Degradation analysis in a controlled flexible drive train subject to torsional phenomena under different wind speed conditions

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Mônica Spinola Félix[1], John J. Martinez[2], Christophe Bérenguer[3], Khaoula Tidriri[4]

***Abstract*— The need for predictive maintenance of wind turbines has increased. Prognostics and Health Management research is working on estimating the Remaining Useful Life with greater accuracy and to determine future operating conditions, taking into account system constraints on safety and reliability when power generation capacity is also an issue. Torsional phenomena contribute to wind turbine life degradation, and the rate of degradation depends on wind profiles. To meet health management requirements, deterioration-aware control plays a role in adjusting control responses to mitigate the resulting stress depending on known wind parameters that characterize different wind speed conditions. Therefore, a degradation analysis is proposed to analyze the degradation results for different Ornstein-Uhlenbeck parameters that express the wind speed and can be estimated with a standard Kalman Filter.**

***Index Terms*— Wind turbine system, Degradation estimation, Post-prognosis decision, Wind speed process, Kalman Filter**

I. Introduction

Wind energy has become one of the most important renewable energy sources, and its technologies, such as Wind Turbines (WT), have now been significantly improved due to its competitive cost and low environmental impact. Moreover, according to [1], the trend in this technology is toward larger turbines and more offshore installations in deeper seas. As a result, [2] predicts that Operation and Maintenance (O&M) costs will inevitably increase. On the other hand, [3] points out that reducing the unplanned maintenance rate is a strategy to reduce O&M costs. Therefore, O&M has improved toward predictive maintenance to avoid unexpected failures and more accurately schedule maintenance using prognostics to estimate Remaining Useful Life (RUL) and post-prognostic to interfere with failure projections.

Prognostics is important in O&M because it aims to forecast the health of the machine and predict the time interval until a failure occurs, known as RUL. However, there are many challenges in accurately calculating RUL in WT systems, which face constant changes in operating conditions, a lack of failure data, and significant variability in failure modes [8]. As a result, many efforts are being made to improve prognostic prediction. These can be model-based approaches, data-driven approaches, experience-based approaches, or the ensemble methods known as hybrid approaches [3].

An example of a model-based approach is proposed in [11], using dissipated energy as an image of degradation. On the other hand, special attention has been given to hybrid approaches that combine physical knowledge about a component or degradation with historical data to overcome the usual challenges of prognostics. For example, physical laws and constraints can be intrinsically embedded in the Machine Learning (ML) studied in [7], and the simulation results of the physical model can be used as input to the ML model.

Another topic covered in O&M is support for post-prognostic decisions, divided into two main categories in [6]: Maintenance Decisions and Operations Decisions. Maintenance decisions focus on maintenance planning, while operations decisions determine the future use of the system based on prognostic projections. The strategy chosen in operations decisions affects future degradation since the latter is a consequence of future operating conditions. An example of an Operation Decision is changing the control system response to maximize energy production while meeting safety and business requirements.

This topic was explored by [12], who analyzed degradation driven by the WT control system and showed that different wind speeds, e.g., laminar or turbulent, can produce more or less torsional effects in the drive train. It also showed the advantage of control configurations adapting to wind profiles when they are known. However, this work did not quantitatively investigate how the degree of turbulence affects loads and degradation, and the influence of different mean wind speeds was not considered.

This paper investigates how a wind speed profile can damage a drive train shaft of WT, relating the wind characteristics to the severity of the damage. The contribution of this work is broaden the perspectives of a RUL control approach for WT where this relationship can be used. First, it is assumed that the wind speed profile is divided into a mean and fluctuations [10], which can be expressed as an Ornstein-Uhlenbeck (OU) process, where the model parameters are considered as wind characteristics. Fluctuations, for example, are modeled as wind turbulence. Next, these wind model parameters are estimated for different wind speeds using a standard Kalman Filter and then related to the associated dissipated energy level for a final degradation analysis. A model of WT that incorporates torsional phenomena is considered to

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estimate the shaft degradation represented by the total energy dissipated in the power generation process.

