

A Predictive Maintenance Policy Based on the Blade of Offshore Wind Turbine

Wenjin Zhu, Troyes University of Technology

Mitra Fouladirad, Troyes University of Technology

Christophe Bérenguer, Gipsa-lab-Control Systems Department, CNRS, Grenoble Institute of Technology

Key Words: Predictive maintenance, monitoring, Paris-Erdogan law, rotor blade, wind turbine

SUMMARY & CONCLUSIONS

Based on the modeling of the deterioration of a blade due to the intrinsic randomness, random shock, random load and dynamic environment, this paper proposes a predictive maintenance policy considering the leading time caused by preparing the maintenance action. The evaluation of the proposed maintenance policy is realized by Monte-Carlo simulation and the minimal average long-run maintenance cost per unit time is obtained. The numerical simulations prove that the proposed policy can reduce the downtime caused by failure or leading time.

1 INTRODUCTION

The wind energy industry has experienced an extensive and worldwide growth during the past few decades owing to the availability of resources and the maturity of the technology. However, due to the lack of space on land and the better quality of the wind resource in the sea, the installation of wind turbines is shifting from onshore to offshore locations [1]. As offshore wind turbines are located at remote sites with limited accessibility, the demand for high reliability much greater than for onshore turbines while minimizing costs [2]. Operation and maintenance (O&M) costs of off-shore wind turbines contribute about 25-30% to the total energy generation costs, which can be estimated to be 50% higher than that of the onshore farm. A considerable fraction of that increased percentage is caused by unexpected failures leading to the necessity of corrective maintenance [1], [3]. Since the operation and maintenance costs represent a substantial portion of the total life cycle costs of wind power generation systems [4], the reliability and maintenance management of wind turbines have drawn increasing interests with the aim of reducing these costs.

According to [4] and [5], the rotor blade is the most costly part of a wind turbine and also fails more frequently than other components. The failure of a blade could be hazardous and even destroy the whole tower. To maintain a blade, certain conditions should be satisfied, these factors include suitability for the weather and availability of equipment. In this paper we focus on the maintenance of the blades of offshore wind turbines. From the review in [6], structural health monitoring

plays an increasingly important role. Further, as investigated by G. Marsh [7], the techniques and price of rotor blade remote surveillance equipment are becoming well proven and affordable respectively. Several monitoring techniques are available, such as the use of accelerometers, acoustic emission detectors and fibre-optical strain gauges.

Components, such as the gear box, high-speed shaft and the yaw drive, are all connected by the bearings and gears, periodic lubrication of these components is therefore necessary. As a result, a routine maintenance as used in [8] is needed. However, the ever changing weather conditions have considerable disparities in different seasons and harsh weather conditions could constrain and delay the reparations [4], [9]. Hence the general assumption of immediate and instant maintenance is no longer suitable and for simplicity we consider an additional leading time containing all the downtime caused by maintenance.

Blade damage is clearly caused by a mechanism of fatigue in the dynamic environment and affected by random factors, such as temperature, humidity, wave motion and lightning. In this paper we model the crack of a blade via the Paris-Erdogan law considering the intrinsic randomness of the fatigue crack propagation, random load and dynamic environment. Also a random shock is taken into account to model the extreme events, such as gale and huge waves. The dynamic environment and external factors are referred to as covariate and modeled by continuous-time and discrete-state Markov chain. As a supplement to the routine maintenance, a reactive maintenance is proposed which takes advantage of the information available through monitoring. In addition, in order to save the downtime caused by the leading time after a failure, the predictive maintenance action can be scheduled in advance.

The remainder of this paper is as follows: in section 2 the extended crack propagation model is employed to model the deterioration of a blade, using the outcome of this, maintenance policies are proposed in section 3. In section 4 the performance of the policies are studied and compared.

2 DETERIORATION MODEL

2.1 Basic Fatigue Crack Propagation Model

The rotor blade is a fatigue critical component and several

factors expose it to fatigue phenomena, such as, its long and flexible structure, vibration in its resonant mode, randomness of the load spectra and continuous operation under different conditions [10]. In general, the fatigue damage variable, D , is a function of time or the number of cycles t , the parameters C and m depending on the property of material and the stress intensity range ΔK :

$$dD/dt = C(\Delta K)^m \quad (1)$$

where ΔK is dependent on D through the relation $\Delta K(D) = \beta\sqrt{D}$ and β is a constant in stable environment.

