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Health-aware Model Predictive Control of Wind Turbines using Stifness Degradation Approach

Hector Sanchez * Teresa Escobet * and Vicenç Puig *

* *Automatic Control Department, Technical University of Catalonia (UPC), Rambla Sant Nebridi 22, 08222 Terrassa, Spain; (e-mail:{hector.eloy.sanchez, teresa.escobet, vicenc.puig}@upc.edu)*

Abstract: Wind turbine blades are under significant gravitational, inertial, and aero-dynamic loads, which cause their fatigue and degradation during the wind turbine operational life. The present work proposes a Model Predictive Control scheme that integrates remaining useful life predictions of the blade based on a stiffness degradation model embedded in a prognostics algorithm. The flapwise blade root bending loads are used as inputs to the damage model which describes the propagation of damage from a microscopical scale manifesting in a macroscopical scale as stiffness loss. The proposed control scheme integrates prognostics information in the MPC formulation in order to optimize the trade-off that exists between the conflictive objectives of producing power and extend the remaining useful life of the blades. The proposed control scheme has been tested using the sensor information from the well known high fidelity wind turbine simulator FAST (Fatigue, Aerodynamics, Structures and Turbulence).

1. INTRODUCTION

Wind turbine blades are components that are subject to highly irregular loading and extreme environmental conditions, especially those located offshore.

One of the aspects that are desirable from operators and original equipment manufacturers (OEMs) perspective is to have information about the damage and remaining useful life predictions provided by condition or health monitoring systems (Frost et al., 2013). Structural health information is necessary for the wind turbine to continue operating and producing power without exceeding some damage thresholds resulting in unscheduled downtime. The challenge is thus to decide maintenance actions on components on the way to continuously reduce and eliminate costly unscheduled downtime and unexpected breakdowns, see (Iung et al., 2008).

As long as wind turbines (WTs) become older or approach to their end of operational life, there will be a need to keep extending the life of its main components. One factor to be considered is the wind turbine rotor blade fatigue.

Previous efforts have been devoted to simplify fatigue load assessments, as e.g. in the work of Zwick and Muskulus (2016), a simplified fatigue load assessment for offshore wind turbines is proposed. In this work, the proposed approach utilizes prognostics to estimate the remaining useful life of the blades taking into account present and estimated future loads for different expected rates of power production.

Control approaches to alleviate or reduce loads in wind turbines is a topic of interest in the research community. In Ng et al. (2016), an H_∞ regulator in combination with a passive mechanism through aeroelastic tailoring is used to reduce loads in wind turbine blades. In Li et al. (2016), an MPC control is integrated with wind forecasts with the objective of mitigate wind intermittency in the capacity of storaging power in a Battery Energy Storage System (BESS). In Le and Andrews (2016), Petri nets are used to model wind turbines degradation for maintenance purposes. A stiffness degradation model for composites is used together with a prognostics algorithm to model the blades degradation.

In this paper, fatigue in the blade root is considered. This component has been identified as a critical area for fatigue in several works such as Sutherland (1999) which shows, that the edgewise blade root bending moment frequency distribution from a small turbine contains two peaks; one originating from the wind loading, the other a result of the blade being loaded by its own weight. Caprile et al. (1995) present histograms of mid-size wind turbine blade edgewise and flapwise blade root moments, showing the same peak for the edgewise loading. For larger rotor blades, the edgewise gravity fatigue loading becomes increasingly relevant for life prediction. Kensche and Seifert (1990) gives typical root bending moments from measurements on wind turbine blades, both the flap and edgewise direction. Several methods for fatigue estimation in wind turbines have been analyzed in Barradas-Berglind and Wisniewski (2016) where the methods are classified into four general groups: cycle counting, spectral, stochastic and hysteresis.

