a_0) * Y \quad Y \sim Beta\left(\frac{v}{4}, \frac{v}{4}\right) \end{cases} \tag{22}$$

(4) Repeating these steps until time points reaching 2^{-m}T.

The advantage of the BSG method is that the existing iteration results can still be used if the higher accuracy is needed by dividing the time points, compared with the ISG method. The BSG method allows the accuracy to be pre-defined and the numerical integration to be terminated when that accuracy is achieved. (Van Noortwijk 2007)

6. OPTIMUM MAINTENANCE STRATEGY

6.1 Maintenance in service life

During service time, significant uncertainties may exist in size of the fatigue cracks of composite blades due to the limitations of the testing facilities, operational experience and offshore environments. The capacity of the composite blades could be quantitatively represented here 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 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 maintenance is undertaken and the fatigue crack length becomes the predetermined threshold by inspection, the structure is considered to reach its service lifetime t_L. In the case with maintenance at time t_{in}, the maintenance takes place to reduce the fatigue crack length from the initial a_{in} to a_{ma}, namely

$$a_{ma} = k a_{in} \tag{23}$$

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

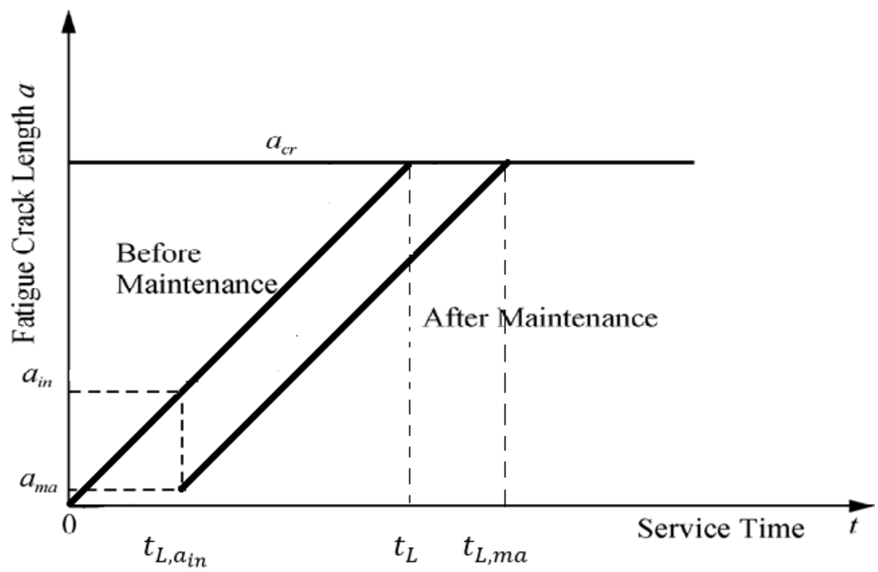

Fig. 4 Influence of maintenance strategy on the service life of composite blades

After the maintenance, the fatigue crack continues increasing until reaching the pre-determined threshold with the structural service lifetime $t_{L,ma}$, as shown in Fig. 4. The service life after maintenance $t_{L,ma}$ can be estimated from

$$t_{L,ma} = t_L + t_{L,ain} - t_{L,ama} \quad (24)$$

where t_L is the service lifetime without maintenance, $t_{L,ain}$ is the service lifetime after reaching a_{in} and $t_{L,ama}$ is the service lifetime after reaching a_{ma}.

6.2 Life-cycle cost analysis of inspection and maintenance

In this study, the life-cycle cost for the management of composite blades in service includes the inspection cost C_{in}, the maintenance cost C_{ma} and the failure risk cost C_{fa}, defined as (Chen 2015).

$$C_t = C_{in} + C_{ma} + C_{fa} \quad (25)$$

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

$$C_{ma} = C_m \cdot (1 - 0.7k)^r \quad (26)$$

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

$$C_{fa} = F(t_i) \cdot C_{re} \quad (27)$$

Consequently, the total life-cycle cost for the management of the composite blades of offshore wind turbines C_t in service can be given as

$$C_t = C_{in} + C_m \cdot (1 - 0.7k)^r + F(t_i) \cdot C_{re} \quad (28)$$

During the life cycle of 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 different amounts 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. In order to select optimal maintenance strategies, the problem can be expressed as finding the minimum cost efficiency per year, C_e, since it is difficult to compare different total cost C_t with different the service life after maintenance $t_{L,ma}$, i.e.

$$Ce = \frac{C}{t_{L,ma}} \quad (29)$$

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

7. NUMERICAL EXAMPLE

7.1 Fatigue crack propagation and gamma jumping process

With the fatigue models described above, a numerical example is adopted to investigate the effectiveness of these three fatigue crack models. The studies of fatigue cracking in composite blades of offshore wind turbines 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 blade failure.