2.2 Crack Propagation Model Considering Random Factors

Based on the basic deterministic model, we consider the random factors such as the intrinsic randomness of the fatigue crack propagation, random load and dynamic environment. Assuming that the initiation time of a crack t_0 is subject to a Weibull distribution with the scale parameter a and shape parameter b . The minimal length of a crack that can be detected by inspection is $D_0 = 0.5$. Once a crack occurs, it will propagate according to a stochastic Paris-Erdogan law. Let $X(t)$ account for the statistical variability of the crack growth rate and it is subject to a log normal distribution $\log(N(0, \sigma_\omega^2))$ as is demonstrated by many literatures, such as [11].

Dynamic environmental conditions, such as temperature, humidity, and salt concentration in the air, always lead to a deterioration process that is much more random than those predicted in a laboratory environment. These environmental conditions are referred to as covariate and will be considered in our model. Let $Z(t)$ denote the covariate state at time t and $\{Z(t), t \geq 0\}$ is a time-homogeneous Markov chain with a finite state space $E_\alpha = \{1, 2, \dots, r\}$. The transition matrix will therefore be $P_\alpha = (p_{ij})_{r \times r}$, where the state transition probability p_{ij} is defined as follows:

$$p_{ij} = P(Z(t+s) = j | Z(s) = i), t, s > 0, i, j \in E_\alpha \quad (2)$$

$$\sum_{j=1}^r p_{ij} = 1, \text{ for } \forall i \in E_\alpha \quad (3)$$

The stationary law of each state can be calculated by solving linear equations that are constrained by (2) and (3). The same load level can bring different damage levels of the blade under a dynamic environment. The covariate affects the random load via Cox's proportional model by a non-negative exponential function $\varphi(Z(t)) = \exp(\gamma_{\{Z(t)=i\}})$, $\forall i \in E_\alpha, \gamma = \{\gamma_1, \dots, \gamma_r\}$.

The load stress $S(t)$ depends on the geometric structure of the blade and also on the wind speed. For simplicity, most current models consider the stress as constant. However this assumption is not suitable for wind turbine blades due to their highly variable and quick changing environment. As the rotor blade runs with different modes depending on the wind speed, it is reasonable to assume that the load stress can be classified into l levels. The switch between the different levels of load is modelled by a time-homogeneous Markov chain, denoted by $\{S(t), t \geq 0\}$ with the state space $E_\beta = \{1, \dots, l\}$. The transition matrix $P_\beta = (p_{ij})_{l \times l}$ with the element p_{ij} as follows:

$$p_{ij} = P(Z(t+s) = j | Z(s) = i), t, s > 0, i, j \in E_\beta \quad (4)$$

$$\sum_{j=1}^l p_{ij} = 1, \text{ for } \forall i \in E_\beta \quad (5)$$

Shocks, such as huge waves, hurricanes and lightning strikes, although infrequent, have the potential to cause serious damages to the wind turbine. Compared with the lifetime of a blade, the duration of the shock can be negligible. Assuming the inter-arrival of the shock is subject to a temporally homogeneous Poisson process with the occurrence rate $1/\mu$. Denote by N_t the number of shocks occurring during time interval t and $\{N_t, t \geq 0\}$ the corresponding counting process. Naturally, the damage of the shock depends on the deterioration state before the shock occurs; when the system is more deteriorated, it is more vulnerable to the shocks. Denote by $Y(t)$ the damage caused by the shock at time t and $Y(t)$ is defined as

$$Y(t) = h(D(t^-))1_{\{A_t\}}, \quad (6)$$

where $h(\cdot)$ is a non-negative real function of the deterioration state D , t^- is the time instant just before time t (respectively, t^+ is the time instant just after time t) and $A_t = \{A \text{ shock occurs at } t\}$; $1_{\{A_t\}}$ is the indicator function with value 1 if A_t is true, or its value is 0.

