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Prognostics-based adaptive control strategy for lifetime control of wind turbines

Edwin Kipchirchir[1], M. Hung Do[2], Jackson G. Njiri[3], and Dirk Söffker[4]

[1,4]Chair of Dynamics and Control, University of Duisburg-Essen, Lotharstr. 1-21, 47057, Duisburg, Germany
[2]School of Heat Engineering and Refrigeration,Hanoi University of Science and Technology
[3]Department of Mechatronic Engineering, Jomo Kenyatta University of Agriculture and Technology, 62000-00200, Nairobi, Kenya

Correspondence: Edwin Kipchirchir (edwin.kipchirchir@uni-due.de)

Abstract. Variability of wind profiles in both space and time is responsible for fatigue loading in wind turbine components. Advanced control methods for mitigating structural loading in these components have been proposed in previous works. These also incorporate other objectives like speed and power regulation for above-rated wind speed operation. In recent years, lifetime control and extension strategies have been proposed to guaranty power supply and operational reliability of wind turbines. These control strategies typically rely on a fatigue load evaluation criteria to determine the consumed lifetime of these components, subsequently varying the control set-point to guaranty a desired lifetime of the components. Most of these methods focus on controlling the lifetime of specific structural components of a wind turbine, typically the rotor blade or tower. Additionally, controllers are often designed to be valid about specific operating points, hence exhibit deteriorating performance in varying operating conditions. Therefore, they are not able to guaranty a desired lifetime in varying wind conditions. In this paper an adaptive lifetime control strategy is proposed for controlled ageing of rotor blades to guaranty a desired lifetime, while considering damage accumulation level in the tower. The method relies on an online structural health monitoring system to vary the lifetime controller gains based on a State of Health (SoH) measure by considering the desired lifetime at every time-step. For demonstration, a 1.5 MW National Renewable Energy Laboratory (NREL) reference wind turbine is used. The proposed adaptive lifetime controller regulates structural loading in the rotor blades to guaranty a predefined damage level at the desired lifetime without sacrificing on the speed regulation performance of the wind turbine. Additionally, significant reduction in the tower fatigue damage is observed.

1 Introduction

Growing demand for wind energy has led to the development of large wind turbines. However, these turbines are less tolerant to system performance degradation and faults (Gao and Liu, 2021). To ensure utility-scale wind turbines operate with respect to their design lifetime, advanced control strategies have been developed in recent years to reduce structural loading of blades and tower. Most of these incorporate additional objectives such as power optimization and rotor speed regulation. The objective of lifetime control of wind turbines using prognostics-based load mitigation strategies has become more important in recent years. Most of the proposed methods focus on controlling the lifetime of one structural component of a wind turbine, typically

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the rotor blade or the tower, without considering the fatigue damage level in other components. These lifetime controllers are also designed to be valid about specific operating points.

A control strategy for extending the maintenance interval of wind turbine blades under assumed crack initiation, detected using a data filtering algorithm, is proposed (Beganovic et al., 2015). In (Beganovic et al., 2018; Njiri et al., 2019), a set of switching controllers with varying degrees of load mitigation are engaged sequentially based on the accumulated damage obtained from an online damage evaluation model to extend the lifetime of rotor blades. An adaptive lifetime controller is proposed in (Do and Söffker, 2019) to guaranty the desired lifetime of the tower. Depending on the damage accumulation and the predicted lifetime provided by a online damage evaluation model, the weights of the lifetime controller are varied. However, in (Beganovic et al., 2015, 2018; Njiri et al., 2019; Do and Söffker, 2019) fatigue damage is considered in only one turbine component. The lifetime controllers used are not adaptive to varying wind conditions. In recent times, resilient control has been proposed in (Acho et al., 2016; Azizi et al., 2019; El Maati and El Bahir, 2020; Jain and Yamé, 2020) to minimize the effect of unanticipated faults or unexpected dynamics to maintain the operation of a wind turbine within a limited degradation tolerance bound. However, resilient control does not address the problem of controlling life consumption in wind turbine components to avoid early fatigue failures. Although new concepts like operational modal analysis (OMA), which relies on measurement data to analyze vibrating structures are becoming the industry standard for condition monitoring and diagnosis especially for offshore wind turbines (Kim et al., 2019; Bajric et al., 2017; Dong et al., 2018; Pegalajar-Jurado and Bredmose, 2019), these concepts are yet to be integrated for prognosis and lifetime control of wind turbines.

In this work an adaptive lifetime control strategy is proposed for controlling ageing of rotor blades to guaranty a desired lifetime while considering damage accumulation level in the tower. A robust disturbance accommodating control (RDAC) proposed in (Do and Söffker, 2021) is used for rotor speed regulation and load mitigation in the tower, while a prognostics-based adaptive independent pitch control (aIPC), which adapts to wind speed variation, is used for lifetime control of rotor blades. By monitoring the accumulated damage using an online structural health evaluation model, the load mitigation level in the blades is controlled by varying the control gains in the respective IPC controllers based on a threshold evaluation of the estimated lifetime. As an improvement to the approaches in the aforementioned contributions, the proposed adaptive lifetime control strategy regulates fatigue loading in the rotor blades to reach a predefined damage limit at the desired lifetime with subsequent reduction in tower damage accumulation. This is realized without trade-off in speed/power regulation performance.

