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Consideration of Lifetime and Fatigue Load in Wind Turbine Control

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Abstract

This paper proposes a novel scheme for extending lifetime of a wind energy conversion system (WECS) by integrating an online damage evaluation model into a control strategy for structural load reduction. Wind turbines are often subjected to continuously changing mechanical stress levels due to intermittent variability of wind speed and the effects of induced loads during power production, leading to premature failure before the desired lifetime is reached. A structural load reduction control strategy with variable gain is applied to define the compromise between power production and the extension of wind turbine service lifetime. In this paper, an online damage calculation model is used to determine damage levels in rotor blades then a variable gain control scheme is employed to offer a trade-off between power production and lifetime extension. Depending on damage accumulation level, power production is slightly sacrificed to extend the service lifetime of wind turbine or to reach given goals with respect to the desired useful lifetime. The results indicate that the proposed method can effectively extend the lifetime of wind turbine without significant reduction in power production. The proposed prognostic-based control approach serves as an example for a new type of service-oriented control algorithms, taking into account diagnostic results from monitoring and supervision algorithms.

Keywords: Remaining useful lifetime, Structural load reduction, Prognostic-based control strategy, Wind power conversion system

1. Introduction

The wind power production has steadily grown for the last few decades because its generation is environmentally friendly. It is projected that if the current growth rate is sustained, nearly 20% of the global energy could be produced from wind by the year 2030 [1]. To meet the growing demand of wind energy, the trend in wind turbine manufacturing is to upscale the turbine's size as well as power rating. This in turn has lead to challenges related to increased structural loads and reduced wind turbine components reliability. Large wind turbines are inherently flexible, especially due to rotor blades and tower. Consequently, this leads to induction of structural loads during wind power production. In the recent years, a number of advanced control schemes for structural loads mitigation in wind turbines have been proposed, especially in large utility-scale wind turbines. Nevertheless, most of the work that have been reported on structural loads mitigation in large wind turbines focused on the minimization of once per revolution (1p) loads using individual pitch controller [2, 3]. The minimization of higher harmonic loads [4, 5] was not within the focus of the majority of reported works. Beside considering structural loads mitigation it is also important to examine other operation objectives such as extension of service life-time of wind turbine. In the realm of large wind turbines, offshore wind farms have a promising economic potential due to high wind speeds in offshore and little environmental interferences. Unlike the land-based wind turbine, the effects resulting from structural loads in offshore application are more complex, where multiple load cases such as unidirectional wind, waves, and current are required to be considered simultaneously [6].

Although the cost of wind power has steadily declined over the last decade, the related production costs are still higher compared to other alternative technologies [7]. This is due to high initial investment cost as well as high operation and maintenance (O&M) costs among other factors. To make wind energy more competitive compared to other alternative sources, its overall production costs need to be reduced. This can partly be achieved by optimizing power production and embracing new technologies that enhance reliability and sustainability. Operation and maintenance costs contribute to a sizeable share of the overall cost of wind power; hence, reducing it would increase cost-competitiveness of wind power. Reduction of O&M costs is realized by adoption of suitable operational and maintenance strategies. One of the operational schemes that can be adopted to reduce the O&M is the employment of appropriate Structural Health Monitoring and Prognosis (SHMP) techniques [8]. After the installation of wind turbine, annual operating expenses (AOE), which include O&M costs and replacement/overhaul costs, are the only adjustable charges that can be minimized to reduce the cost of energy (COE) [9]. In this paper, the COE is considered to be lowered by operating the wind turbine based on the health status so as to extend the remaining useful life (RUL). Accordingly, the assessment of the wind turbine health status and prediction of the RUL can lead to the adoption of condition-based maintenance (CBM) or predictive maintenance such that the planning and scheduling of maintenance tasks are based on the health condition of the components rather than time-based.

Related condition-based operation (CBO), which is the main contribution of this paper, can be successively used to extend the service lifetime by using load mitigation control strategies in conjunction with lifetime prediction models or by downscaling the operation capacity of wind turbine. According to [10], the main causes of downtime in wind energy conversion systems (WECS) are: power module, drivetrain model, and rotor module. Drivetrain and rotor modules are more expensive to repair compared to other modules since they are not easily accessible during maintenance. It is further stated in [11] that maintenance of drivetrain systems and rotor blades accounts for the highest downtime in wind turbine applications. To demonstrate the application of CBO in wind turbines, structural load reduction of rotor blades is considered in this paper as an example of CBO.

Recently, the interest to develop robust and reliable SHMP systems has sharply increased, especially in offshore application due to harsh environmental conditions and related high maintenance cost. According to [12], condition monitoring system should be able to detect the presence of a fault, determine its location, establish the extent of damage, and monitor the propagation behavior of the defect. The prediction of failure behavior in wind turbine is important because it allows optimized decision making with respect to operation and maintenance [13]. The focus of this contribution is on prognostic-based lifetime extension of WECS. Further information on other condition monitoring and fault detection can be found in [14, 15, 16]. In [17], condition monitoring and prognostic challenges are discussed with a view of presenting the requirements that adequately cope with multiple, complex faults, and different failure mode types.

The concept of integrating SPHM into O&M process of offshore wind turbines using rotor blades as application example is discussed in [18]. The key issues discussed in this paper with regard to development of multi-scale modeling and simulation tools are to evaluate the effects of damage on the components' health status and to identify and evaluate turbine structural loads through appropriate control strategy to mitigate exacerbation of dam-

age growth. An optimal prognostic-based maintenance scheme for multiple wind turbines in an offshore wind farm managed via output-based contract such as power purchase agreement (PPA) is presented in [19]. These kind of control schemes are employed to avoid the related penalties that are associated with such contracts.
An automated online fault prognosis scheme is presented in [20, 21, 22]. Here, operation data from a supervisory control and data acquisition (SCADA) system are analyzed to determine the health status as well as extracting prognostic indicators used to realize predictive maintenance. A robust approach is used to classify SCADA data to allows the establishment and detection of fault development.
Although a number of control strategies to mitigate fatigue loads have been proposed [23, 24, 25], the scientific question on how aging model can be used to extend fatigue life of wind turbine system without much sacrifice on other important objectives such as maximization of power production and speed regulation is not extensively discussed in the literature.
In this paper, the idea presented in [23] is detailed and significantly extended with the goal of mitigating the structural loads depending on the level of damage accumulation, hence extending the useful lifetime of wind turbine. Depending on the health status of the rotor blade, a tactical control strategy is employed to mitigate structural loads, albeit at slight compromised on speed/power regulation objectives.
The paper is structured as follows: a description of the algorithm developed to evaluate fatigue loads is outlined in section two. In section three, the control strategy used to optimize the trade-off between power/speed regulation and extension of lifetime is given. In section four condition-based operation strategy used to extend lifetime of wind turbine is discussed. Finally, in section five a method of extending lifetime by operating turbine generator slightly below its rated capacity is introduced.

