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# Remaining Useful Life Control of a Deteriorating Wind Turbine with Flexible-shaft Drive-train

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In this paper, we propose a degradation-aware control approach that allows to control the remaining useful life of a deteriorating wind turbine system. We consider more particularly the degradation caused by the dissipated energy in the drive-train, and we aim at controlling it by acting on the control gain of the generator torque imposed at the output of the drive-train. We propose an observation and control structure for this degradation control problem. By applying control techniques, such as optimal control and state-feedback control, we control the degradation process while guaranteeing the stability of the wind turbine system. A numerical case study illustrates the advantages of controlling the degradation using the proposed approach for a system suffering from load effects with the aim to correct its remaining useful life.

*Keywords*: Wind Turbines, Drive-Train Model, Degradation-Aware Control, Remaining Useful Life, Prognostic and Health Management, End-of-Life Assessment.

## 1. Introduction

Considering the urgency to develop the renewable energy sector, large resources have been invested in the Wind Turbine (WT), which has proven to be a valuable renewable energy technology. However, the competitiveness of WT is greatly affected by its Operation and Maintenance (O&M) costs compared to other green energy alternatives, according to El-Thalji and Liyanage (2012). The way wind turbines respond to the wind to generate energy, especially Horizontal-Axis Wind Turbines (HAWT), leads to unavoidable stresses and causes damage and degradation that eventually leads to failure.

Therefore, control methods have recently been introduced to control and mitigate the loads while finding a good compromise between energy generation and degradation, as is reviewed in Do and Söffker (2021). It is usually referred to as Degradation-Aware Control (DAC) and can be integrated into the system at two different levels: the wind turbine speed control level or a health monitoring level that reconfigures and adjusts the first control level according to the current degradation state and reliability requirements (e.g., an average lifetime). The second level typically has slower dynamics, which has some advantages. For example, real-time constraints can be relaxed and complex algorithms can be used for prediction and decision making to ensure system reliability.

In addition, degradation can also be expressed in terms of Remaining Useful Life (RUL), which relates the reliability of the system to the possible time to failure or End of Life (EoL) with a probability distribution, as studied in Rausand et al. (2021). As a contribution to the DAC approaches applied to WT technology, in this paper we propose a RUL control that aims to impose a desired feature to the EoL distribution (e.g.,

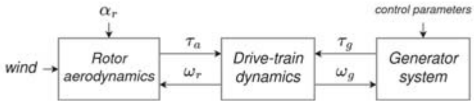


Fig. 1. Drive-train system interactions diagram.

the mean or median lifetime). To illustrate the approach, we focus on the transmission components, i.e., the drive-train represented by a flexible shaft subjected to torsional effects leading to a degradation process. For this system, we introduce a link function to model the degradation dynamics as a function of actionable control inputs and exogenous inputs such as wind turbulence intensity. Using this function, we then propose a control law to reconfigure the control operating point to achieve the desired degradation rate. This is calculated using the current observed degradation, a given lifetime, and knowledge of the uncertainty of the process.

Accordingly, this article is structured as follows. In Section 2 a degradation model of the studied system under torsion effects is presented. In Section 3, a RUL control approach is studied and a control architecture is proposed, and the synthesis for the proposed control system in a specific operating range is also presented. Section 4 shows the results of controlling the RUL by applying the control approach to the studied system for a certain required lifetime. Section 5 provides conclusions and perspectives on this approach.

## 2. System Description

In a HAWT system, the rotor blades respond to the wind with an aerodynamic flow that generates rotational motion. Then, a drive-train connects the rotor to a generator system that converts these mechanical motions into electrical energy. The drive-train interacts with both the rotor and the generator, as shown in Figure 1. And, if we assume that the generator system perfectly converts the energy at a much higher operating rate, we can decouple its dynamics and focus in the following on the aerodynamic parts[a] and the drive-train shaft.

[a]For simplicity, the dynamics of the tower are not considered.