The paper is organized as follows. In section 2, a theoretical background on wind turbine health monitoring is given. In section 3, design of the primary RDAC controller for rotor speed regulation and tower load mitigation, and the prognostics-based aIPC lifetime controller for controlled ageing of rotor blades is outlined. The proposed prognostics-based adaptive lifetime control strategy, which incorporates the primary and lifetime controllers, and an online damage evaluation model is described in section 4. In section 5, simulation results based on performance evaluation of the proposed prognostics-based adaptive lifetime control strategy on a reference wind turbine are discussed. Lastly, summary and conclusions are given in section 6.

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2 Wind turbine health monitoring

over time

Wind speed variability subjects wind turbine components like blades and tower to cyclic loading. This causes damage to be accumulated in these components overtime causing gradual degradation until failure occurs. Therefore, structural health monitoring of wind turbines is important in preventing occurrence of fatigue failure before reaching ~~related~~ design lifetime. Information on the damage evolution in a component can be utilized as a health indicator for failure detection as well as for developing control measures to guaranty desired lifetime. This section outlines the methods used for estimating the damage accumulation in wind turbine components.

2.1 Evaluation of damage accumulation

A Wind turbine endure varying and complex load conditions over its lifetime. Fatigue analysis is therefore important in determining the consumed lifetime of its components. Component degradation starts at micro-scale as micro-cracks resulting from irreversible changes in the microstructure, and propagates gradually until it fails. Assumptions of underlying damage evolution laws are often used to estimate the actual damage level as well as to predict the remaining useful life (RUL) of a component. Component-specific high-cycle fatigue experiments are used to generate S-N curves (Wöhler curve), which describe the relationship between applied stress amplitude S and the number of load cycles N that would cause failure. This forms the basis for the mathematical relation for fatigue analysis in wind turbines components expressed as

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

where s denotes the stress range amplitude, m the Wöhler exponent (typically 3 for steel materials like the tower and 10 for composites like the blade (Ragan and Manuel, 2007)). The material parameter of fatigue damage at failure K e.g., ultimate tensile strength is related to the number of load cycles N.

Wind turbine components are designed for a service lifetime of at least 20 years according to the international electrotechnical commission (IEC) standard, with these structural components facing roughly between 10^8 and 10^9 fatigue load cycles (Ziegler et al., 2018). The component lifetime is typically arrived at using the projected number of fatigue cycles and average wind conditions it will encounter in its lifetime. Additionally, the IEC standard specifies that a wind turbine component should be designed to maintain its structural integrity in case it experiences 50 year extreme wind events during its lifetime.

Fatigue damage in components can be assessed using linear damage accumulation theory based on Miner's rule or nonlinear damage accumulation theories (Yuan et al., 2014). Due to its simplicity, Miner's rule (Miner, 1945) is widely used. Wind speed variability induces varying-amplitude load spectrum on wind turbine components. To use Miner's rule, the complex spectrum of varying load is often transformed using rain-flow counting (RFC) algorithm first proposed by (Matsuishi and Endo, 1968), into simple uniform loading, from which stress range histograms can be extracted and used to assess the accumulated damage. A schematic of this procedure is shown in Fig. 1.

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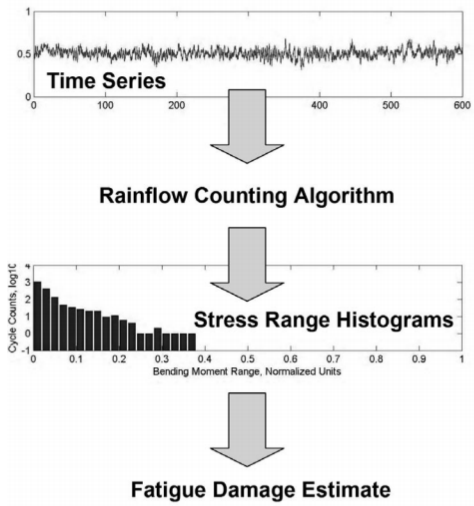

Figure 1. Conventional fatigue load estimation (Ragan and Manuel, 2007).

By combining RFC and Miner's rule, damage accumulation D_k 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 k denotes the total number of related stress range histograms, d_i the incremental damage at the i^{th} stress range histogram, n_i the number of applied load cycles in each histogram bin, N_i the number of cycles to failure at the i^{th} stress range histogram, and s_i the applied load amplitude in each histogram bin. With continual load application, damage in a component progresses from an undamaged state $D_k = 0$ to the point it is considered to have reached its end of life when the accumulated damage, $D_k = 1$. In this case, the component is considered to have exhausted its structural reserves. Although other cycle counting algorithms including level crossing counting, peak counting, and simple range counting exist, RFC algorithms are the most widely applied for fatigue analysis (Musallam and Johnson, 2012).

