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Prognosis-Informed Wind Farm Operation and Maintenance for Concurrent Economic and Environmental Benefits

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Advances in high-performance sensing and signal processing technology enable the development of failure-prognosis tools for wind turbines to detect, diagnose, and predict the systemwide effects of failure events. Although prognostics can provide valuable information for proactive actions in preventing system failures, the benefits have not been fully utilized for the operation and maintenance decision-making of wind turbines. This paper presents a generic failure prognosis informed decision-making tool for wind farm operation and maintenance while considering the predictive failure information of an individual turbine and its uncertainty. In the presented approach, the probabilistic damage growth model is used to characterize individual wind turbine performance degradation and failure prognostics, whereas the economic loss measured by monetary values and environmental performance measured by unified carbon credits are considered in the decision-making process. Based on customized wind farm information input, the developed decision-making methodology can be used to identify optimum and robust strategies for wind farm operation and maintenance in order to maximize economic and environmental benefits concurrently. The efficacy of the proposed prognosis-informed maintenance strategy is compared with the condition-based maintenance strategy and demonstrated with a wind farm case study.

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NOMENCLATURE

O&M = operation and maintenance
WT = wind turbine
CBM = condition-based maintenance
SBI = similarity-based interpolation
RUL = remaining useful life
D = current damage level
dD/dt = rate of damage growth
dN/dt = load cycles acting per hour on WT
C = damage coefficient
ΔK = change in damage-intensity factor
m = damage exponent
β = geometry factor
H_s = load factor
X_s = proportionality factor
C_{tot} = total cost
C_{ins} = total inspection cost
C_{rep} = total repair cost
C_{fail} = total failure cost
C_{trans} = total transportation cost
C_{CMS} = condition monitoring system installation cost
C_{prod} = total cost incurred due to production loss
R = rate of interest
b = cost per KWH
n_{days} = number of days required to perform repair
n_{KWH} = number of units of power produced
CC = carbon credits
d = total number of downtime hours
p = loss of power production per hour in KWH
e = CO_2 emissions in tons per KWH generated by coal power plant
W_j = inverse of the sum of squared error
$D_j^b(t_i)$ = j^{th} damage-growth path data
PoD = probability of detection of damage
P_0 = maximum probability of detection
λ = expected value of smallest detectable damage

1. Introduction

Maintaining wind turbines in top operating condition ensures not only a continuous revenue generation but a reduction in electric power drawn from non-renewable and more polluting sources. Despite the large capital for establishing a wind farm, the operation and maintenance (O&M) activities of wind turbines (WTs) are the primary contributors to wind energy costs. The O&M decision for a wind farm is generally governed by different stochastic parameters, such as health conditions of different WT units, failure and repair costs, spare parts availability, and logistics constraints. The stochastic nature of these parameters during the lifecycle of a WT makes O&M decision-making a prominent but challenging problem. Due to the pervasive nature of O&M activities throughout the wind energy industry, maintenance and lifecycle management could significantly benefit from a good O&M strategy in this regard. Moreover, maintenance and life-cycle management activities constitute a large portion of overhead costs.[1] Unexpected breakdowns can be prohibitively expensive since they immediately result in loss of energy production and poor customer satisfaction. Therefore, the need for O&M planning tools with greater functionality is reaching a critical stage.

Advances in high-performance sensing and signal processing technologies enable the development of prognostics tools applied to WTs to detect, diagnose, and predict the system wide effects of failure events. Although prognostics can provide valuable information for proactive decision making in preventing system failures, the benefits of failure prognostics have not been fully utilized for wind farm O&M. Currently WT maintenance activities are primarily cost oriented, and maintenance planning models mainly account for the economic impact introduced by WT downtimes. Assessment of the environmental impact of power generation should be considered not only in the turbine manufacturing phase but also in the lifecycle use phase.[2-4] However, the current literature in the area of WT lifecycle assessment has primarily focused on the development phase of wind turbine units and wind energy projects, whereas the associated environmental impact due to use phase O&M activities has not been fully studied, and ways to further reduce the environmental impact have not been investigated.

With the increasingly high cost of wind farm O&M and substantial losses of energy production due to failure of WT units, it is essential to develop effective O&M strategies that can concurrently enhance economic and environmental performance of wind turbines. This paper presents a prognosis-informed stochastic decision-making framework for wind farm O&M, which takes into account failure prognostics information for each individual turbine in the O&M decision-making process for wind farms. The remainder of the paper is organized as follows: Section 2 presents the related work of wind farm O&M; Section 3 details the proposed prognosis-informed wind farm O&M decision-making methodology; Section 4 demonstrates the proposed methodology with case studies; and Section 5 presents a brief summary.