### 2.1. *System model*

#### 2.1.1. *Rotor aerodynamics model*

The wind flowing through the blades produces power $P_A$ as a function of wind speed $v$, air density $\rho$, and swept rotor area $A_r$.

$$P_A = \frac{1}{2}\rho_v A_r v^3 \tag{1}$$

The blades respond to the wind with a torque $\tau_a$ that causes movements with angular speed $\omega_r$ and a mechanical power $P_G$.

$$P_G = \tau_a \omega_r \tag{2}$$

This mechanical power is converted into electrical power with a certain efficiency expressed in:

$$C_p(\lambda, \alpha_r) = \frac{P_G(\tau_a, \omega_r)}{P_A(v)}. \tag{3}$$

Power coefficient $C_p$ is the result of the mechanical losses, e.g., inertia and friction, generated during the rotational motion and the aerodynamic force on the blades related to the angle pitch $\alpha_r$ of the blades (with $\alpha_r^{opt}$ generating the maximum force). The mechanical losses are also related to the relationship between blades' tipping movements (corresponding to the rotational motions and the rotor diameter $R_r$) and the wind intensity, expressed as:

$$\lambda = \frac{R_r \omega_r}{v} \tag{4}$$

and is called the tip-speed ratio. There exists an optimal tip-speed ratio $\lambda^{opt}$ that leads to minimal losses. Thus, the optimal $\lambda^{opt}$ and $\alpha_r^{opt}$ leads to maximum efficiency $C_p(\lambda^{opt}, \alpha_r^{opt}) = C_p^{max}$. Figure 2 shows different $C_p$ curves for values of $\lambda$ and $\alpha_r$ for a 5-MW turbine.

Finally, (1) - (4) gives the aerodynamic torque of the drive-train as follows:

$$\tau_a = \frac{1}{2}\rho_v A_r R_r^3 \frac{C_p(\lambda, \alpha_r)}{\lambda^3}\omega_r^2 \tag{5}$$

#### 2.1.2. *Two mass flexible drive-train model*

The drive-train subsystem in Bianchi et al. (2007) is modeled as two rigid bodies (see Figure 3)

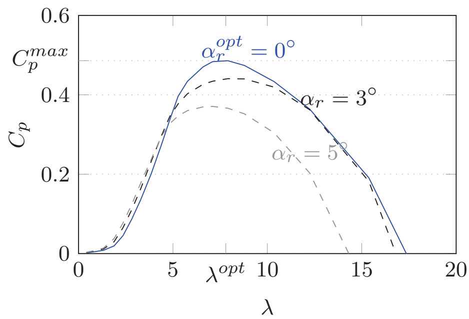


Fig. 2. $C_p(\lambda, \alpha_r)$ curve of NREL 5-MW turbine Jonkman (2012).

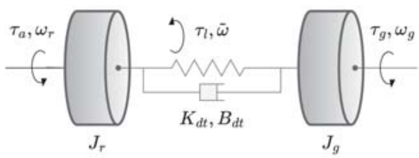


Fig. 3. Two-mass flexible drive-train.

connected by a flexible shaft as follows:

$$\begin{aligned} J_r\dot{\omega}_r &= -B_{dt}\omega_r + B_{dt}\omega_g - K_{dt}\tilde{\theta} + \tau_a \\ J_g\dot{\omega}_g &= B_{dt}\omega_r - B_{dt}\omega_g + K_{dt}\tilde{\theta} - \tau_g \\ \dot{\tilde{\theta}} &= \omega_r - \omega_g \end{aligned} \tag{6}$$

In this model, the drive-train transmits movement $\omega := [\omega_r \ \omega_g]$ through the rotation of a connecting shaft with torsional dynamics with a torsion spring $K_{dt}$ and a torsion damper action $B_{dt}$, where the torsion angle is the difference in rotational positions

$$\tilde{\theta} = \theta_r - \theta_g, \tag{7}$$

and the torsion angle speed is the relative difference between rotor and generator speeds

$$\tilde{\omega} = \omega_r - \omega_g. \tag{8}$$

On the generator side, a controlled braking force $\tau_g$ corrects the shaft speed to follow an operating point $\lambda^*$ that is optimal $\lambda^{opt}$ if it yields $C_p^{max}$.