2.2 Online rain-flow counting

Most standard RFC algorithms generate equivalent load cycles from complex load spectra by pairing local minima and maxima points using 3-point counting rule. Therefore, the entire load history is needed beforehand for the equivalent cycles to be generated. This process is computationally inefficient because the algorithm has to process all the stored loading data. Therefore, standard RFC cannot be used for real-time monitoring or control of life consumption of a component (Musallam and Johnson, 2012).

In (Musallam and Johnson, 2012), a real-time implementation of the RFC algorithm is proposed. By employing a 3-point counting rule recursively, the extremal points of time-series loading data are processed and stored in two flexible stacks as they occur to pick out the full and half cycles. For each identified cycle, and using Miner's rule, the life consumption of a component

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is then calculated and incremented online. This allows for the online determination of the consumed life of a component as well as implementation of lifetime control. In this paper, the online damage evaluation algorithm (Musallam and Johnson, 2012), is adopted for evaluating the accumulated damage in rotor blades and tower. This information is then used to adapt the lifetime controller to guaranty a predefined service life of the wind turbine components.

3 Control strategy for load mitigation and speed regulation

In this paper, a Robust Disturbance Accommodation Controller (RDAC) (Do and Söffker, 2021), proposed for rotor speed regulation and mitigation of tower fore-aft bending moments is extended to include an adaptive Independent Pitch Controller (aIPC), which is used as a dynamic lifetime controller for reducing blade flap-wise bending moments in a wind turbine operating in the above-rated wind speed region. In this section the description of the reference wind turbine (RWT) is outlined. Additionally, the description of the adaptive robust observer-based controller, which is adapted for lifetime control, is summarized.

3.1 Wind turbine model description

what do you mean?

A 1.5 MW WindPACT reference wind turbine developed by NREL (Rinker and Dykes, 2018), which is domicile in Fatigue, Aerodynamics, Structures, and Turbulence (FAST) design code (Jonkman and Buhl Jr., 2005), is chosen as the test-bed for the design and simulation of the proposed adaptive lifetime control strategy. This onshore wind turbine model was developed based on a real-life commercial wind turbine used in the WindPACT program. The specifications of this turbine are summarized in Table 1. It is a 3-bladed, upwind, horizontal axis wind turbine, having 24 Degrees of Freedom (DoFs) describing its flexibility. However, a few DoFs are enabled to obtain a reduced order linear time-invariant (LTI) models used for controller design.

Table 1. 1.5 MW WindPACT reference wind turbine specifications

Parameter	Value	Unit
Rated rotor speed	20.463	rpm
Hub height	84.288	m
Cut-in, Rated, Cut-out wind speed	4, 12, 25	m s^{-1}
Gearbox ratio	87.965	-
Blade radius	35	m
Rated power	1.5	MW
Blade pitch range	0-90	^{o}
Pitch rate	10	^{o} s^{-1}
Optimal Tip-Speed-Ratio (λ_{opt})	7.0	-
Maximum power coefficient ($C_{p_{max}}$)	0.5	-
Optimum pitch angle (β_{opt})	2.6	^{o}

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The nonlinear generalized equation of motion for the wind turbine is expressed as

$$M(q,u,t)\ddot{q}+f(q,\dot{q},u,u_d,t)=0, \tag{3}$$

where M denotes the mass matrix containing inertia and mass components and f is a nonlinear function of the enabled DoFs q and their first derivative $\dot{q}$, as well as the control input u, the disturbance input u_d, and time t. The nonlinear model Eq. (3) available in FAST is linearized about an operating point in the above-rated region. By enabling the DoFs, which capture the most important wind turbine dynamics of interest, and specifying the operating point defined by a constant hub height wind speed, pitch angle, and rotor speed, linearization is carried out numerically in FAST yielding periodic (azimuth dependent) matrices of LTI models.

3.2 Controller for load mitigation and speed regulation

An adaptive robust observer-based controller, which in combination with an online damage evaluation model used for lifetime control of wind turbine components, is briefly outlined.

3.2.1 Robust disturbance accommodating controller

The RDAC controller, proposed in previous work (Do and Söffker, 2021), is briefly outlined for principal understanding. To obtain a linear model for controller design, the nonlinear model Eq. (1) is linearized about an operating point in the above-rated wind speed region defined by a steady hub-height wind speed of $v_{op}=18\,\mathrm{m\,s^{-1}}$, a pitch angle of $\beta_{op}=20^o$, and a rotor speed of $\omega_{op}=20.463$ rpm. To capture the most important dynamics, corresponding to the desired closed-loop performance with respect to structural load mitigation and rotor speed regulation, 11 states x are chosen, including tower fore-aft displacement, drive-train torsional displacement, blades 1, 2, and 3 flap-wise displacements, and there respective velocities, as well as generator speed. The obtained reduced-order LTI model is expressed in state-space form as

$$\begin{aligned}\dot{x}&=Ax+Bu+B_dd\\ y&=Cx,\end{aligned} \tag{4}$$

where A,B,B_d,C denote the state-space system, $u$bthe control input, which is the collective pitch angle, x the states, d the wind disturbance, and y the measured outputs, which include rotor speed and tower-top fore-aft bending moment.