The present work proposes a MPC scheme that integrates remaining useful life predictions of the blade based on a stiffness degradation model embedded in a prognostics algorithm. The flapwise blade root bending loads are used as inputs to the damage model which describes the propagation of damage from a microscopical scale manifesting in a macroscopical scale as stiffness loss. The proposed control scheme integrates prognostics information in the MPC formulation in order to optimize the trade-off that exists between the conflictive objectives of producing power and extend the remaining useful life of the blades. The proposed control scheme has been tested using the sensor information from the well known high fidelity wind turbine simulator FAST (Fatigue, Aerodynamics, Structures and Turbulence).

The reminder of the paper is organized as follows. Section 2 presents the prognostics algorithm using the stiffness degradation approach 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. PROGNOSTICS APPRACH

2.1 Stiffness Degradation Approach

As explained in Vassilopoulos (2013) strength and stiffness degradation fatigue theories have been introduced in order to model and predict the fatigue life of composite materials by taking into account the actual damage state, expressed by a representative damage metric of the material status. The damage metric is usually the residual strength or the residual stiffness. Failure occurs when one of these metrics decreases to such an extent that a certain limit is reached (Brondsted and Nijssen, 2013). Stiffness degradation theories are not linked to the macroscopic failure (rupture) of the examined material but rather to the prediction of its behavior in terms of stiffness degradation. Failure can be determined in various ways, e.g. when a predetermined critical stiffness degradation level is reached; or when stiffness degrades to a minimum stiffness designated by the design process in order to meet operational requirements for deformations; or even as a measure of the actual cyclic strains, e.g. failure occurs when the cyclic strain reaches the maximum static strain (Zhang et al., 2008). Methods that are able to assess the development of the remaining stiffness degradation of a material or a structural component during fatigue life are valuable for damage tolerant design considerations. In situations like this, the effect of local failure and the stiffness degradation caused by the failure must be investigated to ensure structural integrity under the given (acceptable) damage. Life prediction schemes for composite laminates have been developed based on these concepts (Eliopoulos and Philippidis, 2011). In addition, this effective medium description requires the gradual strength and stiffness degradation assessment due to cyclic loading. It is obvious that important experimental effort is necessary for the parameter estimation of such a hybrid (strength and stiffness degradation) modeling process.

According to Van Paepegem and Degrieck (2002), it is commonly accepted that for the vast majority of fibre-reinforced composite materials, the modulus decay can be divided into three stages: initial decrease, approximately linear reduction and final failure (see Figure ??), where E_0 is the undamaged stiffness, E is the stiffness at a certain moment in fatigue life, N is the number of testing cycles and N_f is the fatigue life in cycles.

2.2 Application to Wind Turbines

This section analyzes a fatigue stiffness damage model application based on the model proposed by Van Paepegem and Degrieck (2002). It is assumed that the blade is built with the same composite material. This assumption simplifies the application of the stiffness damage model which is derived for a specific material (fiberglass), which is commonly used in wind turbine blades. The blade root bending moment sensor information from the high fidelity simulator as the input load which is transformed into compressive stress according to the procedure described in Burton et al. (2011). The damage model is used to obtain remaining useful life (RUL) predictions subject to different wind speed scenarios generated by the wind turbine high fidelity simulator FAST.

The model proposed in (Van Paepegem and Degrieck, 2002) defines the model as the sum of an initiation function and a propagation function based on theoretical considerations and a sound modeling of the observed fatigue damage mechanisms. In particular, it proposes models for the tensile and the compressive stresses. The model used in this paper is the one proposed for the compressive stresses since the damage loads considered are the ones that come from the flapwise bending moments at the blade root. Therefore, choosing the flapwise bending moments as the considered damage loads involves the use of the model for compressive stresses. This model has been tested for bending fatigue experiments in Van Paepegem and Degrieck (2002). The impact of control contingency strategies for reducing flapwise blade root moment damage loads have been previously studied in the work of Frost et al. (2013), which makes these type of loads interesting for future research work in damage reduction and the increase of remaining useful life of wind turbine blades. The damage initiation function f_i simulates the sharp decline of the stiffness in the first stage of fatigue life. Matrix cracking is the predominant mechanism in this stage and according to Van Paepegem and Degrieck (2002). The damage propagation function f_p is a function that describes the second and third stage of damage propagation and final failure, respectively.