2. Related Work

Maintenance activities for wind turbines can be broadly classified into two categories: corrective maintenance and preventive maintenance. Corrective maintenance is carried out after a failure event, whereas preventive maintenance is done before the occurrence of a potential failure.[5] Preventive maintenance can be further classified into scheduled maintenance and condition-based maintenance (CBM). Scheduled maintenance is carried out according to fixed scheduled times. Some examples of scheduled maintenance in wind turbines include change of filters, lubrication, etc.[6] CBM is a form of preventive maintenance that involves continuous/periodic health monitoring of a WT unit. Currently the most common practice of maintenance activities at wind farms is scheduled maintenance. However, with the latest developments in the field of sensing and signal processing techniques, CBM has been gradually adopted into maintenance decision making of wind farms.[7] In CBM, condition monitoring systems are installed on different system components, such as the gearbox, bearings, drive train, and generators, in order to record various sensory signals for determining the physical states of these components. Despite different structural analysis methods,[8-10] different types of sensory signals can be used for condition-monitoring purposes,[11-15] such as vibration, sound waves, and electrical signals. Usually CBM in WTs can be executed based on vibration monitoring,[11] oil analysis,[12] acoustic analysis, or electrical signature analysis.[13] With the help of WT health information provided by condition monitoring systems, optimal O&M planning strategies can be ascertained to prevent system failures and improve turbine availability.[16]

Currently, O&M decision-making for wind farms is mostly cost oriented, in which associated environmental impact has seldom been investigated. Pacca and Horvath considered the global warming effect of operational and construction phases of WTs.[2] Life-cycle assessment of a wind farm in the construction and maintenance phases has also been conducted.[17] Emissions during the manufacturing of WT components, and operation and future dismantling of WT systems have been considered as environmental impact factors.[18] Similarly, existing life-cycle assessment reports available in the field[17-22] provide limited information on the O&M phase after manufacturing, which is a very significant dimension over 20 years of turbine life. The operational phase of WTs offers a great opportunity for the environment or life-cycle improvement of green wind energy, even though it has not been integrated into wind farm O&M decision-making processes.

Research on real-time failure prognosis, which interprets data acquired by distributed sensor networks and utilizes such data streams in making critical decisions, provides significant advancements across a wide range of applications.[23] The early awareness of the WT health condition through prognosis-informed maintenance helps in proper planning and scheduling of maintenance activities, which avoids delay in the execution of necessary repair activities, thus minimizing system downtime. The prognostic techniques, which aim to predict the remaining useful life (RUL) of the system, can be classified into three broad categories: model-based prognostics, data-driven prognostics, and hybrid (fusion) prognostics.[24] Most recently, Wang et al. developed a generic framework of structural health prognostics in which a generic health index system, a sparse Bayes learning technique, and a similarity-based interpolation (SBI) technique were proposed and integrated for the RUL prediction and uncertainty management.[25] Although prognostics can provide valuable information for proactive action to prevent system failures, this benefit has not been fully utilized

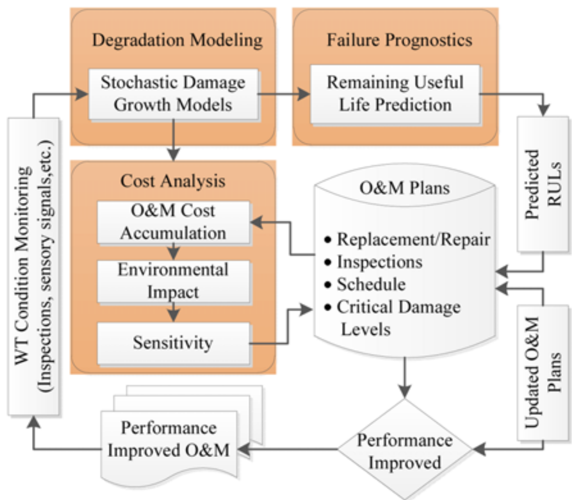

Fig. 1 Architecture of Developed O&M Decision-Making Framework

for wind farm O&M decision making. This paper presents a prognosis-informed stochastic decision-making framework for wind farm O&M that improves concurrently the economic and environmental benefits of WTs. This framework is detailed in the next section.

3. Prognosis-Informed Stochastic O&M Decision-Making Framework

The developed prognosis-informed stochastic O&M decision-making framework, as shown in Fig. 1, is composed of three essential modules: (i) WT performance-degradation modeling based on stochastic damage-growth models; (ii) O&M performance analysis for evaluation of O&M plans, as shown in the bottom left shaded box, which includes O&M cost analysis and environmental impact quantification; and (iii) WT failure prognostics for predicting the remaining useful life with the SBI prognostics technique.

The performance-degradation module models the performance degradation of WT while considering the stochastic effects of loading conditions and randomness of individual turbine units. The stochastic damage-growth model developed in module (i) can realize the failure development process over time and enable the implementation and evaluation of different O&M plans. The O&M performance analysis module will evaluate the total cost and environmental impacts for any given O&M plan over projected wind turbine lifespan and provide the sensitivities for improvements. The WT failure-prognostics module employs the SBI technique to predict the RUL of the WT units. With this prediction, optimum O&M plans can be determined to concurrently improve the economic and environmental performance of WTs. The O&M costs and carbon credits are accumulated throughout the wind farm O&M processes.