The measurement of deterioration in this study is based on the length of the longest crack from the three fatigue models with gamma jumping process. When the crack exceeds a given threshold length, the crack growth propagation accelerates unstably 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 initial crack length follows the gamma distribution, and the number of cracks follows Poisson process with average number of cracks setting at 0.3 per meter length of the blade. It is assumed the threshold of crack length a_N is 100mm for the composite blades of offshore wind turbines. When the crack length reaches the threshold, the crack becomes uncontrolled and the blade fails.

For offshore wind turbines, the typical service life is 20 to 30 years, and the service life time of 25 years is used here. Parameters relating to the crack development models are assumed reasonably to simulate the fatigue crack propagation and to analyse failure probability. Miner model simply assumes that cracks grow linearly and eventually reach the threshold a_N when the service lifetime ends. Hence, the parameters m and C assumed in Paris model are 2.5 and 3.5e-13, respectively (Zhang 2016a). The parameters A and B in Reifsnider model are taken as 0.1 and 0.3, respectively (Zhang 2016c).

Fig. 5 shows crack predictions by the three different models for the fatigue crack evolution composite blades during the service life. The differences between these prediction cracks are significant from 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 life time, crack length becomes unstable and develops rapidly from 5 mm to the threshold length. The crack evolution by Reifsnider model grows shapely and unstably at beginning and reaches nearly 30 mm within two years. After this, fatigue crack increases slowly and gradually as the service time increases between 2 and 20 years. When the fatigue damage reaches around 70 mm, the fatigue crack becomes unstable again and increases quickly to the crack length threshold.

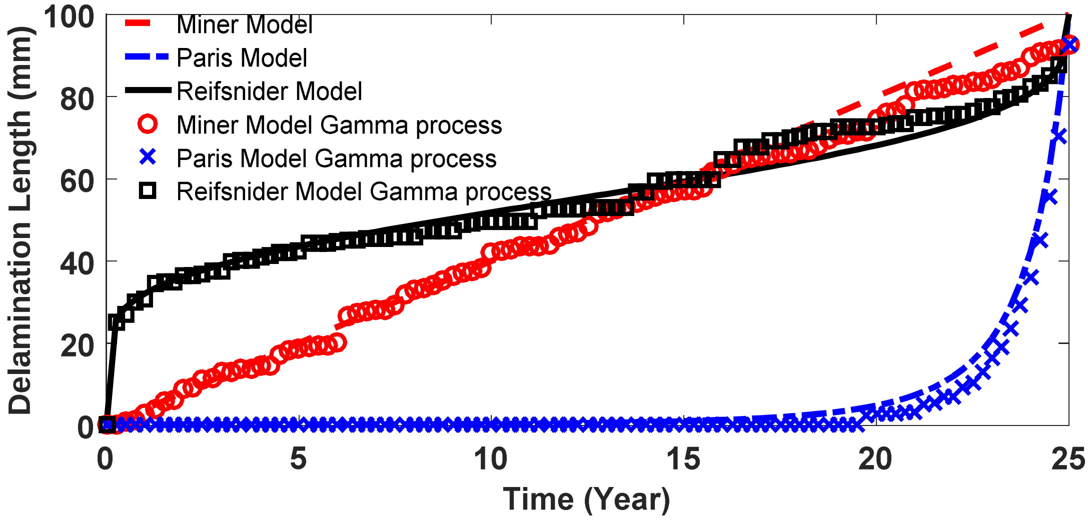

Fig. 5 Propagation of fatigue crack of composite blades under three fatigue models with each gamma jumping process

The prediction for propagation of fatigue crack of the composite blade from these models with gamma jumping process are also plotted in Fig. 5. 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 predicting by the 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 environment changes.