The crack propagation equation considering the above assumptions is inspired by [12] and [13] as follows:

$$dD/dt = CX(t)[S(t)\varphi(Z(t))\sqrt{D}]^m + Y(t) \quad (7)$$

When the time step τ is small enough, Equation (7) can be discretized as:

$$D_j = D_{j-1} + CX(\tau_j)[S(\tau_j)\varphi(Z(\tau_j))\sqrt{D_{j-1}}]^m \tau + Y(\tau_j) \quad (8)$$

where time $\tau_j = j\tau$ and D_j is the deterioration state at time τ_j . According to [13], without considering the shock, the increment rate follows a log normal distribution:

$$\Delta D_j/\tau \sim \log N\left(\ln C [S(\tau_j)\varphi(Z(\tau_j))\sqrt{D_{j-1}}]^m, \sigma_\omega^2\right) \quad (9)$$

It can be seen that the random deterioration growth rate at time τ_j is conditional based on the deterioration state and covariate at time τ_{j-1} . The analytical life time distribution is a function of complicated convolutions whose precise form is difficult to obtain. Hence the following work will rely on simulations.

3 MAINTENANCE POLICY

3.1 Assumption

The study of fatigue damage in wind turbine blades shows that superficial cracks are the most common form of damage. It is possible that more than one cracks can propagate at the same time, however the crack with the largest length is the one that ultimately finally causes the blade failure. Our measurement of deterioration in this paper is therefore based on the length of the largest crack. When the deterioration exceeds a given threshold L_c , the blade deterioration accelerates in short time and finally damages the components which are connected to and the components embedded in it. Once this situation happens, the turbine can be seen as failed and a corrective replacement will be necessary. In order to avoid this kind of failure, a preventive maintenance will be considered when the deterioration already arrives at a serious degree and implies a pending failure. The threshold that controls the preventive maintenance is L_p and it is one of the

parameters that need to be optimized. The blade is repairable and the crack can be repaired through spot repair, such as filling with resin; and through structural repair, such as fibre reinforcement in [14]. As the cracks tend to propagate, the repairs get more complicated and expensive with time. However, the repair simply remedies the cracks that have emerged but it can't solve the underlying deterioration mechanism. The assumption is realistic that the repair in our study is imperfect and the reduction of the deterioration after an imperfect repair is dependent on the state just before the repair.

Inspection will reveal the failure and deterioration state. It will be realized through some equipment and a shutdown is necessary. Thus each inspection causes an amount of expenditure. The continuous monitoring of the random load of the blade is considered with the initial installation cost. The covariate state and the occurrence of a shock can also be monitored. The remainder context is based on the following assumptions:

- The failure and deterioration state $D(t)$ can only be revealed perfectly by the inspection.
- The repair is imperfect and the time for executing a repair is negligible. After a repair the deterioration follows the same law as before, unlike the assumption in [15].
- The replacement is as good as new and the additional leading time L is constant for all replacements.

3.2 Routine Policy

A periodic routine maintenance is scheduled at fixed time interval T_r . This maintenance usually maintains a block of wind turbines and thus the expenditure of the transport can be shared between wind turbines. The availability of the staff and the equipment can be guaranteed in advance. Besides the regular upkeep to the other components, a routine maintenance will inspect the deterioration state of the blade and schedule the maintenance in response to the inspection. It consists of the following steps, at the j th routine maintenance at time jT_r :

- (A1) if $D(jT_r) > L_c$, a corrective replacement will be scheduled; after the leading time L the replacement is executed and the blade works as new;
- (A2) if $L_p < D(jT_r) < L_c$, a preventive replacement will be scheduled and the system will be shut down immediately; after L the replacement is executed and the blade works as new;
- (A3) if $D(jT_r) < L_p$, an imperfect repair will be executed immediately and reduce the deterioration as $D(jT_r^+) = g(D(jT_r))$, where $g(\cdot) > 0$ is a real function.