3.1 Stochastic Damage-Growth Model

Within the proposed framework, growth models are employed to characterize the performance degradation of WTs over time. Damage growth over time is modeled by the influence of stochastic parameters such as loading factors, primarily wind or a combination of both wind and wave height in the case of offshore WTs, weather conditions, and lead times involved in the accumulation of required resources to perform maintenance activities. The damage-growth model is most widely used for fatigue crack growth and provides a relationship between damage growth over time and load cycles acting on the component based on the Paris law. The Paris law is primarily applied to study the damage-growth rate in the field of fracture mechanics and material science. In this study, the performance degradation of WTs is modeled with a stochastic damage-growth model as,[5,26]

$$\frac{dD}{dt} = \frac{dN}{dt} \cdot C \cdot \Delta K^m \tag{1}$$

where dD/dt is the rate of damage growth, dN/dt is the load cycles acting per hour on the WT, C is the damage coefficient, ΔK is the change in the damage intensity factor, and m is the damage exponent.

Furthermore, the change in the damage intensity factor can be given as

$$\Delta K = \beta \cdot H_s \cdot X_s \cdot \sqrt{\pi D} \tag{2}$$

where β is the geometry factor, H_s is the load factor, X_s is the proportionality factor to estimate the uncertainty in the cyclic damage range, and 'D' is the current damage level. The damage level 'D' of WT components is given on a relative scale, where "0" indicates that there is no damage in the system, and "1" indicates that the system has failed completely.

3.2 Operation and Maintenance Cost Model

Various costs incurred during the use phase of WTs are modeled mathematically to compute the accumulated risks involved in the O&M process. The total cost incurred is denoted as total O&M cost, C_{tot}. The risk of O&M activities is measured by the cost induced by O&M events, such as inspection, part repair or replacement, and probabilities of an occurrence of these events. The C_{tot} incurred can be given as

$$C_{tot} = C_{ins} + C_{rep} + C_{fail} + C_{trans} + C_{CMS} + C_{prod} \tag{3}$$

where C_{ins} is the total inspection cost, C_{rep} is the total repair cost, C_{fail} is the total failure cost, C_{trans} is the total transportation cost, C_{CMS} is the condition monitoring system installation cost, and C_{prod} is the total cost incurred due to loss of production during the entire lifespan of a WT. All individual costs C_T at time of occurrence T are discounted into present values C, based on the rate of interest r. The present cost C_T is given as

$$C_T = \frac{C}{(1+r)^T} \tag{4}$$

Eq. (4) is utilized for determining the different O&M costs in the lifespan of WTs. The cost incurred due to loss of production is provided as

$$C_{prod} = \frac{b \cdot n_{KWH} \cdot n_{days}}{(1+r)^T} \tag{5}$$

where b is the cost per KWH, n_{days} is the number of days required to perform the repair, and n_{KWH} is the number of units of power produced based on the WT's capacity. Estimation of the total cost during the operation stage of the WT is used to optimize the O&M decision parameters to minimize the total O&M cost as well as the environmental impact.

3.3 Quantification of Environmental Impact

The downtime of a WT forces the use of other conventional and more-polluting energy sources, such as a coal-fired power plant, to generate electricity to compensate for the loss of power production by wind farms. Therefore, the downtime of a WT should be taken into account for this environmental hazard. Each renewable-energy, power-generation resource earns carbon credits, denoted as CC, for generating energy that avoids emitting carbon into the atmosphere. One carbon credit is measured as one metric ton of CO_2 emissions. Similarly, the environmental impacts of O&M events that cause WT downtimes can be quantified by the loss of carbon credits, i.e., the total number of carbon credits that a WT failed to earn during its usage due to downtime, which can be calculated as

$$CC = d*p*e \tag{6}$$

where d represents total number of downtime hours (hours), p is the loss of power production in one hour measured by KWH (KWH/hour), and e represents the average CO_2 emissions in metric tons that a coal-fired power plant will generate in order to produce the same amount of power (metric tons of CO_2 per KWH). The average CO_2 emission rate by coal-source electricity production is 2.3 lbs of CO_2/KWH.[27] The loss of carbon credits during downtime as the result of failure and repair will be calculated as CC_{fail} and CC_{rep}, respectively.

3.4 Wind Farm O&M with Prognostics

Activities of condition monitoring and remaining useful life prediction are of great importance in the decision-making process of WT O&M. In the proposed prognosis-informed stochastic decision-making framework, the similarity-based interpolation technique is employed to accomplish the prognostics task, which assesses the current health condition of a WT and predicts the time of occurrence for the next failure event.[25] The SBI technique involves both offline training and online prediction processes. In the offline training process, the SBI will develop background health knowledge, which consists of n number of random realizations of individual WT run-to-failure degradation paths. In the online prediction process, the SBI technique will interpolate the partially degraded WTs over the background health knowledge to generate similarity weights and predict the RUL using these weights. The detailed steps involved in the SBI technique are outlined in Table 1.