The damage initiation function f_i is defined as:

$$f_i(\sigma, D) = \left[c_1 \sum (\sigma, D) \, \exp\left(-c_2 \frac{D}{\sqrt{\sum (\sigma, D)}} \right) \right]^3, \tag{1}$$

and the damage propagation function f_p is defined as:

$$f_p(\sigma, D) = c_3 \, D \, \Sigma(\sigma, D)^2 \left[1 + \exp\left(\frac{c_5}{3} \left(\Sigma(\sigma, D) - c_4 \right) \right) \right] \tag{2}$$

where $\sum(\sigma, D)$ is the failure index which is a function of the damage variable D defined as a measure for the stiffness reduction in the considered material element due to matrix cracks and σ is the stress measure.

The fatigue failure index for the purposes of this work is given by:

$$\sum(\sigma, D) = \frac{\sigma}{(1-D)X_C} \tag{3}$$

where the damage variable X_C is the ultimate compressive static strength.

Practical implementations of (1) and (2), requires to make a distinction on the level of the damage growth rate equation dD/dN, because the damage increment is calculated after each cycle and this damage increment is extrapolated to the next simulated cycle. The final layout of the fatigue damage model is as follows:

$$\begin{aligned} \frac{dD}{dN} = & \left[c_1 \Sigma \exp\left(-c_2 \frac{D}{\sqrt{\Sigma}} \right) \right]^3 \\ & + c_3 D \Sigma^2 \left[1 + \exp\left(\frac{c_5}{3} (\Sigma - c_4) \right) \right], \end{aligned} \tag{4}$$

where the constant c_1 determines the amplitude of the damage initiation rate, while the exponential function is a decreasing function of damage D. Constant c_2 together with c_1 are used to model the first stage decrease of the stiffness. Once a certain damage value has been reached, the contribution of the damage initiation function becomes negligible. c_3 is the damage propagation rate, c_4 is a sort of threshold below which no fibre initiates and c_5 is a model parameter used to keep the exponential function strongly negative as long as failure index $\sum(\sigma, D)$ remains below the threshold c_4, but switches to a large positive value once the threshold has been crossed. In Van Paepegem and Degrieck (2002), the model is tested for different values of the damage propagation rate c_3, which shows that final failure occurs much earlier if this parameter is increased.

2.3 Damage Prognostics

For predicting the RUL of a composite structure such as a wind turbine blade, we are interested in predicting the time when the damage grows beyond a predefined acceptable threshold (Saxena et al., 2010). The time or cycle at which it occurs is known as the expected end of life (EOL).

The wind turbine is expected to continue operating and producing power without exceeding the EOL threshold for the blade given by the accumulated stiffness fatigue damage $D = 0.8$ provided by (4), which is set as the maximum stiffness reduction allowed considered in this work.

Once the EOL threshold is determined, the remaining useful life can be readily obtained as $RUL_n = EOL - n$, where n stands for the current time or cycle.

A simplified algorithmic description for the RUL prediction is provided below:

(1) The stiffness damage at the current cycle and the future loads are required.
(2) Calculate damage for the next cycle provided by degradation model (4).
(3) Increase the number of cycles to failure.
(4) If the current damage is less than EOL repeat steps 2-4.
(5) If the current damage is greater than EOL, the RUL is equal to the number of cycles to failure accumulated.

Figure 1 shows the damage progression for different wind speeds using the stiffness degradation damage model (4) considering the parameters in Table **??**.