3.3 Reactive Policy

If we take advantage of the information available through monitoring, a reactive maintenance policy including both the routine maintenance and reactive intervention will be proposed. The monitoring stress load and covariate state at time t can be denoted by $\tilde{S}(t)$ and $\tilde{Z}(t)$ respectively. An online controller $\tilde{D}(t)$ consists of the simulated deterioration

state by using the real-time monitoring information. $X(t)$ is subject to the lognormal distribution and it is approximated by the mean in the controller. The online controller is simulated as follows:

$$\tilde{D}_{\tau_j} = \tilde{D}_{\tau_{j-1}} + CE(X(\tau_j)) \left[\tilde{S}(\tau_j) \rho(\tilde{Z}(\tau_j)) \sqrt{\tilde{D}_{\tau_{j-1}}} \right]^n \tau + \tilde{Y}(\tau_j) \quad (10)$$

where the occurrence of a shock is monitored and the damage it causes to the blade, $\tilde{Y}(\tau_j)$, depends on \tilde{D}_{j-1} . Between two periodic inspections, the threshold L_m , corresponding to the controller $\tilde{D}(t)$, decides the reactive maintenance action by scheduling an inspection immediately:

- (B1) if $\tilde{D}(t) > L_m$ and $D(t) > L_c$, a corrective replacement is scheduled without waiting for the next routine maintenance; after the leading time L the blade is replaced by a new one;
- (B2) if $\tilde{D}(t) > L_m$ and $L_p < D(t) < L_c$, a preventive replacement is performed after the leading time L ;
- (B3) if $\tilde{D}(t) > L_m$ and $D(t) < L_p$, an imperfect repair is executed immediately; after the repair $D(t^+) = g(D(t))$ and $\tilde{D}(t^+)$ adapts as $D(t^+)$.

L_m controls the frequency of the reactive maintenance. When L_m is large enough, the reactive policy degenerates to the routine policy. In this paper it is considered that $L_m = kL_p$, $k > 0$ and k is the parameter to be optimized. The reactive policy can trace the real-time information but it is not enough to grasp the incoming tendency. A predictive policy can make it up.

3.4 Predictive Policy

According to the assumption, the leading time L is a part of the downtime and is determined. If the residual life of the blade can be predicted, the replacement can hence be scheduled in advance of the leading time and the downtime lost caused by the preparation work of replacement can be avoided. There are already many literatures concerning the prediction issue, such as [13] and [16]. Due to the complexity of the deterioration model, in our study the residual life $T_{rf}(t)$ at time t is simulated. The covariate and the stress load are modelled by the Markov chain and the stationary law can be employed as an approximation of their limiting behavior. The shocks in future are simulated by its occurrence rate. The simulation is realized by the accumulation of a series of incremental steps. The time for scheduling a predictable replacement is denoted by T_s . The simulation will be run N times and the mean value for T_s will be chosen.

At an inspection, whether routine or reactive, if no replacement is needed and after the imperfect repair, the residual life of the blade will be simulated by the following algorithm:

Algorithm

1. At time $t_j = j\tau$, if $\text{mod}(t_j, T_r) = 0$, a routine inspection is executed; if no replacement is needed, whether preventive or corrective, simulate the residual life $T_{rf}(t_j^+)$ and

update $\tilde{D}(t_j^+)$ as $D(t_j^+)$.

2. Compare $T_{rf}(t_j^+)$ and T_r . If $T_{rf}(t_j^+) > T_r$, then $j = j + 1$; else if $T_{rf}(t_j^+) < T_r$, then schedule a predictable maintenance at time $T_s = t_j + T_{rf}(t_j^+) - L$.
3. If $\text{mod}(t_j, T_r) \neq 0$, then compare $\tilde{D}(t_j)$ and L_m . If $\tilde{D}(t_j) > L_m$, a reactive maintenance is scheduled and the detailed procedure is the similar as (B1)-(B3). If no replacement is needed, then simulate $T_{rf}(t_j^+)$ and repeat the procedure of step 2.