In this study, the offline training process of the SBI technique is accomplished through n simulation runs of the stochastic damage-growth model, which produces n number of individual WT run-to-failure damage-growth paths. The next process is to determine the similarity weights of online WTs. For an online WT, the similarity weight based on the j^{th} offline WT in the background health knowledge, W_j, can be defined as the inverse of the square-sum error comparing the damage-growth path of an online WT unit with those of offline training units as

$$W_j = \left[\sum_{t=0}^{T}(D(t) - D_j^b(t))^2\right]^{-1} \tag{7}$$

where $D(t)$ and $D_j^b(t_i)$ are the damage level at the current time t for the online WT and the j^{th} damage-growth path data in the background health knowledge, respectively. As W_j is set to the inverse of the square-sum error, a larger similarity weight will be given to the RUL predicted based upon the offline WT with greater similarity to the online one. The predictive RUL of an online WT unit can then be interpolated based on the similarity weights as

$$RUL = \frac{1}{W}\sum_{j=1}^{n}(W_j \cdot RUL_j) \quad \text{where} \quad W = \sum_{j=1}^{n} W_j \tag{8}$$

where RUL_j is the projected RUL on the j^{th} damage growth curve, and W_j is the j^{th} similarity weight. The detailed version of this method can be found in.[25] Therefore, the weighted RUL of each WT is determined, and the 90% confidence interval values of the weighted RULs can be calculated as the next predicted maintenance period of the wind farm. In the next section, a case study is employed to demonstrate two different O&M plans—CBM and the proposed prognostics-informed CBM—while considering both of the following: economic benefits and environmental impacts.

Table 1 Procedure for WT O&M Prognostics

Step 1:	Generate n number of random realizations of stochastic degradation process model
Step 2:	Develop background health knowledge with n runs- to-failure degradation paths
Step 3:	Interpolate the partially degraded WT over the background health knowledge to generate similarity weights
Step 4:	Determine the weighted RUL for each online WT in the wind farm based on similarity weights

4. Case Study

The wind farm employed in this case study consists of 100 WTs, and its O&M is decided primarily by considering two different O&M plans of the wind farm. Case I considers condition-based maintenance of the wind farm, and case II considers CBM with failure-prognostics information while making CBM decisions. The lifespan of WTs is assumed to be 20 years in both cases. The stochastic parameters affecting the O&M of WTs are estimated based on the failure rates of the WT failure modes. Damage growth over time is estimated in a CBM environment based on the Paris law, as given in Eq. (1), where dN/dt is considered to be 360/hour. Damage growth is simulated for every eight hours and updated using the Euler's method as

$$\mathrm{D}_{t+\Delta t} = \mathrm{D}_t + \frac{dD}{dt}\cdot\Delta t \tag{9}$$

where D_t is the damage index at time t, and $D_{t+\Delta t}$ is the updated damage index after a Δt of eight hours. The capacity of the WT is considered to be 5 MW, and the power generated is monitored for every hour. The amount of power generated is assumed to be affected by the load acting on the WT and also on the rate of damage growth. The effectiveness of maintenance activities, such as health monitoring, and the damage detection are modeled based on a probabilistic approach to account for

Table 2 Random Parameters in Case Study

Parameters	Mean	COV	Distribution
C	9.26E-10	0.2	Lognormal
Xs	11.5	0.1	Lognormal
m	2	-	Deterministic
B	1	-	Deterministic
D_0	0.02	-	Exponential

Table 3 Parameter Values for Cost Model

Parameters	Symbol	Value
Failure cost	C_{fail}	\$20,000
Repair cost	C_{rep}	\$10,000
Inspection cost	C_{ins}	\$2,500
Power price	b	\$0.04/KWH
Rate of interest	r	5%/year
Transportation cost	C_{trans}	\$10,000
CMS installation cost	C_{CMS}	\$15,000

the uncertainties involved during the WT O&M process. Inspection during the normal CBM process is scheduled for every 180 days, and in the prognostics-informed CBM, the next maintenance period is determined based on the prognostics results, and the O&M costs are calculated for the lifetime of the WT. The probability of detection of damage is considered to be dependent on the current damage level and is given as

$$PoD = P_0 \cdot (1 - e^{(-D(t)/\lambda)}) \tag{10}$$

where P_0 is the maximum probability of detection, which is considered as 1 in this case study, and λ is the expected value of the smallest detectable damage and is considered to be 0.4.

The critical damage value, D_c, to perform the repair activity will be determined using sensitivity analysis. The D_c values are chosen such that the failure of the system does not occur before the next inspection. The repair activity is also affected by the inspection effectiveness, which is characterized by the probability of detection. For simpler calculations, it is assumed that there are no false indications during damage detection. The repair activity is carried out based on the comparison of the detected damage $D(t)$ with the D_c. If $D(t)$ is greater than D_c, then the repair will be executed; thus, the repair cost will be accumulated, and after repair, the damage level of the system is set to D_0.

If the damage level reaches 1, corrective maintenance is performed and the current damage level of the system is set to D_0. In this scenario, the failure cost is accumulated, and the loss of production cost is calculated as given in Eq. (5). Finally, the total cost incurred during the life span of the WT is calculated based on Eq. (3). Tables 2 and 3 provide the random parameters and model parameter values, respectively, used in this case study. In Table 3, the parameters such as power price, inspection cost, repair cost, and rate of interest are utilized from,[3] and the other parameters are assumed.