2. Fatigue Load Evaluation

During the operation of wind turbine, most of its components are subjected to varying mechanical stresses due to variability of wind speed. In turn this leads to gradual degradation of individual components until a failure occurs. This process starts in micro-scale due to irreversible changes in microstructure and propagates with time until its manifests itself as a defect leading to loss of functionality of a given component [20]. The knowledge on how a component degrade with time is very important since it can give an estimate of remaining useful life (RUL) before it looses its functionality. To extend the service lifetime of wind turbine, the knowledge of the consumed lifetime (or accumulated damage) is required. On the other hand, damage accumulation is directly related to the fatigue load experienced by the wind turbine. In the literature, a number of models have been proposed to evaluate fatigue life of machine components [26, 27]. For general applications, load cycle counting-based (rainflow counting and Palmgren miner) algorithm is popular due to its simplicity. The Palmgren miner damage rule assumes a linear damage accumulation. Other complex nonlinear fatigue damage models exist [28, 29]. In this paper a linear load cycle counting model is assumed.

2.1. Evaluation of Consumed Lifetime

As depicted in Fig. 1, load counting algorithms use time series input data and calculate the remaining useful life of the turbine through extrapolation. Additionally, a constant magnitude equivalent fatigue load (EFL) that give rise to an equivalent fatigue damage as a varying amplitude load over the same number of cycles can be determined using the similar scheme. Damage degradation in machine components can be described by a Wöhler equation as

$$s^m N = K, \tag{1}$$

where N is the number of cycles to failure for a given stress range s. The constants m and K are material specific parameters. In wind turbine applications, m is referred to as Wöhler coefficient and is taken to be equal to 3

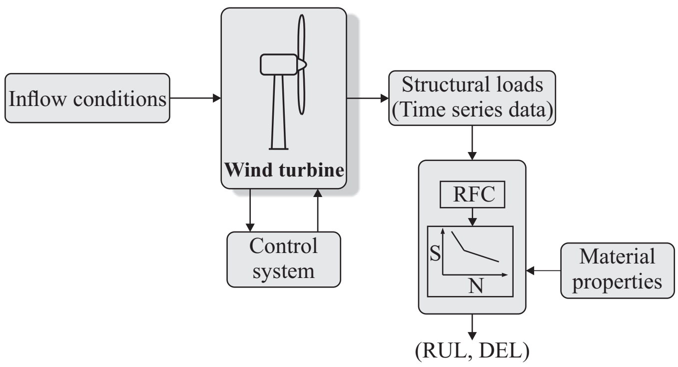

Figure 1: General procedure for determining the remaining useful lifetime

for components made of steel and 10 for rotor blades made of fiber composite material [26]. Using rainflow counting and Palmgren-Miner rule, damage accumulation is calculated as

$$D_k = \sum_{i=1}^{k} d_i = \sum_{i=1}^{k} \frac{n_i}{N_i} = \sum_{i=1}^{k} \frac{n_i s_i^m}{K}, \tag{2}$$

where s_i denotes stress range corresponding to the i_{th} stress cycle, d_i is the damage corresponding to a given stress cycle, n_i represents the number of applied load cycles, N_i is the number of cycles the material endures until it fails, and k is the total number of cycles. The component under investigation is considered to have reached the end of life if D_k is equal to one. The end of lifetime is evaluated as

$$T_f = T_k D_k^{-1}, \tag{3}$$

where T_f is the time to failure and T_k denotes principal load units required to accumulate damage D_k. Accordingly, the remaining useful lifetime (RUL) can be calculated if the turbine service lifetime is given per design and therefore known by the manufacturer. To calculate EFL, Eqn. (2), is modified as

$$EFL = \left(\sum_{i=1}^{k} \frac{s_i^m}{N_i} \right)^{\frac{1}{m}}. \tag{4}$$

The linear damage accumulation method for fatigue load evaluation assumes that the operation conditions do not change during the entire service lifetime, which is rarely the case in real life operation. Moreover, this method does not consider downtime due to maintenance; it assumes 100% availability for the entire lifetime. Furthermore, this algorithm cannot predict component life at stress ratios different from those used to develop its stress-cycle curve (S-N curve) [30]. To address some of these shortcomings, National Renewable Energy Laboratory (NREL) modified this algorithm to include load cycles over a wider spectrum of stress ratios as well as adding other enhanced features to come up with a fatigue analysis tool called MLife [31]. Like Mcruch tool, the MLife tool is typically used as a post processing program and cannot be used for online fatigue load evaluation since it requires the load history for the entire load spectrum.

2.2. Online Rainflow Counting

To evaluate fatigue load online, rainflow counting (RFC) algorithm developed by Musallam et al. [32] is adopted in this paper. Unlike the traditional

