Health-aware Model Predictive Control of Wind Turbines using Fatigue Prognosis

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Abstract: Wind turbines components are subject to considerable fatigue due to extreme environmental conditions to which are exposed, especially those located offshore. Interest in the integration of control with fatigue load minimization has increased in recent years. The integration of a system health management module with the control provides a mechanism for the wind turbine to operate safely and optimize the trade-off between components life and energy production.
The research presented in this paper explores the integration of model predictive control (MPC) with fatigue-based prognosis approach to minimize the damage of wind turbine components (the blades). The controller objective is modified by adding an extra criterion that takes into account the accumulated damage. The scheme is implemented and tested using a high fidelity simulator of a utility scale wind turbine.

1. INTRODUCTION

The main objective of operational control of wind turbines is to maximize the extracted wind power from the wind. However, wind turbines components are subject to considerable fatigue due to extreme environmental conditions to which are exposed, especially those located offshore. For this reason, interest in the integration of control with fatigue-based prognosis of components has increased in recent years.

According to Lio et al. [2014], in the recent years many advanced control strategies have been proposed for the operational control of wind turbines. Unfortunately, they were not adopted by the industry. However, the application of model predictive control (MPC) to wind turbines has started to attract the attention of the academia and industry because of the possibility of dealing with the conflicting power optimization and fatigue load reduction problem as it has been shown in a number of publications. For example, the use of MPC for switching between partial and full load operation of the wind turbine while reducing tower fore-aft fatigue loads was reported in Adegas et al. [2013]. This paper also addresses pole placement based objective functions, and a discussion of implementation structures for the MPC solution with the existing wind turbine controller as well. A Full Load Control (FLC) with wind speed predictions based on LIDARS is proposed in Soltani et al. [2011]. Switch-less control considering tower fore-aft displacement by MPC is the focus of [Evans et al., 2014], where the prediction model is data driven. Nonlinear MPC has been used to tackle the non-linearities in the wind turbine [Dang et al., 2008].

Fatigue can be understood as the breakdown of the material subject to stress, specially when repeated series of stresses are applied. It is a phenomena that occurs in a microscopic scale, manifesting itself as deterioration or damage. Consequently, it has been widely and exhaustively studied from different perspectives.

Wind turbine are subject to a highly irregular loading due to wind, gravity, and gyroscopic effects being specially vulnerable to fatigue damage. Due to the high number of load cycles which occur during the life of the turbine, fatigue considerations are of particular importance in wind turbine control.

The research presented in this paper explores the integration of MPC with fatigue-based prognosis to minimize the damage of wind turbine components (the blades). The integration of a systems health management module with MPC control provides the wind turbine with a mechanism to operate safely and optimize the trade-off between components life and energy production. The controller objective is modified by adding an extra criterion that takes into account the accumulated damage. The scheme is implemented and tested using a high fidelity simulator of a utility scale wind turbine.

The reminder of the paper is organized as follows. Section 2 introduces the fatigue modeling and its application to wind turbines. Section 3 describes how to implement health-aware control using MPC to wind turbines. Section 4 describes the case study based on the wind turbine benchmark, where the proposed approach is assessed and the results obtained. Section 5 highlights the concluding remarks and some future research directions.

2. FATIGUE MODELING

2.1 Fatigue modeling background

Fatigue loads can be represented in different ways. For wind turbines, two types of load distributions are mainly used: rainflow cycle and magnitude distributions. The rainflow cycle distributions (often simply called cycle distributions or rainflow spectra) represent the occurrence probability of load cycles with different ranges. They are usually derived from time series by means of rainflow counting procedures (RFC). As an alternative, probability distributions of load cycles can also be calculated in the frequency domain. Because of the often nonlinear behavior of wind turbines over their operational range, time domain methods are however much more common than frequency domain approaches.

RFC method, first introduced by Endo et al. [1967], has a complex sequential and nonlinear structure in order to decompose arbitrary sequences of loads into cycles. Its name comes from an analogy with roofs collecting rainwater to explain the algorithm (sometimes also referred as pagoda roof). Typically to compute a lifetime estimate from a given structural stress input, the RFC method is applied by counting cycles and maxima, jointly with the Palmgren-Miner rule to calculate the expected damage. The input signal is obtained from time history of the loading parameter of interest, such as force, torque, stress, strain, acceleration, or deflection [Lee et al., 2005]. The Fig. 1 depicts the whole procedure.