Accordingly, this paper is organized as follows: Section II addresses the perspective of an adaptive controller that accounts for degradation effects. Next, Section III deals with the considered wind speed model and the WT model, which physically represents the dynamics of WT, including the torsional effects on a shaft at the rotor level. In addition, this section describes the Kalman Filter used to estimate the wind speed parameters. Finally, Section IV shows the results of the parameter estimation, and Section V provides an analysis of the total energy dissipated due to different wind speed profiles in simulated and real wind cases.

II. Degradation-aware control

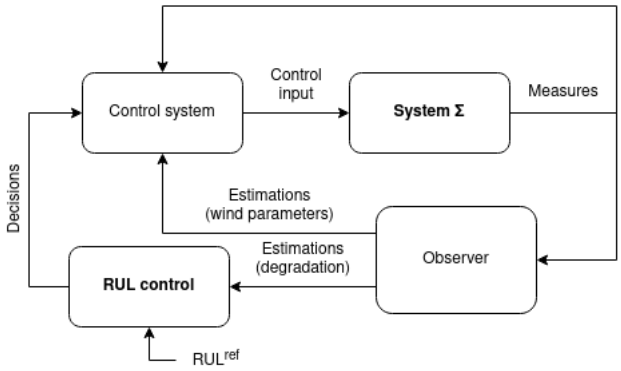


Fig. 1: Degradation-aware control framework.

This paper is concerned with determining the relationship between wind characteristics and the rate of deterioration. However, this analysis is part of a broader discussion of a framework for Degradation-Aware Control, a controller that incorporates prognostic information into the control loop and uses estimated wind parameters to adjust its configurations to manage the trade-off between power generation and reliability.

Degradation-Aware Control, also referred to as Health-Aware control in [9], has been explored in some works that provide indications of how the control loop can be used to govern the RUL of a machine and to support decision making in post-prognostics. For example, in [8], the authors demonstrated the possibility of extending the life of a WT by using prognostic to adjust control weights through load mitigation control. Another work is presented in [11], which proposes to control the RUL for a friction drive system by using a dynamic system model to estimate the state of deterioration and adjust the angular velocity reference, making the control objectives more reliable.

More specifically, Deterioration-Aware control means that the deterioration state of the machine is taken into account in the control objectives. An example of this is adding a RUL reference to the control objectives, such as power generation and stability. Fig. 1 illustrates a framework for the control approach. First, an estimate is made of how much stress is allowable for power generation. This is calculated by a RUL controller that takes into account the degradation accumulated up to the time of the decision and the RUL target, given by maintenance requirements. Once the stress limit is set, the control law can adjust the control parameters to meet these requirements and control deterioration response. However, the loading responses depend also on the environmental conditions to which the system is subjected. In the case of wind turbines, this condition is related to wind speed, e.g., intensity and fluctuations. Therefore, the control system should be adjusted depending on the estimated parameters expressing these wind characteristics.

An example of adaptive control in this framework could be gain scheduling that considers estimated wind parameters. For instance, determining the relationship between these parameters and degradation allows the controller to adjust its weights as a function of wind speed parameters to mitigate the estimated degradation rate. Moreover, hybrid models can estimate degradation or predict RUL if this relationship between degradation data and wind profile is embedded in a ML model. Finally, approaches that respond to other types of decisions, such as maintenance actions, could also be proposed with this framework.

III. System model

This section covers the model to represent the system studied in this paper. First, it explores the wind speed model and its characteristic parameters. Then, the WT simplified model dynamics, including torsion of the drive train shaft effects is presented. Finally, an approach based on Kalman Filter is used to estimate the wind speed parameters.

A. Wind speed model

According to [4], the wind speed can be decomposed into a mean term $\bar{V}$ and fluctuations $\tilde{v}$, as shown in (1). While the mean term is the low-frequency term, the fluctuations are the high-frequency turbulence term.

$$v(t) = \bar{V} + \tilde{v}(t) \tag{1}$$

[10] modeled the fluctuation part as an Ornstein-Ullenbeck process (OU) with a stochastic differential equation (SDE) as seen in (2) to represent the wind speed behavior.

$$dV(t) = \alpha(V(t), t)(t)dt + \beta(V(t), t)dW \tag{2}$$

The OU process is stochastic, and the wind $V(t)$ is a stationary autocorrelated diffusion. It contains a strictly negative drift term $\alpha(V(t), t)$ and a diffusion term, $\beta(V(t), t)$, which determines the magnitude of dW, the Brownian motion.