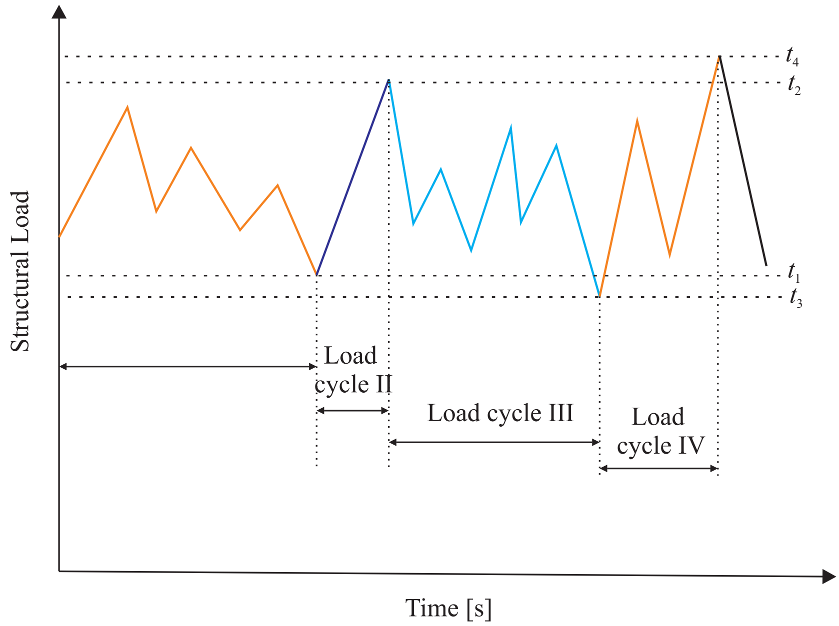

Figure 2: Implementation of online rianflow counting algorithm

rainflow algorithm in which the load history for the entire spectrum is required, this method processes the extremum points (minima or maximua value) as they occur in time series load data with the help or two flexible buffers to evaluate the corresponding half and full loading cycles. The minima or maxima data point is identified by applying a 3-point counting rule which is applied recursively as depicted in Fig. 2. Here, different colors are used to distinguish the crossing of extremum values defined by t_1, t_2, t_3, and t_4. In this paper, root blade flapwise bending moments are considered for evaluation of fatigue load damage. The RFC algorithm is used in conjunction with Palmgren-Miner damage accumulation rule to calculate the consumed lifetime (or damage accumulation). It is important to note that run-to-failure data is not used to determine the service life of wind turbine, rather a representative time series data is used to extrapolate the time it would take to fail when it is subjected to similar loading conditions.

3. Control Loop for Load Reduction

In this paper, a multiple-input multiple-output (MIMO) control scheme described in [23] is extended to include the actuator dynamics and together with an aging model, a novel prognostic-based control strategy is applied to extend the service lifetime of wind turbine. A frame that integrates load reduction strategy and prognosis model is illustrated in Fig. 3. Here, a variable gain MIMO control scheme is designed to mitigate the structural load on wind turbine. This controller is designed to establish a compromise between structural load reduction and output power/speed regulation. Concurrently, an online damage evaluation model is used to determine fatigue damage accumulation during the operation of wind turbine. Depending on the predefined thresholds, the control strategy is adjusted to the structural loads, although at a slight compromise of power/speed regulation; hence, extending the service lifetime of the wind turbine. Here, the threshold evaluation model is based on a monotonic damage accumulation such that the switching between different controllers is triggered by different levels of the accumulated damage. Therefore, the stability is guaranteed during switching between different controllers. The proposed prognostic-based control scheme aims to optimize the trade-off between speed/power regulation and reliability of wind turbine in the sense of extending its lifetime. The RUL is computed as $T_f(1 - D_k^{-1})$, where D_k is the consumed lifetime and T_f is the end of lifetime. In this paper, the RUL is controlled indirectly by deploying different load reduction controllers depending on the accumulated damage level to reach the desired end of lifetime which is assumed to be known. Assuming

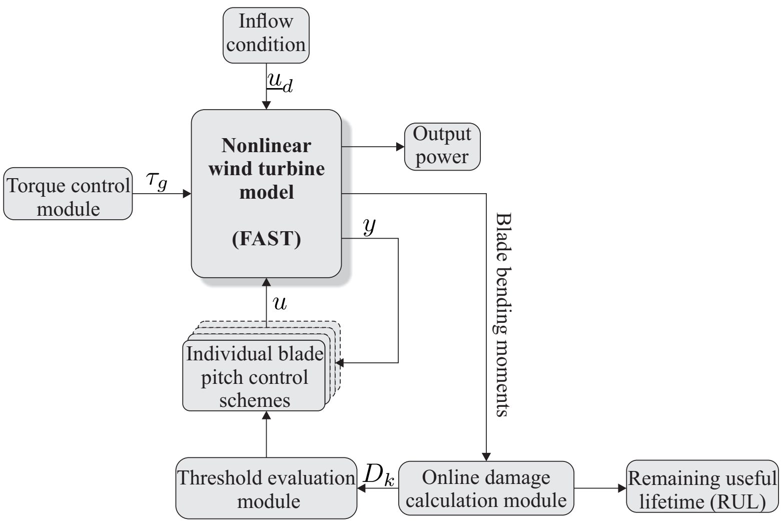

Figure 3: Control strategy which integrates online damage evaluation model

that the presence of a fault can be accurately detected by fault detection algorithms, the prognostic-based control scheme proposed can be used to extend the lifetime of a faulty turbine to reach its desired lifetime without causing collateral damage to other critical components. As illustrated in Fig. 4, a fault appears at t_i. A prognostic-based control scheme is employed to ensure that the turbine reaches end of lifetime at t_{end} by reducing damage levels per sampling time, although at a slightly compromised power/speed regulation. If a fault is induced, this will lead to increased damage development and therefore reduced remaining useful lifetime. In this illustration, a faulty system is considered to have reached the end of lifetime at t_f if nominal controller is still employed after fault has occurred. On the other hand if structural load mitigation control scheme is employed, lifetime can be extended by Δt_f to reach the initial the desired end of lifetime. Such damage can result from extreme operation conditions such as gust wind and other unforeseen occurrences. It is important to note that the proposed scheme is based on online damage accumulation and it is independent of the wind profile acting on wind turbine.

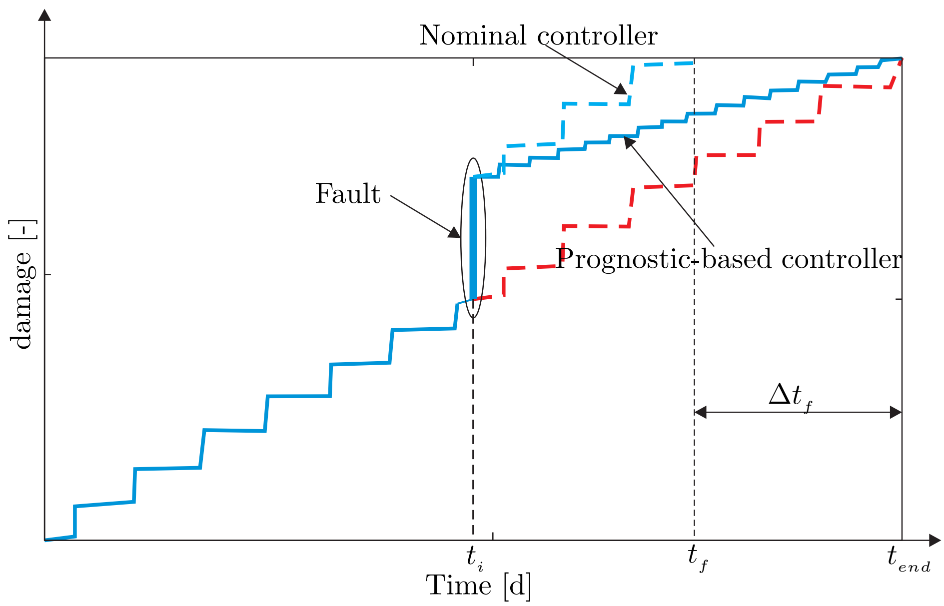

Figure 4: Lifetime extension for a faulty turbine

Table 1: Wind turbine specifications [33]