The model Eq. (4) is augmented with a pitch actuator model, which accounts for the slow pitch actuator dynamics. To counteract wind disturbance effects, the model is extended with an assumed step disturbance waveform (Wright, 2004; Wright and Fingersh, 2008), which approximates sudden uniform rotor effective wind velocity fluctuations. To meet the rotor speed regulation objective with zero steady-state tracking error, the model is further extended with a partial integral action.

To ensure closed-loop system stability, robustness and optimality, a mixed-sensitivity H_∞ norm of the closed loop transfer function is used as a cost function to optimize the disturbance accommodating controller(DAC) parameters including observer gain L_x, state controller K_x disturbance rejection controller K_d, and the integral gain K_i in a single step. The mixed sensitivity

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H$_\infty$ optimization problem is formulated as

$$R^* = \underset{R \in \mathcal{R}}{argmin} \left\| \begin{matrix} W_1 S \\ W_2 RS \\ W_3 T \end{matrix} \right\|_\infty , \tag{5}$$

where R^* denotes the optimized controller, $\mathcal{R}$ a set of controllers R that stabilize the plant. The weighting functions W_1, W_2, and W_3 are introduced to ensure desired robust performance while S, RS, and T denote the related sensitivity, control effort, and complementary sensitivity functions, respectively. The problem to find an optimal RDAC controller $RDAC^*$ is formulated as

$$RDAC^* = \underset{RDAC \in \mathcal{RDAC}}{argmin} \parallel G_{zd}(P, RDAC) \parallel_\infty , \tag{6}$$

where $\mathcal{RDAC}$ denotes a set of controllers $RDAC$ that stabilize the generalized plant P, and G_{zd} is the transfer function from the exogenous inputs d to the controlled outputs z.

Nonsmooth H$_\infty$ synthesis proposed in (Apkarian and Noll, 2006), used for problems with structural and stability constraints is applied to find an optimal controller $RDAC^*$ with robust gains L and K for tower load mitigation and rotor speed regulation. It is implemented in MATLAB using *hinfStruct* command (Apkarian and Noll, 2017). In Fig. 2 application of the RDAC controller to the 1.5 MW NREL RWT is shown. An actuator transfer function is included in the generalized plant P, to account for the blade pitch actuator dynamics. Hub height wind disturbance d excites the wind turbine dynamics in above rated operation. Measurement outputs including rotor speed ω and tower fore-aft bending moment ζ are fed to the RDAC controller, which generates a collective pitch angle β as a control signal for regulating rotor speed at the rated value and for reducing tower fore-aft bending moment oscillations. The RDAC controller is robust against modeling errors and wind disturbances. The desired trade-off between robust stability and performance is achieved by choosing suitable weighting functions W$_{11}$,

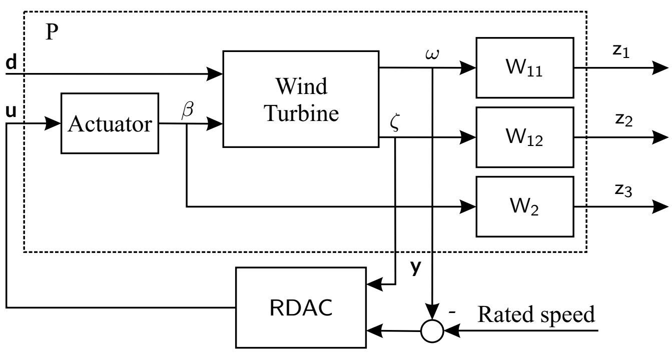

Figure 2. RDAC for wind turbines.

W$_{12}$, and W$_2$. To effect rotor speed response and ensure robustness against wind disturbances, W$_{11}$ is designed as an inverted low-pass filter. To reduce the first mode of tower fore-aft oscillation, W$_{12}$ is designed as an inverted notch filter centered at 2.56 rad/s. To reduce controller activity at high frequencies thereby increasing robustness, W$_2$ is chosen as high-pass filter.

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envelope

Both objectives of rotor speed regulation and tower load reduction for wind turbines operating in above-rated wind speed region are met while ensuring robustness against modeling errors and wind disturbances. However, $RDAC^*$ is only valid within its design operating point and suffers performance deterioration outside this envelop. Additionally, its control input signal is a collective pitch angle, hence cannot be applied for reducing blade oscillations due to vertical wind shear, which can only be achieved through IPC control.

3.2.2 Adaptive independent pitch controller

This controller is desired to counteract periodic aerodynamic loading of the rotor blades due to vertical wind shear. It is designed to reduce 1P (0.333 Hz) blade flap-wise oscillations and is adaptive to change in the operating point due to horizontal wind speed fluctuations. Five IPC controllers, each designed to be operational over a particular wind speed bin in the above-rated wind speed region, together with a switching mechanism based on the incoming wind speed are used to realize aIPC. The linear models, used for designing respective IPC controllers are extracted from the nonlinear wind turbine model Eq. (1) at different operating points as shown in Table 2.