7.2 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 critical crack lengths from these three fatigue models, i.e. a_{cr}=50 mm, 60 mm and 70 mm, are shown in Figs. 6-8, respectively.

The trends of the probability of failure curves for different critical lengths under three fatigue crack models appear similar. At first, the probability of fatigue failure grows slowly, which indicates the structure behaviours normally. As the service time increases, the failure probability increases gradually until reaching certain point, and then the curve has a rapid rise when the fatigue crack reaches the defined 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.

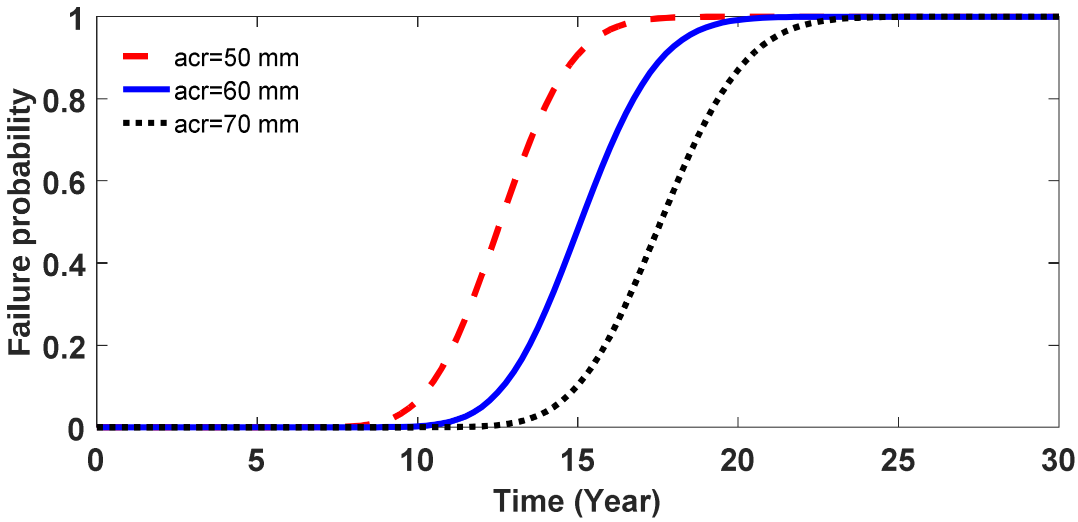

Fig. 6 Failure probability over time for various critical fatigue crack lengths, i.e. a_{cr}= 50 mm, 60mm & 70mm, by Miner model

However, the differences of these three models are also significant as shown in Figs. 6-8. For linear model such as Miner model shown in Fig. 6, the time when failure probability becomes unstable is around 10 years. With lower critical crack length, the unstable time is slight earlier and vice versa. The shapes of failure probability curves for different critical crack length are similar with different unstable time starting points. The time of failure probability reaching close to unity about 20 years where the blade needs to be repaired or replaced.

