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Health-aware LPV Model Predictive Control of Wind Turbines

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Abstract: Wind turbine components are subject to considerable stress and fatigue due to extreme environmental conditions to which they are exposed to, especially when located offshore. Interest in the integration of control with system health monitoring has increased in recent years. The integration of a health management module with model predictive control (MPC) provides the wind turbine a mechanism to operate safely and optimize the trade-off between components' life and energy production. In this paper, a health-aware LPV model predictive control approach for wind turbines is proposed. The proposed controller establishes a trade-off between the economic objective based on maximizing the energy production but at the same time taking into account the minimization of accumulated stress on the wind turbine blades. The controller uses an LPV model for dealing with the non-linearity of the wind turbine model and the inclusion of the stress model. The proposed approach is tested on a well-known wind turbine case.

1. INTRODUCTION

Wind energy has seen an immense growth over the last decades, becoming one of the most promising renewable energy resources that exists today. However, wind turbines operate in turbulent and often times unpredictable environmental conditions which makes their efficiency and reliability highly dependent on a well designed control strategy. The wind turbine control objectives are mainly to optimize wind energy conversion, and to reduce dynamic loads experienced by the plant's mechanical structure.

Wind turbines exhibit non-linear dynamics and operate in different operating zones depending on the range of wind speeds, which motivates their modelling and control using parameter-varying models (Shirazi et al., 2012), (Inthamoussou et al., 2014). The Linear Parameter Varying (LPV) paradigm has become a standard formalism for analysis and controller synthesis (Shamma, 2012) for non-linear systems. The advantage of using this class of systems is the use of an extension of linear techniques to perform gain-scheduling control of non-linear systems.

On the other hand, wind turbines are subject to highly irregular loadings due to wind, gravity, and aerodynamic effects which makes them especially vulnerable to fatigue damage. Thus, integrating wind turbine components' health information in the control algorithm will make wind turbines operate safely and enable an optimization process involving trade-offs between components' life and energy production.

MPC has attracted particular interest for implementing health-aware control schemes for wind turbines owing in part to the ability to explicitly include in the optimization certain engineering requirements such as health indices for a desired outcome. In (Barradas Berglind and Soltani, 2015), a data-based MPC strategy that incorporates fatigue estimation has been presented. In (Odgaard et al., 2015), an approach that includes dynamic inflow into the MPC controller has been proposed to decrease fatigue load. (Sanchez et al., 2015) also presents an approach of integrating MPC with a fatigue-based prognosis based on blade root moments to minimize the damage of wind turbine blades.

This paper presents a health-aware control (HAC) that takes into account the information about the system's health in the control law, with the objective of extending the useful life of the wind turbines, specifically the blades. The controller is implemented using MPC where some new terms that take into account the system's health, i.e. the accumulated blade loadings are included in the control objectives. This leads to solving a multi-objective optimization problem where a trade-off between system's health and performance is established. The MPC HAC approach is based on an LPV model of the wind turbine to accommodate the time-varying nature of the system leading to a convex optimization problem. Finally, the proposed approach is tested using the same wind turbine case study proposed in Sanchez et al. (2015), where a linearized model of the wind turbine was considered instead of an LPV one.

The remainder of the paper is organized as follows. Section 2 introduces the fatigue analysis and estimation of the wind turbine blades. In Section 3 the wind turbine quasi-LPV model is presented. The health-aware MPC controller is introduced in Section 4 and some simulation results

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are presented and discussed in Section 5. Finally, some concluding remarks are given in Section 6.

2. FATIGUE ESTIMATION OF WIND TURBINE BLADES

Fatigue in structures occurs when subjected to cyclic stress resulting in a localized, progressive and eventual permanent structural alteration (cracks or complete fracture) (Boyer, 1986). Estimating fatigue in wind turbine structure subjected to stochastic wind loadings is not new in literature. There have been many studies to compute fatigue life of components of wind turbines to enable predesigns, either active or passive, which averts rapid loss of structural strength for a longer operational lifetime enhancing the economic viability of wind energy technology against other competing options.