#### 2.1.3. *Dissipated energy model*

The torsional phenomena on the shaft caused by the relative differential speed $\tilde{\omega}$ result in torsional losses expressed as dissipated energy as follows:

$$P_D = B_{dt}\tilde{\omega}^2 = B_{dt}(\omega_r - \omega_g)^2 \tag{9}$$

The accumulated energy dissipation is then

$$E_D = \int P_D \tag{10}$$

which express how much the shaft has suffered from torsion effects during its lifetime.

### 2.2. *Rotor speed control benchmark*

At low wind speeds, the controller aims to control rotor speed around an operating point, usually chosen to maximize energy efficiency through Maximum Power Point Tracking (MPPT) control, as proposed in Johnson et al. (2006) with the corresponding control law:

$$\tau_g = K_{mppt}\omega_g^2, \tag{11}$$

where $K_{mppt}$ is calculated as

$$K_{mppt} = \frac{1}{2}\rho_r A_r R_r^3 \frac{C_p^*}{\lambda^{*3}}, \tag{12}$$

chosen to force the shaft dynamic to follow the equality $C_p(\lambda) = \mathcal{F}(\lambda)$ with a given $C_p^*$ inherent to that point, where

$$\mathcal{F}(\lambda) = \frac{C_p^*}{\lambda^{*3}}\lambda^3. \tag{13}$$

The function $\mathcal{F}(.)$ with respect to $\lambda^*$ places the MPPT around an operating point on the curve $C_p(\lambda)$. For example, Figure 4 shows different possible operating points for different values of $\lambda^*$[b].

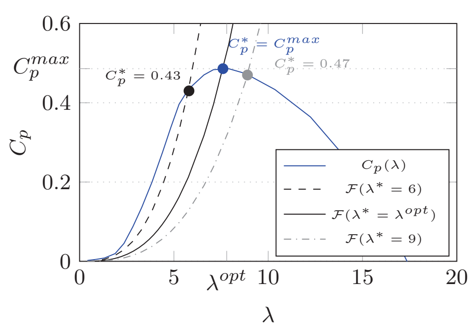


Fig. 4. Operating points ($C_p(\lambda) = \mathcal{F}(\lambda)$) for different values of $\lambda^*$ and $\alpha_r = \alpha_r^{opt}$.

[b]Note that $\lambda^* \neq \lambda^{opt}$ results in $C_p^* < C_p^{max}$.

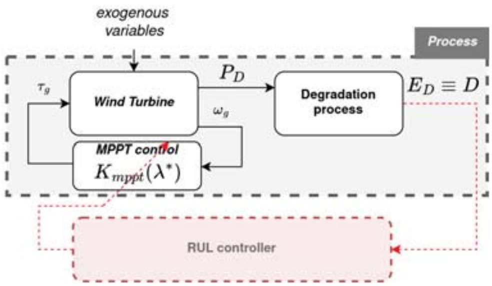


Fig. 5. Principle of the proposed control architecture

According to Johnson et al. (2006), the controlled system is asymptotically stable for different values of $K_{mppt}$ (respecting a certain operating range) and guarantees tracking of the maximum point $C_p^*$ of power generation of the selected operating point. Moreover, Romero et al. (2021) has investigated that different values of $K_{mppt}$ produce different amounts of dissipation energy from torsion. Therefore, assuming that the system degradation can be monitored or estimated, it is possible to control the torsion effects produced by the actuator response by controlling the value of $\lambda^*$ to adapt the control gain $K_{mppt}$ to produce a desired amount of dissipation energy while producing electrical energy near the optimal point with MPPT control, using a control architecture sketched in Figure 5.