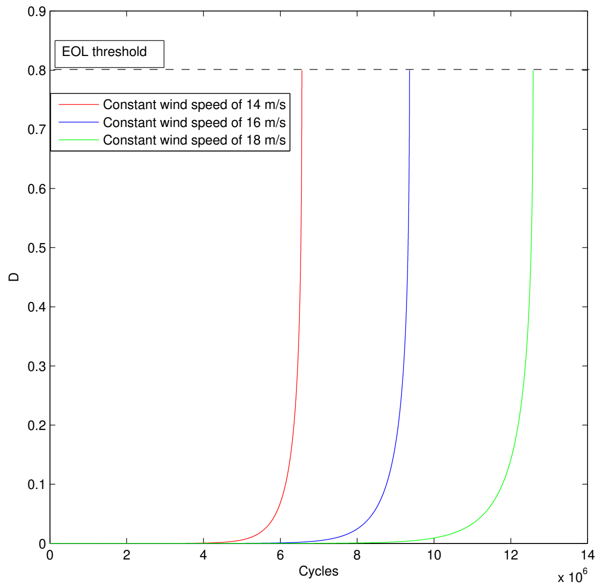

Fig. 1. Damage progression in the stiffness degradation model for different loads due to three different wind speed scenarios

The results show that the damage progression is faster for lower wind speeds, resulting in the reach of the EOL threshold earlier as it can be seen in the Figure 1. This is due to the fact that wind turbine is operating in control region 3. In region 3, the wind turbine rotational speed is maintained constant at the rated speed by pitching the turbine blades (Frost et al., 2013). In lower wind speeds, the blades are pitched in a higher angle against the wind in order to reach the rated rotational speed and this translates into higher flapwise blade root bending loads. When the wind speed is higher blades are pitched out of the wind in order to maintain the wind turbine rotating at the rated speed, therefore the flapwise damage loads are lower. When the flapwise damage loads are lower at the blade root (i.e. lower stress input to the stiffness degradation model) and consequently the end of life threshold (EOL) is reached later in comparison to when there are lower wind speeds, in which case the end of life threshold is reached earlier.

3. HEALTH-AWARE MPC

As described in previous section, the degradation process of the wind turbine blade can be evaluated using the model (4). In this section, a new objective will be included in the MPC controller to extend the RUL of the blade.

As discussed in Section (2.3), the evaluation of the RUL using the model (4) is done trough an algorithmic procedure that is not easy to include in the MPC optimization problem. Alternatively, here an approximate calculation for the RUL is proposed based on linear model

$$RUL(k) = a_0 + a_1 P_g(k) + a_2 v_w(k), \quad (5)$$

with the parameters a_0, a_1 and a_2 determined experimentally as follows and where P_g is the power generated by the wind turbine and v_w is the wind speed.

The power is a function of the generator speed and torque

$$P_g(t) = \eta_g T_g(t)\omega_g(t) \quad (6)$$

where

$$\omega_g(t) = N\omega_r(t) \quad (7)$$

and η_g is the generator efficiency.

After the substitution of the linear expression for the power (6) the proposed model is

$$RUL(k) = a_0 + a_1 \tfrac{\partial P_g}{\partial \omega_r}\omega_r(k) + a_1 \tfrac{\partial P_g}{\partial T_g} T_g(k) + a_2 v_w(k), \quad (8)$$

Therefore the proposed RUL model considers the influence of the rotor speed, the applied torque and the wind speed at the hub height.

The model parameters are estimated applying least squares algorithm, for wind speeds in the control region 3 and different rated powers obtaining the following values for the parameters $a_0 = 9.1094 \times 10^9$, $a_1 = -2.1451 \times 10^9$ and $a_2 = 2.4323 \times 10^8$.

Assuming a cycle with a constant wind speed and knowing the sampling time T_s, the number of samples per cycle L can be determined. The proposed linear RUL prediction model establishes a relation between a control signal T_g, the system state ω_r and a disturbance v_w with the RUL prediction of the blade:

$$RUL(k)^* = \frac{m}{L}(a_0 + a_1 \tfrac{\partial P_g}{\partial \omega_r}\omega_r(k) + a_1 \tfrac{\partial P_g}{\partial T_g} T_g(k) + a_2 v_w(k)), \quad (9)$$

where $RUL(k)^*$ is the approximated RUL prediction and m is a scaling factor used in the implementation of the linear approximated model in the MPC formulation. Thus, equation (9) can be included in the MPC as a new output of the state space model and an additional objective is added to the MPC objective function to increase the RUL.