Table 2. Design operating points for the IPC controllers

IPC Controller	Wind speed bin [m s^{-1}]	Steady wind speed [m s^{-1}]	Blade pitch angle [^{o}]	Rotor speed [rpm]
1	12 - 15	14	13.10	20
2	15 - 17	16	16.75	20
3	17 - 19	18	19.83	20
4	19 - 21	20	22.47	20
5	21 - 25	22	24.84	20

Seven states x including blade flap-wise displacement for each blade and respective velocities, and generator speed are selected to capture important dynamics with respect to blade load mitigation. To capture periodicity due to vertical wind shear, 24 equispaced azimuth positions are selected for linearization. To integrate this periodicity in controller design, multi-blade coordinate (MBC) transformation proposed in (Bir, 2010) is used to transform blade dynamics from the rotating to the non-rotating frame. The MBC transformed reduced order models are then averaged to obtain a weakly periodic LTI model described in state-space form as

$$\begin{aligned} \dot{x} &= Ax + Bu + B_d d \\ y &= Cx + v, \end{aligned} \tag{7}$$

where A, B, B_d, C denote the state-space system, $u = [\Delta\beta_1 \ \Delta\beta_2 \ \Delta\beta_3]^T$ denotes the perturbed independent pitch angles, and d the wind disturbance. The measurements y, which include the blade root flap-wise bending moment for each blade are assumed to be distorted with noise v.

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Using linear quadratic gaussian (LQG) control method, Eq. (7) is used to design an observer-based controller. The full-state feedback controller K is designed using linear quadratic regulator (LQR) technique by minimizing the cost function

$$J_{QR} = \int_{0}^{\infty} (x^T Q x + u^T R u) dt, \tag{8}$$

while solving the algebraic Riccati equation (ARE) $A^T P + PA - PBR^{-1}B^T P + Q = 0$, assuming $(A,\ B)$ is fully controllable. Here Q and R denote the state and control input weighting matrices respectively, whose elements are tuned to achieve the desired dynamic response with respect to blade load mitigation and rotor speed regulation, while P is the solution to the ARE. To implement optimal full-state feedback control $u = K\hat{x}$ using estimated states $\hat{x}$, a Kalman state estimator is used to design the observer gain L by minimizing the state estimation covariance error $E((x-\hat{x})(x-\hat{x})^T)$, while solving the ARE $AP_f + P_f A^T - P_f C^T R_f^{-1} C P_f + Q_f = 0$, assuming $A,\ C)$ is fully observable. Here, Q_f and R_f are process disturbance and measurement noise covariance matrices, respectively, while P_f is the solution to the ARE.

Figure 3 illustrates the implementation of one of the five IPC controllers. The wind profile d excites the dynamics of the wind turbine in the above-rated wind speed region. The perturbed blade root flap-wise bending moment measurements Δy are transformed from the rotating to the fixed coordinate frame of controller design, using an inverse MBC transformation matrix $T(\psi)^{-1}$, which relies on real-time rotor azimuth angle measurements ψ. The perturbed independent pitch angles $\Delta\beta_i$ are obtained by transforming the control input u back to the rotating frame using the MBC transformation matrix $T(\psi)$. By summing $\Delta\beta_i$ and the collective pitch angle β_c from the RDAC controller, the IPC signal β_i obtained.

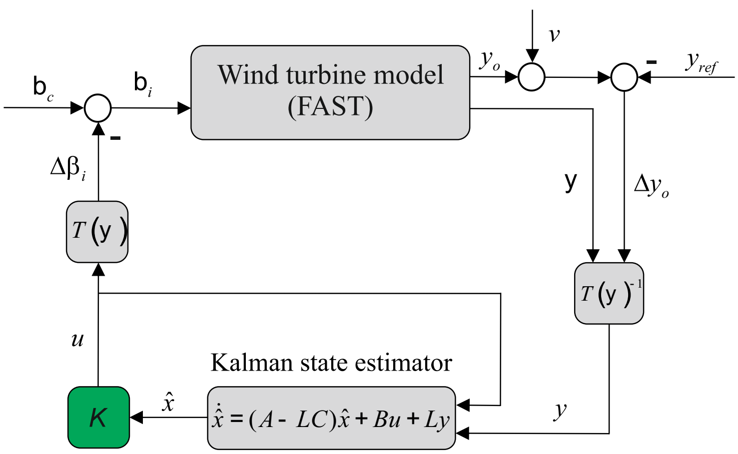

Figure 3. Independent pitch controller

The five IPC controllers are designed following this procedure, each at a predefined operating point, to cover the entire range of operation in the above-rated regime. A switching mechanism is then implemented to activate each controller at a predefined operating range based on the prevailing wind speed.

what exactly is the prevailing wind speed,
how it is defined.