## 3. Proposed Remaining Useful Life (RUL) Control

### 3.1. *Tracking problem*

Let us consider RUL as the time remaining for the system to continue functioning under normal conditions $RUL_k = t_{final} - k$, where degradation $D$ occurs at a certain rate $\beta$ until a maximum degradation $D_{max}$ is reached at $t_{final}$. This rate $\beta$ fluctuates as a function of the shaft dynamics and exogenous inputs. We consider that the fluctuations occur in a range that depends on the control conditions and is controlled by control parameters (e.g., $K_{mppt}$, $\lambda^*$).

$$\dot{D} = \beta \tag{14}$$

$$\beta = g(\lambda^*) + \eta \tag{15}$$

with a monotonic relationship $g(.)$, and $\eta$ modelling the uncertainty on this fluctuation.

As suggested in Obando et al. (2021), we consider here that the deterioration is the dissipated energy $D := E_D$, which is the accumulation of the dissipated power $\beta := P_D$ due to the torsion of the shaft and has a linear behavior according to (9)-(10). Thus, assuming a constant rate of deterioration $\beta_k$, $RUL_k$ at time $k$ can be predicted as the time interval in which $D_k$ continues to increase until it reaches $D_{max}$:

$$RUL_k = \frac{D_{max} - D_k}{\beta_k} \tag{16}$$

Then, the RUL control problem consists in finding at each time the $\lambda^*$ that brings the system to an operating point that produces deterioration rate around a desired level (denoted here as $\beta^{ref}$) determined with respect to a desired RUL ($RUL^{ref}$). So, to enforce a given $RUL_k^{ref}$ at time $k$, a degradation rate $\dot{D} := \beta^{ref}$ is needed, which is calculated as follows:

$$\beta_k^{ref} = \frac{D_{max} - \hat{D}_k}{RUL_k^{ref}} \tag{17}$$

where $\hat{D}_k$ is the current deterioration that can be estimated. If an expected lifetime $t_{final}$ (or EoL) is specified instead of RUL, then $RUL^{ref}$ is calculated as follows:

$$RUL_k^{ref} = t_{final}^{ref} - k. \tag{18}$$

### 3.2. *Deterioration link function*

Assuming that the deterioration rate (here $P_D$) varies in a range that depends on the values of $\lambda_*$, a control parameter, it is necessary to find a deterioration link function relating $P_D$ for different values of $\lambda_*$, and then a control solution to the tracking problem can be proposed.

For this purpose, let us now consider that the wind speed $v$ has a behavior that can be divided into a static part $\bar{v}$ and a fluctuation part $\tilde{v}$, also referred to turbulence intensity:

$$v = \bar{v} + \tilde{v}. \tag{19}$$

When there is no wind fluctuations ($\tilde{v} = 0$), the MPPT controller is able to maintain the shaft angular velocity at a static point, referred to here as the equilibrium point ($eq$), with the equilibrium tip-speed ratio $\lambda^*$. Then (4) yields

$$\omega_r^{eq} = \omega_g^{eq} = \frac{\lambda^*}{R_r}\bar{v} \tag{20}$$

However, in the case of wind turbulence ($\tilde{v} \neq 0$), the system is perturbed and $\omega_r$ is affected by the current rotor torque ($\omega_r \neq \omega_r^{eq}$). At this moment, we assume the angle speed on the rotor side follows:

$$\omega_r \approx \frac{\lambda^*}{R_r}v \tag{21}$$

Due to inertia, the generator has a delay at the equilibrium point $\omega_g^{eq}$ before being affected by $\omega_r$, as given in (6). This phenomenon leads to a relative differential velocity and, at the time of the disturbance, we consider $\tilde{\omega}$ as follows:

$$\tilde{\omega} = \omega_r - \omega_g^{eq}. \tag{22}$$

Therefore, from Eq. (9) and Eqs. (19)-(22), at this point ($\omega_r \neq \omega_g$), we propose the following expression to approximate the power dissipation:

$$P_D \approx \gamma {\lambda^*}^2 \tag{23}$$

where $\gamma = \frac{B_{dt}\tilde{v}^2}{R_r^2}$, for $0 < \gamma_{min} \leq \gamma \leq \gamma_{max}$ if $0 < \tilde{v}_{min} \leq \tilde{v} \leq \tilde{v}_{max}$, where $\tilde{v}$ denotes the wind turbulence intensity.