This model can be used to represent 99% of the wind speed profile, and [10] proposed a variant (3) to describe the increment of the wind speed sequence.

$$\dot{v}(t) = -\alpha(v(t) - \bar{V}) + \beta\eta_v \tag{3}$$

In this equation (3), α is the mean reversal dynamics and the velocity of turbulence variance, $\bar{V}$ is the average wind speed, η_v is the Brownian motion that is weight by β. The wind profile is a stochastic process and is considered

non-stationary here. Therefore, α and $\bar{V}$ are parameters that change with time, but can be estimated. Also, higher turbulence is expected to be associated with higher values of α.

[12] has shown that high turbulence in wind speed produces more loads than lower turbulence, but the intensity of wind speed, or mean $\bar{V}$, also affects loads. In addition, estimates can be made based on real wind speed, and knowing the relationship with accumulated damage leads to a way to mitigate the load based on these estimated parameters.

B. Wind turbine mechanical model

Energy is generated by a WT system due to its response to wind flows that produce kinetic energy, and the wind power can be expressed as follows:

$$P_{wind} = \frac{1}{2}\rho\pi R^2 v^3, \tag{4}$$

where ρ (kg/m^3) is the air density, R (m) is the rotor ratio and v (m/s) is the wind speed.

This power P_{wind} is converted into rotational motion in the rotor with an angular velocity ω_r and a torque τ_r, producing a power P that can be calculated as follows:

$$P = \tau_r \omega_r \tag{5}$$

Wind energy is not completely extracted, and the energy conversion efficiency, called C_p, depends on the blade's angle β and the ratio between the rotor angular velocity and the available wind speed, called the tip- speed ratio λ.

$$C_p(\beta, \lambda) = \frac{P}{P_{wind}} \tag{6}$$

Usually, the control law aims to maximize C_p and achieve the best power generation performance by finding the best arrangement of β and λ.

The modeling of these systems can be very complex, but we neglect loads in the tower and in the blades to focus on a simplified model to represent the forces and dynamics in aerodynamics and in the flexible shaft drive train, proposed in [5].

$$\dot{\omega_r}(t) = \frac{1}{J_{eq}}\tau_r(t) - \frac{K_{dt}}{J_{eq}}\theta_\Delta(t) - \frac{B_{dt}}{J_{eq}}(\omega_r(t) - \omega_g(t)) \tag{7}$$

$$\dot{\omega_g}(t) = \frac{K_{dt}}{J_{eq}}\theta_\Delta(t) + \frac{B_{dt}}{J_{eq}}(\omega_r(t) - \omega_g(t)) - \frac{1}{J_{eq}}\tau_g(t) \tag{8}$$

$\dot{\omega}_r$ and $\dot{\omega}_g$ are the rotor and generator acceleration, respectively. $\dot{\omega}_g$ is controlled by a torque at the generator level τ_g, while $\dot{\omega}_r$ is controlled by τ_r, the aerodynamic forces resulting from (4)-(6).

$$\tau_r = \frac{K_T C_p(\beta, \lambda) v^3(t)}{\omega_r(t)}, \tag{9}$$

where $K_T = \frac{1}{2}\rho\pi R^2$. [5] modeled the drive train subsystem as two rigid bodies connected by a flexible shaft. The rigid bodies correspond to all mechanical parts on both sides of the effective shaft. Accordingly, the terms rotor moment of inertia (J_{eq}), generator moment of inertia (J_{eq}), drive train torsional stiffness (K_{dt}) and drive train torsional damping coefficient (B_{dt}) denote physical parameters of the model.

The dynamics suffers from the influence of inertia J_{eq} and a stiffness K_{dt} and damping factor B_{dt} of a torsion defined as the difference θ_Δ between the angular position of rotor θ_r and generator θ_g.

$$\theta_\Delta(t) = \theta_r(t) - \theta_g(t) \tag{10}$$

In this work, one considers a WT of 2 MW with the parameters shown in Table I.

