



# Long-term degradation estimation of wind turbine drive-train under a gain-scheduling control strategy according to the weather conditions

Elena Esther Romero Fandino, John Jairo Martinez Molina, Christophe Bérenguer

## ► To cite this version:

Elena Esther Romero Fandino, John Jairo Martinez Molina, Christophe Bérenguer. Long-term degradation estimation of wind turbine drive-train under a gain-scheduling control strategy according to the weather conditions. AMEST 2022 - 5th IFAC Workshop on Advanced Maintenance Engineering, Services and Technologies - AMEST 2022, IFAC; Universidad de los Andes; Tecnológico de Monterrey, Jul 2022, Bogotá, Colombia. pp.13-18, 10.1016/j.ifacol.2022.09.177 . hal-03796669

**HAL Id: hal-03796669**

**<https://hal.science/hal-03796669>**

Submitted on 4 Oct 2022

**HAL** is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



Distributed under a Creative Commons Attribution - NonCommercial - NoDerivatives 4.0 International License

# Long-term degradation estimation of wind turbine drive-train under a gain-scheduling control strategy according to the weather conditions

Elena E. Romero \* Christophe Bérenguer \* John J. Martinez \*

*\* Univ. Grenoble Alpes, CNRS, Grenoble INP, GIPSA-lab, 38000  
Grenoble, France.*

*(e-mail: elena-esther.romero-fandino@grenoble-inp.fr,  
christophe.berenguer@grenoble-inp.fr,  
john-jairo.martinez-molina@grenoble-inp.fr)*

---

## Abstract:

This paper proposes a methodology to analyze the long-term degradation of a wind turbine drive-train using a gain-scheduling control strategy considering the variation in the wind conditions. The degradation in the transmission is modeled through a simplified dynamical system based on contact mechanics, employing the dissipated energy as an indicator of the degradation in the shaft. In addition, a gain-scheduling control strategy is considered to assign a control gain according to the wind flow conditions. The long-term simulation is based on the accelerated degradation due to turbulent wind compared to the laminar flow. Numerical experiments were considered to illustrate the proposed approach, assuming a 2 MW variable speed-fixed pitch turbine with a horizontal axis and fixed gearbox.

*Keywords:* Deteriorating Modeling, Wind Turbine Control, Gain-Scheduling Control Strategy, Wind Conditions.

---

## 1. INTRODUCTION

The global renewable electricity sector is expected to develop 60% by 2026, where wind energy plays a critical role. By 2030, the wind generation sector is expected to cover 21% of the global electricity demand and will continue growing until it reaches 35% for 2050. Today, the efforts to increase the coverage of the wind turbine sector continue expanding; just in the United States it grew at a record pace in 2020, representing the largest source of recent additions to the U.S. electric-generating capacity with 17 MW (Lee and Zhao (2021); American Clean Power Association (2021); Komusanac et al. (2021)).

However, the drive-train wind turbine is susceptible of degradation and anticipated failure, affecting the efficiency of this technology and improving the necessity of maintenance works. Numerous studies found that the cost of operation in a wind turbine is approximately 35% of the capital expenditure, where 80% is related to unscheduled maintenance issues, and 17% of the failures are related to some part of the shaft (Merainani et al. (2022); Tchakoua et al. (2014)).

The variability in wind speed represents a factor decreasing the lifetime of the components in the turbine transmission due to the fatigue damage and vibrations in the shaft (Romero et al. (2021); Bianchi et al. (2007); Ma et al.

(2018)). Therefore, in Romero et al. (2022), a procedure to adapt the control strategy to varying wind conditions was proposed to mitigate the effect of random change in the wind, based on a control gain switch depending on regime flow for a short period of analysis.

On the other hand, the useful lifetime of a wind turbine is designed to be approximately 20 years; for this reason, in the industry, the maintenance strategies are designed to evaluate the deterioration in the long term. However, the system can be affected when the change in wind intensity occurs in minutes. Consequently, it is necessary to have a strategy to predict deterioration in the long term, considering the wind changes in a short time.