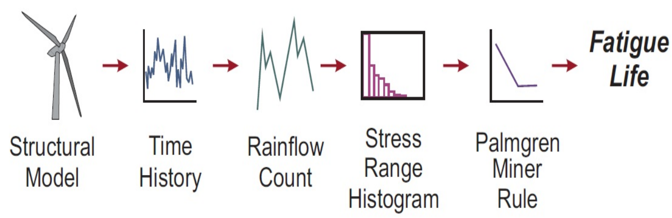

Fig. 1. Rainflow counting damage estimation procedure.

Different types of RFC algorithms have been proposed in the literature [Downing and Socie, 1982][Rychlik, 1987]. The algorithm used in this paper is introduced in Niesłony [2009], and is implemented as a Matlab toolbox. This algorithm calculates the stress for each rainflow cycle in four steps:

- the stress history is converted to an extremum sequence of alternating maxima and minima;
- for each local maximum M_j, the left and right region where all stress values are below M_j is identified, denoted respectively as m_j^- and m_j^+;
- the minimum stress value is computed being $m_j = min\{m_j^-, m_j^+\}$
- the equivalent stress per rainflow cycle s_j associated with M_j is given by the amplitude $s_j = M_j - m_j$ or the mean value $s_j = \frac{M_j+m_j}{2}$.

The damage, D, at each stress cycled is computed using S-N curve [Hammerum et al., 2007]. The S-N curve is a graphical representation of the stress, s, versus the number of stress cycles, N. An often-used model for the S-N curve is

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

where the quantities K and c_W are material properties, being c_W the Wöler-coefficient. The damage imposed by a stress cycle with a range s_j is computed as

$$D_j \equiv \frac{1}{N_j} = \frac{1}{K} s_j^{cw} \tag{2}$$

The linear damage accumulation after M cycles can be computed using the Palmgren-Miner's damage rule, given by

$$D_{ac} = \sum_{j=1}^{M} \frac{1}{K} s_j^{cw} \tag{3}$$

These sequences are shown in Fig. 2. On the top left, the input stress is shown and on the top right the same signal converted into a sequence of maxima and minima (turning points) is presented. In the bottom part of Fig. 2, the damage and accumulated damage, respectively, are shown.

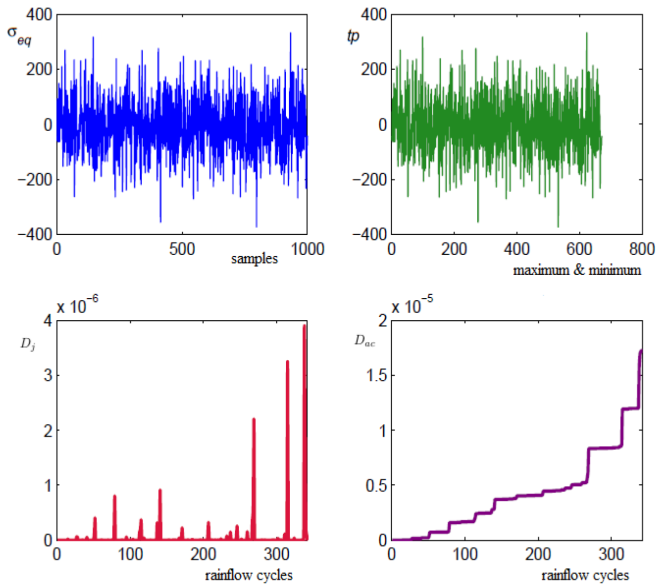

Fig. 2. Rainflow counting damage estimation procedure.

2.2 Application to the wind turbine

For real-time applications, applying the traditional rain flow counting algorithm is very challenging. Significant amounts of data must be stored and processed periodically to obtain a magnitude of the data in equivalent regular cycles. In addition, the algorithm must be applied to a stored set of data. To address this challenge, an approach based on the rainflow counting algorithm in real time has been proposed. In previous works, efficiency of rainflow counting implementations have been proposed, see for example [Musallam and Johnson, 2012].

One of the objectives of this paper is to analyze the fatigue due to the wind turbine load. Loads in wind turbine structure arise from several factors [Jelavic et al., 2008], being the main cause the spatial variations of wind speed caused by the turbulent nature of wind. This spatial difference in wind speeds upon blades results in different loading of the wind turbine blades depending on their intermittent position. The paper [Jelavic et al., 2008] concludes that the most pronounced contribution to the blade root loading happens at the frequency given by the blades speed, and this loading is the main source of fatigue at blades and the hub.