Figure 2 shows the proposed linear RUL prediction model formulated in (5) as function of the produced power P_g and the mean wind speed v_w. This model is proposed for winds speeds in control region 3 and it can be observed than the minimum RUL prediction is obtained when the wind turbine is operating at the maximum rated power of 5MW and at the lower mean wind speed of 13 m/s. The maximum RUL prediction is obtained when the wind turbine is operating in a derated power of 2.75 MW and at the higher mean wind speed of 25 m/s. The figure is obtained for RUL predictions calculated at starting damage $D = 0$, end of life threshold $EOL = 0.2$ representing a 20% stiffness reduction where the parameters of the stiffness degradation model are shown in Table **??** with $c_3 = 4 \times 10^{-6}$.

Taking into account (9), the MPC problem (10) can be formulated as follows:

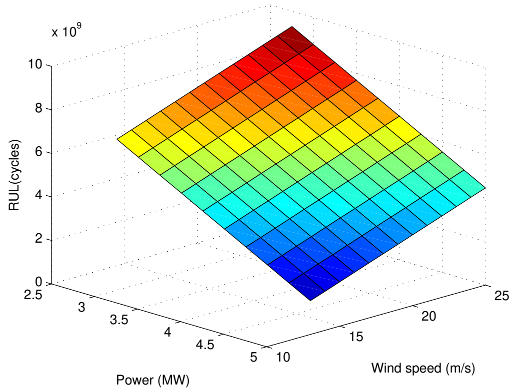

Fig. 2. Remaining useful life $RUL(k)$ as a function of produced power and mean wind speed

$$\min_{\mathbf{u}_k} \sum_{i=0}^{H_p-1} [\|e(k+i|k)\|^2_{W_e} + \|u(k+i|k)\|^2_{W_u} + \|\Delta u(k+i|k)\|^2_{W_{\Delta u}} + \|RUL^*(k+i|k) - K_{RUL}\|^2_{W_{RUL}}], \quad (10a)$$

subject to

$$\begin{aligned} &x(k+i+1|k) = Ax(k+i|k) + Bu(k+i|k) + E\hat{w}(k+i|k),\\ &e(k+i+1|k) = r(k+i+1|k) - Cx(k+i|k),\\ &RUL^*(k) = \frac{m}{L}(a_0 + a_1 \tfrac{\partial P_g}{\partial \omega_r}\omega_r(k) + a_1 \tfrac{\partial P_g}{\partial T_g} T_g(k) + a_2 v_w(k))\\ &\Delta u(k+i|k) = u(k+i|k) - u(k+i-1|k),\\ &u(k+i|k) \in \mathbb{U},\\ &x(k+i|k) \in \mathbb{X},\\ &(x(k|k), u(k-1|k), \hat{w}(k|k)) = (x_k, u_{k-1}, \hat{w}_k), \end{aligned} \quad (10b)$$

where an additional objective of tracking a higher constant value K_{RUL} for the $RUL^*(k)$ is defined with the corresponding weight W_{RUL} added to the MPC cost function (10a) to increase the remaining useful life (RUL).

4. CASE STUDY

4.1 Benchmark description

The wind turbine NREL 5 MW benchmark model implemented in FAST simulator developed by NREL for scientific research (Jonkman et al., 2009) is used as the simulation benchmark. This 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 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 $T_s = 0.05$ s.