This paper proposes a methodology to simulate deterioration in the mechanical components of the drive-train in a wind turbine for the extended term, when subjected to control strategy adapted to follow the variations in the wind conditions. The approach allows simulating degradation by first learning an empirical relationship with random effect between Dissipated Energy and Time, and then generating new information using the learned relation with the inferred probability law for the random parameters. Furthermore, the methodology was tested for different periods of the useful theoretical lifetime of a wind turbine, considering the variation in the wind conditions changing between laminar and turbulent flow, using a sequence generated with a Markov Chain. Finally, the results allow knowing the percentage of degradation that

---

\* Elena E. Romero, John J. Martinez and Christophe Bérenguer are with the Univ. Grenoble Alpes, CNRS, Grenoble INP, GIPSA-lab, 38000 Grenoble

can be reduced if a gain-scheduling control approach is implemented, taking into account the wind conditions.

## 2. DRIVE-TRAIN DEGRADATION MODEL UNDER AN GAIN-SCHEDULING CONTROL STRATEGY

### 2.1 Wind Turbine Dynamical Model

The dynamics of a drive-train in a Variable Speed-Fixed Pitch (VS-FP) wind turbine can be modeled as two rigid bodies connected by a flexible drive-train, as suggested in Bianchi et al. (2007). The generator (low-speed mass) and the rotor (high-speed mass) are linked by a flexible shaft deformed with an angle  $\theta_s$  when the generator speed ( $\omega_g$ ) and rotor speed ( $\omega_r$ ) are different. In this type of system, it is common to employ a simplified model to describe the wind energy dynamics, considering the torsional loads and resonance mode in the drive-train as follows:

$$\begin{pmatrix} \dot{\theta}_s \\ \dot{\omega}_r \\ \dot{\omega}_g \end{pmatrix} = \begin{pmatrix} 0 & 1 & -1 \\ -\frac{K_s}{I_r} & -\frac{B_s}{I_r} & \frac{B_s}{I_r} \\ \frac{K_s}{I_g} & \frac{B_s}{I_g} & -\frac{B_s}{I_g} \end{pmatrix} \begin{pmatrix} \theta_s \\ \omega_r \\ \omega_g \end{pmatrix} + \begin{pmatrix} 0 & 0 \\ \frac{1}{I_r} & 0 \\ 0 & -\frac{1}{I_g} \end{pmatrix} \begin{pmatrix} \tau_r \\ \tau_c \end{pmatrix} \quad (1)$$

where  $I_r$  and  $I_g$  are the rotor and generator inertia correspondingly,  $B_s$  the damping of the transmission and,  $K_s$  the stiffness of the transmission.

The forces created on a wind turbine shaft by an airflow are referred to as aerodynamic torque ( $\tau_r$ ), and can be calculated as:

$$\tau_r = \frac{1}{2} \rho \pi R^3 \frac{C_p(\lambda, \beta)}{\lambda} V^2 \quad (2)$$

With  $\rho$  the air density,  $R$  the rotor radius, and  $V$  is the wind speed. Concerning the power coefficient ( $C_p(\lambda, \beta)$ ), it is an efficiency measure that relates the wind speed with the actual electric power produced by the system. There exists different methods for estimating  $C_p(\lambda, \beta)$ ; however, this work considers the numerical approximation proposed in Saint-Drenan et al. (2020) that takes into account the pitch angle  $\beta$  and the tip speed ratio  $\lambda$ .

In order to reach the maximum energy produced,  $\omega_r$  must be adjusted in relation to the  $V$  to maintain the optimal tip speed-ratio ( $\lambda = \lambda_0$ ), which is achieved when  $C_p(\lambda, \beta)$  is in the maximum point ( $C_{p_{max}}$ ) and  $\beta \approx 0$  (Bianchi et al. (2007)). The generated energy during the time  $t$  is defined as:

$$E_g = \int_0^t P_g dt \quad (3)$$

with  $P_g$  defined as the product of  $\tau_c \omega_r$ , where  $\tau_c$  is the generator torque, which is given as a function of the  $\omega_r$  and the optimal feedback control gain  $K_c$  (see for instance Johnson et al. (2006)):

$$\tau_c = K_c (\omega_r)^2 \quad (4)$$

The control objective is to maximize the energy captured by operating the turbine at  $C_{p_{max}}$  and  $\lambda_0$ . For variable speed turbine, the theoretical control gain  $K_c^{nom}$  is defined

as in equation (5), with  $A$  as the rotor swept area (Johnson et al. (2006)).

$$K_c^{nom} = \frac{1}{2} A R^3 \frac{C_{p_{max}}}{\lambda_0^3} \quad (5)$$

### 2.2 Degradation Model

The deterioration phenomena can be estimated using the dissipated energy ( $E_d$ ) as an image of the degradation mechanical components on the shaft following a model presented in Romero et al. (2021).