TABLE I: Wind turbine parameters

Symbol	Description	Unit	Value
J_{eq}	Equipment moment of inertia	$[kgm^2]$	1.1×10^6
K_{dt}	Torsional stiffness	$[kg/s]$	1.0×10^8
B_{dt}	Damping coefficient	$[kg/s^2]$	7.5×10^5

C. Dissipated energy model

Heat and vibration, commonly used for fault diagnosis, are phenomena in which energy is dissipated. For this reason, [11] has suggested using dissipated energy to estimate accumulated deterioration. In this context, the dissipated energy E_d is a sum of the dissipated power P_d expressed as follows:

$$E_d = \int_0^t P_d dt \tag{11}$$

Torsional effects lead not only to degradation of the material but also to loss of energy in the motions, and the dissipated power P_d can be calculated in as:

$$P_d = \tau_d(\omega_r - \omega_g), \tag{12}$$

where the damping force τ_d is a product of a damping factor B_{dt} that depends on the material and the relative angle velocity in the shaft:

$$\tau_d = B_{dt}(\omega_r - \omega_g) \tag{13}$$

D. Synthesis of a standard Kalman filter for wind parameters estimation

The model in equation (3) is a continuous-time form of the discrete-time AR (1) model and can be represented in a state-space model. Let the system (3) be formatted as follows:

$$v_k = v_{k-1} + \alpha v_{k-1} + \alpha\bar{V} + \beta\eta_k \tag{14}$$

Denoting

$$y_k = v_k - v_{k-1}, \tag{15}$$

we have

$$y_k = C_k x_k + e_k, \tag{16}$$

where $C_k = \begin{bmatrix} v_{k-1} & 1 \end{bmatrix}$, $x_k = \begin{bmatrix} \alpha & \alpha\bar{V} \end{bmatrix}^T$ and e_k is the residual error expressed as $e_k = \beta\eta_k$ with $\eta \sim \mathcal{N}(0, 1)$. One assumes wind speed is stochastic and the change in x_k is random and independent from last value, thus

$$x_{k+1} = A_k x_k + \epsilon_k \tag{17}$$

where $A_k = I$ and ϵ_k, an innovation factor. So, the model can be represented under a state-space form as follows:

$$\begin{cases} x_{k+1} = x_k + \epsilon_k \\ y_k = C_k x_k + e_k \end{cases} \tag{18}$$

A standard Kalman Filter is proposed to estimate the parameters $X \in \mathbb{R}$. This filter aims to estimate the values of x with a filter gain that updates the values by learning with innovations of the wind speed signal (15).

To this aim, the innovation covariance S_k is obtained as follows:

$$S_k = C_k P_k C_k^T + R \tag{19}$$

and the Kalman gain K_k as follows:

$$K_k = P_k C_k^T S_k^{-1} \tag{20}$$

The update of the state estimate is then:

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k(y_k - C_k \hat{x}_{k|k-1}) \tag{21}$$

Finally, the a posteriori covariance matrix can be updated with.

$$P_{k|k} = (I - K_k C_k) P_{k|k-1} \tag{22}$$

IV. Estimation of OU parameters with KF

This section shows the results of using a KF to estimate the parameters of the OU process.

A. Wind speeds experimental data

In order to investigate the performance of using a KF to estimate the OU parameters, the wind speed is simulated using the wind speed model proposed in [10]. With this model it is possible to generate different wind classes of wind, where the transition between the different winds follows a Markov chain (MC) distribution. A first MC governs the transition of the mean wind speed between several values, and another governs the fluctuation part of the OU process. Fig. 2a shows the resulted wind speed simulated for 12 hours using [10] with a sampling rate of 1 Hz. Real wind speed measurements are also used to test the performance of the estimator. It corresponds to 1 h measurements with a sampling rate of 1 Hz, as shown in Fig. (2b).

Remark that the estimator must be able to identify the OU parameters such as $\hat{\alpha}$ and $\hat{\bar{V}}$ for all degrees of turbulence. We consider the residual error $e = y - C\hat{x}$ and that $\sigma_e = \beta\sigma_n$ and $\sigma_n = 1$ when $\eta \sim \mathcal{N}(0, 1)$. Thus, β factor is calculated using variance σ_e.