Using the RFC method the accumulated damage is obtained as function of the cycles of the blade root moment stress signal. In order to have available an accumulated damage variable that can be integrated with a linear MPC model a simplified approach to calculate fatigue on a time series signal is proposed based on RFC theory explained in Section 2.1. The result of this approach is that the accumulated damage is obtained as a function of time instead of the number of cycles. The proposed approach detects the changes of sign which corresponds to a cycle in the stress time signal. The obtained function at each sample step k is the following:

$$D(k) = \begin{cases} 0 & if \quad I(k) = I(k-1) \\ \frac{1}{K}(s(k))^{cw} & if \quad I(k) \neq I(k-1) \end{cases} \tag{4}$$

where $s(k)$ is the stress at time k

$$s(k) = \frac{1}{L} \sum_{p=k-L}^{k} M_{B,i}(p) \tag{5}$$

where L is the number of samples per cycle and $M_{B,i}$ is the blade root moment of blade i. On the other hand, $I(k)$ is the signal adapted to detect cycles (6)

$$I(k) = M_{B,i}(k) - s(k) \tag{6}$$

Then, the accumulated damage is calculated by (3).

The accumulated damage evaluated with Eqs. (4)-(6) has been compared with the original method using the RFC Matlab toolbox, using both the blade root moment as stress signal. Fig. 3 shows the accumulated damage value obtained with both approaches. Notice that at the end of the scenario the accumulated damage is almost the same. The difference as explained before relies on the fact that the damage obtained by the RFC method is expressed function of the cycles count while the one evaluated using Eqs. (4)-(6) is a function of time.

After observing that the proposed approach gives a very close approximation of the accumulated damage obtained by the RFC method, the slope m of the accumulated damage curve in function of time is calculated and used as one of the parameters in the linear fatigue-damage model proposed in this work.

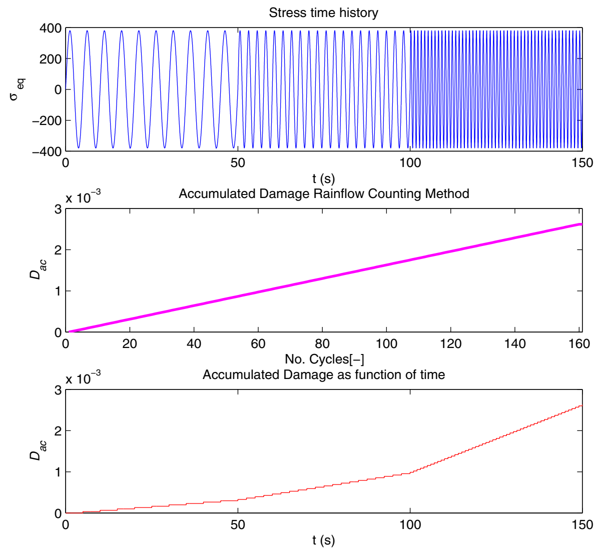

Fig. 3. Accumulated Damage Comparison

3. HEALTH-AWARE MPC

3.1 Standard MPC

MPC uses a mathematical model to calculate the optimal control actions according to a given cost function [Maciejowski, 2002]. In this paper, it is assumed that the system behavior can be described at each time instant $k \in \mathbb{Z}$ by the following discrete-time difference equation:

$$x(k+1) = Ax(k) + Bu(k) + Ew(k), \tag{7}$$

where $x \in \mathbb{R}^{n_x}$ is the state of the system, $u \in \mathbb{R}^{n_u}$ is the vector of manipulated variables, and $w \in \mathbb{R}^{n_w}$ is a vector of measurable disturbances. Moreover, A, B, and E are time-invariant matrices of proper dimensions. It is also considered that the system is subject to hard state and input constraints, which can be posed as

$$x \in \mathcal{X} \triangleq \{x(k) \in \mathbb{R}^{n_x} | \; |x(k)| \leq g, \; \forall k\}, \tag{8a}$$
$$u \in \mathcal{U} \triangleq \{u(k) \in \mathbb{R}^{n_u} | \; |u(k)| \leq f, \; \forall k\}, \tag{8b}$$