The most common method used in literature and in practice is the rain flow counting (RFC) method together with the Palmgren-Miner to compute resultant damage from a history of stress. The rain flow counting method was initially proposed by Endo et al. (1967) to interpret complex cyclic behaviour of stress as the probability of occurrence of load cycles in different ranges, ideally extracting closed loading reversals (or cycles). Fluctuating stress and strain on structures are represented as peaks in the RFC method. Counting these peaks results in a histogram of peaks in which the random history of stress (or strain) can be transformed into a statistical distribution of amplitudes of the fluctuating stress or strain as a function of time.

For this study, only the flap-wise loading which is dependent on aerodynamic load, wind is considered. The cyclic stress signals from the flap-wise root moment is consequently used as input into the RFC algorithm.

Many cumulative damage procedures exists that seek to predict the fatigue of materials. Palmgren-Miner's rule, first proposed by (Palmgren (1924)) and developed by (Miner (1945)) is the predominant method used due to it's simplicity. In using this method, the stress is assumed to be constant, neglecting iterations and sequence effects that may have significant impart on the overall estimated damage (Berglind and Wisniewski (2014)). The S-N curve, a relation of cycle amplitude of the stress and the number of cycles to failure .i.e. stress (s) versus number of stress cycles (N) is used to compute damage accrued at each cycle, given as a line in a log-log scale:

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

where the constants c and K are the composite's parameters and N is the number of cycles to failure at an amplitude of stress s. Given a time history of stress, damage is given per the Palmgren-Miner rule as:

$$D(T) \equiv \sum_{j=1}^{T} \Delta D_j = \sum_{j=1}^{T} \frac{1}{N_t}, \tag{2}$$

from (2), and with the associated incremental damage ΔD_j at each counted cycle of the load factor and considering the relation between the number of cycles to failure, N_t and the stress amplitude from the S-N curve (1), the accumulated damage after T counted cycles is given as:

$$D_{ac} = \sum_{j=1}^{T} \frac{1}{K} s_j^c. \tag{3}$$

With available time series data of the load factor (flap-wise blade root moment), the RFC method and the Palmgren-Miner's rule can thus be used to estimate the accumulated damage. From a previous work done by Sanchez et al. (2015), which will be shown in the preceding section, a linear model of the blade root moment $M_{B,i}(k)$ is estimated from the time series data, which is then incorporated into the MPC controller for a multi-objective optimization process of maximizing extracted power from kinetic wind energy whilst minimizing accumulated stress from the blade root moment, a function of the accrued damage as shown in (4) and other conflicting performance indices. The accumulated damage is therefore calculated as a function of time with the RFC method, obtained at each time step k as

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

where $s(k)$ is the stress at time instant k (5), $I(k)$ is the signal adapted to detect cycles (6), L is the number of samples per cycle and $M_{B,i}$ is the blade root moment of each blade i.

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

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

The accumulated damage can thus be calculated from (3), which is normally restricted to a predefined failure threshold beyond which damage is assumed to be above tolerance levels, but not necessarily a complete non-usability of the material under study. In the next sections the accumulated stress which is an input to the damage model (2) from the rainflow and Palmgren-Miner rule will be setup in an optimization problem of an the MPC formulation with the objective of decreasing stress $M_{B,i}$ from (5) from loadings hence reducing damage accumulation $D(k)$ against producing power from the turbine.

3. LPV MPC OF WIND TURBINES

3.1 Non-linear model

In this work, a suitable low order model that captures key dynamics of the wind turbine is used for the MPC design, even though more detailed models exist. Neglecting torsion angle and friction and with the assumption that the low and high speed shaft are one complete model, the model is described as:

$$\dot{w_r} = \frac{1}{J}(T_a - N_g T_g), \tag{7a}$$
$$\ddot{V_t} = \frac{1}{M_t}(T_r - K_t V_t - B_t \dot{V_t}), \tag{7b}$$
$$\dot{\beta} = \frac{1}{\tau_p}(-\beta + \beta_r), \tag{7c}$$
$$\dot{T_g} = \frac{1}{\tau_g}(-T_g + T_{g_r}), \tag{7d}$$