B. Estimation for simulated case

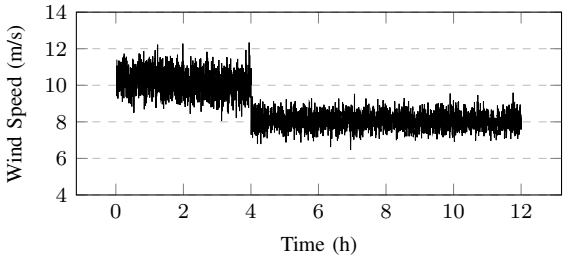
The results for the simulated case in Fig. (3a) show that KF estimates the parameter $\hat{\alpha}$ (black line) such that it converges to the true value parameter (red line) and every transition of α is registered. Note that $\alpha = 1$ represents wind type 1 and low α represents wind type 2. Changes on $\hat{\bar{V}}$ and $\hat{\beta}$ were also identified and estimated, Figs. (3b) and (3c). Thus, the standard KF was enough to estimate OU process parameters for a simulation scenario.

C. Estimation for real case

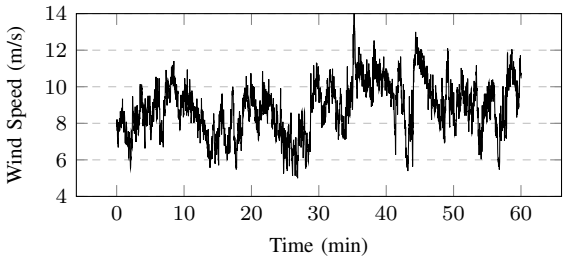
For the real wind data, estimated values results is seen in Fig. 4. Note that the actual parameters are unknown. But, α converges to a constant of a wind type 2, whereas β varies between 0.40 and 0.45. A significant change in the trend of $\hat{\bar{V}}$ is identified, from 8 m/s to 9 m/s at 35 min. It is also possible to express the results in terms of their means and variance, as shown in Table II.

TABLE II: Estimated parameters for real data

Parameters	Mean	σ
$\hat{\alpha}$	0.0657	0.0245
$\hat{\beta}$	0.4363	0.0307
$\hat{\bar{V}}$	8.93	0.7535



(a)



(b)

Fig. 2: Wind speeds used in the study case: (a) 12 hours of generated wind data using [10] and (b) 1 hour of measured wind speed.

V. Numerical experiments: dissipated energy as degradation image for different wind speeds

As explored in [12], the wind turbine shaft deteriorates at a rate that depends on the wind conditions. Therefore, the observation of wind characteristics can be used by a control strategy to mitigate the loads and more accurately control the trade-off between performance and degradation. Remark that the wind fluctuations have different degrees of turbulence and can be represented by the α and β parameters. Also, the mean wind speed, represented here by $\bar{V}$, affects the degradation dynamics. Thus, to investigate how α, $\bar{V}$ and β affect the torsional phenomena, it is proposed to compare and quantify the dissipated energy for different values of OU parameters that generates different wind speed conditions.

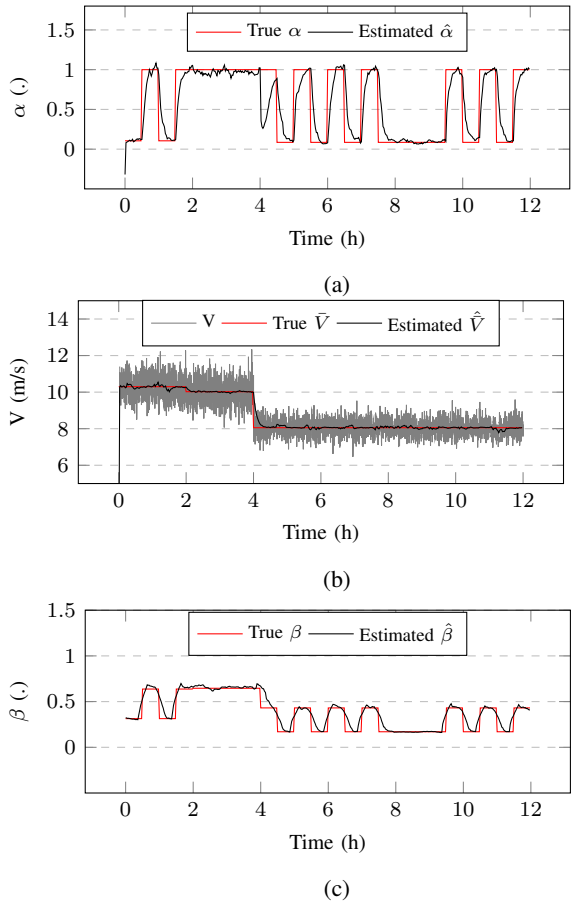


Fig. 3: Estimation of OU parameters (a) $\hat{\alpha}$ (b) $\hat{\bar{V}}$ and (c) $\hat{\beta}$ of generated wind data using [10].