The control goal is to minimize a convex (possible multi-objective) cost function $\ell(x, u) : \mathcal{X} \times \mathcal{U} \to \mathbb{R}$, which might bear any functional relationship to the operating cost of the system. From the model in (7), let $w(k : k+\ell-1) \triangleq (w(k), w(k+1|k), \ldots, w(k+\ell-1|k))$ be the sequence of disturbances over a fixed time prediction horizon $P \in \mathbb{Z}_+$. The first element of the sequence is measured, while the rest of the elements, i.e., $w(k+i|k)$, denote estimates of future disturbances computed by an exogenous system and available at each time instant k. Hence, the MPC controller design is based on the solution of the following finite horizon optimization problem (FHOP):

$$\min_{\bar{u}(0:\ell-1)} \sum_{i=0}^{\ell-1} \mathcal{J}(\bar{x}(i), \bar{u}(i)) \tag{9a}$$

subject to:

$$\bar{x}(i+1) = A\bar{x}(i) + B\bar{u}(i) + E\bar{w}(i), \tag{9b}$$
$$\bar{x}(i+1) \in \mathcal{X}, \tag{9c}$$
$$\bar{u}(i) \in \mathcal{U}, \tag{9d}$$
$$\bar{x}(0) = x(k), \quad \bar{w}(0) = w(k), \tag{9e}$$
$$\bar{w}(i) = w(k+i|k) \quad \forall i \in \mathbb{Z}_1^{\ell-1}, \tag{9f}$$

where vectors $\bar{x}$,$\bar{u}$, and $\bar{w}$ denote the predicted value of the states, inputs and measured disturbances at the prediction step i. Notation $\mathbb{Z}_a^b$ expresses the set of integer numbers from a to b, both limits included, i.e., $\{a, a+1, \ldots, b\}$.

Assuming that (9) is feasible, i.e., there exists a non-empty solution given by the optimal sequence of control inputs $\bar{u}^*(0:\ell-1) \triangleq (\bar{u}^*(0), \bar{u}^*(1), \ldots, \bar{u}^*(\ell-1))$. Then, the receding horizon philosophy relies on applying the control action

$$u(k) = \bar{u}^*(0), \tag{10}$$

and disregards the rest of the sequence of the predicted manipulated variables. At the next time instant k, the FHOP (9) is solved again using the current measurements of states and disturbances and the most recent forecast of these latter over the next future horizon.

3.2 MPC with health-aware objective

This section addresses the inclusion of wind turbine stress information in the predictive control law as an additional state of the linear system. As described in Section 2.2, the degradation process of the wind turbine blade can be evaluated using the blade root moment sensor information. In order to include a new objective in the MPC that aims to reduce the accumulated damage, the rain-flow counting model is approximated by means of a linear model.

As a first approximation, after observing that the proposed approach gives a very close approximation of the accumulated damage obtained by the RFC method (Fig. 2), the slope m of the accumulated damage curve in function of time is calculated and then used as one of the parameters in the linear fatigue-damage model proposed in this work.

In a preliminary work [Sanchez et al., 2015], after conducting several tests performed on the wind turbine benchmark implemented in FAST simulator, an experimental model that relates the mean values of the blade root moment and pitch angle signals in steady state was proposed. Figure 4 shows the relation between the mean blade root moment as function of the pitch angle and others marks are used to represent it relation considering a first, second and third order polynomials.

The proposed model for the blade root moment dynamics is a first order blade root moment mean model with an slope of a_1 plus a constant value a_0:

$$\bar{M}_{B,i}(k) = a_1 \beta_i(k) + a_0 \tag{11}$$

Assuming a cycle with a constant wind speed, w_r, and knowing the sampling time, T_s, the number of samples of one cycle L can be known. Finally, a linear fatigue-damage model is proposed as function of the pitch value signal which establishes a relation between the control signal and the accumulated damage of the blade root moment:

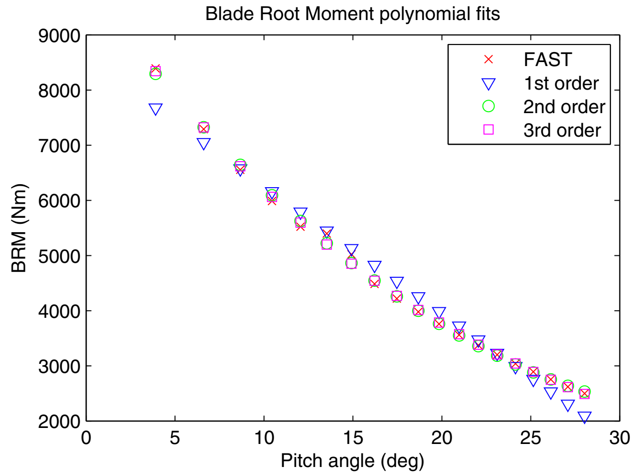

Fig. 4. Estimated blade root moments models

$$z(k+1) = z(k) + \frac{m}{L}(a_1 \beta_i(k) + a_0) \tag{12}$$

where $z(k+1)$ is the accumulated damage of the blade root moment. Equation (12) can be included in the MPC as a new state and additional objective is added in the MPC cost function (9a) to minimize the accumulated damage.