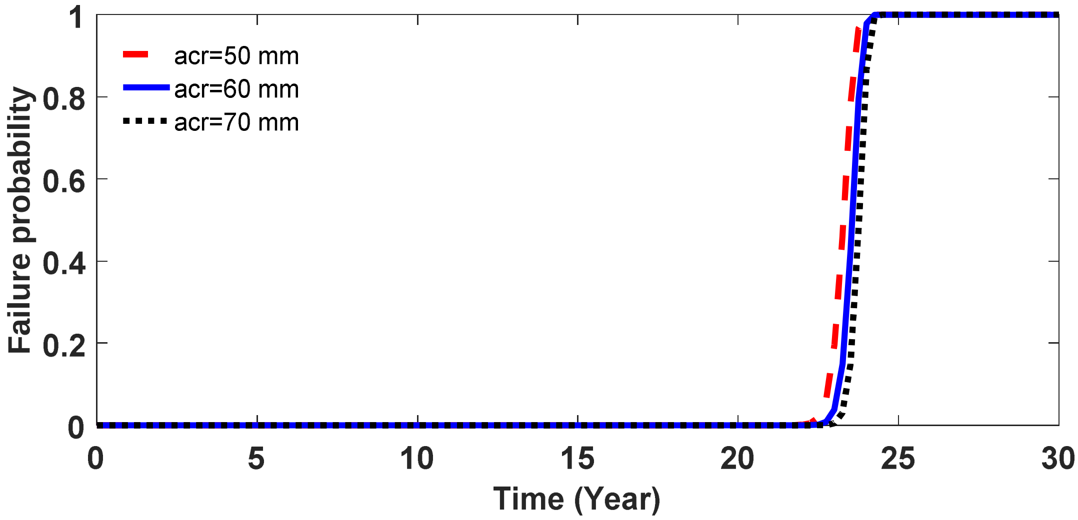

Fig. 7 Failure probability over time for various critical fatigue crack lengths, i.e. a_{cr}= 50 mm, 60mm & 70mm, by Paris model

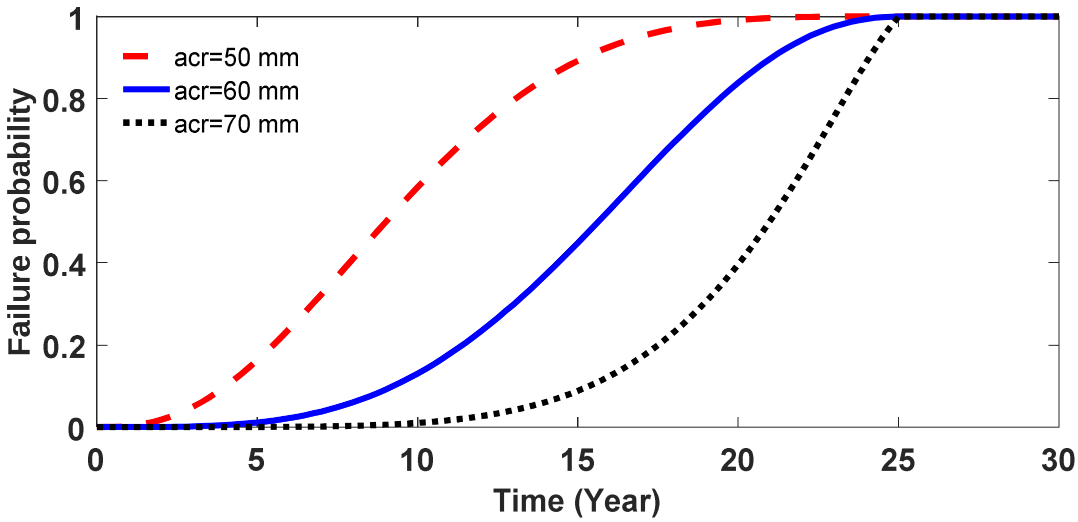

Fig. 8 Failure probability over time for various critical fatigue crack lengths, i.e. a_{cr}= 50 mm, 60mm & 70mm, by Reifsnider model

From the failure probability results by Paris model shown in Fig. 7, it is obvious that all three curves of failure probability are very close. The time when failure probability becomes unstable is approximately 23 years. With different critical crack length, the unstable time point remains nearly unchanged. The rapid increase in failure probability occurs between 21 and 23 years, which rises from 10% to unity in 2 years, where the structure fails. The reason for this situation is that the Paris model has a rapid crack growth at around 20 years after stable crack growth.

