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IFAC PapersOnLine 55-6 (2022) 402–407

A Set-Based Prognostics Approach for Wind Turbine Blade Health Monitoring

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Abstract: This paper presents a model-based prognostics procedure using a zonotopic Kalman filter in tandem with a zonotopic set-based propagation of degradation, aiding in the quantification of uncertainties associated with prognostics. The prognostics procedure is then applied to the degradation of a wind turbine blade material subjected to a forecasted bounded set description of wind profile. To facilitate an online condition based implementation, an otherwise nonlinear based Kalman filter from the nonlinear wind turbine model is presented in a pseudo-linear form, a polytopic linear parameter varying representation, decreasing computational cost and easing in the propagation of the positive invariant zonotopic uncertainty sets to a reachable set that triggers an end of life. Using this information of health, the remaining useful life with its associated uncertainties can be predicted.

Keywords: Zonotopic Kalman filter, Linear parameter varying methodologies, Prognostics, Reachability analysis, Wind turbine.

1. INTRODUCTION

Productive operation of wind turbines requires structural installation at most often unforgiving environmental conditions which invariably leads to a high rate of component damage. Due to the inevitability of these occurrences, the knowledge of the life expectancy of these components subject to adverse conditions is of importance for the effective planning of maintenance and operation to minimize the levelized cost of energy (LCoE); increasing profits and accelerating wind energy's contribution to a more environmentally sustainable energy mix. Prediction of the life expectancy of components at a specific time in a plant operation involves an efficient design of prognostics tools to establish whether operational goals can be fulfilled, whilst also considering the possibility of including online decision-making frameworks such as fault-mitigation, operational replanning and other prescriptive policies (Sankararaman and Goebel, 2013).

Some algorithms for wind turbines prognostics have already been proposed following model-based (Asgarpour and Sørensen, 2018; Valeti and Pakzad, 2018) and data-based (Cao et al., 2018; Zhao et al., 2016) approaches. Uncertainty in prognostics is inevitable since it involves an assumed knowledge of future operational conditions and also present prediction of states and/or parameters which are uncertain. Therefore, it makes no sense to predict a RUL without an accompanying uncertainty description. Quantification of uncertainty in prognostics according to Sankararaman and Goebel (2013) is categorized into the classical (frequentist) and Bayesian (subjective) schools of thought and can be posed as an uncertainty propagation problem. Quantification can either be an online or offline procedure. Sikorska et al. (2011) acknowledges the fact that the main bottleneck of online implementation is the computational burden that most methodologies present. Instead of this, it is imperative to propose prognostics algorithms that are practical for easy deployment.

In this paper, a set-based prognostics of a wind turbine blade is proposed and is formulated as a reachability analysis problem. During the estimation step, for lesser computational burden, a Zonotopic Kalman filter (ZKF) is formulated taking into account a damage-appended wind turbine model in a linear parameter varying (LPV) format such that at each propagation time, with the estimated state (degradation) and its uncertainty, a propagation of zonotopic sets can be undertaken.

The structure of the paper is as follows: In Section 2, the considered degradation model for wind turbine blades is presented. In Section 3, the wind turbine and degradation model is expressed in LPV form. In Section 4, the set-based prognostics approach is presented. Section 5 describes the RUL approach based on the set-based prognostics approach. Finally, Section 6 draws the main conclusions.

2. DEGRADATION OF WIND TURBINE BLADES

2.1 Blade stiffness degradation model

This paper will focus of the prognostics of the wind turbine blades. According to Vassilopoulos et al. (2010), the modulus decay of most fibre reinforced composite materials occurs in three stages: E_0 is undamaged stiffness, E is the stiffness at a specific point in the material fatigue life cycle, N is the total test cycles and N_f is the fatigue life in cycles. In the first stage, there is a rapid degrading of stiffness of about 2-5% mostly due to transverse matrix cracks, at this stage microscopic cracks in the material