Note that this function aims to find a monotonic relationship between $P_D$ and $\lambda^*$ for control purposes, not to predict the states of the process.

### 3.3. *Control design*

Having found the function in Eq. (23), we can now propose a control solution to the given tracking problem where $P_D \equiv \beta$ and the goal is to track $\beta^{ref}$ with respect to $RUL^{ref}$ by controlling $P_D$, i.e., $\beta$, with the decision on the values of $\lambda^*$ around the MPPT point.

Based on the RUL architecture presented in Félix et al. (2023), a final control architecture is proposed, shown in Figure 6, consisting of a state controller and an observer to control the evolution of degradation by adjusting $K_{mppt}$ according to a $\beta^{ref}$ with reference to a $RUL^{ref}$ and the estimable states of the degradation process $x := [D\ \dot{D}]$.

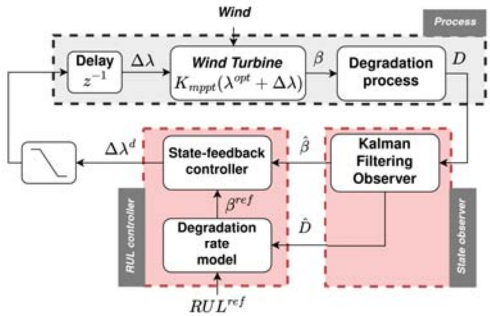


Fig. 6. Complete and detailed RUL control architecture

#### 3.3.1. *Control problem*

The control aims to track a given $\beta^{ref}$ by taking actions $\Delta\lambda$ on values of $\lambda^*$:

$$\lambda_k^* = \lambda^{opt} + \Delta\lambda_k \tag{24}$$

where $\Delta\lambda$ is the deviation of the values of $\lambda$ around the optimal point $\lambda^{opt}$.

We consider a model delay $\Delta\lambda_{k+1} = \Delta\lambda_k^d$, between the decision point and the control action. Finally, the proposed control law is calculated as follows:

$$\Delta\lambda_k^d = -K_p \cdot \Delta\lambda_k - K_i \cdot z_k \tag{25}$$

with an integral action to minimize tracking errors, and is implemented as follows:

$$z_{k+1} = z_k + \left(\hat{\beta}_k - \beta^{ref}\right) \tag{26}$$

And the final system model to find the optimal control around the optimal point can be considered as follows:

$$\begin{bmatrix}\Delta\lambda_{k+1}\\ z_{k+1}\end{bmatrix} = \begin{bmatrix}0 & 0\\ \tilde{\gamma} & 1\end{bmatrix}\begin{bmatrix}\Delta\lambda_k\\ z_k\end{bmatrix} + \begin{bmatrix}1\\ 0\end{bmatrix}\Delta\lambda_k^d + \begin{bmatrix}0\\ -1\end{bmatrix}\Delta\beta^{ref} \tag{27}$$

where $\tilde{\gamma} = 2\frac{B_{dt}\tilde{v}_m^2}{R_r^2}$, and $\Delta\beta^{ref}$ as the desired variation of the deterioration rate around the MPPT point ($\lambda^{opt}$).

Note that this does not prevent the system from deteriorating as it remains in an operating range, but it does allow us to correct for variations in the rate of deterioration to meet $RUL^{ref}$ requirements.

Using the found model, a Linear-Quadratic Regulator (LQR) can be implemented whose found parameters are as follows:

$$K_p = 0.8755, \ K_i = 0.3528. \qquad (28)$$

Saturation can be added to the system to ensure that $\lambda$ remains in the operating range.