4.1 Strategy A: CBM

This maintenance strategy considers condition-based maintenance in which the WT is monitored periodically. The flowchart shown in

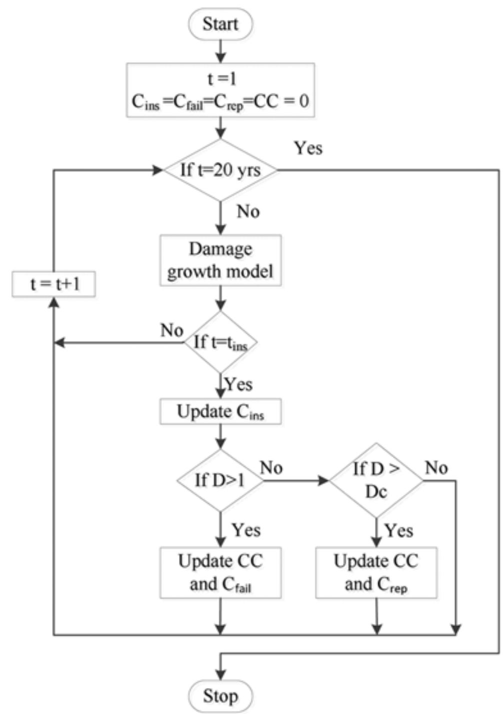

Fig. 2 Decision-Making Flowchart for Strategy A

Fig. 2 indicates the procedure involved in the O&M strategy of a wind farm based on CBM. The regular inspection interval of the WT is once in 180 days, and the process is repeated for 20 years. The initial damage level in the WT component is considered to be D_0, which is exponentially distributed with a mean of 0.02. The performance degradation is simulated based on the stochastic damage growth model in which the damage level is estimated every eight hours, and the maintenance strategy is performed based on the current damage level.

The three important conditions through which the maintenance strategy is implemented are as follows: (i) $D(t) > 1$, (ii) $D(t) < D_c$, and (iii) $D_c < D(t) < 1$. If $D(t) > 1$, then corrective replacement is performed, and the total cost constitutes the failure cost, transportation cost, and loss-of-production cost. If the current damage level of the system reaches 1, which indicates that there is a complete system failure, then the number of days required to perform the repair is determined. If $D(t) < D_c$, then no repair activity is needed and damage growth continues. If $D_c < D(t) < 1$, then the repair activity is performed on the same day, and the total cost constitutes the inspection cost, repair cost, transportation cost, and loss-of-production cost. Damage growth over the lifetime is estimated using the Paris law, and the costs associated with O&M are calculated. Since damage growth in a WT is affected by stochastic parameters, the variability in O&M costs is observed. Environmental impact analysis is determined by calculating the loss of carbon credits during the downtime of a WT unit. Economic analysis is evaluated using monetary values and environmental impact analysis by determining the loss of carbon credits during the downtime of WT are determined by the simulation of the wind farm over its lifetime. The critical damage level, D_c, which minimizes the total cost and total loss of carbon credits, is determined by plotting the different D_c levels versus total cost and total carbon credits, as shown in Figs. 3 and 4 respectively.