Peer review under responsibility of International Federation of Automatic Control.
10.1016/j.ifacol.2022.07.162

starts. Stage two involves a gradual degradation over the fatigue lifetime. Damage here is mostly caused by edge delaminations and additional longitudinal cracks. Eventually in the final state, degradation occurs in abrupt steps, culminating in an overall fatigue failure of the specimen. From Van Paepegem and Degrieck (2002), under the assumption that the UUT (unit under test), the blade is a solid beam, the damage model considering compressive stress can be described as:

$$\frac{dD}{dN} = f_i(\phi, D) + f_p(\phi, D), \tag{1}$$

where f_i is the initial stage function of steep declines in stiffness and f_p is the damage propagation function of the second and final stages. These two functions are given by

$$f_i(\phi, D) = \left[C_1 \Sigma(\phi, D) \exp(-C_2 \frac{D}{\sqrt{\Sigma(\phi, D)}}) \right]^3, \tag{2a}$$

$$f_p(\phi, D) = C_3 D \Sigma(\phi, D)^2 \left[1 + \exp(\frac{C_5}{3}(\Sigma(\phi, D) - C_4) \right]. \tag{2b}$$

where failure index $\Sigma(\phi, D)$ is a function of the damage D resulting in material strength reduction and the stress value ϕ

$$\Sigma(\phi, D) = \frac{\phi}{(1 - D)X_c}. \tag{3}$$

The constant X_c is the comprehensive static strength. The damage growth model from initiation to final fatigue failure is thus given as :

$$\frac{dD}{dN} = \left[C_1 \Sigma \exp(-C_2 \frac{D}{\sqrt{\Sigma}}) \right]^3 + C_3 D \Sigma^2 \left[1 + \exp(\frac{C_5}{3}(\Sigma - C_4) \right]. \tag{4}$$

where C_1 and C_2 are the material constants, C_3 is the damage propagation rate, C_4 is a threshold below which there is no initiation of fibre fracture. When the threshold C_4 is crossed, the initial fibre fracture occurs on the specimen, which causes an exponential rapid decrease in strength and enables the final fatigue failure of the material. As long as the failure index is below the threshold C_4, the parameter C_5 assumes a large value to ensure a strongly negative exponential function. When C_4 is crossed, it assumes a large positive for accelerated degradation of the material. The third power is used for compressive stress as they show from experiments to have considerably less effect than tensile stress. From Van Paepegem and Degrieck (2002), the parameters for a damage model for a fibre-reinforced composite of which some wind turbine blades are made up of with the stiffness degradation algorithm is given in Table 1. Even though the UUT is presumed to have reached a predefined threshold of damage after this test, it is by no means the indication that the component is not usable. Ideally, the natural assumption is to run the algorithm till a 100% deterioration of material strength, but it must be noted that since most of these predictive or statistical methods, are thought of as not exact, under conditions of fluctuating mean stress or pronounced sequence effects, a value below 1 is normally chosen.

To obtain the effective stress value ϕ, which effects a damage event has on the composite material, a cycle counting

Table 1. Parameters for stiffness degradation model.

Parameter	Value	Unit
C_1	0.002	(1/cycle)
C_2	30	-
C_3	4×10^{-4}	(1/cycle)
C_4	0.85	-
C_5	93	-
X_c	341.5	Mpa

tool such as the rainflow counting to detect closed loading reversals or cycles is used.

2.2 Stress in wind turbines

Stress on wind turbine blades results mainly due to flap-wise or edge-wise loadings. The former is due to aerodynamic loadings whilst the latter is a product of gravitation from the blade weight, as well as torque loads. For this study, only the flap-wise loading is considered. Sanchez et al. (2015) established a relationship between the flap-wise root moment, the pitch angle and the exogenous wind, resulting in a stress function through least-squares, taking into account different wind conditions from the high fidelity FAST (Jonkman et al., 2009) like in Fig. 3. With the stress function equation,

$$\phi(t) = a_1 \beta(t) + a_2 w(t) \tag{5}$$

where (1) is included in the wind turbine model for the prognostics procedure.