The model considers a system of two rigid bodies (generator and rotor) connected by a spring (flexible shaft). Considering a mechanical contact principle (Hunt and Crossley (1975)), the damping in the transmission ( $B_s$ ) is modeled as a non-linear function of the torsion angle ( $\theta_s$ ), also taking into account the stiffness of the transmission ( $K_s$ ) and a parameter that depends on the material ( $\alpha$ ) (Romero et al. (2021)):

$$B_s(\theta_s) = \frac{3}{2} \theta_s \alpha K_s \quad (6)$$

Besides, the dissipated energy ( $E_d$ ) is defined as a function of  $B_s(\theta_s)$  and the square of the rotational speed difference as follows:

$$E_d = \int_0^t B_s(\theta_s) (\omega_g - \omega_r)^2 dt \quad (7)$$

### 2.3 Gain-Scheduling Control Strategy

The degradation of a wind turbine is significantly affected when the control system is adjusted without considering the wind flow conditions. The analysis presented by Romero et al. (2021) demonstrated an accelerated degradation when the control gain is different from the nominal gain ( $K_c^{nom}$ ). Besides, the changes in the wind flow lead to an increment of dissipated energy.

Nevertheless, Romero et al. (2022) presented a gain-scheduling control strategy that allows optimizing the lifetime of the mechanical transmission components using a trade-off between generated energy and dissipated energy while the turbine is exposed to variations in the wind flow.

The strategy proposes to consider two scenarios of wind conditions (laminar and turbulent), and to use two possible suitable control gains ( $K_c^{laminar}$  and  $K_c^{turbulent}$ ) to

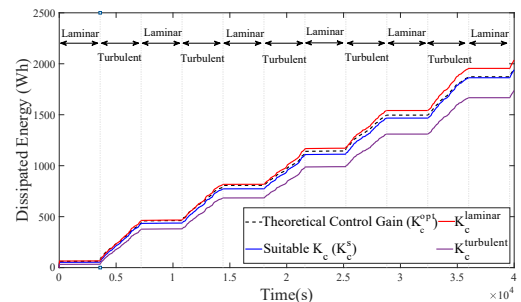


Fig. 1. Dissipated Energy for different control feedback gains  $K_c$ . (Romero et al. (2022)).

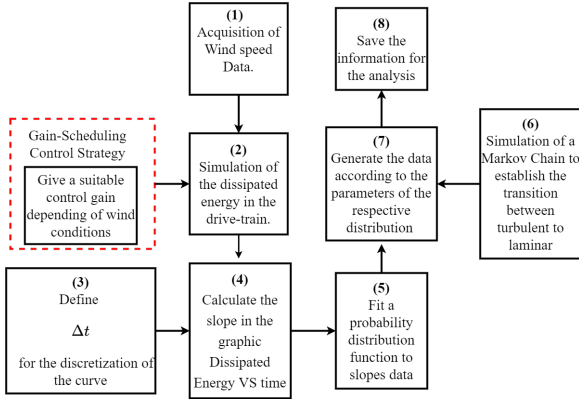


Fig. 2. Diagram for the simulation of long term deterioration analysis.

obtain a reduction in  $E_d$ . For the case of  $K_c^{laminar}$ , the optimal control gain can take values 11% above  $K_c^{nom}$ , and for the turbulent case 15% below  $K_c^{nom}$ .

In addition, various scenarios were considered for the validation of the strategy: in three scenarios, the control gain was set in a constant value ( $K_c^{nom}$ ,  $K_c^{laminar}$ , and  $K_c^{turbulent}$ ), and in an other scenario a suitable gain-scheduled control gain was established according to the wind conditions.