3.5 Evaluation of Maintenance Policy

The cost of the installation of monitoring equipment is C_{mi} . The inspection, repair, preventive replacement, corrective replacement and the unit downtime cost are C_i , C_{re} , C_p , C_c , and C_d respectively. The transport to the offshore wind farm also needs to be considered. For the periodic routine maintenance, the transport cost is C_t ; the reactive maintenance will be more expensive than C_t , denote by C_u . The total cost for a turbine in $[0, t]$ is therefore:

$$C(t) = (C_i + C_t)N_i(t) + (C_u + C_i)N_u(t) + C_{re}N_{re}(t) + C_p N_p(t) + C_c N_c(t) + C_d d(t) + C_{mi} \quad (11)$$

where $N_i(t)$, $N_u(t)$, $N_{re}(t)$, $N_p(t)$, $N_c(t)$ are the number of inspections, reactive transports, repairs, preventive and corrective replacements until time t respectively. $d(t)$ is the accumulated downtime until time t . The expected long run average cost can be calculated by:

$$C_\infty(t) = \lim_{t \rightarrow \infty} \frac{C(t)}{t} \quad (12)$$

3.6 Cost Optimization

In the framework of the periodic routine policy, the optimization problem aims to find the optimal threshold L_p^* and the routine interval T_r^* according to the cost criterion:

$$(T_r^*, L_p^*) = \arg \min_{T_r, L_p} (C_\infty(T_r, L_p)) \quad (13)$$

For the reactive policy and predictable policy, the optimization problem contains the optimal threshold L_p^* , the interval T_r^* and also L_m^* the threshold that controls the frequency of reactive maintain:

$$(T_r^*, L_p^*, L_m^*) = \arg \min_{T_r, L_p, L_m} (C_\infty(T_r, L_p, L_m)) \quad (14)$$

C_∞^* is the minimum average long-run maintenance cost associated with (T_r^*, L_p^*) or (T_r^*, L_p^*, L_m^*) .

4 NUMERICAL SIMULATION

4.1 Parameters Setting

For the deterioration model, let $m = 0.35$, $C = 0.045$; $X(t) \sim \log N(0, 1.5)$; $(a, b) = (2, 0.25)$, $S(t) = \{0.5, 1, 1.5\}$; $E = \{1, 2, 3\}$ and let $\gamma = \{0.05, 0.1, 0.2\}$ represent the influence of the covariate. The state transition of the stress load and covariate satisfy P_β and P_α which take values as the form:

$$P_x = \begin{pmatrix} 1-x & x & 0 \\ x/2 & 1-x & x/2 \\ 0 & x & 1-x \end{pmatrix}$$

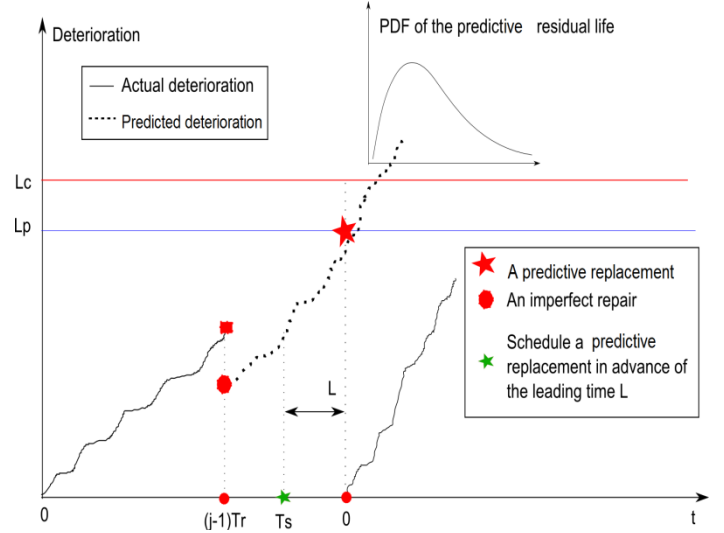


Figure 1. An illustration of the predictable reactive maintenance policy

Substitute x by $\beta = 0.5$ and $\alpha = 0.2$ respectively. $\mu = 60$ is the mean time interval of the shock. $h(x) = 0.3x$ represents the damage caused by the shock; $g(x) = \omega x$ represents the deterioration after the repair, where $0 \leq \omega \leq 1$ controls the level of the repair, for example, $\omega = 0$ means the repair is as good as new and $\omega = 1$ means the minimal repair. Let $L_c = 50$, $C_c = 100$, $C_p = 60$, $C_i = 2$, $C_t = 4$, $C_u = 10$, $C_d \in \{20, 60\}$ per time unit; $C_{mi} \in \{20, 40, 60\}$; $C_{pa} = 10$.