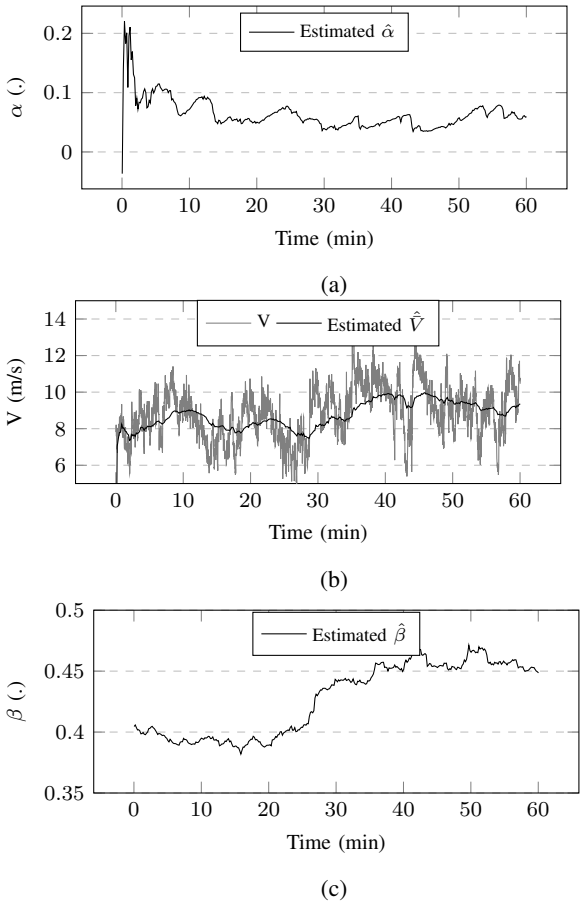


Fig. 4: Estimation of OU parameters (a) $\hat{\alpha}$ (b) $\hat{\bar{V}}$ and (c) $\hat{\beta}$ of real measured wind data.

A. *Validation of wind simulated to degradation analysis*

For each parameter, wind speeds are generated using [10] to simulate different wind speed conditions used as input to the WT model to calculate the dissipated energy. Initially, it is proposed to validate whether the dissipated energy corresponding to the simulated wind speed is comparable to the dissipated energy caused by a real wind speed condition. To this end, a first experiment tests whether a wind generated using the average of the estimated parameters from Table II produces a total dissipated energy equivalent to the real wind, with varying and actual parameters, for the same amount of time. The resulting wind from the averaged values is shown in Fig 5.

The dissipated energies in Fig. 6 corresponds to 32308 Wh for 60 minutes of real wind speed and 32601 Wh for 60 minutes of simulated wind speed, indicating that the generated wind from OU model can be used to represent a similar degree of dissipated energy, corresponding here to the total degradation.

B. *Analysis of dissipated energy for different values of OU parameters*

Finally, experiments are proposed to evaluate the dissipated energy as a function of different OU parameters that

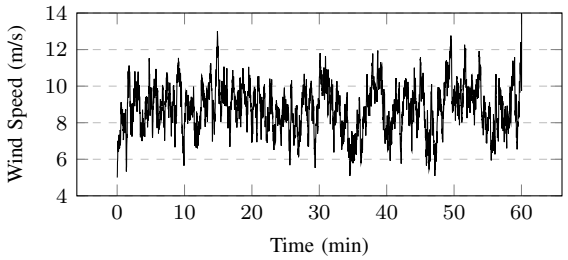


Fig. 5: Wind speed generated using mean values of Table II.

results in different wind speeds. The set of values proposed to represent different degrees of turbulent winds was $\alpha = \{0.01 - 1\}$ and $\beta = \{0.01 - 1\}$ and $\hat{V} = \{6 - 16\}(m/s)$.