Rated rotor speed	20 rpm
Hub height	84.288 m
Configuration	3-blades, upwind
Cut_in, Rated, Cut_out wind speed	4 m/s, 12 m/s, 25 m/s
Gearbox ratio	87.965
Blade diameter	70 m
Rated power	1.5 MW
Blade pitch range	$0 \sim 90^o$

3.1. Example Model: Task and Description

A fictitious WindPACT 1.5 MW model developed by National Renewable Energy Laboratory (NREL) is used to generate linear time invariant (LTI) models at different operation points. The specifications of this model are outlined in Tab. 1. This model describes an upwind, three-bladed, horizontal axis variable speed wind turbine. The model has a total of 24 degree of freedoms (DOF) which describes the flexibility of the wind turbine. For the purpose of controller design only the relevant DOFs are enabled in this paper. To mitigate structural loads on rotor blades and tower, five DOFs are considered: tower first fore-aft mode τ_f, variable generator speed $\varPsi$, and individual blades first flapwise mode ζ_1, ζ_2, and ζ_3. Like most of mechanical systems, wind turbine is represented by a nonlinear model given by

$$M(\underline{q}, \underline{u}, t)\underline{\ddot{q}} + f(\underline{q}, \underline{\dot{q}}, \underline{u}, \underline{u}_d, t) = 0, \tag{5}$$

where, M denotes matrix containing mass and inertia, f is a nonlinear function describing relationship between enabled DOFs, control inputs $\underline{u}$, and exogenous inputs $\underline{u}_d$, while $\underline{q} = [\tau_f, \varPsi, \zeta_1, \zeta_2, \zeta_3]$ represents the DOFs used to extract linear models from the nonlinear model described by Eqn (5). Because the structural loads are more pronounced during high wind speed region (above the rated wind speed region), five linear models are extracted from aeroelastic nonlinear model at 14 m/s, 16 m/s, 18 m/s, 20 m/s, and 22 m/s wind speeds. However, the resulting linear model are highly periodic due to deterministic influences such as tower shadow, vertical wind shear, and yaw misalignments. It is important to note that the effects of periodicity become more pronounced as the turbine grows in size. To account for periodic dynamics of wind turbine during controller design, a multi-blade coordinate (MBC) transformation discussed in [34] is used to express the dynamics in the rotating coordinate of reference to a fixed coordinate of reference. After transformation, linear periodic models are averaged to realize an approximation of linear time invariant (LTI) model which is weakly periodic about azimuth position. This model is used as an example in this contribution. It is worth noting that the variables of linear model are normally perturbed about the point of linearization.

3.2. Multi-Input Multi-Output Control Design for Load Reduction

In this paper, an approximated LTI model is used to design structural load reduction scheme. For controller design, wind turbine is described by following state-space dynamic model

$$\begin{aligned} \dot{x}_n &= A_n x_n + B_n u_n + B_{n_d} u_{n_d}, & \text{(6a)} \\ y_n &= C_n x + v, & \text{(6b)} \end{aligned}$$

where $x_n \in \mathbb{R}^n = \left[\Delta \underline{q},\ \Delta \underline{\dot{q}}\right]^T$ is the state space vector, $u_n \in \mathbb{R}^m = [\Delta\beta_1,\ \Delta\beta_2,\ \Delta\beta_3]^T$ denotes the control input, $y_n \in \mathbb{R}^p$ is the measurement output, $A \in \mathbb{R}^{n\times m}$ represents system matrix, $B \in \mathbb{R}^{n\times m}$ is the input matrix, and $C \in \mathbb{R}^{p\times n}$ denotes the output measurement matrix. In addition to unknown exogenous disturbances u_{n_d}, the measurement y_n is assumed to be distorted with v as additive noise.

The blades in wind turbines are affected by different aerodynamic loads at different azimuth positions and rotational speeds. Hence, it is important to equip modern turbines with pitch actuators to manipulate each blade independently. In some utility-scale wind turbines, a hybrid actuators are used to take advantages of both the hydraulic and electromechanical actuators.

As pointed out in [35], FAST model does not integrate pitch actuator dynamics; hence, leading to the loss of important dynamics that might affect the overall performance of the wind turbine. Because the pitch actuator dynamics are faster than dynamics of other mechanical subsystems, the actuator dynamics are represented by a first order linear model relating the commanded pitch angle to manipulated input pitch angle. To account for pitch actuation dynamics, the actuator is modeled as first order system

$$\frac{\beta}{\beta_{com}} = \frac{1}{s\tau_{\beta} + 1}, \tag{7}$$

as suggested in [36], where β_{com} represents the commanded pitch angle, β denotes the actual pitch angle that manipulates the rotor blade, and $\tau_{\beta} = 0.2$ represents the time constant. As depicted in Fig. 5, the actual pitch angle is maintained within desired limits with magnitude and the rate constrains. In individual blade control scheme, each blade pitch actuator can be represented by first order model (7), written in state space form as

$$\begin{bmatrix} \dot{\beta}_1 \\ \dot{\beta}_2 \\ \dot{\beta}_3 \end{bmatrix} = \begin{bmatrix} -\dfrac{1}{\tau_{\beta 1}} & 0 & 0 \\ 0 & -\dfrac{1}{\tau_{\beta 2}} & 0 \\ 0 & 0 & -\dfrac{1}{\tau_{\beta 3}} \end{bmatrix} \begin{bmatrix} \beta_1 \\ \beta_2 \\ \beta_3 \end{bmatrix} + \begin{bmatrix} \dfrac{1}{\tau_{\beta 1}} & 0 & 0 \\ 0 & \dfrac{1}{\tau_{\beta 2}} & 0 \\ 0 & 0 & \dfrac{1}{\tau_{\beta 3}} \end{bmatrix} \begin{bmatrix} \beta_{com1} \\ \beta_{com2} \\ \beta_{com3} \end{bmatrix}. \tag{8}$$