where w_r is the rotor speed, T_g is the generator torque, β, the pitch angle for capturing wind depending on wind speeds w and $\dot{V_t}$ is the the nacelle fore-aft velocity from the tower oscillations. The model parameters J, N_g, M_t, K_t, B_t, τ_p, τ_g are the rotor inertia, gear ratio, the tower fore-aft inertia, the tower fore-aft rigidity, the mechanical damping, the time constant of the pitch and the time constant of the generator respectively. The rotor and aerodynamic torques (T_r and T_a) which are dependent on the power and thrust coefficients C_p and C_q, both of which are functions of the pitch angle β and blade tip speed λ are given as:

$$T_a = \frac{1}{2}\rho\pi R^3 \frac{C_p(\lambda,\beta)}{\lambda} w^2, \tag{8a}$$
$$T_r = \frac{1}{2}\rho\pi R^2 C_q(\lambda,\beta) w^2, \tag{8b}$$
$$\lambda = \frac{R w_r}{w}. \tag{8c}$$

3.2 LPV model

An LPV model of the wind turbine can be obtained from the non-linear model (7) by means of the non-linear embedding approaches described in (Rugh and Shamma (2000)). After Euler discretization with a sampling time of T_s for MPC control purposes, the dynamic model can be expressed as follows:

$$x(k+1) = A(\theta(k))x(k) + B(\theta(k))u(k) + B_w(\theta(k))w(k), \tag{9}$$

where $x = [w_r\, V_t\, \dot{V}_t\, \beta\, T_g]^T \in R^n$ are the states, $u = [T_{g_r}\, \beta_r]^T \in R^m$ the inputs and $w(k) \in R^d$ is the disturbance from the wind.

The system matrices of the LPV model (9) are as follows:

$$A(\theta(k)) = I + T_s \begin{bmatrix} 0 & 0 & 0 & -\frac{N_g}{J} & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & -\frac{B_t}{M_t} & -\frac{k_t}{M_t} & 0 & 0 \\ 0 & 0 & 0 & -\frac{1}{\tau_p} & 0 \\ 0 & 0 & 0 & 0 & -\frac{1}{\tau_g} \end{bmatrix},$$

$$B(\theta(k)) = T_s \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & \frac{1}{\tau_p} \\ \frac{1}{\tau_g} & 0 \end{bmatrix},$$

$$B_w(\theta(k)) = T_s \begin{bmatrix} k_1\theta_1(k) \\ 0 \\ k_1 R\theta_2(k) \\ 0 \\ 0 \end{bmatrix}.$$

where the matrix, $B_w(\theta(k))$ depends on the following varying parameters: $\theta_1(k) = \frac{C_p(\lambda(k),\beta(k))}{\lambda(k)}$ and $\theta_2(k) = C_q(\lambda(k), \beta(k))$ under the assumption of known states and wind speed at each time instant k. The rest of the parameters are constant as defined in (7).
Hence at every time instant the dynamics of the system is obtained from a linear model determined by parameters θ_i, $\forall i \in Z_{\leq 4}$, that varies in the defined operational region.

An LPV model of the wind turbine which is dependent on the system states in a polytopic form is setup. The system matrices are linear time variant and functions of the scheduling parameters which are bounded in a compact polytopic set. This enables the non-linear terms in (7) from (8) and the bilinearity in (15) which would have otherwise warranted a complex optimization procedure to be subsequently solved with linear optimization tools.

Therefore with n_θ varying parameters, a polytopic representation of the dynamic matrices is given as the linear combination of $n_v = 2^{n_\theta}$ vertices (θ_{p_i}) of a polytope as follows

$$A(\theta(k)) = \sum_{i=1}^{n_v} \alpha_i(k) A(\theta_{p_i}) \;,\; B(\theta(k)) = \sum_{i=1}^{n_v} \alpha_i(k) B(\theta_{p_i}) \tag{10}$$

$$B_w(\theta(k)) = \sum_{i=1}^{n_v} \alpha_i(k), B_w(\theta_{p_i}),$$

where

$$\sum_{i=1}^{n_v} \alpha_i = 1,\; \alpha_i = [0,1]. \tag{11}$$

3.3 LPV MPC of wind turbines

The MPC controller uses the mathematical model (9) of the wind turbine to calculate the optimal control actions using a receding horizon philosophy.