4.2 Numerical Examples

The disparity between routine policy with prediction and reactive policy with prediction lies in the latter employing the monitoring information and making timely response. When the inspection is cheap, the way to minimize the total cost is to inspect frequently. Hence the advantage of the reactive policy has been offset by frequent inspections as shown in Fig 2. However the shutdown inspection cost may be expensive, in this case the inspection should be scheduled carefully in order to counterbalance the inspection cost as well as the failure loss. The reactive policy makes the constraints favorable and the superiority becomes more evident with increasing the inspection cost. It also can be noticed from Fig 2 that when the preventive cost and downtime cost are more expensive, the reactive policy with prediction is more cost efficient even when the inspection cost is cheap as $C_i = 5$. The optimal k of the two subfigures of Fig 2 are 0.95 and 0.85 respectively. In the case of the second subfigure, more reactive maintenances are scheduled to avoid the failure loss.

In Figure 3 and 4, with the increase of the proportion of the leading time L compared with the mean life time of the blade, the average long run costs increase for both cases: routine and reactive. However the growth rate shrinks with

increasing leading time. The predictive maintenance mainly reduces the down time caused by the leading time. As the proportion of the leading time out of the whole down time is asymptotically stable, the performances of the maintenance policies with prediction will also become stable.

The cost for installing the monitoring equipment almost has no effect on the long-term running cost in all the cases studied.

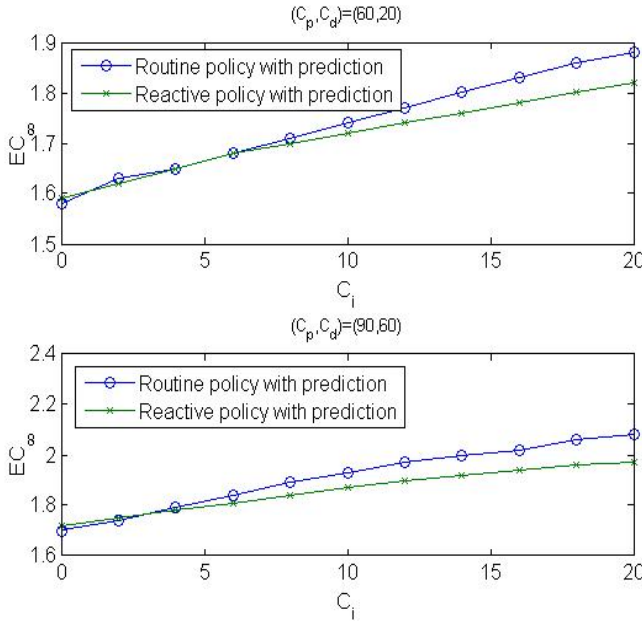


Figure 2. Comparison of the two policies with varying inspection cost for fixed leading time L (1%)

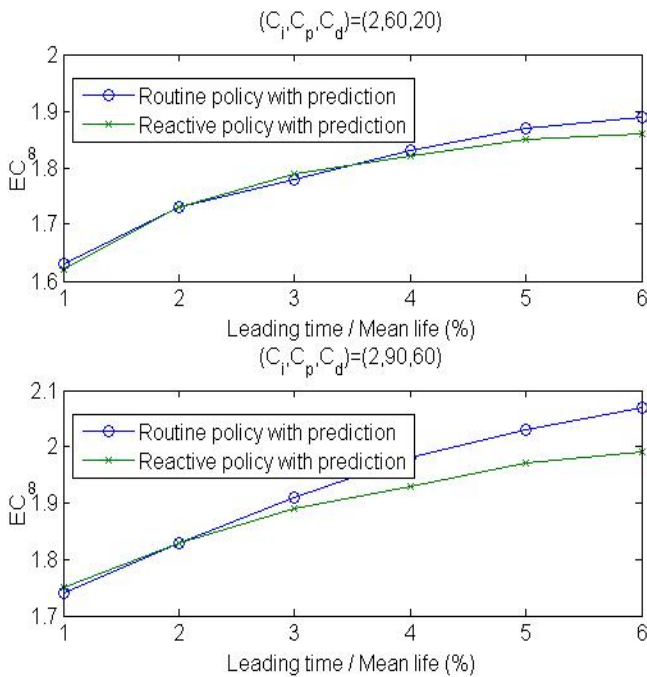


Figure 3. Comparison of the two policies with varying leading time for fixed $C_i = 2$