The results from Fig.1 show the behavior of  $E_d$  for the different cases in simulations of 12 hours. The figure demonstrates that turbulent wind leads to accelerated degradation. However, it is possible to observe that implementing a gain-scheduling control strategy can decrease the energy dissipated.

Note that the case with  $K_c^{laminar}$  always leads to a major degradation than with  $K_c^{turbulent}$  due a greater  $K_c$  always leads to a major amount of dissipated energy, as is mentioned in Romero et al. (2021). Nevertheless, the behavior can be approximated to the hypothetical control case using a suitable control gain.

### 3. PROPOSED METHODOLOGY FOR LONG TERM DETERIORATION SIMULATION

A wind turbine is designed to operate for approximately 20 years, and in most cases, it hardly achieves a useful life of 7 years without replacing a transmission part. Besides, analyzing degradation in the long-term usually does not reflect the effects of variations in the wind conditions as in an analysis second-wise during a short period, (Jantara et al. (2020)).

However, the gain-scheduling control strategy proposed in Romero et al. (2022) can allow extrapolated analysis of deterioration in the drive-train for a long-term simulation considering the variations in the wind. For example, in Fig. 1, it is possible to observe that the slope of the curve is more pronounced in the periods when the wind is turbulent than in the laminar case.

This paper presents an approach to evaluate the deterioration in the long-term of a drive-train in a wind turbine by learning the curve of Dissipated energy vs. Time for different wind conditions and using a Markov chain to estimate the transition between each case of wind conditions.

The process for the simulation of deterioration in the long term is illustrated in Fig.2, and comprises the following steps:

Steps (1) to (5) have to be made for each wind condition separately. This work will consider two wind conditions (laminar and turbulent).

- (1) Acquisition of Wind Speed Data: To get the wind speed data, consider utilizing the information of each wind condition.
- (2) Simulation of the dissipated energy in the drive-train implementing the gain-schedule control strategy, using the deterioration model presented in Section. 2.2 for simulating the dissipated energy. Moreover, use a suitable control gain depending on the wind conditions (in this work,  $K_c^{laminar}$  and  $K_c^{turbulent}$ , depending on the wind conditions).
- (3) Define  $\Delta t$  for the discretization: Define a constant or discrete interval  $\Delta t$  to analyze the information of dissipated energy with a sampling period of one second. e.g., for one day of simulation (86.400s), it is possible to use a discretization of 10 minutes ( $\Delta t = 600s$ ).
- (4) Calculate the slope in the Dissipated Energy VS time curve: Estimate the slope of the Dissipated Energy VS time curve for each  $\Delta t$  period. e.g., for the case of  $\Delta t = 600s$  and one day of simulation (86.400s), this leads to 144 data of slopes.
- (5) Fit a probability distribution function to slopes data: Find an appropriate probability distribution and estimate the respective parameters that fit the data of the slopes in each case of interest.
- (6) Simulation of a Markov Chain to establish the transition between turbulent to laminar: To simulate long-term wind conditions, it is necessary to establish a sequence of changes between laminar and turbulent wind; using a Markov chain allows modelling the transition probability between laminar and turbulent and the probability of sojourn in each flow regimen.

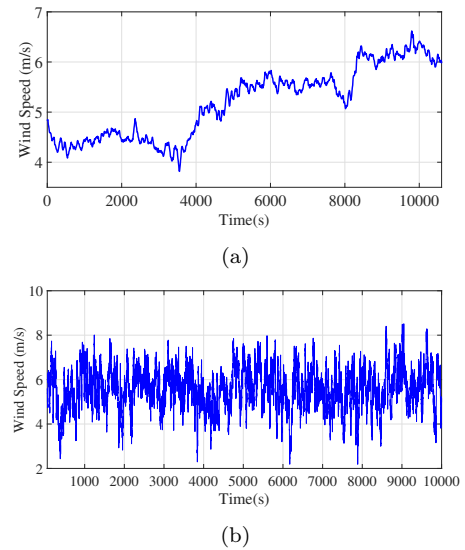


Fig. 3. Considered wind speed conditions: (a) laminar and (b) turbulent

- (7) Generate new slopes data: Considering a Markov Chain sequence, generate new slope data using the fitted probability distribution function.
- (8) Save the information for the analysis.