The control goal is to minimize the cost function in the prediction horizon

$$\Psi_w(w_r - w_r^*)^2 + \Psi_\beta(\beta - \beta^*)^2 + \Psi_t(T_g - T_g^*)^2 + \Psi_{\Delta\beta}(\Delta\beta_r)^2. \tag{12}$$

where w_r^*, T_g^* and β^* are the reference rotor speed, reference torque and reference pitch angle respectively, with $\Delta\beta_r$ as the slew rate of the blade actuator. Control strategies are undertaken differently at specific ranges of wind speeds for maximizing extraction of energy from wind and maintaining rated power to a certain speed limit with the aid of tuning appropriate weights Ψ_w, Ψ_β, Ψ_t and $\Psi_{\Delta\beta}$.

The model (9) cannot be assessed before solving the MPC optimization problem, due to the future state sequence is unknown and cannot be determined. In reality, $x(k+1)$

depend on future control inputs $u(k)$ and also on the future scheduling parameters, thus LPV model cannot be instantiated offline but instead should be evaluated online at each time instant k. In this way, the MPC optimization problem can be formulated as a quadratic programming (QP) problem by using an estimation of scheduling variables, $\hat{\theta}$ instead of utilizing θ. That means the scheduling variables in the prediction horizon are estimated using the values from the previous MPC iteration and applied to update the model matrices of the MPC controller. Indeed, the sequence of the control input is utilized to change the model matrices used in the prediction horizon. Therefore, the predicted parameters and sequence of states can be obtained.

Hence, the LPV MPC controller design is based on the solution of the following finite horizon optimization problem (FHOP):

$$\min_{u(0:\ell)} \sum_{i=0}^{\ell-1} \mathcal{J}(x(i), u(i)) \tag{13a}$$

subject to:

$$\begin{aligned}
& x(i+1) = A(\theta(k))x(i) + B(\theta(k))u(i) + B_w(\theta(k))w(i), \\
& x(i+1) \in \mathcal{X}, \quad \forall i \in \mathbb{Z}_1^{\ell}, \\
& u(i) \in \mathcal{U}, \quad \forall i \in \mathbb{Z}_0^{\ell-1}, \\
& w(k) = \hat{w}_i, \quad \forall i \in \mathbb{Z}_1^{\ell-1}, \\
& \theta(k) = \hat{\theta}_i, \quad \forall i \in \mathbb{Z}_1^{\ell-1}, \\
& x(0) = x_0, \quad w(0) = w_0, \quad \theta(0) = \theta_0.
\end{aligned}$$

where x_0, w_0 and θ_0 is the initial state, disturbance and parameters obtained from measurements. $\hat{w}_i$ and $\hat{\theta}_i$ corresponds to the predicted value of disturbances and parameters all obtained at time instant k. 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 (18) is feasible, i.e., there exists a non-empty solution given by the optimal sequence of control inputs $(u^*(0), u^*(1), \ldots, u^*(\ell-1))$, then the receding horizon philosophy commands to apply the control action

$$u(k) = u^*(0). \tag{14}$$

and disregards the rest of the sequence of the predicted manipulated variables. At the next time instant k, the optimization problem (18) is solved again using the current measurements of states and disturbances which is assumed known at each time instant and the most recent forecast of these latter over the next future horizon.

4. HEALTH-AWARE LPV MPC OF WIND TURBINES

Component replacement costs and downtime lead to an increased overall cost of operation and those are some consequences of not taking into consideration a plant's health in design of machines. Due to the ability to pose a multi-objective optimization problem in MPC, it allows for the addition of objectives mostly conflicting to the main performance index, such that certain important engineering requirements (e.g. health of components) can be considered. In this breath, most MPC applications in wind turbines include health-aware capabilities to ensure a longer operational lifetime keeping in mind that wind turbines are exposed to extreme conditions. In most research works, for example in (Körber and King (2010)) and (Evans et al. (2015)), minimization of the velocity of the nacelle fore-aft from the tower oscillations is taken into account. In this work, the accumulated stress from the blade root moment which is included in the model is minimized to ultimately decrease the rate of fatigue on the blades. The result is subsequently a trade off between the maximization of power and the health aware index.