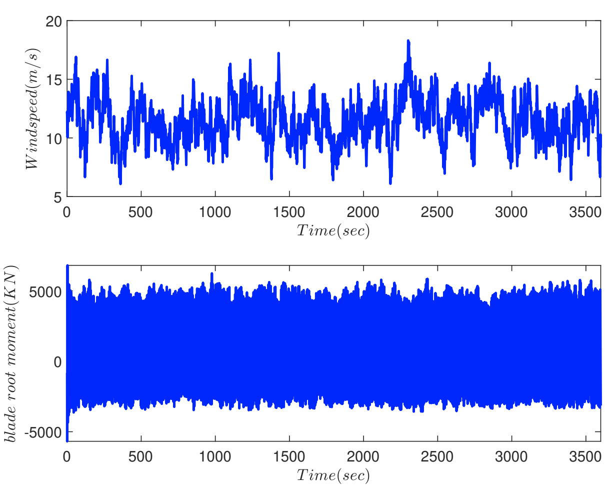

Fig. 1. (*Above.*)Average wind speed of $12m/s$ (*Below.*) Flapwise blade root moment of a blade.

3. LPV WIND TURBINE AND DEGRADATION MODEL

3.1 Non-linear model wind turbine

Neglecting torsion angle and friction and with the assumption that the low and high speed shaft, a simple wind turbine model is used in this paper:

$$\dot{w}_r = \frac{1}{J}(T_a - N_g T_g) \tag{6a}$$

$$\dot{\beta} = \frac{1}{\tau_p}(-\beta + \beta_r) \tag{6b}$$

$$\dot{T}_g = \frac{1}{\tau_g}(-T_g + T_{g_r}) \tag{6c}$$

where w_r is the rotor speed, T_g is the generator torque and β the pitch angle for capturing wind depending on wind speeds w. The model parameters J, τ_p, τ_g are the rotor inertia, the time constant of the pitch and the time constant of the generator, respectively. The rotor torque (T_a) which is dependent on the power coefficient C_p, which is a function of the pitch angle β and blade tip speed λ is given as:

$$T_a = \frac{1}{2}\rho\pi R^2 C_q(\lambda, \beta) w^2, \tag{7a}$$

$$\lambda = \frac{R w_r}{w}. \tag{7b}$$

where (1) must be converted from cycles to time domain to be included into the wind turbine model. Since the rainflow counting algorithm produces a discontinuous output, from its algorithmic branches and loop policy. (1) can be thought of as a discontinuous function and thus problematic for direct online implementation. Luckily some works have employed the use of *Light Detection and Ranging* (LIDAR) devices to circumvent this problem, by essentially taking advantage of the delay of wind contact with the blades, with some pre-knowledge of the wind profile to have a post process stage which enables an online implementation. Löw et al. (2020) applies this technique in model predictive control, using a *Parametric Online Rainflow-counting* (PORFC). Similarly, the LIDAR is used to evaluate the change of cycles per sampling time in measured wind within specific time frame determined by the delay given as the contact time (t_c) between wind and the structure

$$t_c = \frac{d}{v_w}. \tag{8}$$

where d is the measuring distance and v_w the mean flow velocity. Therefore with the known number of cycles n_c within a time frame t_c, an estimated cycle per sampling time T_s is taken as:

$$\Theta(t) = \frac{T_s}{t_c} \cdot n_c$$

The prognostics model is therefore given as :

$$\dot{w}_r = \frac{1}{J}(T_a - N_g T_g), \tag{9a}$$

$$\dot{\beta} = \frac{1}{\tau_p}(-\beta + \beta_r), \tag{9b}$$

$$\dot{T}_g = \frac{1}{\tau_g}(-T_g + T_{g_r}), \tag{9c}$$

$$\dot{D} = \Theta(t)(f_i(\phi, D) + f_p(\phi, D)). \tag{9d}$$

3.2 LPV model

The non-linear model is posed as an LPV model by embedding the nonlinearity in scheduling parameters $\theta(k)$. In this way, the resultant nonlinear time varying degradation model is formulated mathematically into a pseudo-linear form through embedding. For brevity, the procedure is not elaborated here. The LPV model in discrete-time with a sampling time T_s is therefore:

$$x(k+1) = A(\theta(k))x(k) + Bu(k), \tag{10}$$

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

The system matrices are given as follows:

$$A(\theta(k)) = I + T_s \begin{bmatrix} k_1\theta_1(k) & 0 & -\frac{N_g}{J} & 0 \\ 0 & -\frac{1}{\tau_p} & 0 & 0 \\ 0 & 0 & -\frac{1}{\tau_g} & 0 \\ 0 & \theta_2(k) & 0 & \theta_3(k) \end{bmatrix},$$

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

where $k_1 = \frac{1}{2}\rho\pi R^2$, and the scheduling parameters are: $\theta_1(k) = \frac{C_p(\lambda(k),\beta(k))}{\lambda(k)w_r(k)}$, $\theta_2(k) = \Theta(k)(\frac{1}{(1-D(k)X_c})^3(a_1^3\beta(k)^2 + 3a_1^2\beta(k)(a_2w(k)) + 3a_1(a_2w(k))^2 + (a_2w(k))^3)$ and $\theta_3(k) = \Theta(k)C_3\Sigma(k)^2\left[1 + \exp(\frac{C_5}{3}(\Sigma(k) - C_4)\right]$.

4. SET-BASED PROGNOSTICS

4.1 Description

The proposed prognostics approach is primarily based on the generic model-based prognostics formalism, adapted to a set-based description of uncertainties. The plant model is subject to control and exogenous disturbance (wind) inputs $u(k)$ and $w(k)$, under sensor noise $v(k)$ conditions, such that $w(k)$ and $v(k)$ are described as unknown but compact convex sets,

$$x(k+1) = f(x(k), \theta(k), u(k), w(k), k), \tag{11}$$

$$y(k) = h(x(k), \theta(k), u(k), v(k), k). \tag{12}$$

where $v(k) \in \mathcal{V}$ and $w(k) \in \mathcal{W}$, with the compact sets $\mathcal{V}$ and $\mathcal{W}$ described as zonotopic sets. The output data $y(k)$ and information from the model, under uncertainty is used in the ZKF estimation of zonotopic bounded states including the damage variable.

This compact sets description is subsequently used as the premise to predict the EOL and RUL at a specific time instant k_p that take their values from resultant feasible compact uncertainty propagated sets that retain desirable properties for interpretability due to the initial zonotopic set. Future conditions during predictions are also considered bounded in sets and influence the penultimate degradation reachable set and thus the EOL and RUL, $\Box EOL(\Box x(k_p), \theta(k_p)|\Box y(k_p))$ and $\Box RUL(\Box x(k_p), \theta(k_p)|\Box y(k_p))$, respectively. Considering $T_{EOL} \in R^{n_x} \times R^{n_\theta}$ as a threshold of failure, T_{EOL}

maps to a Boolean domain, such that a failure is 1 and 0, otherwise. $T_{EOL} : R^{n_x} \times R^{n_\theta} \rightarrow B$, the $EOL(k_p)$ is formalised in (Daigle et al., 2012) as

$$\begin{aligned} EOL(k_p) = \inf\{k \in N : k \geq k_p \wedge \\ T_{EOL}(x(k), \theta(k), u(k)) = 1\}, \end{aligned} \tag{13}$$

The remaining useful life, at k_p is thus given as (14) in set form:

$$\square RUL(k_p) = \square EOL(k_p) - k_p. \tag{14}$$

4.2 ZKF Implementation

As stated earlier, the stages of prognostics, estimation and prediction, involve uncertainties, which may arise due to modelling errors, sensor noise, modelling parameters, state estimation at prediction time, assumed future knowledge of conditions or environmental conditions. Due to the sensitivity of this process, it is important to quantify all uncertainty sources appropriately. The zonotopic uncertainties in this paper are considered to be additive and constructed from symmetric interval sets. The quantified uncertainties are (i) the sensor noise, $v(k) \in [-\Delta v \ \Delta v]$ (ii) modelling uncertainties which is considered to emanate from the uncertain measured wind in the nonlinear embedded nonlinearities, from θ_1 and θ_2, which are calculated from appropriate interval analysis operation, such that, $\theta_1 \in [-\Delta\theta_1 \ \Delta\theta_1]$ and $\theta_2 \in [-\Delta\theta_2 \ \Delta\theta_2]$ and (iii) Uncertainty from the exogenous wind input, $w(k) \in [-\Delta w \ \Delta w]$. From the interval sets, the zonotopic sets are formulated for the Kalman filter procedure.

Considering that the dynamical LPV system can be represented as

$$x(k+1) = A(\theta(k))x(k) + Bu(k) + E_w w(k) \tag{15a}$$

$$y(k) = Cx(k) + E_v v(k) \tag{15b}$$

where E_w and E_v are set up to represent the resultant uncertainty bounds from all the uncertainty sources. w and the noise v are assumed bounded in a unitary hypercube centered at the origin, $w \in [-1, \ 1]^{n_w} = \langle 0, \ I_{n_w}\rangle$ and $v \in [-1, \ 1]^{n_v} = \langle 0, \ I_{n_v}\rangle$, $I_{n_w} \in R^{n_w \times n_w}$ and $I_{n_v} \in R^{n_v \times n_v}$ are identity matrices. Considering the quasi-LPV model (10), a polytopic LPV model is used to formulate the estimation, such that the estimated states $\hat{x}(k)$ with n_θ varying parameters is given as:

$$\begin{aligned} \hat{x}(k+1) = \sum_{i=1}^{2^{n_\theta}} (\mu_i(\theta(k)))\,(A_i(\theta(k))x(k) + Bu(k)) + \\ + L\,(\theta(k))\,(y(k) - \hat{y}(k)) \end{aligned} \tag{16}$$

The observer gain $L\,(\theta(k)) \in R^{n_x \times n_y}$ takes its solution from the convex hull of a 2^{n_θ} vertex polytope.

$$L\,(\theta) = \sum_{i=1}^{2^{n_\theta}} \mu_i\,(\theta)\,L_i \tag{17}$$

$$\sum_{i=1}^{2^{n_\theta}} \mu_i\,(\theta) = 1$$

where L_i are the 2^{n_θ} observer gains for each of the polytope's vertices.

Assumption 1: The system matrices A$(\theta(k))$ and C are observable for any realization of $\theta(k)$.

The gains L_i are obtained by solving an LQC duality problem. Let the observer gain tuning parameters be $Q = Q^T = H^T H \geq 0$ and $R = R^T > 0$ and A_i be for each vertex of the polytope. Thus, with an optimal bound γ, the polytopic observer gains are obtained by solving an LMI minimization problem to find Υ and W_i.

$$\min_{\gamma, \Upsilon=\Upsilon^T, W} \gamma \tag{18}$$

subject to

$$\begin{bmatrix} \gamma I_n & I_n \\ I_n & \Upsilon \end{bmatrix} > 0 \tag{19}$$

$$\begin{bmatrix} -\Upsilon & \Upsilon A_i - W^T C & \Upsilon H^T & W^T \\ A_i^T \Upsilon - C^T W & -\Upsilon & 0 & 0 \\ H\Upsilon & 0 & I_{n_x} & 0 \\ W & 0 & 0 & -R^{-1} \end{bmatrix} < 0 \tag{20}$$

$$\begin{bmatrix} -r\Upsilon & q\Upsilon + A_i^T \Upsilon - C^T W \\ q\Upsilon + \Upsilon A_i - WC & -r\Upsilon \end{bmatrix} < 0 \tag{21}$$