4. CASE STUDY

Some results will be presented by including the fatigue model in the MPC controller developed in Odgaard et al. [2015] and by adding some control objective regarding fatigue minimization.

4.1 Benchmark description

The wind turbine benchmark model implemented in FAST simulator is based on a 5 MW three bladed variable speed wind turbine developed by NREL for scientific research [Jonkman et al., 2009]. This model has been used to establish the reference specifications for a number of research projects supported by the U.S. DOEs Wind and Hydropower Technologies Program, the integrated European Union UpWind research program and the International Energy Agency (IEA).

The NREL 5 MW model has been, used as a reference by research teams throughout the world to standardize baseline offshore wind turbine specifications and to quantify the benefits of advanced land- and sea-based wind energy technologies. The turbine's hub height is 89.6 m and the rotor radius is 63 m with a rated rotor speed is 12.1 rpm while the generator speed is 1200 rpm. The simulator also include baseline controllers that allow to control the three pitch angles, generator and converter torques and yaw position. Different measurements are available from sensors as well as the control references. The sampling period used in the simulations is $T_s = 0.01$ s.

Figure 5 presents a block diagram of the wind turbine simulation model, provided with the benchmark, including the feedback loops corresponding to the pitch, yaw and torque variables. In this figure, it also appears the fault diagnosis block that will be designed in this paper.

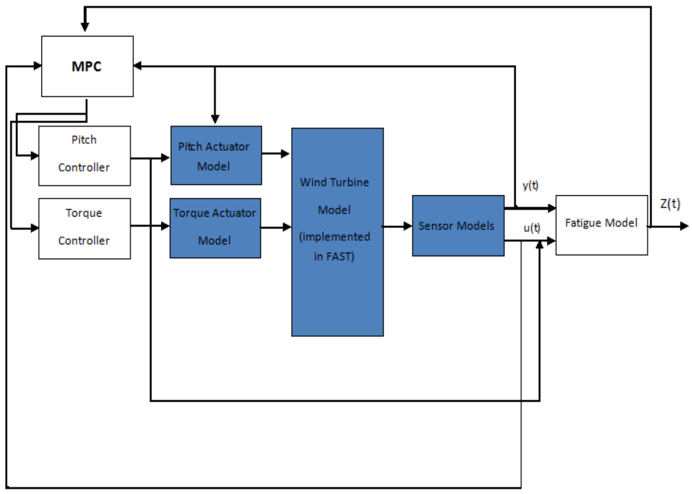

Fig. 5. Block diagram of wind turbine simulation and fatigue model

4.2 Wind turbine control model

Control of wind turbines deals with a number of objectives and tasks. Many of these are conflicting in nature, in this work a subset of these objectives are considered. The idea is to design a model predictive controller which deals with the conflicting objectives of generating nominal power while minimizing the blade root health state and the tower fore-aft fatigue loads, when operating the wind turbine at above rated wind speed.

The control model is used as a prediction model in a MPC scheme, which is simulated using FAST from NREL which is a high fidelity aero elastic wind turbine model, see Jonkman and Jr. [2005], and the 5 MW NREL reference turbine is used as the wind turbine, see Jonkman et al. [2009].

A linearized prediction model is used, and this model is fitted to the performance of the FAST model in the used operational point. The model include states representing the rotor speed, ω_r, the tower fore-aft displacement, d_t, the tower fore-aft velocity, the generator torque, T_g, the pitch angle, β. In addition to these standard states, the first order dynamic inflow model from Knudsen and Bak [2013] is included. The controlled inputs are generator torque and pitch references, respectively $T_{g,ref}$ and β_{ref}. The wind speed v_w is a measured non-controlled input. The model outputs are the generated power, P_g, the tower fore-aft velocity v_t and the rotor speed ω_r. Based on the states, inputs and outputs a linear state space representation of the form below is used.