As stated in the Section 2, the load factor for fatigue estimation, in this case the blade root moment is estimated as done by (Sanchez-Sardi et al., 2017). The blade root moment was parametrically estimated as a first order linear function of the generator torque, the rotor speed and wind speed resulting in a bilinear function of the states T_g and w_r in the form

$$M_b = a_0 + a_1 T_g w_r + a_2 w, \tag{15}$$

The accumulated stress on the blades ($M_{b_{acc}}$) due to wind thrust over it's lifetime which inherently leads to fatigue and in the long run failure is posed as:

$$M_{b_{acc}}(k+1) = M_{b_{acc}}(k) + M_b(k). \tag{16}$$

For an in depth understanding on how the function (15) is acquired, reader is referred to (Sanchez et al. (2015)). The LPV model (9) is augmented to include the accumulated stress (16) as a new state, such that $\bar{x} = [w_r\, V_t\, \dot{V}_t\, \beta\, T_g\, M_{b_{acc}}]^T$. The augmented system matrices obtained considering the dynamic stress equation (16) are as follows:

$$\bar{x}(k+1) = \bar{A}(\theta(k))\bar{x}(k) + \bar{B}(\theta(k))u(k) + \bar{B}_w(\theta(k))w(k), \tag{17}$$

where

$$\bar{A}(\theta(k)) = I + T_s \begin{bmatrix} 0 & 0 & 0 & -\frac{N_g}{J} & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & -\frac{B_t}{M_t} & -\frac{k_t}{M_t} & 0 & 0 & 0 \\ 0 & 0 & 0 & -\frac{1}{\tau_p} & 0 & 0 \\ 0 & 0 & 0 & 0 & -\frac{1}{\tau_g} & 0 \\ a_1\theta_3(k) & 0 & 0 & 0 & a_1\theta_4(k) & 1 \end{bmatrix},$$

$$\bar{B}(\theta(k)) = T_s \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & \frac{1}{\tau_p} \\ \frac{1}{\tau_g} & 0 \\ 0 & 0 \end{bmatrix},$$

$$\bar{B}_w(\theta(k)) = T_s \begin{bmatrix} k_1\theta_1(k) \\ 0 \\ k_1 R\theta_2(k) \\ 0 \\ 0 \\ \frac{a_o}{\theta_5(k)} + a_2 \end{bmatrix}.$$

The varying parameters in the augmented LPV model are the same as the LPV model including $\theta_3(k) = \frac{T_g(k)}{2}$, $\theta_4(k) = \frac{w_r(k)}{2}$ and $\theta_5 = w(k)$ from the stress model (16).

Hence, the MPC controller optimization problem presented in (18) is modified by including the augmented LPV model (17) with a modified objective function, $\bar{\mathcal{J}}(\bar{x}(i), u(i))$, which includes an extra term $\Psi_{m_b} M_{b_{acc}}$ that accounts for the accumulated stress (i.e stress model, a function of Damage (4)) with the remaining objectives in (12) as follows:

$$\min_{u(0:\ell-1)} \sum_{i=0}^{\ell} \bar{\mathcal{J}}(\bar{x}(i), u(i)) \tag{18}$$

subject to:

$$\begin{aligned}
&\bar{x}(i+1) = \bar{A}(\theta(k))\bar{x}(i) + \bar{B}(\theta(k))u(i) + \bar{B}_w(\theta(k))w(i),\\
&\bar{x}(i+1) \in \bar{\mathcal{X}}, \quad \forall i \in \mathbb{Z}_1^{\ell},\\
&u(i) \in \mathcal{U}, \quad \forall i \in \mathbb{Z}_0^{\ell-1},\\
&w(k) = \hat{w}_i, \quad \forall i \in \mathbb{Z}_1^{\ell-1},\\
&\theta(k) = \hat{\theta}_i, \quad \forall i \in \mathbb{Z}_1^{\ell-1},\\
&\bar{x}(0) = \bar{x}_0, \quad w(0) = w_0, \quad \theta(0) = \theta_0.
\end{aligned}$$

5. SIMULATION RESULTS AND DISCUSSIONS

In this section, the MPC-LPV controller design procedure is implemented on a 5MW non-linear wind turbine plant that is modelled with the non-linear model (7) with the parameters detailed in Table 1.