$q = 0$ and $r = 1$ are the center and radius of a unitary circle, respectively. Eq. (21) is included to guarantee the stability of the observer. The disturbances ($\omega \in R^{n_x}$) and measurement noise ($v \in R^{n_y}$) are unknown but assumed to be bounded and represented by zonotopes

$$\mathcal{W} = \langle c_\omega, R_\omega \rangle \tag{22a}$$

$$\mathcal{V} = \langle c_v, R_v \rangle \tag{22b}$$

where c_ω and c_v are the centers of the sets with $R_\omega \in R^{n_x \times n_x}$ and $R_v \in R^{n_y \times n_y}$ as their generator matrices representing the uncertainties. The state is thus estimated as $\hat{x} = \langle c_x, R_x \rangle$.

$$c_x(k+1) = c_p(k) + L\,(y(k) - Cc_p(k)) \tag{23a}$$

$$R_x(k+1) = [(I - LC)\,R_p(k), -LE_v] \tag{23b}$$

$$c_p(k+1) = \sum_{i=1}^{2^{n_\theta}} \mu_i(\theta(k)) A_i(\theta(k)) x(k) + Bu(k) \tag{24}$$

$$A(\theta(k)) = \sum_{i=1}^{2^{n_\theta}} \mu_i(\theta(k)) A_i(\theta(k)) \tag{25}$$

$$R_p(k+1) = [A(\theta(k)) R_x(k) \quad E_\omega] \tag{26}$$

where L is given as in (17).

With the estimated c_x state and associated uncertainty R_x description as shown in Fig. 2, the prediction stage at each designated prediction time can start.

5. PREDICTION OF THE RUL

The time prediction distribution of the EOL at prediction instants k_p can be thought of as a reachability analysis problem based on set propagation considering initial set conditions from the estimator .i.e $\hat{\mathcal{X}}_{k_p} \subset \langle c_{x_{k_p}}, \ R_{x_{k_p}} \rangle$, with inputs sourced through random sampling from an assumed known distribution of inputs. Assuming the matrices $A(\theta(k))$ are always stable, then the propagation of the sets with respect to the system ensures that a set of positive invariant sets, $[\zeta(k_p), \zeta(k_p+1)....\zeta(k_{EOL})]$, can be constructed. Thus, the evolution of the centers of the

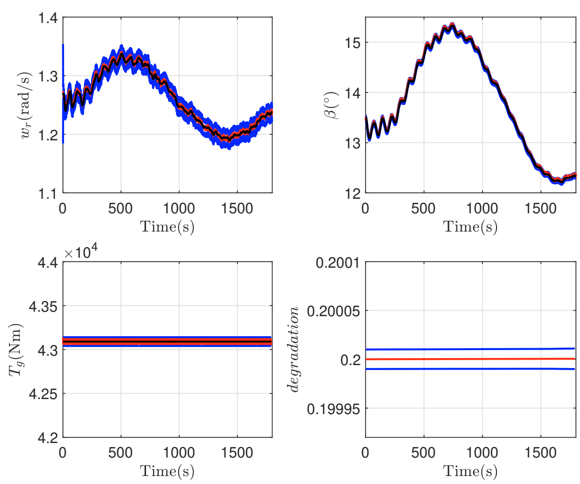

Fig. 2. Estimation of states by ZKF with bounded sets

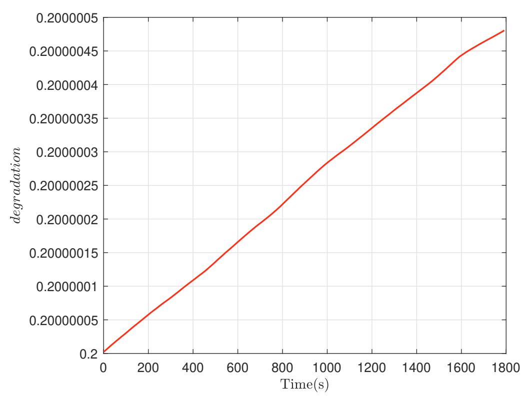

Fig. 3. Monotonic degradation function

set is guaranteed to be $x(k) \subset \zeta(k)$. The propagated positive invariant sets are just unions of the constituents convex sets (27) and the uncertainty sets constructed via Minkowski sums (28):