$$x(k+1) = Ax(k) + Bu(k) + Ew(k), \tag{13}$$
$$y(k) = Cx(k). \tag{14}$$

where

$$u = \left[T_{g,ref} \;\; \beta_{ref}\right]^T, \tag{15}$$
$$d = [v_w], \tag{16}$$
$$x = \left[\omega_r \;\; d_t \;\; v_t \;\; T_g \;\; \beta \;\; \alpha_f\right]^T, \tag{17}$$
$$y = \left[P_g \;\; v_t \;\; \omega_r\right]^T. \tag{18}$$

4.3 Wind turbine MPC with health-aware objective

The MPC implemented in the simulator is given by

$$x(k+1) = A_d x(k) + B_d u(k) + Ew(k), \tag{19}$$
$$y(k) = C_d x(k). \tag{20}$$

where A_d, B_d and C_d are state space matrix of proper dimension with includes the accumulated damage given in Eq.(12),

$$u = \left[T_{g,ref} \;\; \beta_{ref}\right]^T, \tag{21}$$
$$d = [v_w], \tag{22}$$
$$x = \left[\omega_r \;\; d_t \;\; v_t \;\; T_g \;\; \beta \;\; \alpha_f \;\; z\right]^T, \tag{23}$$
$$y = \left[P_g \;\; v_t \;\; \omega_r \;\; z\right]^T. \tag{24}$$

To include the health-aware objective, a new fatigue state model as in (12) has been included in the augmented MPC formulation presented in Section 3.2. MPC has been implemented using prediction horizon $\ell = 200$. The MPC objective function (9a) contains two objectives:

- the maximum wind power is obtained while the tower fore-aft movements are minimized.
- the accumulated damaged evaluated as (12) is minimized.

In Fig. 6 is shown the evolution of the accumulated damages obtained with (blue) and without (red) health-aware objective in the MPC. The simulation is performed with a constant wind speed of 14 m/s.

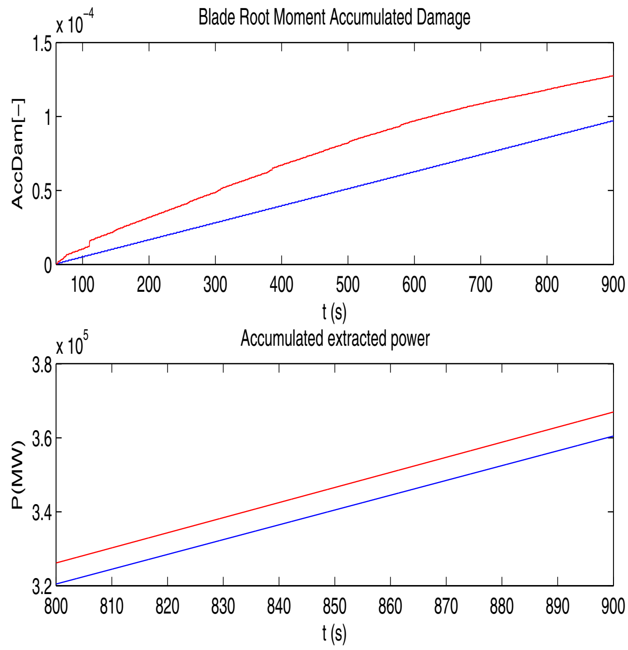

Fig. 6. Evolution of accumulated damages and accumulated extracted power with (blue) and without (red) health-aware objective in the MPC

From Figure 6, it can be observed that the inclusion of the fatigue objective mitigates 26% of the accumulated damage (assessed on the blade root moment with the approach proposed in this paper). But, on the other hand, the energy extracted from the wind (accumulated extracted power) is reduced only in 1.9% (to appreciate better this small percentage, the figure is zoomed in the last 100 s of simulation). This shows the trade-off between maximizing the extracted power and minimizing the accumulated damage in the blades. It is an open research topic to find the best trade-off between maximum power extraction while reducing the accumulated damage.

5. CONCLUSIONS

The research presented in this paper has explored the integration of MPC with fatigue-based prognosis to minimize the damage of wind turbine components. The integration of a systems health management module with MPC control has provided the wind turbine with a mechanism to operate safely and optimize the trade-off between components life and energy production. The controller objective has been modified by adding an extra criterion that takes into account the accumulated damage. The scheme has been satisfactorily implemented and tested using a high fidelity simulator of a utility scale wind turbine. The results obtained show that there exists a trade-off between maximum power and the minimization of the accumulated damage. As future research, a way to find the optimal tuning of this trade-off will be investigated using multi-objective optimization techniques.

ACKNOWLEDGMENTS

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