Equation (8) can be represented in a generalized state space form as

$$\dot{x}_a = A_a x_a + B_a u_a, \tag{9a}$$
$$\dot{y}_a = C_a x_a, \tag{9b}$$

with $x_a = [\Delta\beta_1\ \Delta\beta_2\ \Delta\beta_3]^T$, $u_a = [\Delta\beta_{com1}\ \Delta\beta_{com2}\ \Delta\beta_{com3}]^T$, and $y_a = x_a$. As stated in [37], the nominal wind turbine model (6) can be augmented with pitch actuator to account for pitching actuator dynamics in the FAST model. Here, it is assumed that the control input signal does not directly influence the measured output; hence, the feedthrough matrices D and D_d are assumed to be null matrices. Therefore, the extended model which includes the pitch actuator dynamic is given by

$$\begin{bmatrix} \dot{x}_n \\ \dot{x}_a \end{bmatrix} = \begin{bmatrix} A_n & B_n C_a \\ 0 & A_a \end{bmatrix} \begin{bmatrix} x_n \\ x_a \end{bmatrix} + \begin{bmatrix} 0 \\ B_a \end{bmatrix} u_a + \begin{bmatrix} B_{nd} \\ 0 \end{bmatrix} u_{n_d} \tag{10a}$$
$$\begin{bmatrix} y_n \\ y_a \end{bmatrix} = \begin{bmatrix} C_n & 0 \\ 0 & C_a \end{bmatrix} \begin{bmatrix} x_n \\ x_a \end{bmatrix} + \begin{bmatrix} 1 \\ 0 \end{bmatrix} v. \tag{10b}$$

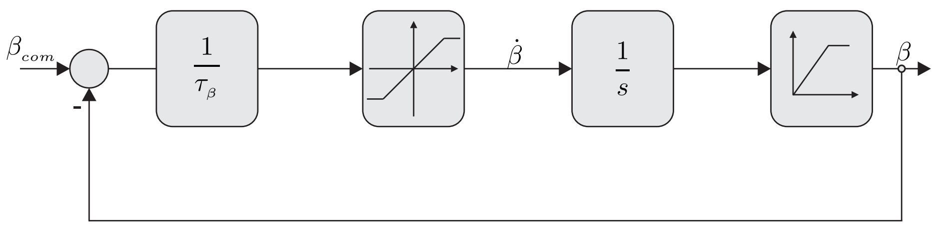

Figure 5: Block diagram of pitch actuator model

In this paper, an LTI model represented by Eqn. (10) is used to design an individual blade pitch control scheme. For convenience, this model can be presented as

$$\dot{x} = Ax + Bu + B_d u_d \tag{11a}$$
$$y = Cx + v. \tag{11b}$$

Although the model expressed in Eqn. (11) is LTI, it weakly captures periodic dynamics of wind turbine due to the application of MBC transformation. To actuate individual rotor blade, control input signal u is transformed back to the mixed reference coordinate system by inverse MBC transformation. It is important to emphasize that although a linear model is used to design controllers, the simulations are carried out using a nonlinear model which contains more degrees of freedom than those used to design the controller.

To design a full state feedback controller, all state variables must be avail-

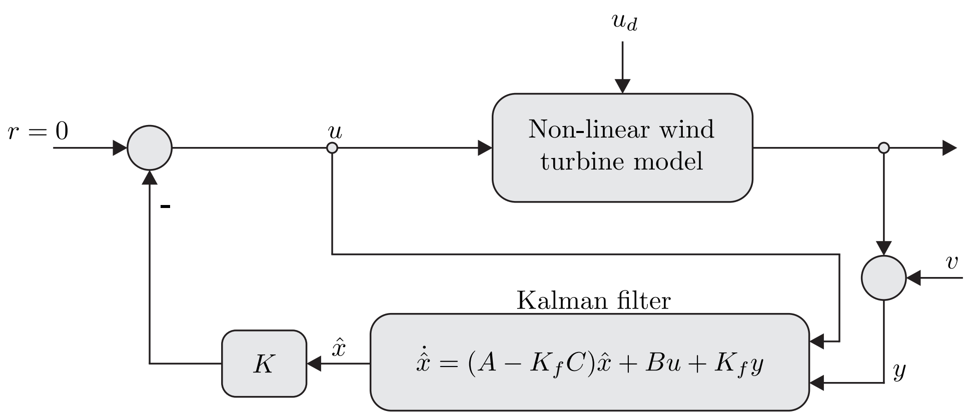

Figure 6: Full state feedback and optimal state estimator

able for feedback. In some practical applications, not all state variables are available for measurement; hence, it desirable to use a few just a few measurements to estimate all states for feedback. Furthermore, it is cost effective to use just a few measurements to estimate the states, especially for a complex systems that have many state variables. As depicted in Fig. 6, the control problem can be divided into two levels, i.e, determination of feedback gain K using linear quadratic (LQ) control method and the estimation of state variables using Kalman filter. To design a linear quadratic regulator (LQR) controller, the control gain K is evaluated such that the following performance index is minimized

$$J = \int_0^t \left[x^T(t)Qx(t) + u^T(t)Ru(t)\right] dt. \tag{12}$$

The state weighting matrix $Q \in \mathbb{R}^{n\times n} = Q^T \geq 0$ and control weighting matrix $R \in \mathbb{R}^{m\times m} = R^T > 0$ are used to optimize a trade-off between state regulation and control input usage. The feedback gain $K = R^{-1}B^TP$ is determined by solving the following algebraic Riccati equation

$$A^TP + PA + Q - PBR^{-1}B^TP = 0, \tag{13}$$

where $P = P^T \geq 0$ is an unknown $n \times n$ symmetric matrix assuming that the system (A, B) is controllable. The matrix Q and R are tuned to get a series of control gains that correspond to different structural load levels and different output power. Depending on the predefined damage levels, the control gains are changed to reduce the structural loads, albeit at a slight compromise on speed regulation objective.