$$\zeta(k_{EOL}) \subseteq \mathcal{R}_{[k_p,\ k_{EOL}]}(\hat{\mathcal{X}}_{k_p}, \mathcal{W}_{k_p}) = \bigcup_{k=k_p}^{k_{EOL}} \mathcal{R}_{k\tau}\left(\mathcal{R}_{[0,\ \tau]}(\hat{\mathcal{X}}_{k_p})\right). \tag{27}$$

$$\Delta X(k_p+j) \subseteq \bigoplus_{j=1}^{k_{EOL}} A(\theta(j))^j \Delta x(k_p) \oplus A(\theta(j))^{(j-1)} B\Delta u(k_p+j-1) \oplus E_w \Delta w(k_p+j-1)). \tag{28}$$

Since the control inputs are dependent on the wind conditions and the degradation a function of only the wind, only a distribution of the wind is considered. $\mathcal{W}_{k_p} \supset [w(k_p)+\Delta w(k_p),\ w(k_p+1)+\Delta w(k_p+1), ...w(k_{EOL})+\Delta w(k_{EOL})]$.

Remark 1 Since the degradation model is strictly monotonous with respect to the initial state $x_0 \in R^n$ and inputs $w_i \in R^w \subset \mathcal{W}$, for all trajectories $\upsilon(t, x_0, w) : R_{>0} \times X \times R^w \rightarrow X, : x_2 > x_1, \upsilon(t_2, x_2, w_2) >> \upsilon(t_1, x_1, w_1)$. From Althoff et al. (2021), it can be inferred,

Algorithm 1. Prediction of RUL

Inputs $\{(c_{x_{k_p}}, R_{x_{k_p}}, \mathcal{W}_{k_p}, A(\theta(k_p)), k_p\}$
Output $\{RUL, \overline{RUL}, \underline{RUL}\}$
$c(k) \longleftarrow c_{x_{k_p}},\ R_x(k) \longleftarrow R_{x_{k_p}},\ A(\theta(k)) \longleftarrow A(\theta(k_p))$
for $k = k_p, k_p+1, ...$ **do**
  while $T_{EOL}(\underline{D_{k_{min}}(k)}) = 0$ **do**
    $D_{cen}(k) \longleftarrow D(c(k))$ ▷ Propagation of damage center
    $\underline{D_{min}}(k) \longleftarrow D(c(k) - rs(R_x(k)))$ ▷ Propagation of damage lower bound
    $\overline{D_{max}}(k) \longleftarrow D(c(k) + rs(R_x(k)))$ ▷ Propagation of damage upper bound
    $c(k+1) = (A(\theta(k))c(k) + Bu(k)$ ▷ Propagation of states
    $R_x(k+1) = [(A(\theta(k))R_x(k) \quad E_w]$ ▷ Propagation of uncertainty bounds

    if $T_{EOL}(D_{k_{cen}}(k)) = 1$
      then $k_{cen} \longleftarrow k$
    if $T_{EOL}(\underline{D_{k_{min}}}(k)) = 1$
      then $\underline{k_{min}} \longleftarrow k$
    if $T_{EOL}(\overline{D_{k_{max}}}(k)) = 1$
      then $k_{max} \longleftarrow k$
  end while
  $RUL \longleftarrow k_{cen} - k_p$
  $\overline{RUL} \longleftarrow k_{min} - k_p$
  $\underline{RUL} \longleftarrow k_{max} - k_p$
end for

that $\forall x_0 \leq \overline{x}, w \leq \overline{w}$, each state trajectory can be constructively, bounded as in $\forall i \in N^+, t > 0, \upsilon_i(t, x_{i,0}, w) < \upsilon_i(t, \overline{x_i}, \overline{w})$ and $\upsilon_i(t, x_{i,0}, w) > \upsilon_i(t, \underline{x_i}, \underline{w})$.

The reachable zonotopic convex sets $\zeta(k)$ are therefore over approximated with hypercubes. Hypercubes are themselves zonotopes, so the process involves a mapping of a zonotope to another zonotope that invariably increases conservativeness but for the purposes of interpretability. The RUL prediction can be summarized in Algorithm 1.