Table 1. Model parameters

Parameter	*Value*
N_g	97 [-]
J	4.217×10^7 [kg/m^2]
R	63 [m]
ρ	1.23 [kg/m^3]
B_t	-9025 [Ns/m]
M_t	4.054×10^5 [kg/m^2]
K_t	-1.719×10^6 [N/m]
τ_p	0.02 [s]
τ_g	0.02 [s]
a_0	6468 [-]
a_1	7.82 [-]
a_2	-248.83 [-]
k_1	7.6684×10^3 $(\frac{1}{2}\rho A)$ [kg/m]

Normal operations of reference tracking to achieve maximum wind energy capture, from low wind speeds and ensuring nominal power for speeds above the rated speed $(wind_{rated})$ of 12.5 m/s through pitch and generator torque actuator actions are illustrated. The wind speed profile considered is a gradient wind speed profile of two regions of operation for figure 1 to validate the LPV model. The behaviour with the inclusion of the health ware performance index is then shown accordingly considering constant wind speed of 13 m/s.

From Figure 1, with a sampling time T_s of 0.05 sec at low wind speeds $w \leq wind_{rated}$, appropriate weights Ψ in (12) are selected to ensure the pitch angle is at 0°, allowing maximum exposure of the blades to wind for

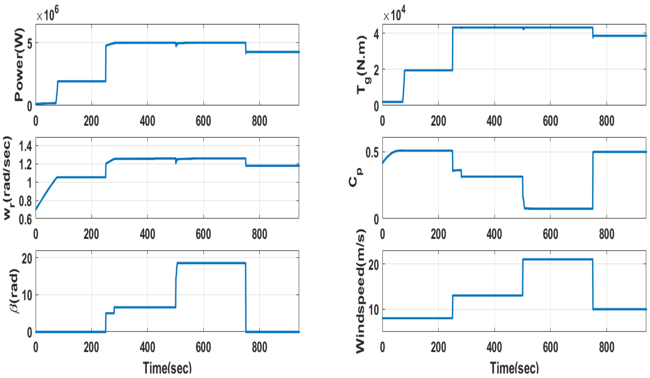

Fig. 1. Control of wind turbine subjected to gradient wind profile

utmost energy available. Therefore below $wind_{rated}$, only the reference torque actuator is operational. For wind speeds $w \geq wind_{rated}$ but less than the cut- off wind speed 25 m/s, the blade actuator varies accordingly to information of varying wind which is assumed known, such that the blade angle of attack is reduced accounting for less energy from wind to ensure rated power without overspeeding, protecting plant components. In this region both the torque (T_g) and the rotor speed (w_r) is kept at their respective rated values, see Figure 1. For the purpose of calculating the accumulated damage with a constant stress input, wind speeds above the rated speed $(wind_{rated})$ which produces constant power is considered for the health ware LPV-MPC design.