### 3.3.2. *Observer problem*

An observer can be used to determine the current values of $\hat{D}$ and $\hat{\beta}$ at the time of decision $k$. Because Eq. (23) is only an approximation of the relation between the deterioration and the control parameters, we propose an observer based on the Langevin equation that models the fluctuations of $\beta$ as follows:

$$\dot{\beta} = -c\beta + \varepsilon \qquad (29)$$

Then we have an observer model for the deterioration as follows:

$$\dot{\hat{x}} = \begin{bmatrix} 0 & 1 \\ 0 & -c \end{bmatrix} x + K(y - \hat{y}) \qquad (30)$$

where $y := D + \varepsilon_m$ with some noise $\varepsilon_m$. Based on this model, the gain $K$ can be found using a Kalman Filter solution to estimate $\hat{x} := [\hat{D} \ \hat{\beta}]$.

## 4. Numerical Experiments

Numerical experiments are proposed to evaluate the proposed solution. The parameters used in the simulation for the wind turbine and the wind conditions are given in Table 1. The observer gain is calculated using the observer parameters given in Appendix 5.

### 4.1. *Lifetime distribution vs generated energy analysis*

The first experiment consists in analyzing the lifetime and the generated energy for $10^3$ simulated wind turbines in operation, experiencing different wind speeds and wind turbulence intensities for (a) no RUL control to adjust $K_{mppt}$, (b) with RUL control adjusting $K_{mppt}$ to follow a given $RUL^{ref}$. The simulations consider a sampling period of $T_s = 1$s, $D_{max} = 10$W and $t^{ref}_{final} =$ 4000s. Considering the need to run a large number of simulations, a low maximum deterioration was chosen, as well as life expectancy, to perform faster simulations.

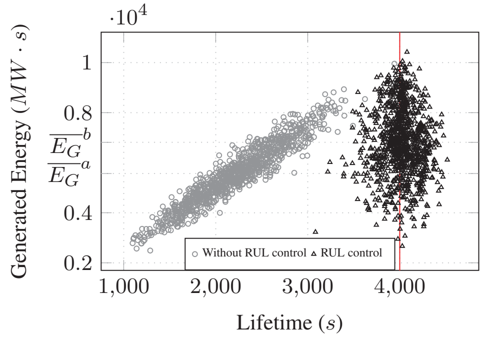


Fig. 7. Generated energy and lifetime for $10^3$ simulated realizations with and without RUL control ($EoL^{ref}$ equal to 4000s).

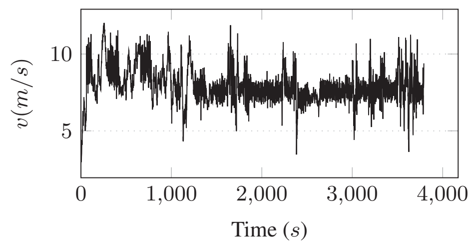


Fig. 8. Wind speed intensity for one realisation.

Figure 7 presents the generated energy as a function of the WT lifetime for each of there simulated histories. The results show that the system with standard MPPT control has a lifetime between 1096s and 3900s, with a generated energy proportional to the total operating time. The wide lifetime distribution is due to the different wind histories, and the absence of a RUL control scheme. For a WT with RUL control (with a $EoL^{ref}$ equal to 4000s), it can be observed that the proposed RUL control approach can shift the lifetime distribution to a desired (mean) EoL. Moreover, this lifetime extension allows an average generated energy $\overline{E_G}^b$ larger than the $\overline{E_G}^a$ generated by the usual MPPT control, summarized in Table 2. These results show that the proposed controller is able to track a given $RUL^{ref}$ while ensuring power generation.

### 4.2. *Adaptive control for one realization*

We propose to consider one realization to get a better insight into the behavior of the proposed

Table 1. Table of wind turbine parameters.

| Parameter | Description | Value |
|---|---|---|
| $\bar{v}$ | Average wind | 10 $ms^{-1}$ |
| $\tilde{v}_m$ | Average wind turbulence intensity | 2 $ms^{-1}$ |
| $\rho_v$ | Air density | 1.22 $kgm^{-3}$ |
| $R_r$ | Rotor radius | 50 m |
| $B_{dt}$ | Torsion damping | 755 $Nmsrad^{-1}$ |
| $K_{dt}$ | Torsion stiffness | $2.7 \cdot 10^9$ $Nmrad^{-1}$ |
| $J_r$ | Rotor moment of inertia | $55 \cdot 10^6$ $kgm^{-2}$ |
| $J_g$ | Generator moment of inertia | $55 \cdot 10^6$ $kgm^{-2}$ |
| $K_{mppt}^{opt}$ | MPPT optimal gain | $6.65 \cdot 10^5$ |
| $C_p^{max}$ | Max. power coefficient | 0.48 |
| $\lambda^{opt}$ | Optimal tip-speed ratio | 7.6 |

*Source*: 4.8MW HAWT parameters Simani and Farsoni (2018).