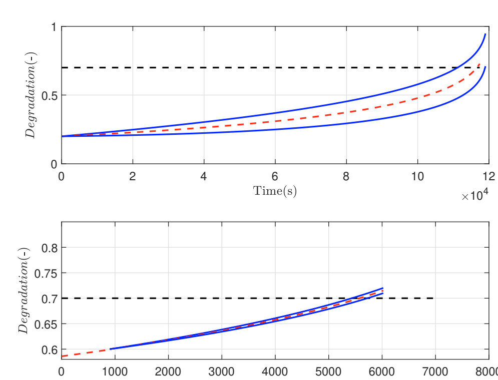

Fig. 4. Propagation of degradation uncertainty set to EOL.

To show the efficacy of the proposed methodology an accelerated degradation experiment is undertaken by amplifying the otherwise small degradation events. A degradation threshold of 0.7 is chosen and the degradation is assumed to start from 0.2. Fig. 5 and Fig. 6 mainly show desirable results of a more certain EOL and thus remaining useful

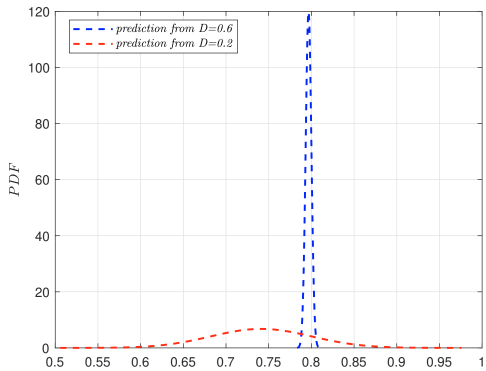

Fig. 5. PDFs of degradation at the EOL.

life when the degradation of the material is close to the threshold, conversely, the uncertainty is more distributed when prediction time is far from the threshold. It must be noted that the prediction times are selected set of instants during online operation of the plant with the estimator.

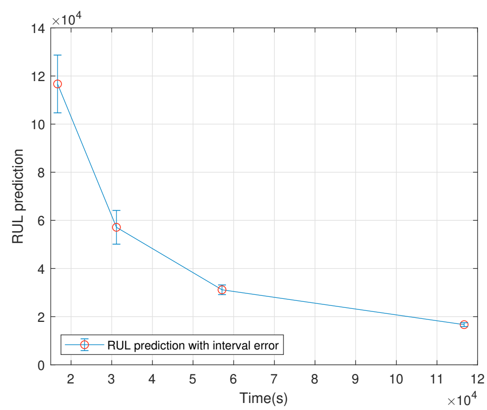

Fig. 6. Remaining useful life Predictions .

6. CONCLUSION

This paper has proposed a model-based prognostics procedure using a zonotopic Kalman filter that is able to provide a set-based propagation of degradation, aiding in the quantification of uncertainties associated with prognostics. The prognostics procedure is then applied to the degradation of a wind turbine blade material subject to a forecasted bounded set description of wind profile. To facilitate an online condition based implementation, a nonlinear based Kalman filter from the nonlinear wind turbine model is presented in a pseudo-linear form, a polytopic linear parameter varying representation, decreasing computational cost and easing in the propagation of the positive invariant zonotopic uncertainty sets to a reachable set that triggers an end of life. Using this information of health, the remaining useful life with its associated uncertainties can be predicted. The proposed approach has been tested in a benchmark wind turbine using a high-fidelity simulator.

ACKNOWLEDGEMENTS

This work has been co-financed by the Spanish State Research Agency (AEI) and the European Regional Development Fund (ERFD) through the project SaCoAV (ref. MINECO PID2020-114244RB-I00), by the European Regional Development Fund of the European Union in the framework of the ERDF Operational Program of Catalonia 2014-2020 (ref. 001-P-001643 Looming Factory) and by the DGR of Generalitat de Catalunya (SAC group ref. 2017/SGR/482).

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