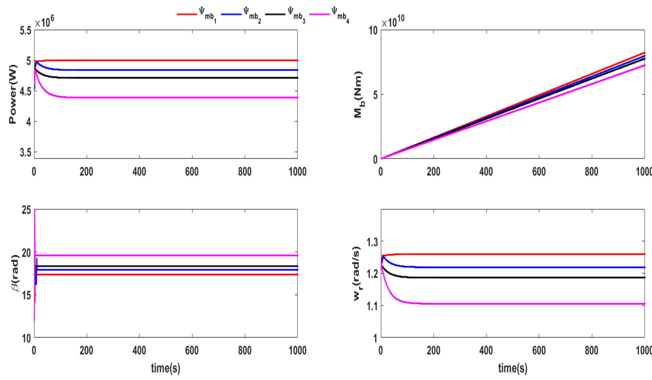

Fig. 2. Health Aware LPV-MPC control with varied weights Ψ_{mb_i}

There is a trade off between the minimization of accumulated root moment m_b and the maximization of output power from Figure 2, after selection of weights $\Psi_{mb_i} = [\Psi_{mb_4} > \Psi_{mb_3} > \Psi_{mb_2} > \Psi_{mb_1}]$ in the updated health aware cost function (18). Considering that wind speed > $wind_{rated}$, the torque T_g is therefore kept constant from figure 3. The blade pitch angle therefore increases (i.e reduced angle of attack) with more priority on minimization of the accumulated stress resulting in a decrease in rotor speed (w_r) leading to less output power as shown in figure 2.

Table 2 shows the trade-off in numbers between the steady state power and it's associated accumulated stress calculated as the area under each function, M_b from figure

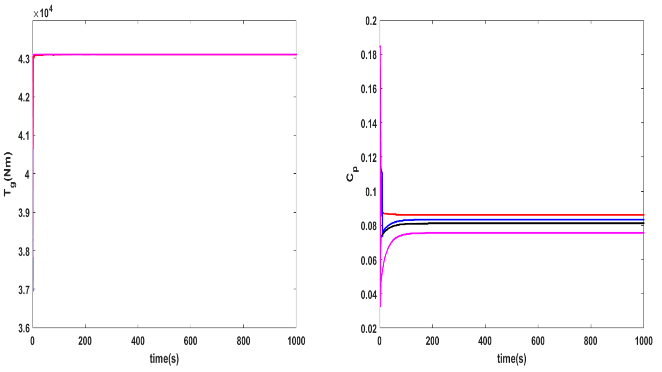

Fig. 3. Torque and Power coefficient after varied weights Ψ_{mb_i}

2 with respect to different selected Ψ_{mb} after simulation time of 1000 seconds.

Table 2. Table showing power and accumulated stress with varied weights, Ψ_{mb_i}.

Ψ_{mb}	**Power(MW)**	$M_{b_{acc}}(kN.m)$
Ψ_{mb_1}	5	4.11×10^{10}
Ψ_{mb_2}	4.54	3.74×10^{10}
Ψ_{mb_3}	4.164	3.43×10^{10}
Ψ_{mb_4}	3.97	3.26×10^{10}

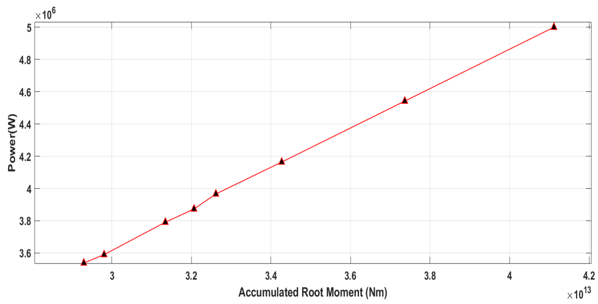

Fig. 4. Pareto front of power and accumulated stress

Depending on Ψ_{mb}, it could be realised from the Pareto front in figure 4 that for a reduced accumulated stress on the blades, the control actions from the MPC results in the deration of power, which involves an increase of pitch angle to decrease the blades exposure to varying wind loading, decreasing aerodynamic thrust in the process.

6. CONCLUSIONS

This research paper investigated the integration of health aware capabilities in a wind turbine control action for a longer operational lifetime of components. Taking into account that the wind turbine presents a non-linear system and the stress estimated is a bilinear function, the model was approximated as an LPV system in a polytopic form. Results from simulations of the multi-objective problem subsequently showed a trade off between the power produced from the wind turbine and the minimization of the accumulated stress which is an input to the fatigue estimation model described in section 2 on the wind turbine blades, therefore necessitating a deration of wind turbines for a longer blade lifetime. As further research it will be interesting to explore Economic MPC due to the difficulty in appropriately tuning the tracking weights, a problem cited by practitioners as stated by (Gros and Schild (2016)).

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