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4 Control of wind turbine lifetime: An illustrative example using the 1.5 MW NREL reference wind turbine

To control the lifetime consumption in wind turbine blades, the adaptive robust observer-based controller (RDAC+aIPC), implemented using two control loops is combined with an online damage evaluation model as shown in Fig. 4. A wind profile excites the wind turbine dynamics in the above-rated regime. The RDAC controller (Do and Söffker, 2021), which is robust against modeling errors generates the primary CPC signal for rotor speed regulation and tower load mitigation, while aIPC is used as the lifetime controller to dynamically control the damage accumulation of the rotor blades. The IPC angles are perturbed about the CPC signal from RDAC, forming the control input u to the wind turbine.

does it mean only wind shear and no turbulence

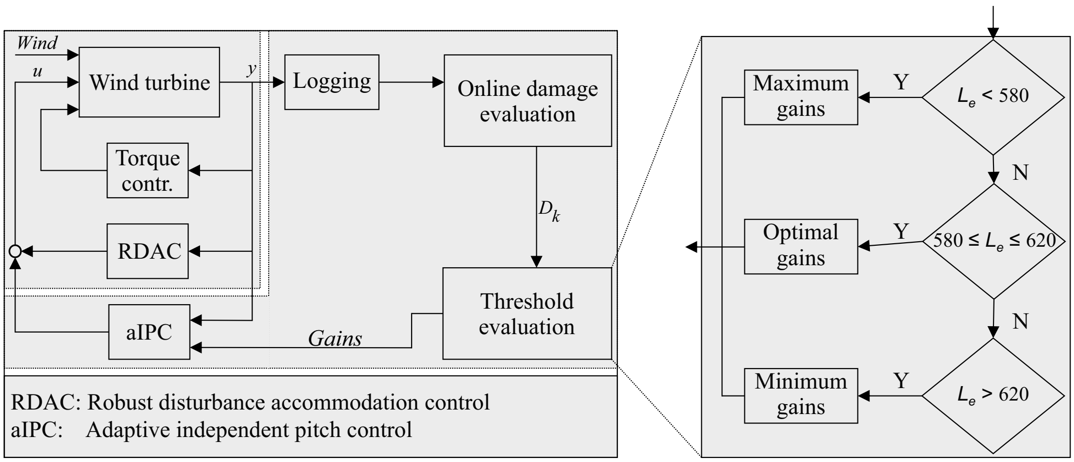

Figure 4. Prognostics-based adaptive lifetime control

The blade-root flap-wise bending moment measurements y are logged into memory during simulation. The online damage evaluation model based on the real-time implementation of the RFC algorithm (Musallam and Johnson, 2012), calculates the accumulated damage at every time-step D_k. The estimated lifetime of the blade L_e used as a state-of-health (SoH) indicator, is calculated as

$$L_e = \frac{T_k}{D_k} D_d, \tag{9}$$

where T_k denotes the current time step while D_d denotes the accumulated damage at the design lifetime. At every time step T_k, the estimated RUL can be calculated as

$$RUL = L_e - T_k = T_k(\frac{D_d}{D_k} - 1). \tag{10}$$

Based on the threshold evaluation of L_e, the load mitigation level in the respective IPC controllers is controlled by selecting the appropriate gains L and K every 10 seconds, which is the time interval chosen for lifetime threshold evaluation. For illustrative purposes a lifetime of 600 seconds is chosen. Three threshold levels are set such that if L_e is below the lower

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limit of the desired lifetime ($L_e < 580$), maximum gains of respective IPC controllers are selected to increase the blade load mitigation level. If L_e falls within a range of the desired lifetime ($580 \leq L_e \geq 620$), optimum gains, which strike a balance between load mitigation and speed regulation are selected. On the other hand, if the value of L_e is higher than the desired lifetime ($L_e > 620$), hence blade load mitigation level can be compromised, minimum gains are chosen.

5 Results and discussion

Is the wind speed uniform over the rotor ?

This section presents and discusses the simulation results obtained from evaluating the adaptive lifetime control strategy using the 1.5 MW NREL RWT in FAST design code. A 600 seconds stochastic wind profile with a mean hub-height wind speed of 18 m/s and a turbulence intensity of 17 % is used for simulation. The wind profile having vertical wind shear with a power-law exponent of 0.2 is shown in Fig. 5a. The performance of the lifetime control scheme in different blade load mitigation scenarios as shown in Fig. 5b. As shown, the adaptive lifetime control strategy controls the damage accumulation in the blades to reach the predefined damage limit at the desired lifetime of 600 seconds. While the control strategy with maximum load mitigation achieves the same desired result, the lifetime control scheme spreads the incremental damage accumulation over the entire operation window by dynamically switching between the different load mitigation levels.