Table 2. Average results for a $D_{max} = 10$W and $t_{final}^{ref} = 4000$s.

| $10^3$ simulations | $\overline{E_G}$ $(MW \cdot s)$ | $\overline{EoL}$ $(s)$ |
|---|---|---|
| $(a)$ Without RUL control | $5.56 \cdot 10^3$ | 2226 |
| $(b)$ With RUL control | $6.81 \cdot 10^3$ | 4015 |

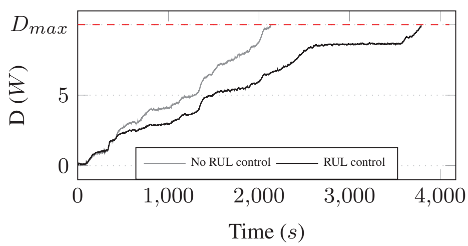


Fig. 9. Degradation evolution of one realisation without and with adaptive $K_{mppt}$ for a $D_{max} = 10$W and $t_{final}^{ref} = 4000$s.

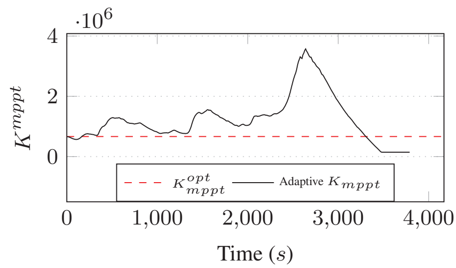


Fig. 10. Adaptive values of $K_{mppt}$ of one realisation with a $D_{max} = 10$W and $t_{final}^{ref} = 4000$s.

RUL control scheme. The wind speed of this realization is shown in Figure 8. The result of the dissipated evolution can be seen in Fig. 9 While the standard MPPT control leads to a lifetime of 2133s, the RUL control extends the operation to 3791s.

Figure 10 shows that the RUL control adjusts the gain value $K_{mppt}$ to produce less dissipated energy and compensate for the rate of the increase caused by wind turbulence, which deviates the lifetime from the desired one.

## 5. Conclusions

The End-of-Life (EoL) of a deteriorating machine is the result of a sequence of deterioration rates caused by load effects during the life of the machine. In this paper, a control method is proposed to correct the RUL of a wind turbine to meet reliability requirements. This method introduces a state-space control architecture with a state observer and a control law based on an available link function and the deterioration model of a flexible shaft under torsional effects. In the case studied, the link function was obtained from the interaction of operating points of the system, determined by the selected optimal tip-speed ratio and wind turbulence intensity, with deterioration behavior. The results show that this approach can control the EoL of a WT system despite the uncertainties and random effects that system degradation is subject to (e.g., the random nature of wind turbulence and the different operating points). Future work consists of studying the control for other operating ranges where the optimal point depends on the rated power. In addition, the studies can be extended to a varying RUL reference to meet the operation and maintenance objectives of wind turbine power generation.

**Appendix A. Observer parameters**

The Kalman Filter requires initial condition and given covariance matrices. Therefore, we consider the observation covariance matrix:

$$R = 0.01 \tag{A.1}$$

assuming noise variances are known and equal to 0.01. And the process noise covariance matrix $Q$:

$$Q = diag(0.01, 2.5 \cdot 10^{-5}) \tag{A.2}$$

The posteriori estimate covariance matrix has initial condition $P_{0|0}$:

$$P_{0|0} = diag(100, 2.5 \cdot 10^{-3}) \tag{A.3}$$

## Acknowledgement

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