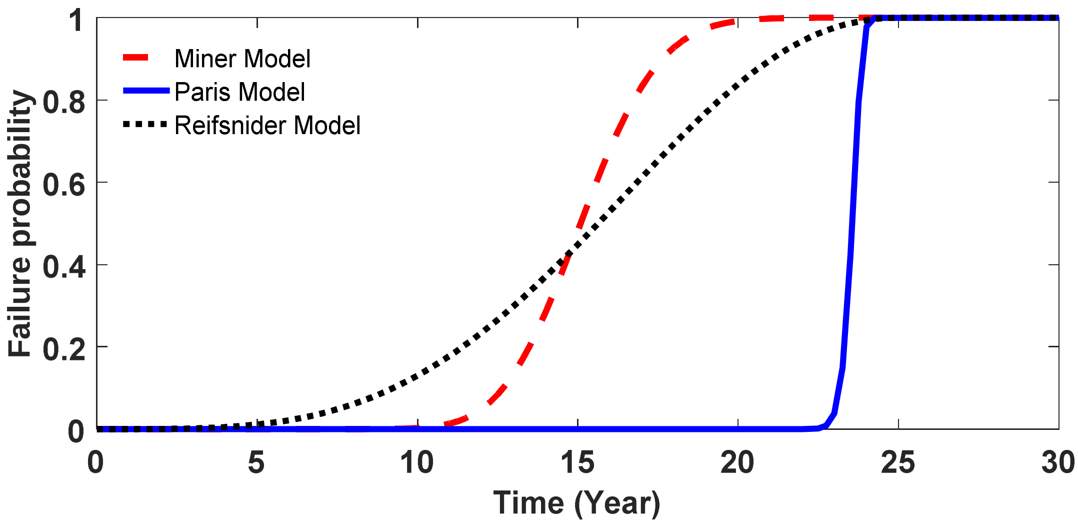

Fig. 9 Comparisons of failure probability over time for critical fatigue crack length of 60mm by three different models

In Reifsnider model, the times when failure probability has a shape increase and becomes unstable are obviously different, as shown in Fig. 8. Lower critical crack length makes 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 on given limited values, where the structure needs to be replaced or repaired.

From the results from these three different fatigue models, the linear Miner 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. The failure probability by Reifsnider model gives more reasonable results as the assumed critical lengths significantly influence the results. Fig. 9 compares the results for failure probability from these three models with the critical crack limit of 60 mm. Reifsnider model gives more reasonable failure probability results under gamma stochastic model.

7.3 Optimum maintenance strategy

The Reifsnider model is selected here to reproduce the fatigue crack evolution of composite blades during the service life. It is assumed here that the critical value of the fatigue crack length a_{cr} is 60 mm. Also, the inspection cost C_{in}=50 k$, the maintenance cost factors C_m= 1,500 k$ and r=10, and the failure replacement cost C_{re}=150 k$ are assumed in this example. The maintenance coefficient k is taken as 0.5, 0.7 and 0.9, respectively.

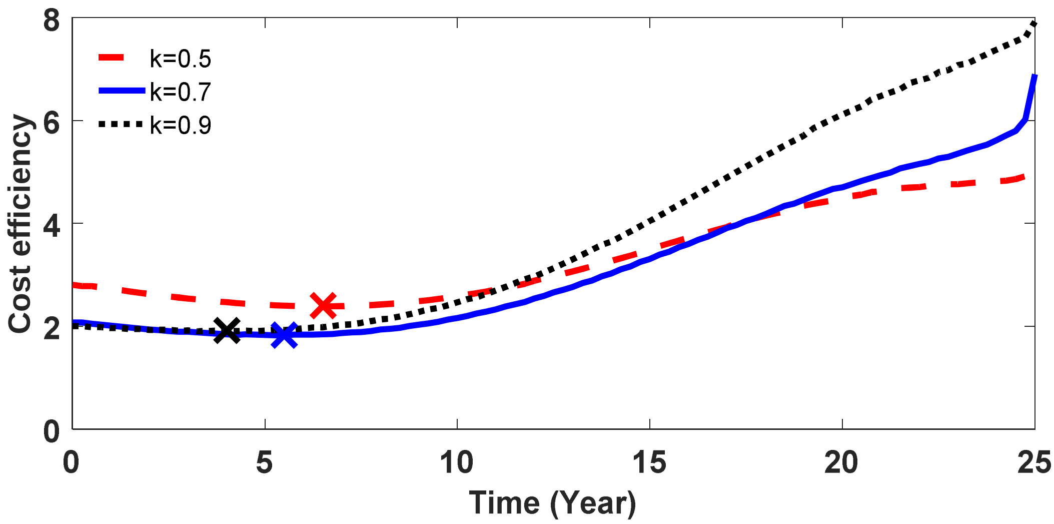

Fig. 10 The optimum maintenance cost efficiency over different maintenance times for the composite blade under various maintenance coefficients *k*, i.e. 0.5, 0.7 and 0.9

The optimum maintenance strategies for the fatigue damage crack in composite blade are shown in Fig. 10, where various maintenance coefficients are considered, i.e., *k*=0.5, 0.7 and 0.9, respectively. As expected, the optimal cost efficiency drops down in the beginning until around 5 years, then increases quickly after the minimum value. The minimum values of cost efficiency and other parameters after maintenance are summarised in Table 1.