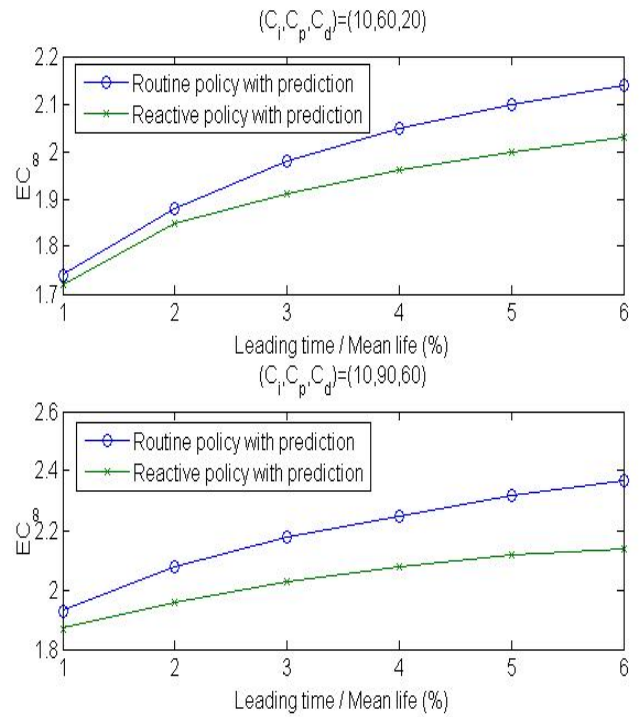


Figure 4. Comparison of the two policies with varying leading time for fixed $C_i = 10$

5 CONCLUSION

In this paper the predictable reactive maintenance policies are studied based on a fatigue crack propagation model of the wind turbine blade considering random shocks and dynamic covariates. The effect of leading time has been considered instead of the ideal assumption that replacement is instantaneous. The numerical examples show that the inspection cost influences the choice of the maintenance policy. The proportion of the leading time out of the mean life affects the average long run cost and this effect will tend to stability as the leading time increases.

In the future, in order to reduce the failure in series caused by other components, the interaction between the blade and the other components of the turbine will also be considered. As a result, the routine maintenance will be scheduled in multi-steps, such as two kinds of routine maintenance with two different time intervals according to the different failure rates.

REFERENCES

1. M. D. Esteban, J. J. Diez, J. S. López, and V. Negro, "Why offshore wind energy?" *Renewable Energy*, vol. 36, pp. 444-450, 2011.
2. E. Wiggelinkhuizen, "Assessment of condition monitoring techniques for offshore wind farm," *Journal of Solar Energy Engineering*, vol. 130, pp. 031004-1-9, 2008.
3. A. Kovács, G. Erdős, Z. J. Viharos and L. Monostori, "A system for the detailed scheduling of wind farm maintenance," *CIRP Annals-Manufacturing Technology*,