The procedure can be done with as many repetitions as desired to improve the exactitude of the analysis, as well as different wind conditions (e.g., considering different levels of turbulence).

#### 4. SIMULATION SETTING

In this work, a VS-FP wind turbine was simulated with a power of 2 MW, 100 m of rotor diameter, fixed gearbox, and horizontal axis. Furthermore, a simplified representation was considered to analyze the transmission system, where the rotor and generator are represented by two rigid bodies connected by a flexible shaft (drive-train).

This section presents the process of acquiring wind data and implementing the deterioration model to obtain the information necessary for estimating the dissipated energy in the long term considering the gain-scheduling control strategy. All the simulation presented in this work, were made in Matlab Software.

##### 4.1 Wind Speed Generation

In this paper, different wind conditions are taken into account to simulate the deterioration under a realistic scenario:

- For the simulation of the laminar flow, real wind data is used to feed the model.
- To reproduce the different levels of turbulence, a stochastic model with two levels of Markov Chain was used as proposed by Ma et al. (2018). The stochastic equation (8) allows to change the intensity of the variation in the wind, using a drift ( $\hat{a}(V(t), t)$ ) and diffusion ( $\hat{b}(V(t), t)$ ) terms, as well as  $dW$  for the standard Wiener process. The possibles values for the

parameters of equation (8) is given for a two-level Markov chain presented in Ma et al. (2018).

$$dV(t) = -\hat{a}(V(t) - \hat{u})dt + \hat{b} dW(t) \quad (8)$$

The resulting laminar and turbulent wind are shown Fig. 3a and Fig. 3b respectively. In both scenarios, wind speed data is register in second by second during 10.000 seconds.

##### 4.2 Gain-Scheduling Control Strategy Setting

Let assume that the turbine under analysis has  $C_{p_{max}} = 0.4615$  at  $\lambda_0 = 6.4$  and considering the equation (5),  $K_c^{nom} = 9.5065e5$ . A gain-scheduling control strategy is implemented to determine a suitable control gain for each wind condition ( $K_c^{laminar}$  and  $K_c^{turbulent}$ ). The dissipated energy was investigated under the following cases:

- Laminar wind with  $K_c^{laminar}$
- Laminar wind with  $K_c^{nom}$
- Turbulent wind with  $K_c^{turbulent}$
- Turbulent wind with  $K_c^{nom}$

The values of  $K_c^{laminar}$  and  $K_c^{turbulent}$  were defined considering the results in Romero et al. (2022):

- For laminar wind:  $K_c^{laminar}$  can take values up to 11% above of  $K_c^{nom}$
- For turbulent wind:  $K_c^{turbulent}$  can take values down to 15% below of  $K_c^{nom}$

##### 4.3 Simulation of Long Term Deterioration

In this work, the discretization of the curve Dissipated Energy vs. Time was made assuming that  $\Delta t = 600s$ , due to the fact the transition between wind conditions is not instantaneous and the record time in some systems is usually 10 minutes (e.g., SCADA).

Probability distribution functions were fitted of slopes data in each case using the Distribution Fitter app (Matlab Software). The results shows that the better fit for each case are:

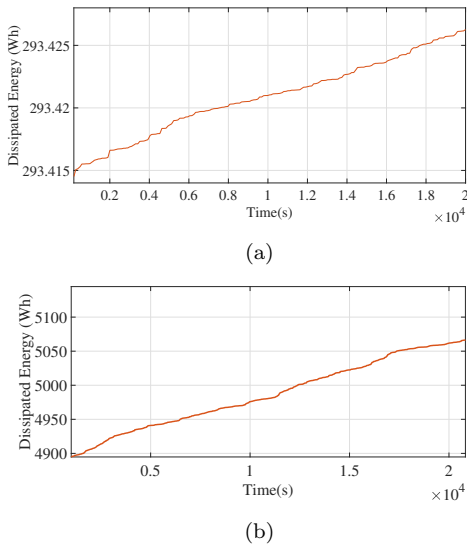


Fig. 4. Dissipated Energy with  $K_c^{nom}$ : (a) Laminar wind and (b) Turbulent wind