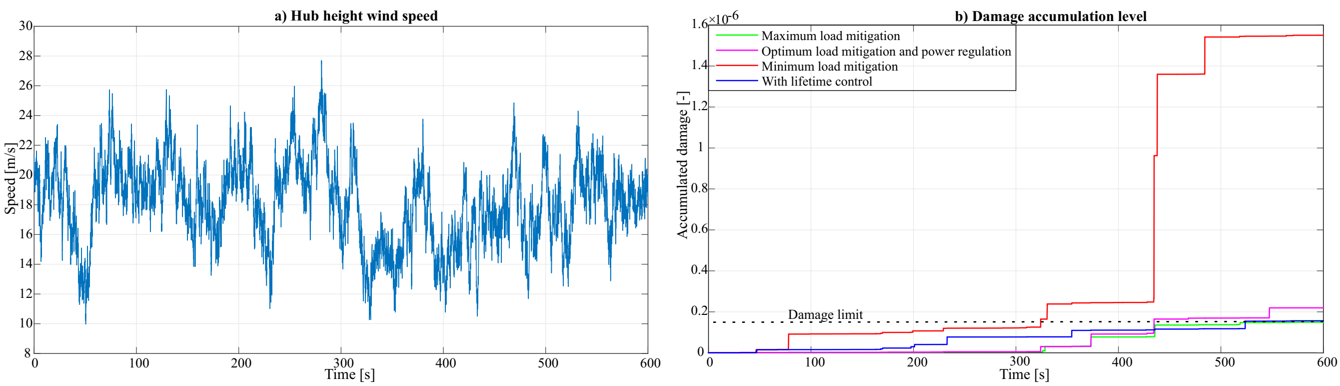

Figure 5. Adaptive lifetime control performance

A comparison in blade fatigue load mitigation performance with and without (RDAC only) lifetime control is also evaluated. Figure 6a shows that with lifetime control, the blade flap-wise bending moment reduces, with a 11.26 % reduction in standard deviation being achieved. Additionally, there is significant reduction in the accumulated damage as shown in Fig. 6b.

Performance of the adaptive lifetime control strategy in mitigating tower loads is also evaluated. As illustrated in Fig. 7a, significant reduction in tower fore-aft oscillation is observed, with the standard deviation reducing by 16.08 %. A reduction in tower damage accumulation can be seen in Fig. 7b. This shows that lifetime control of blades, which reduces 1P fatigue loads, leads to reduced damage accumulation in tower due to 3P fatigue loads.

Despite the adaptive lifetime controller achieving improved performance in reducing damage accumulation in both rotor blade and tower, this does not compromise the speed/power regulation performance. To illustrate this, the rotor speed and

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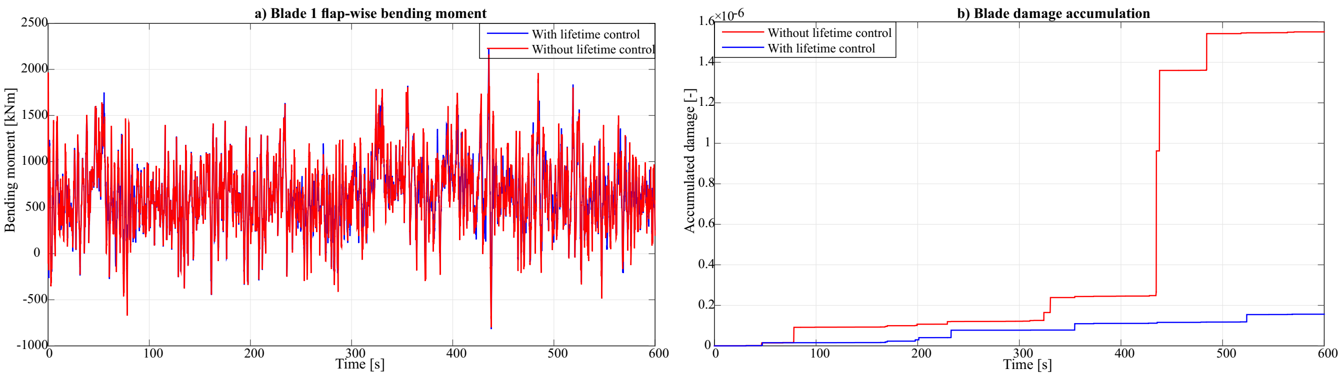