4.2 Wind turbine control model

This section presents the results of the health-aware MPC approach using RUL predictions proposed in Section 3. The health-aware MPC is implemented using Matlab MPC toolbox using a prediction horizon $H_p = 200$ with a sampling time of $T_s = 0.05$ s. The MPC objective function (10a) considers the following objectives: track the reference power $P_{g,ref}$ and rotor speed $\omega_{r,ref}$, while the RUL as (9) is maximized. The health-aware MPC model can be formulated as follows:

$$x(k+1) = Ax(k) + Bu(k) + E_d w_d(k), \tag{11}$$
$$y_d(k) = C_d x(k) + F_d w_d(k), \tag{12}$$

where the output vector is given by $w_d = [v_w - v_w^* \ a_0]^T$ and $y_d = \left[P_{g,m} - P_g^* \ v_{t,m} - v_t^* \ \omega_{r,m} - \omega_r^* \ RUL^*\right]^T$. The matrices are defined as

$$E_d = \begin{bmatrix} \frac{T_s}{J}\frac{\partial T_a}{\partial v_\omega} & 0 & \frac{T_s}{M_t}\frac{\partial F_t}{\partial v_\omega} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}^T \tag{13}$$

$$C_d = \begin{bmatrix} T_s \frac{\partial P_g}{\partial \omega_r} & 0 \ 0 \ 0 & T_s \frac{\partial P_g}{\partial T_g} \\ 0 & 0 \ 1 \ 0 & 0 \\ 1 & 0 \ 0 \ 0 & 0 \\ \frac{m \ a_1}{LT_s}\frac{\partial P_g}{\partial \omega_r} & 0 \ 0 \ 0 & \frac{m \ a_1}{LT_s}\frac{\partial P_g}{\partial T_g} \end{bmatrix} \tag{14}$$

$$F_d = \begin{bmatrix} 0 \ 0 \ 0 \ \frac{m \ a_2}{LT_s} \\ 0 \ 0 \ 0 \ \frac{m}{LT_s} \end{bmatrix}^T \tag{15}$$

In the following figures, the health-aware MPC controller results are presented for the RUL predictions approach when the wind turbine is operating in the pitch control region 3 for several wind speeds and varying the weight of associated to the blade health W_{RUL}.

Figure 3 presents the approximated RUL approximated predictions in a turbulent wind of 14 m/s mean speed and the performance of the system assessed in terms of different wind turbine variables such as the rotor speed, the pitch angle and the generated power. When a higher emphasis is placed on the RUL term $RUL^*(k)$ the health-aware MPC derates the wind turbine producing less power, rotating at a lower speed and pitching the blades to a higher angle. A higher blade pitch angle is equivalent to a lower angle of attack of the blades against the wind which leads to reduced flapwise blade root moment loads and therefore the RUL of the blade is increased. The inclusion of the RUL objective extends the remaining useful life of the blade (assessed with the blade root moment and the RUL predictions using a stiffness degradation model). The RUL prediction shown in Figure 3 is obtained assuming no initial damage in the blade and future loads obtained when operating around mean wind speeds values of 14 m/s.

From Figures 4.(a)-4.(c), it can be observed the curves for remaining useful life predictions for the wind turbine blade for three different weights of the RUL term W_{RUL} (0, 6.25 and 10) of the MPC controller where the parameter