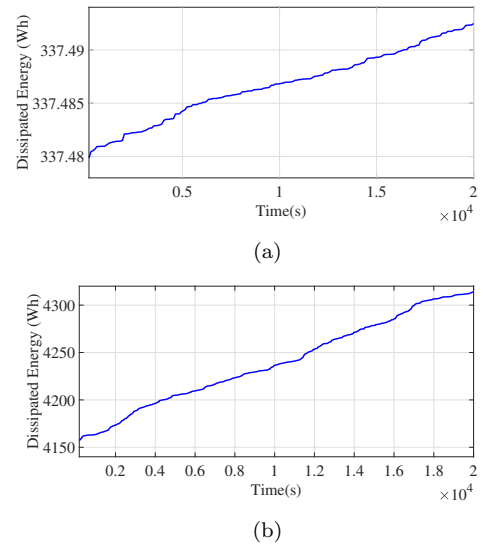


Fig. 5. Dissipated Energy with: (a) Laminar wind with  $K_c^{laminar}$  and (b) Turbulent wind with  $K_c^{turbulent}$

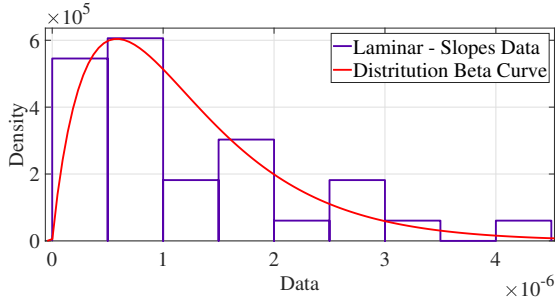


Fig. 6. Density function of a Beta distribution using a data-set of slopes in a curve Dissipated Energy VS Time . Case: Laminar with  $K_c^{laminar}$ .

- Slopes data from dissipated energy curve in laminar case: Beta distribution
- Slopes data from dissipated energy curve in turbulent case: Gamma distribution

**Markov Chain Setting** A Markov Chain with a transition matrix  $T$  was established for the simulation of the transition between laminar and turbulent flow. In this work, the transition probability matrix controlling the change between turbulent and laminar is given as follows:

$$T = \begin{pmatrix} 0.7 & 0.3 \\ 0.3 & 0.7 \end{pmatrix} \quad (9)$$

meaning that at each time step of 600 s, there is a 70 % chance of staying in turbulent flow, 30 % chance of changing from turbulent to laminar flow.

## 5. RESULTS AND DISCUSSIONS

The degradation in the drive-train of the considered turbine was simulated using the dynamic system presented in equation(1). In addition, the variability in the wind between laminar and turbulent flow was taken into account to know the deterioration behavior under realistic conditions.

The wind profile that was used during the validation of the approach is presented in Fig.3. In the case of laminar wind, real measured data was implemented, and in the case of turbulent flow, data was simulated through a stochastic model with a Markov Chain, allowing to generate different levels of turbulence. In both scenarios, it was considered that the conditions were constant during 5.5 hours (20.000s)

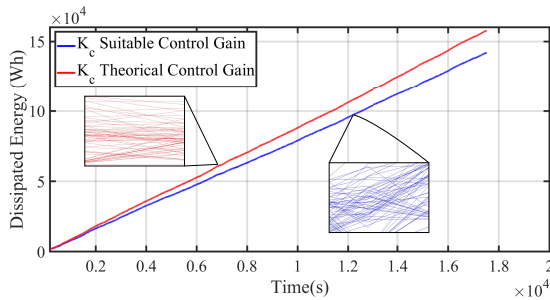


Fig. 7. Dissipated Energy in one year of simulation using a suitable control gain and theoretical control gain

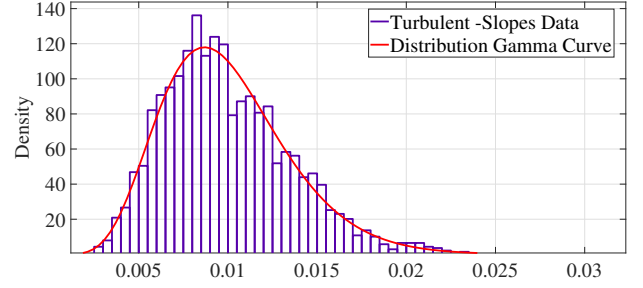


Fig. 8. Density function of a Gamma distribution using a data-set of slopes in a curve Dissipated Energy VS Time . Case: Turbulent with  $K_c^{turbulent}$ .