Since the incoming wind possesses stochastic properties and the fact that the output measurements are noisy, Kalman estimator can be effectively used to reconstruct the system states using control input and noisy measurement signals. The process noise u_d and the measurement noise v are assumed to be uncorrelated, zero-mean Gaussian noise, i.e, $E[u_d] = E[v] = 0$, $E[u_d u_d^T] = Q_f$, $E[vv^T] = R_f$. Here, Q_f and R_f are process and measurement noise covariance matrices, respectively. The continuous Kalman estimator is defined by the following dynamic model

$$\begin{aligned} \dot{\hat{x}} &= A\hat{x} + Bu + L(y - C\hat{x}), \\ \hat{y} &= C\hat{x}, \end{aligned} \tag{14}$$

where $\hat{x}$ is the estimated state, while $\hat{y}$ is estimated measured output, and $K_f = P_fC^TR_f^{-1}$ denotes the Kalman gain. The matrix $P_f = P_f^T \geq 0$ is the solution of the following filter algebraic Riccati equation (FARE)

$$P_fA^T + AP_f + Q_f - P_fC^TR_f^{-1}P_f = 0 \tag{15}$$

Unlike the classical in Luenberger observer, the gain L is designed such that state estimation error covariance $E\left[(x - \hat{x})(x - \hat{x})^T\right]$ is minimized in a sense of a given quadratic performance index related to disturbance and measurement noise covariance matrices. A realized feedback controller is designed using estimated states as

$$u = K\hat{x}, \tag{16}$$

where K is optimally designed by minimizing the performance index given by Eqn. (12). It should be noted that the stability and stability margin in LQR design are guaranteed assuming that all states are available for the feedback.

4. Extension of Wind Turbine Lifetime: An Illustrative Example using NREL 1.5 MW Turbine

Modern wind turbines have an approximate lifespan of 20 years or 2.7×10^8 fatigue stress cycles [38], but most of the cases there is a likelihood to fail before reaching this time due to fatigue damage. Consequently, a lot of efforts are being made to develop models that monitor wind turbine deterioration process or predict its lifetime before it fails. Another approach being employed to extend the service lifetime of wind turbine is to use control strategies that mitigate structural loads. While this approach is promising, very little has been reported on the integration of control strategies with damage

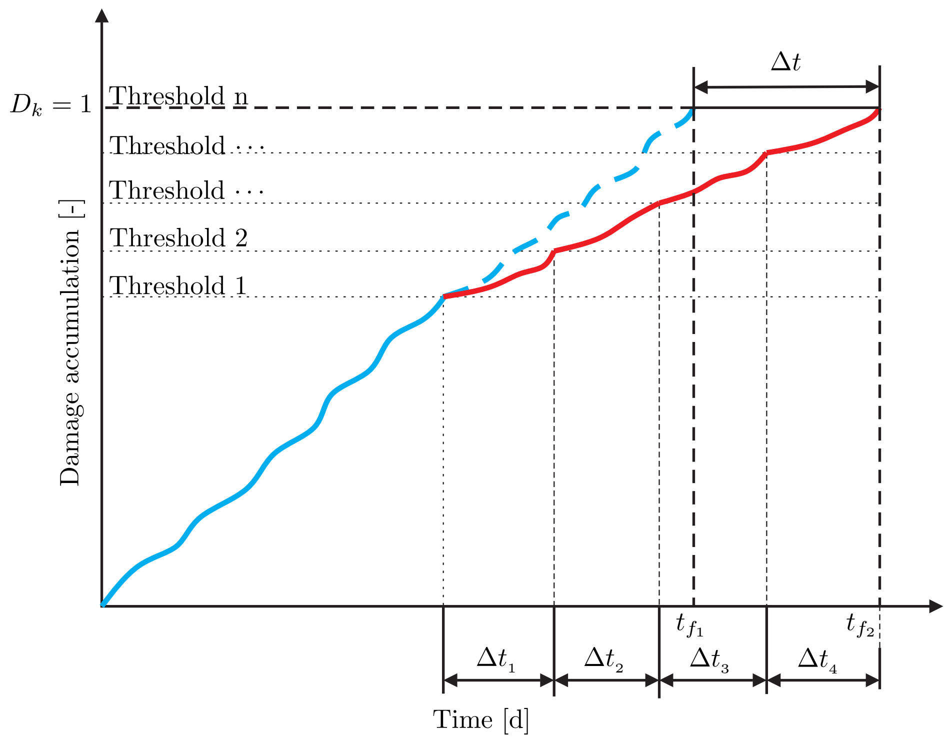

Figure 7: A scheme for extension of the remaining useful lifetime

evaluation models in order to quantify the extent of lifetime extension. This paper aims at combining structural load reduction control strategy with lifetime prediction model so as to extend the lifetime of wind turbine. In Fig. 7, a generalized scheme of using an aging model together with a load reduction strategy to delay the degradation of wind turbine is shown.
Without structural load reduction consideration, the turbine looses its functionality at time t_{f_1} which is lower than the expected life time t_{f_2}. Assuming that this loss of lifetime can be quantitatively defined by a suitably designed diagnosis scheme, the remaining life time will be shortened if control scheme is not changed. With the proposed prognostic-based control strategy, the objective is to extend the lifetime of wind turbine by Δt to compensate for the lost URL, hence reaching the desired lifespan. Using the introduced Wöhler/Palmgren Miner calculation which assumes a linear damage accumulation, the nominal and the resulting lifetime of the damaged/faulty systems can be assumed as known [39, 40]; therefore, the control strategy is used to make sure that the wind turbine does not cease before its desired lifespan. Likewise, similar control strategies can be used to extend the lifetime of slightly damage wind turbine to reach it nominal end of lifetime to avoid unwarranted downtime. In this paper power production is optimum when load reduction control method is not employed. In other words, the load reduction control strategy is used to optimize the trade-off between the extension of wind turbine lifetime and the quality of output generated power. At first the wind turbine is operated at optimum power without considering load reduction strategy, then it is operated until the accumulated damage reaches a certain predefined threshold. Consequently, the load reduction control strategy is engaged at varying degrees till the turbine reaches the end of lifetime. In Fig. 8 damage accumulation levels for different wind speeds and different controllers with varying load reduction capabilities is depicted. The wind speeds are varied from 12 m/s to 22 m/s at step of 2 m/s. In this paper, controller 1 represents a case where the objective of speed/power regulation is perfectly realized, but with a penalty of slightly increased structural loads. On the other hand, controller 5 has strong structural load mitigation ability though at at slightly compromised output power/speed regulation. It is evident from Fig. 8 that structural loads reduce as wind speed reduces. It is important to mention that a full-field turbulent wind profiles generated by NREL TurbSim simulation code are used in this paper to determine fatigue related damages. In this paper, different wind profiles with different wind speed but same turbulence intensity are used to demonstrate the application