Figure 6. Blade fatigue load mitigation

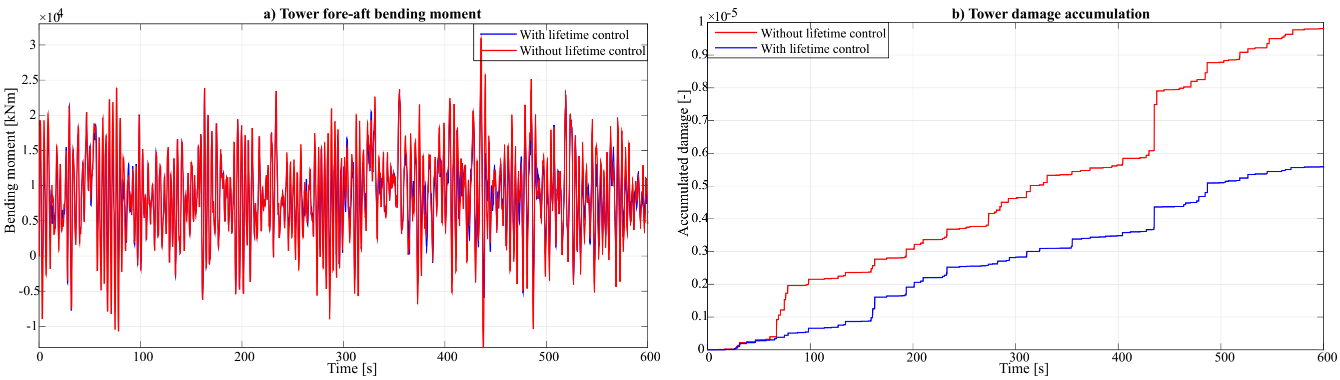

Figure 7. Tower damage accumulation

generator power are evaluated as shown in Fig. 8. With lifetime control, improvement is realized in both speed and power regulation, with the standard deviation in rotor speed and generated power reducing by 5.03 % and 10.29 % respectively. This is attributed to improved transient performance by the aIPC controller.

6 Summary and conclusion

In this paper, a prognostics-based adaptive control strategy for lifetime control of wind turbines is presented. A robust disturbance accommodating controller (RDAC) designed using mixed sensitivity H_∞ control, is used as the primary controller for mitigating tower loads and regulating rotor speed using a CPC-signal. On the other hand, aIPC controller designed using LQG control method is used as a lifetime controller. The gains of each of its five IPC controllers are adapted based on the state of health of the rotor blades obtained using an online damage evaluation model to strike a compromise between lifetime control through load mitigation and speed regulation.

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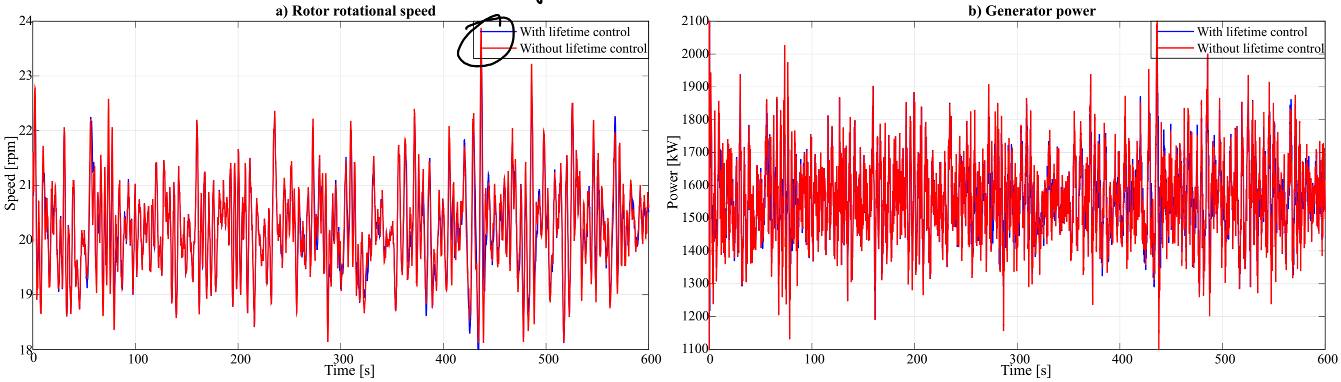

Figure 8. Speed/power regulation performance

Through simulation using a 1.5 MW wind turbine model, it is demonstrated that the adaptive lifetime control strategy controls the damage accumulation in the blades to guaranty a given damage limit at the desired lifetime. Reduction in accumulated damage in the tower is also realized. This can potentially be used for optimizing maintenance scheduling in wind farms by synchronizing ageing of wind turbine components, hence reducing O&M costs, and increasing operational reliability. This improvement is realized without compromise in the speed/power regulation performance. However, the result is achieved based on a slightly increased pitch actuator duty cycle, which can potentially increase fatigue loading in the pitch actuator system components. In the future, adaptive lifetime control based on nonlinear damage accumulation models will be considered. Additionally, use of new concepts for state of health indicators such as change in modal parameters for structural health monitoring will be explored.

Code availability. Code is not publicy available and can not be shared.

Author contributions. DS and JGN proposed the original idea of combining an online damage evaluation model with a switching IPC load mitigation control scheme for lifetime extension of wind turbine blades. MHD and DS extended the work of JGN by developing an adaptive lifetime controller (RDAC) to control life consumption in the tower. Based on these ideas and with supervision from DS, EK developed an adaptive lifetime controller (aIPC), which is adaptive to wind speed changes, and in which the gains of each IPC controller are adapted to dynamically control the damage accumulation of rotor blades while monitoring the life consuption of the tower. EK evaluated the prognostics scheme (RDAC+aIPC) on a 1.5 MW RWT by running simulations and analysing obtained results. With valuable input from DS, EK wrote the manuscript. All authors contributed to this work from concept to manuscript stage.

Competing interests. The authors declare that they have no conflict of interest.

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