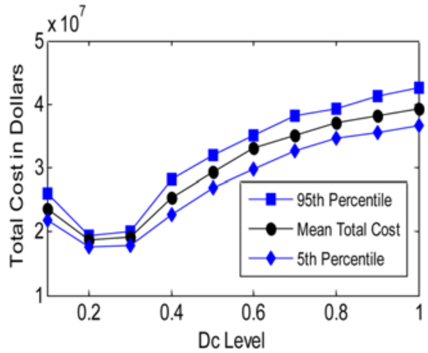

Fig. 3 Total Cost versus Dc Level of Strategy A

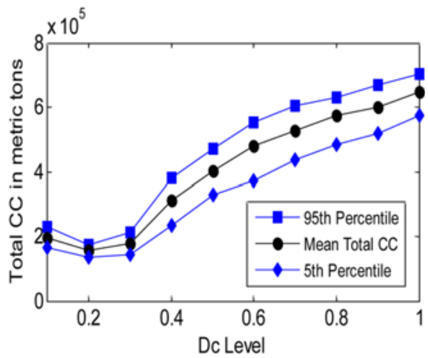

Fig. 4 Total Carbon Credits versus Dc Level of Strategy A

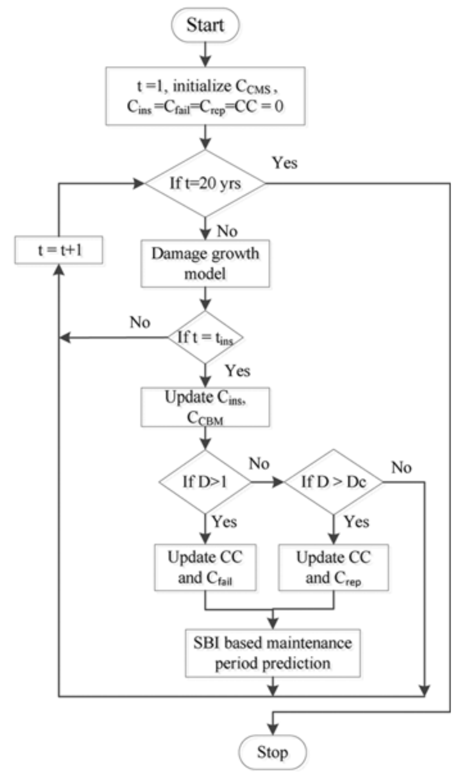

Fig. 5 Decision-Making Flowchart of Strategy B

These graphs show that initially, with an increase in D_c level, the total cost and carbon credits decrease until it reaches the critical damage level of 0.2. But after the point 0.2 is reached, the total cost and carbon credits increase with an increase in D_c level. The optimal D_c level for the minimum total cost and total carbon credits is determined as 0.2. The results indicate that the optimal damage level, based on economic analysis and environmental impact analysis, is the same. The corresponding total cost and total carbon credits are found to be 1.89×10^7 and 1.56×10^5, respectively, at the critical damage level, $D_c = 0.2$. The optimal critical damage-level result obtained is similar to the results of Nielsen and Sorensen[5] because the optimal damage level lies between 0.1 and 0.2.

4.2 Strategy B: Prognosis-Informed CBM

This maintenance strategy considers the same wind farm as in Strategy A, with 100 WTs with failure prognostics information in order to identify the next maintenance period. The flow chart shown in Fig. 5 indicates the procedure involved in the prognostics-informed CBM strategy of this wind farm. Damage growth over a lifetime is estimated using the Paris law, and the costs associated with O&M are calculated. Since the damage growth in the WT is affected by stochastic parameters and the variability in O&M costs is observed, the statistical analysis is implemented for different O&M costs, such as inspection costs, repair costs, failure costs, and total costs.

The maintenance will be carried out in the predicted next maintenance period. The prognostics model of wind farm O&M is developed by generating degradation models of 100 offline WTs, and the RUL is determined for each online unit based on the SBI, as discussed in Section 3. The weighted RUL for each online WT is determined, and the next maintenance period is predicted as 90% confidence interval of the weighted RULs of the WTs at the wind farm. Inspection is carried out during the predicted maintenance period, and the cost of inspection is accumulated. As discussed in plan A, there are three important conditions through which the maintenance strategy is implemented: (i) $D(t) > 1$, (ii) $D(t) < D_c$, and (iii) $D_c < D(t) < 1$. The process is repeated for the entire lifespan of the WTs, which is assumed to be 58,400 hours.

Results are obtained for different critical damage values from 0 to 1 to ascertain the optimal strategy for O&M. The critical damage level, D_c, which minimizes total cost and total loss of carbon credits, is determined by plotting the different D_c levels and their corresponding total cost and total carbon credit values, as shown in Figs. 6 and 7, respectively. The 5^{th} and 95^{th} percentiles of the total cost and total carbon credits are plotted along with the mean total costs and mean carbon credits at each D_c level in Figs. 6 and 7, respectively. These graphs show that an increase in D_c level decreases the total cost and carbon credits until it reaches the critical damage level of 0.8. But after $D_c = 0.8$, the total cost and carbon credits increase with an increase in D_c level. The optimal D_c level, for the minimum total cost and total carbon credits, is determined to be 0.8. The results of this case study indicate that the optimal damage level based on the economic analysis is the same as the one obtained based on environmental impacts. The corresponding total cost and total carbon credits are found to be 8.52×106 and 4.76×104, respectively, at the critical damage level of $D_c = 0.8$.

The total cost and total carbon credits at $D_c = 1$ for Strategy A are greater than that for Strategy B, mainly because the failure cost and loss of energy production incurred in Strategy A are much higher as for $D_c = 1$ only corrective maintenance will be performed. Moreover, Strategy B has a CMS installed, which can track the current health condition of the WT, and the next maintenance period is scheduled