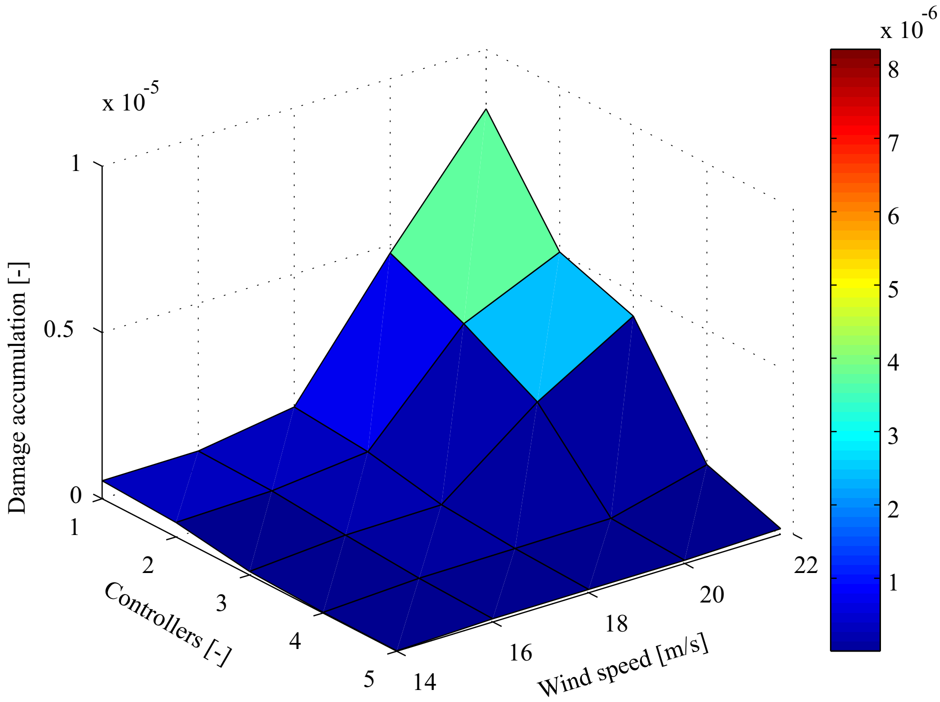

Figure 8: Damage accumulation for different controllers and wind speeds

of prognostic-based control scheme.
In Fig. 9, the correlation between structural load mitigation and power variation is shown. In this case, independent blade pitch controllers with varying degrees of structural load mitigation are designed. It is observed that the variation of mean output power fluctuation increases as the DEL reduces, although at a small rate: a 21.38% reduction in DEL results to 1.55% increment in mean output power fluctuation. Though the influence on output power variation might not be significant, structural load reduction might lead to undesirable actions such as increased pitch actuation duty cycle (ADC); hence, a careful trade-off between various performance characteristic is paramount in achieving the overall objective of extending lifetime and output power regulation. For 600 s simulation window, it is evident that the level of accumulated damage reduces as the controllers are switched from 1 to 5.
To demonstrate the concept of integrating prognosis model into control loop, five multi-variable controllers with different load reduction capacity are designed for wind speed of 18 m/s. These controllers are switched depending

on the level of damage for the machine part under investigation. For a simulation period of 600 s, the accumulated damaged reduced by around 40% when damage evaluation model is integrated in control loop as illustrated in Fig. 10. At about 70 seconds, controllers are switched from 1 to 5 depending on accumulated damage level resulting to an overall reduction in damage accumulation by 40%. As mentioned, the aim of this paper is to strike balance between lifetime extension and power regulation objective as depicted by Fig 9.