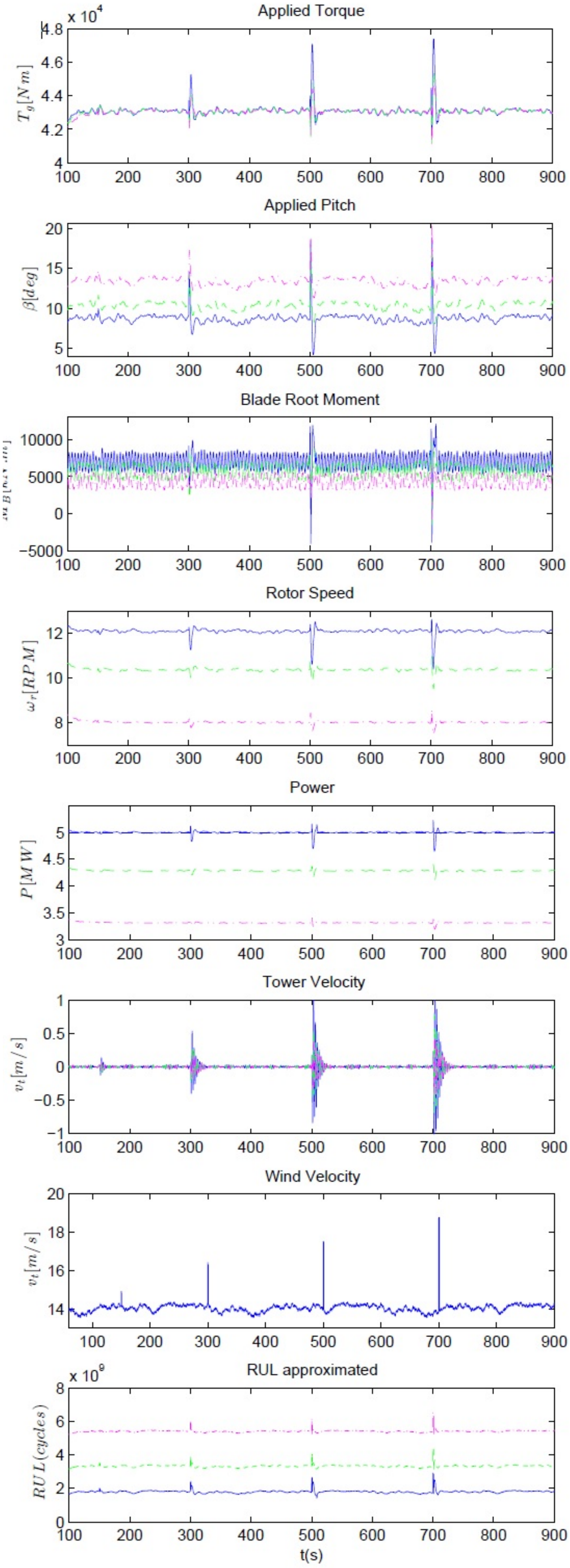

Fig. 3. Wind turbines performances for $W_{RUL} = 0$ (in blue), $W_{RUL} = 6.25$ (in – green) and $W_{RUL} = 10$ (in -. pink)

$\alpha = 0.9$ is used to set the confidence level of the RUL predictions bounds at 95% confidence. The figures show that higher RUL predictions are obtained when the weight of the RUL term is increased.

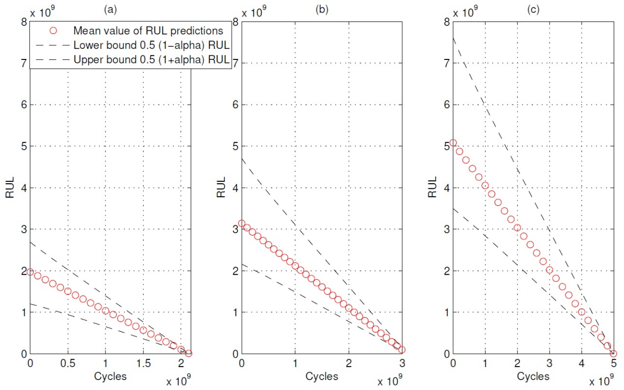

Fig. 4. RUL predictions for $W_{RUL} = 0$,$W_{RUL} = 6.25$ and $W_{RUL} = 10$ shown in (a,b,c) respectively

Tables 1 summarizes the values of different wind turbine variables altogether with the remaining useful life RUL for different values on the weight W_{RUL} (0, 6.25 and 10) of the MPC controller. A wind speed scenario (14 m/s) lasting for 900 seconds simulations is analyzed. From this tables, it can be observed that increasing the value of the weight W_{RUL} the remaining useful life of the blade is increased but at the price of decreasing the generated power.

Table 1. Wind turbine performances for a turbulent wind with mean speed of 14 m/s.

Weight W_{RUL}	**BRM (kN m)**	**Power (MW)**	**Rotor speed (rpm)**	**RUL (cycles)**
0	8249.47	5	12.1	2.1087×10^9
6.25	6894.5	4.28	10.32	3.0860×10^9
10	5494.52	3.31	7.88	4.9927×10^9

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.

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