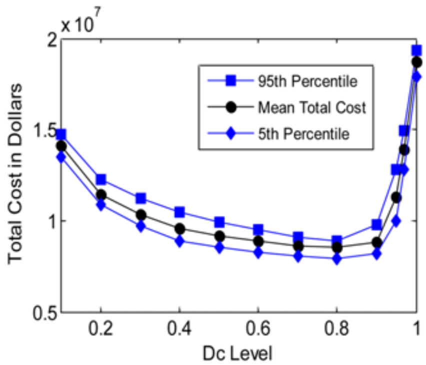

Fig. 6 Total Cost versus D_c Level of Strategy B

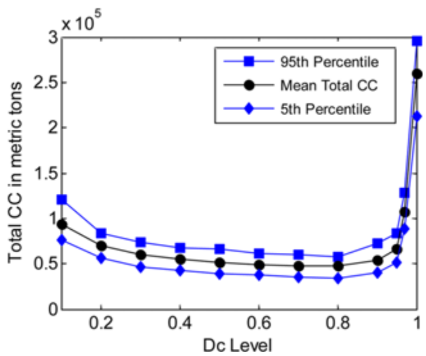

Fig. 7 Total Carbon Credits versus D_c Level of Strategy B

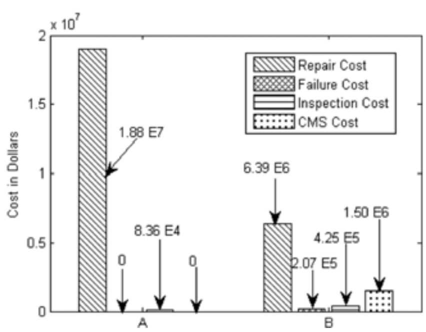

Fig. 8 Cost Comparisons of Strategies A and B

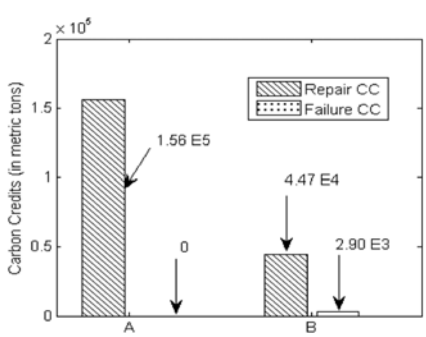

Fig. 9 Carbon Credits Comparisons of Strategies A and B

accordingly in order to avoid potential loss of production due to complete system failure. The comparison of Strategies A and B at their optimal critical damage levels based on economic analysis and environmental impact are shown in Figs. 8 and 9, respectively. The CBM case has a high repair cost with no CMS installation cost compared to the prognostics-informed CBM. Although, the repair cost of the prognostics-informed CBM is the major portion of its total O&M costs, the repair cost of CBM is around 2.8 times the repair cost of prognostics-informed CBM.

The comparison of loss of carbon credit due to wind turbine downtime is presented in Fig. 9. As shown, the only portion of total carbon credits in Strategy A is due to the repair activities for the WT, whereas the prognostics-informed CBM in Strategy B involves both repair carbon credits and failure carbon credits. Overall, the total carbon credits led by Strategy A are approximately three times larger than the one induced by the prognostics-informed CBM of Strategy B. Based on the case study results, the proposed prognosis-informed stochastic decision-making framework with concurrent consideration of economic benefits and environmental impacts generates better economic benefits and less environmental impact compared to the traditional CBM technique for the discussed case study.

5. Conclusion

This paper presents a prognosis-informed stochastic decision-making framework for the operation and maintenance (O&M) of wind turbines with concurrent consideration of economic benefits and environmental impacts. In the presented approach, the probabilistic damage-growth model is used to characterize performance degradation of an individual WT and conduct failure prognostics. Based on the customized wind farm information input, the developed decision-making methodology can be used to identify optimum and robust strategies for wind farm O&M in order to maximize the economic and environmental benefits concurrently. The proposed O&M decision-making methodology is compared with the existing condition-based maintenance (CBM) models and demonstrated with one wind farm case study. Case study results indicate that the prognosis-informed stochastic decision-making framework for wind farm O&M performs better than the traditional CBM technique, by substantially reducing economic losses and environmental impacts concurrently. Additionally, case study results reveal that the optimal damage level determined, based on economic benefits, is equivalent to the one obtained by minimizing environmental impacts for both the CBM strategy and the proposed prognosis-informed CBM strategy.

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REFERENCES

1. Byon, E., Ntaimo, L., and Ding, Y., “Optimal Maintenance Strategies for Wind Turbine Systems under Stochastic Weather Conditions,” IEEE Transactions on Reliability, Vol. 59, No. 2, pp. 393-404, 2010.

2. Pacca, S. and Horvath, A., "Greenhouse Gas Emissions from Building and Operating Electric Power Plants in the Upper Colorado River Basin," Environmental Science & Technology, Vol. 36, No. 14, pp. 3194-3200, 2002.

3. Wang, P., Youn, B. D., and Hu, C., "A Probabilistic Detectability-Based Structural Sensor Network Design Methodology for Prognostics and Health Management," Annual Conference of the Prognostics and Health Management Society, 2010.

4. Wang, P., Youn, B. D., and Hu, C., "A generic sensor network design framework based on a probabilistic detectability measure," Proc. of the ASME International Design Engineering Technical Conference and Computers and Information in Engineering Conference, Vol. 3, pp. 1013-1022, 2010.

5. Nielsen, J. and Sorensen, J., "On Risk-Based Operation and Maintenance of Offshore Wind Turbine Components," Reliability Engineering and System Safety, Vol. 96, No. 1, pp. 218-229, 2011.

6. Nilsson, J. and Bertling, L., "Maintenance Management of Wind Power Systems Using Condition Monitoring Systems—Life Cycle Cost Analysis for Two Case Studies," IEEE Transactions on Energy Conversion, Vol. 22, No. 1, pp. 223-229, 2007.

7. Byon, E., Perez, E., Ntaimo, L., and Ding, Y., "Simulation of Wind Farm Operations and Maintenance Using DEVS," Simulation, Vol. 87, No. 12, pp. 1093-1117, 2010.