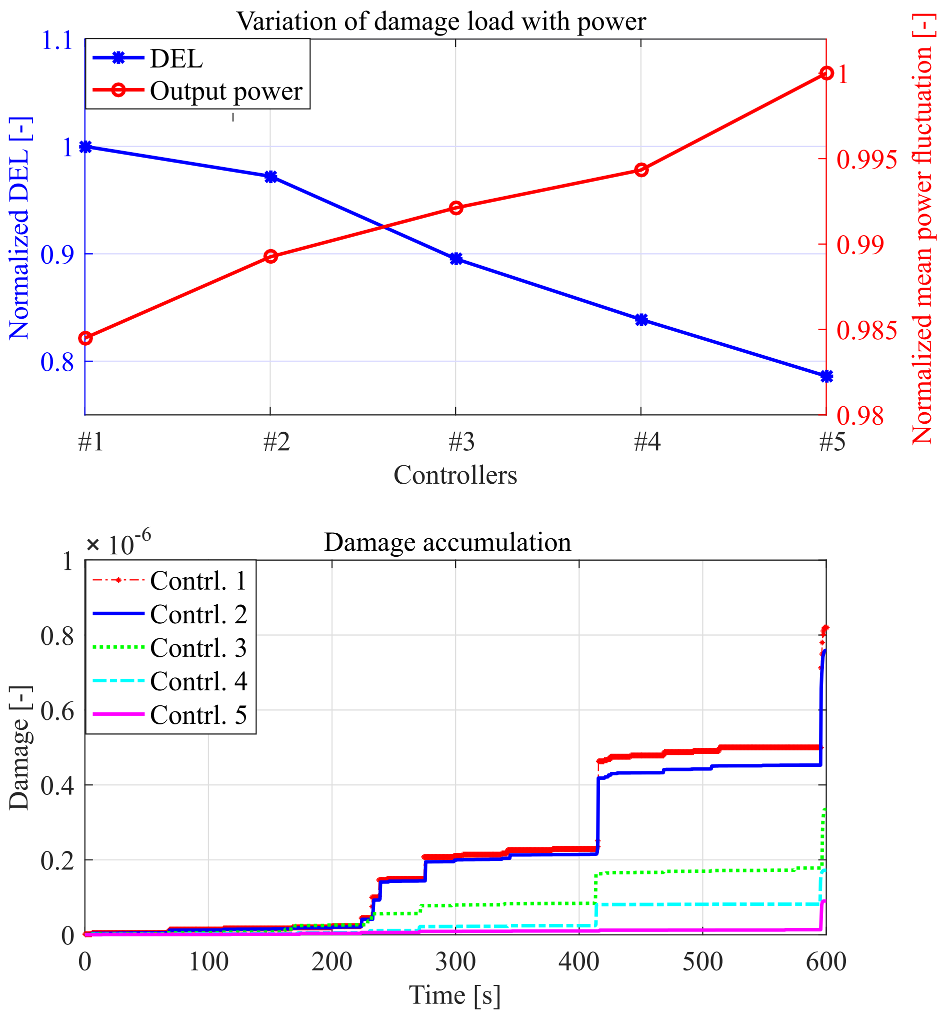

Figure 9: Correlation between load reduction and power production

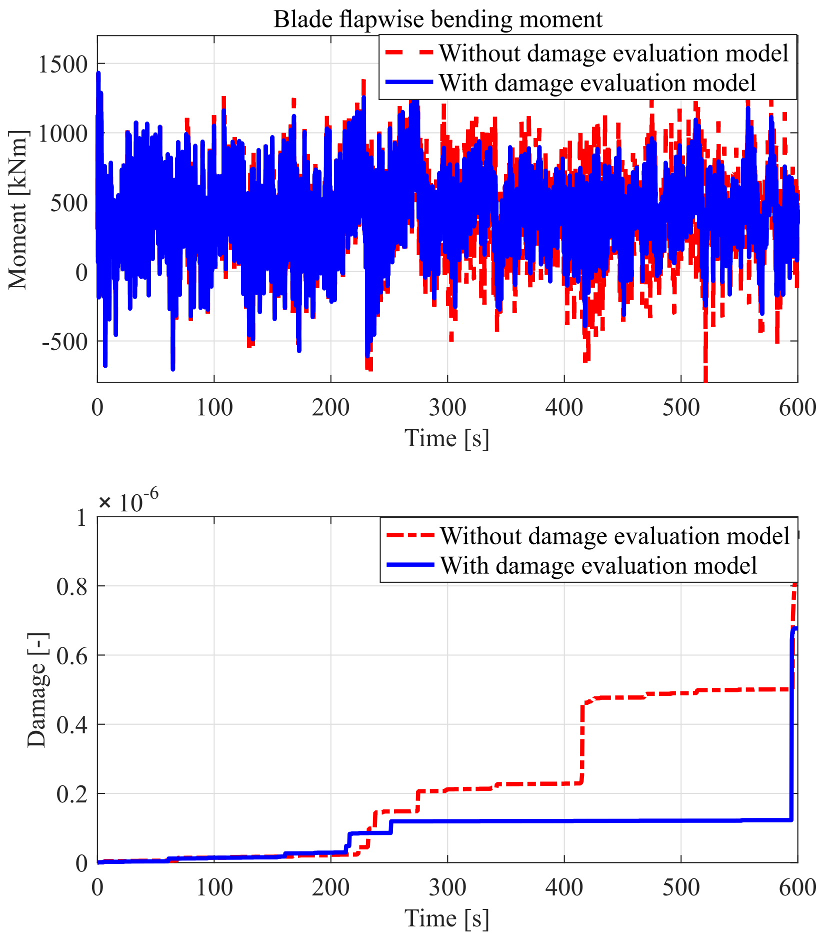

Figure 10: Comparison of damage accumulation with and without prognostic model

5. Lifetime Extension by De-rating Generator

If the occurrence of a fault and its mode of propagation can be predicted, tactical operation can be employed to extend the service lifetime of the wind turbine till the next planned/scheduled maintenance, although at a reduced power production or at a cost of compromising other important objectives such as regulation of speed/power. One of the tactical operation that can be employed in wind energy harvesting is to run turbines at a downscaled operation capacity. The aim of this approach is to optimize the trade-off between power production maximization and extension of the wind turbine lifetime. This condition-based operation strategy is very crucial in applications where

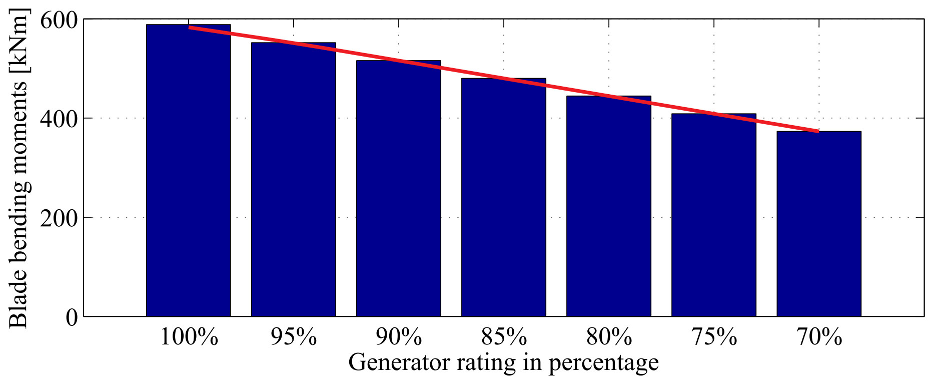

Figure 11: Reduction of load by de-rating of the generator

wind power is supplied under contractual obligations such as PPA or in situations where lead time before replacement/repair of damaged turbine is long due to logistics challenges, especially in offshore applications [41]. The adoption of condition-based operation can significantly reduce the occurrence of unscheduled maintenance which contribute to a substantial portion of the overall O&M cost. Additionally, the chances of collateral damage to other wind turbine components can be significantly reduced if the defective components are identified and timely appropriate corrective action is taken.
In large composite rotor blades, defect can manifest itself in a form of delamination and if the severity level of damage are not acute the RUL of such blade can still be utilized with a view of optimizing the production cost of wind power; albeit at a compromised performance. In model-based approaches of investigating the performance of defective wind turbine blades, faults can be induced by altering the local flap-wise and edge-wise stiffnesses along the blade span length [42, 43]. In Fig. 11 the effect of de-rating wind turbine generator on the flapwise rotor blade bending moments is illustrated. Here, the generator is de-rated from 100% to 70% of the rated value. As a result, the blade flapwise bending moment is reduced by 36.6%. Similar trend is expected in edgewise bending moments, although flapwise loads are more pronounced compared to edgewise blade loads.

6. Conclusion

In this paper, a framework integrating an online damage evaluation model into the main control loop of wind turbine is presented. The aim of this

scheme is to extend the service lifetime of wind turbine either by optimizing the trade-off between structural load reduction and speed/power regulation, or mitigation of structural loads and maximization of power production. The knowledge of how components in wind turbine system degrade during power production is an important aspect in planning and scheduling of maintenance which can lead to increased availability and reduction of overall production cost of wind power.
An online fatigue damage evaluation model is adopted in this paper to adjust structural load control strategy to compromise between reliability and optimization of power regulation. It is important to note that a damage evaluation model based linear damage accumulation is used in this study just for the purpose of demonstration; otherwise, fault propagation in wind turbine might be highly nonlinear due to variability of wind speed and other inherent nonlinearities in turbine itself. It has also been demonstrated that severity of damage propagation can be abated by operating wind turbine at a scaled down capacity. Again this strategy can be used to optimize the maintenance scheduling. The results demonstrate that the proposed prognostic-based operation can lead to optimized wind energy production, especially in offshore application due to logistic challenges related to maintenance.

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