Table 1 The minimum values of cost efficiency for different maintenance coefficients

Maintenance coefficient k	Optimum maintenance time (year)	Cost efficiency (k$/year)	Service time after maintenance (year)	Total cost (k$)
0.5	6.5	2.39	31	73.98
0.7	5.5	1.82	29.5	53.80
0.9	4	1.91	26.5	50.65

In order to find the most effective maintenance strategy, the results in Fig. 11 shows the cost efficiency as a function of both maintenance coefficient *k* and maintenance time. The global minimum cost efficiency value is 1.81, when *k* equals 0.742 and the maintenance time is 5.25 years. The total cost is 52.998 k$ and the service time after maintenance will reach 29.25 years.

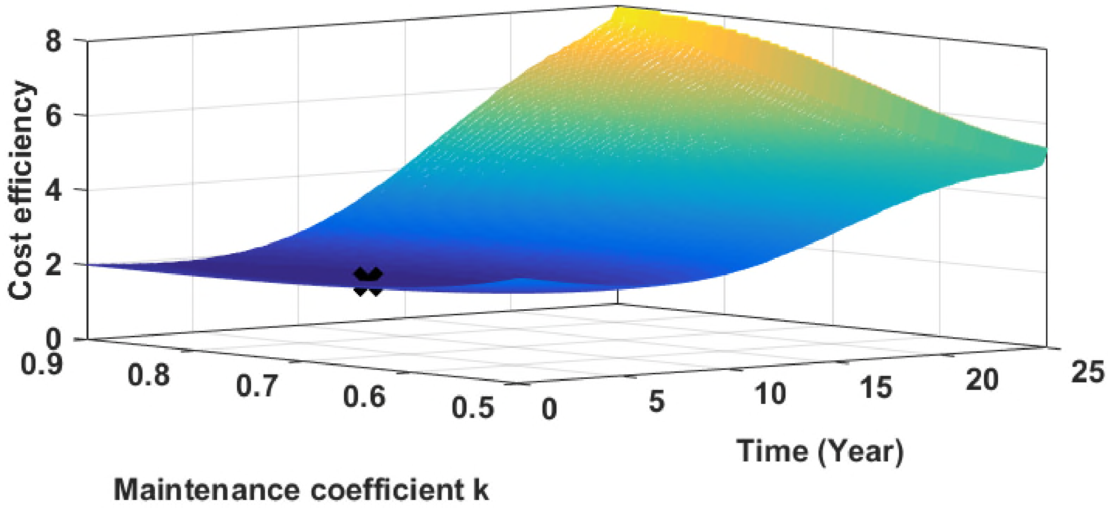

Fig. 11 The optimum maintenance cost efficiency of the composite blades as function of maintenance coefficient and maintenance time

8. CONCLUSIONS

This paper adopts a stochastic method to analyse fatigue crack evolution for the composite blades of wind turbines. A numerical case study is presented to investigate the effectiveness of the proposed stochastic methods with different fatigue crack evolution models. The results show that stochastic fatigue models give reliable results and can be used for analysing the failure probabilities of the composite blades. On the basis of the obtained results, the following conclusions can be drawn.

(1) Based on the fatigue models during the service time, the gamma jumping process model gives good simulations on fatigue crack evolution of wind turbine composite blades with considering uncertain conditions in offshore environments.

(2) The failure probability obtained by stochastic gamma model is reliable and trustful. This method evaluates the lifetime distribution of probability of fatigue failure for composite blades, and can be used to assist in the inspection and maintenance of the composite blades in operation.

(3) Depending on the assumed critical lengths, Reifsnider model gives more reasonable results compared with other models. Reifsnider model can better simulate the crack growth of composite blades under the practical situation

(4) The proposed optimum maintenance strategy based on the stochastic modelling and the Reifsnider model can give a better balance between the remaining service life and the total cost for optimising maintenance strategy of the composite blades of offshore wind turbines.

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