8. Natarajan, B., Lee, J., Lim, J., and Shin, S. J., "Structural analysis of composite wind turbine blade using advanced beam model approach," Int. J. Precis. Eng. Manuf., Vol. 13, No. 12, pp. 2245-2250, 2012.

9. Kang, B.-Y., Han, J.-Y., Hong, C.-H., and Moon, B.-Y., "Dynamic analysis of hybrid wind power composite blades according to stacking properties method," Int. J. Precis. Eng. Manuf., Vol. 13, No. 7, pp. 1161-1166, 2012.

10. Hsu, D. K., Lee, K.-S., Park, J.-W., Woo, Y.-D., and Im, K.-H., "NDE inspection of terahertz waves in wind turbine composites," Int. J. Precis. Eng. Manuf., Vol. 13, No. 7, pp. 1183-1189, 2012.

11. Shi, W., Wang, F., Zhuo, Y., and Liu, Y., "Research on Operation Condition Classification Method for Vibration Monitoring of Wind Turbine," Proc. of Power and Energy Engineering Conference APPEEC, pp. 1-6, 2010.

12. Lu, W. and Chu, F., "Condition Monitoring and Fault Diagnostics of Wind Turbines," Proceedings of 2010 IEEE Prognostics and Health Management Conference, pp. 1-11, 2010.

13. Yang, W., Tavner, P., and Wilkinson, M., "Wind Turbine Condition Monitoring and Fault Diagnosis Using Both Mechanical and Electrical Signatures," Proc. of the 2008 IEEE/ASME International Conference on Advanced Intelligent Mechatronics, pp. 1296-1301, 2008.

14. Bang, H.-J., Kim, H., and Lee, K.-S., "Measurement of strain and bending deflection of a wind turbine tower using arrayed FBG sensors," Int. J. Precis. Eng. Manuf., Vol. 13, No. 12, pp. 2121-2126, 2012.

15. Kim, C., Kim, K., Kim, H., Paek, I., Yoo, N., Nam, Y., Campagnolo, F., and Bottasso, C., "A method to estimate bending moments acting on a wind turbine blade specimen using FBG sensors," Int. J. Precis. Eng. Manuf., Vol. 13, No. 7, pp. 1247-1250, 2012.

16. Yang, W., Tavner, P., Crabtree, C., and Wilkinson, M., "Cost Effective Condition Monitoring for Wind Turbines," IEEE Transactions on Industrial Electronics, Vol. 57, No. 1, pp. 263-271, 2010.

17. Hapke, H., Haapala, K. R., Wu, Z., and Brekken, T. K. A., "Life Cycle Assessment of Modern Wind Power Plants," Proc. ASME IDETC/CIE: 15th Design for Manufacturing and the Lifecycle Conference, Paper No. DETC2010-28749, pp. 395-403, 2010.

18. Martinez, E., Sanz, F., Pellegrini, S., Jimenez, E., and Blanco, J., "Life Cycle Assessment of a Multi-Megawatt Wind Turbine," Renewable Energy, Vol. 34, No. 3, pp. 667-673, 2009.

19. Schleisner, L., "Life Cycle Assessment of a Wind Farm and Related Externalities," Renewable Energy, Vol. 20, No. 3, pp. 279-288, 2000.

20. Lenzen, M. and Munksgaard, J., "Energy and CO2 Life-Cycle Analyses of Wind Turbines— Review and Applications," Renewable Energy, Vol. 26, No. 3, pp. 339-362, 2002.

21. Crawford, R. H., "Life Cycle Energy and Greenhouse Emissions Analysis of Wind Turbines and the Effect of Size on Energy Yield," Renewable and Sustainable Energy Reviews, Vol. 13, No. 9, pp. 2653-2660, 2009.

22. Overcash, M., Twomey, J., and Isaacs, J., "Manufacturing Unit Process Life Cycle Inventories (Uplci)," Proc. of the 9th PerMIS, pp. 30-31, 2009.

23. Hu, C., Youn, B. D., and Wang, P., "Ensemble of Data-Driven Prognostic Algorithms for Robust Prediction of Remaining Useful Life," Reliability Engineering and System Safety, Vol. 103, pp. 120-135, 2012.

24. Oppenheimer, C. H. and Loparo, K. A., "Physically Based Diagnosis and Prognosis of Cracked Rotor Shafts," Proc. of SPIE: Component and Systems Diagnostics, Prognostics, and Health Management II, Vol. 4733, pp. 122-132, 2002.

25. Wang, P., Youn, B. D., and Hu, C., "A Generic Probabilistic Framework for Structural Health Prognostics and Uncertainty Management," Mechanical Systems and Signal Processing, Vol. 28, pp. 622-637, 2012.

26. Sorensen, J., "Framework for Risk-Based Planning of Operation and Maintenance for Offshore Wind Turbines," Wind Energy, Vol. 12, No. 5, pp. 493-506, 2009.

27. Barnwell, G., "Your Contribution to Global Warming," National Wildlife, Vol. 28, No. 2, p. 53, 1990.