The simulation of the dissipated energy for each case of interest can be analyzed with the Fig. 4 and 5. The energy dissipation with laminar flow with  $K_c^{nom}$  (Fig. 4a) is lower during the period of the analysis than the case with  $K_c^{laminar}$  (Fig. 5a). However, for the turbulent scenario a greater degradation is reached with  $K_c^{nom}$  (Fig. 4b) than with the optimum  $K_c$ .

For learning the behavior of the curve, the slopes were calculated every 10 minutes ( $\Delta t = 600s$ ), and each set of data was fit with a probability distribution function as follows:

- Laminar Flow: The data in the case of  $K_c^{nom}$  and  $K_c^{turbulent}$  was fit with a Beta distribution. Fig. 6 shows the graphic of density function for the data-set of slopes calculated from the curve of Dissipated Energy vs. Time with Laminar flow and  $K_c^{laminar}$ . Similar results were obtained for the nominal case.
- Turbulent Flow: In the case of the turbulent flow, the Gamma distribution shows a better fitting to the data of slopes calculated from the curve of Dissipated Energy vs. Time with turbulent flow and  $K_c^{turbulent}$  (Fig. 8).

With fitted probability laws, it is possible to generate new slopes data. Nevertheless, this work aims to reproduce wind alternating between the laminar and turbulent flow. The sequences of changes between both flow regimes were selected through a Markov chain and were implemented using the transition matrix in equation(9).

The analysis was performed for different periods to obtain an image of the degradation during the useful lifetime of the wind turbine and considering 100 replicates in each case, providing a big picture under varied sequences of changes between the laminar and turbulent flow. For example, Fig.7 shows the dissipated energy after one year of simulation, with 100 replicates.

Besides, the process was made for different periods (1,5,10,15 and 20 years). The analysis considered the average energy dissipated for the case with  $K_c^{nom}$  and used the optimum gain of laminar and turbulent ( $K_c^{opt}$ ). Also, the analysis yields the percentage of the difference between the optimized case and the nominal one after the period under evaluation, as shown in Table 1.

The results indicate a significantly greater energy dissipation when the  $K_c$  is not switched when necessary and suitable to the wind conditions; in all the periods under



Table 1. Comparison of dissipated energy in different periods

Number of years	Diss. Energy $K_e^{opt}$ (Wh)	Diss. Energy $K_e^{nom}$ (Wh)	Difference (%)	Average time (sec)
1	1.446e5	1.570e5	9.307	8.271
5	7.152e5	7.906e5	9.535	8.816
10	1.419e6	1.572e6	9.694	9.913
15	2.139e6	2.369e6	9.702	11.216
20	2.843e6	3.150e6	9.743	11.956

evaluation, the difference is more than 9%, which indicates a significant increase in the deterioration when no suitable mechanism of the control gain is implemented. Besides, in table 1 appears the average time for run the simulation during the different periods, demonstrating the short time necessary to obtain an image of deterioration for long term periods.

A t-Test was performed to ensure the variability in the samples; in all the cases, the test rejected the hypothesis that the means of the replicate-wise dissipated energy are equal for both simulated scenarios (static vs suitable gain), and the  $p - value \approx 0$  indicates there is robust evidence in favor of the alternative hypothesis.

## 6. CONCLUSIONS

This paper proposes a methodology to analyze the long-term degradation of a drive-train wind turbine using a gain-scheduling control strategy and considering the variation in the wind conditions.