This experiment takes the wind generated from the average values of Fig. (5) and changes one parameter each time based on the set of values proposed. As a result, it is possible to observe in Fig. 7 the energy dissipated, resulting in each parameter value estimated with a KF. The red mark corresponds to the dissipated energy and parameter of the real wind speed.

It is considered turbulent winds when diffusion term β and drift term α have high values, and it confirms that more energy is dissipated as a function of higher values of

these terms. Furthermore, mean speed $\bar{V}$ also increases the degradation. In all cases, a nonlinear relationship can be observed. Also, high values of β led to more fluctuating results, concluding that the dissipated energy is more sensitive for high values of diffusion term. For instance, the higher values in Fig. (7c) present a higher variance, which can be explained because high values of β can affect the system's instability. The results of real wind speed fit the resulting curves and represent low energy dissipated for the three parameters.

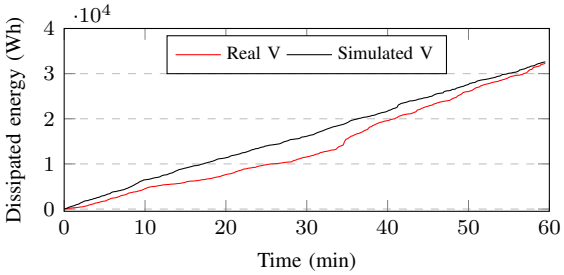


Fig. 6: Energy dissipated of simulated wind (black) with mean values parameters and real wind with actual varying parameters (red).

VI. Conclusion

This article aims to analyze the degradation caused by different wind speed profiles quantitatively. First, the concept of degradation-aware control was explored, where this type of analysis is helpful. Then, a standard KF was used to estimate the parameters of an OU process that can distinguish two wind classes, laminar and turbulent, and different degrees of wind fluctuations. The results showed a link between wind speed characteristics, represented by these parameters, and the dissipated energy. Once the parameters are estimated, they can be used to distinguish different wind conditions by a gain-scheduling control or degradation-aware control that accounts for the relationship between these parameters and degradation explored in this work. Future work includes enriching this analysis with other degradation models, such as the fatigue model commonly used in RUL prediction, and using this information to develop a degradation-aware control. In addition, further real wind measurements of other profiles can help create a data-driven or hybrid model to represent the degradation rate as a function of the wind parameters that can be estimated.

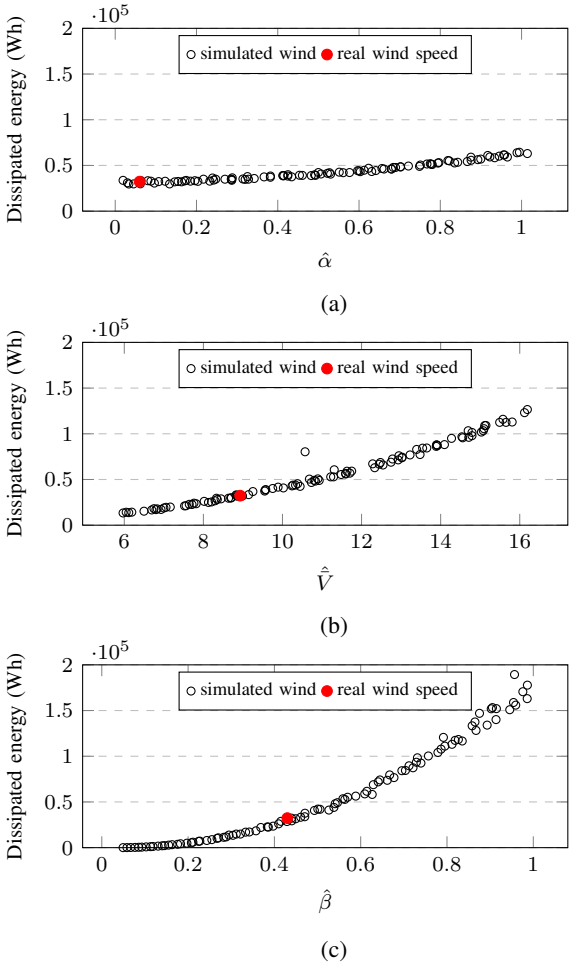


Fig. 7: Dissipated energy as a function of (a) drift term α (b) mean speed $\bar{V}$ and (c) diffusion term β, OU parameter values estimated with a KF.

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