- vol. 60, pp. 497-501, 2011.
4. E. Byon, Y. Ding, "Season-dependent condition-based maintenance for a wind turbine using a partially observed Markov decision process," *IEEE TRANSACTION ON POWER SYSTEMS*, vol. 25, pp. 1823-1834, 2010.
 5. F. Spinato, P. J. Tavner, G. J. W. van Bussel and E. Koutoulakos, "Reliability of wind turbine subassemblies," *IET Renew. Power Gener.*, vol. 3, no. 4, pp. 387-401, 2009.
 6. C. C. Ciang, J. R. Lee, H. J. Bang, "Structural health monitoring for a wind turbine system: a review of damage detection methods," *MEASUREMENT SCIENCE AND TECHNOLOGY*, vol. 19, pp. 122001 (20pp), 2008.
 7. G. Marsh, "In-service monitoring of turbine blades," *Reinforced plastics*, pp. 24-29, May 2008.
 8. E. Deloux, B. Castanier, C. Bérenguer, "Predictive maintenance policy for a gradually deteriorating system subject to stress," *Reliability Engineering and System Safety*, vol. 94, pp. 418-431, 2009.
 9. E. Byon, L. Ntamo, Y. Ding, "Optimal maintenance strategies for wind turbine systems under stochastic weather conditions," *IEEE TRANSACTIONS ON RELIABILITY*, vol. 59, no. 2, pp. 393-404, June 2010.
 10. M. M. Shokrieh, R. Raiffee, "Simulation of fatigue failure in a full composite wind turbine blade," *Composite Structures*, vol. 74, pp. 332-342, 2006.
 11. K. Farhangdoost, J. W. Provan, "A stochastic systems approach to fatigue reliability-an application to Ti-6Al-4V," *Engineering fracture mechanics*, vol. 53, no. 5, pp. 687-706, 1996.
 12. F. Cadini, E. Zio, D. Avram, "Model-based Monte Carlo state estimation for condition-based component replacement," *Reliability Engineering and System Safety*, vol. 94, pp. 752-758, 2009.
 13. E. Zio, G. Piloni, "Particle filtering prognostic estimation of the remaining useful life of nonlinear components," *Reliability Engineering and System Safety*, vol. 96, pp. 403-409, 2011.
 14. G. Marsh, "Meeting the challenge of wind turbine blade repair," *Reinforced plastics*, pp. 32-36, July/August 2011.
 15. R. P. Nicolai, J. B. G. Frenk, R. Dekker, "Modelling and optimizing imperfect maintenance of coatings on steel structures," *Structural Safety*, vol. 31, pp. 234-244, 2009.
 16. Z. Xu, Y. Ji, D. Zhou, "A new real-time reliability prediction method for dynamic systems based on on-line fault prediction," *IEEE TRANSACTION ON RELIABILITY*, vol. 58, pp. 523-538, September 2009.

Wenjin Zhu, PhD Student
 Laboratory of Modelling and System Safety
 University of Technology of Troyes
 12 rue Marie Curie
 Troyes, 10010, France

e-mail: wenjin.zhu@utt.fr

Wenjin Zhu is a PhD student at the University of Technology of Troyes since September 2010. Now she is working on stochastic modeling, optimization of maintenance policy in the framework of deteriorating work in dynamic environment with Christophe Bérenguer and Mitra Fouladirad within Systems and Dependability Group from the Charles Delaunay Institute.

Mitra Fouladirad, PhD, Associate Professor
 University of Technology of Troyes
 12 rue Marie Curie
 Troyes, 10010, France

e-mail: mitra.fouladirad@utt.fr

Mitra Fouladirad after a Master degree in statistical mathematics from University of Paris VI joined the Troyes University of Technology (UTT) where she obtained a PhD degree in statistical fault detection in 2005. She is associated professor at the Statistics, Operations Research and Numerical Simulation Department since 2006. She is member of Charles Delaunay Institute CNRS FRE 2848 (Systems Modeling and Dependability Group). Her main field of activity is condition-based maintenance of gradually deteriorating systems. She focused on the use of on-line monitoring especially the on-line change detection algorithms in the framework of maintenance of deteriorating systems.

Christophe Bérenguer, PhD, Professor
 Gipsa-lab - Control Systems Department
 CNRS, Grenoble Institute of Technology
 11, rue des Mathématiques - BP46
 38402 Saint Martin d'Hères cedex - France

e-mail: christophe.berenguer@grenoble-inp.fr

Christophe Bérenguer is a professor of reliability engineering and control systems at Gipsa-Lab and Grenoble Institute of Technology (Grenoble, France). From 1997 to 2011, he was a professor at Troyes University of Technology (Troyes, France). He has served as an officer (treasurer) for the European Safety and Reliability Association from 2005 to 2010. He is a member of the Editorial Boards of Reliability Engineering and System Safety, and Journal of Risk and Reliability. His research interests include system health monitoring, stochastic modeling of systems deterioration, performance evaluation and optimization of dynamic maintenance policies, and probabilistic safety assessment.