Real measurements of laminar wind were implemented; besides, the turbulent flow was simulated using a stochastic model based on a Markov chain. Moreover, the dissipated energy was estimated employing a dynamic model based on contacts mechanics for the case of laminar and turbulent flow, considering the theoretical control gain and an optimized control gain depending on the win conditions.

The dissipated energy rate for turbulent flow is more accelerated than in the laminar case. As a result, the slope is more pronounced in the Dissipated Energy VS. Time curve. It is possible to learn the slope of the curve to use this behavior in extrapolation and keep the effect of the wind in a second-wise simulation.

Different probabilistic distribution functions were employed to generate new slope data using the function parameters, and a Markov Chain was simulated to know the sequences of the transitions between the laminar and turbulent flow.

The proposed methodology was tested under different periods to know the degradation behavior during the useful life of the wind turbine with an extrapolation of the Dissipated Energy vs. Time curve. The results show that using the gain-scheduling control strategy, it is possible to reduce by more than 9% the energy dissipation in the drive-train compared with the nominal theoretical case.

## REFERENCES

- American Clean Power Association (2021). Acp market report fourth quarter 2020. Technical report, AmericanCleanPowerAssociation.
- Bianchi, F.D., Mantz, R.J., and Battista, H.D. (2007). *Wind Turbine Control Systems*. Springer.
- Hunt, K. and Crossley, E. (1975). Coefficient of restitution interpreted as damping in vibroimpact. *Journal of Applied Mechanics*, 42. doi:10.1115/1.3423596.
- Jantara, V.L., Basoalto, H., and Papaelias, M. (2020). A damage mechanics approach for lifetime estimation of wind turbine gearbox materials. *International Journal of Fatigue*, 137, 105671. doi: 10.1016/j.ijfatigue.2020.105671.
- Johnson, K., Pao, L., Balas, M., and Fingersh, L. (2006). Control of variable-speed wind turbines: Standard and adaptive techniques for maximizing energy capture. *IEEE Control Systems Magazine*, 26, 70–81. doi: 10.1109/MCS.2006.1636311.
- Komusanac, I., Brindley, G., Fraile, D., and Ramirez, L. (2021). Wind energy in europe 2020 statistics and the outlook for 2021-2025. Technical report, WindEurope Business Intelligence.
- Lee, J. and Zhao, F. (2021). GWEC - global wind report 2021. Technical report, Global Wind Energy Council.
- Ma, J., Fouladirad, M., and Grall, A. (2018). Flexible wind speed generation model: Markov chain with an embedded diffusion process. *Energy*, 164, 316–328.
- Merainani, B., Laddada, S., Bechhoefer, E., Chikh, M.A.A., and Benazzouz, D. (2022). An integrated methodology for estimating the remaining useful life of high-speed wind turbine shaft bearings with limited samples. *Renewable Energy*, 182, 1141–1151. doi: 10.1016/j.renene.2021.10.062.
- Romero, E.E., Martinez, J.J., and Berenguer, C. (2021). Degradation of a wind-turbine drive-train under turbulent conditions: effect of the control law. In *Proc. 2021 5th International Conference on Control and Fault-Tolerant Systems (SysTol)*, 335–340. IEEE. doi: 10.1109/SysTol52990.2021.9595837.
- Romero, E.E., Martinez, J.J., and Berenguer, C. (2022). Adapting wind-turbine control to mitigate the effects of weather conditions on the drive-train degradation. In *Submitted to 11th IFAC Symposium on Fault Detection, Supervision and Safety for Technical Processes - SAFE-PROCESS*. IEEE.
- Saint-Drenan, Y.M., Besseau, R., Jansen, M., Staffell, I., Troccoli, A., Dubus, L., Schmidt, J., Gruber, K., Simões, S.G., and Heier, S. (2020). A parametric model for wind turbine power curves incorporating environmental conditions. *Renewable Energy*, 157, 754–768. doi: 10.1016/j.renene.2020.04.123.
- Tchakoua, P., Wamkeue, R., Ouhrouche, M., Slaoui-Hasnaoui, F., Tameghe, T., and Ekemb, G. (2014). Wind turbine condition monitoring: State-of-the-art review, new trends, and future challenges. *Energies*, 7, 2595–2630. doi:10.3390/en7042595.