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Impact of 10 Minute Average Wind Speed SCADA Data on the Wind Turbine Blade Damage Prediction Compared to 1 Second Signal †

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Abstract: This work aims to underline the sampling frequency impact of the SCADA data on the wind turbine blades damage estimation. Previous studies emphasize on the needs of a 1 Hz frequency signal to carry out wind turbine blades damage computation based on physical models without proving this assumption. But the fatigue calculation based on physical models over the whole lifetime of the wind turbine requires a large memory capacity regarding to the lifespan of the wind turbines as well as strong calculation resources, restricting the application of this method in the current wind farms. The present study investigates on the impact of the wind speed sampling frequency on the blades damage estimation of a 5 MW wind turbine numeric model from the NREL library submitted to real wind turbine wind speed history, to determine what is the error involved working with 10 min SCADA data compared to 5 s one.

Keywords: wind turbine; damage estimation; Rainflow counting; composite materials; predictive maintenance.

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1. Introduction

The wind energy part in the overall electricity production is expected to rise from 5% today to 45% in 2050 to support an always growing need of energy in the context of fossil deposits exhaustion and global warming [1]. In order to achieve this production growth, the levelized cost of energy (LCOE) is one of the key drivers. One of the main elements in the reduction of the LCOE is around operation and maintenance (O&M) optimization. It is expected that 30% of the WT energy production cost decrease from 2020 to 2050 relies on the operation and maintenance cost reduction [1]. Wind turbine blades (WTB) are a key component of a wind turbine (WT) and their repair or replacement cost is very high, because they involve rope-access

Currently, the research efforts focus on the predictive maintenance of the WTB to minimize their associated O&M costs or evaluate the possibility of WT life extension. The predictive maintenance relies on smart and suitable acts planification to avoid expensive corrective action costs as well as to avoid expensive repair operation costs linked to reactive maintenance. One of the most promising predictive maintenances relies on physical models [2]. Those models are known to provide accurate estimation of the damage behavior. But the associated computations are time consuming when considering the complete lifetime of a WT, limiting the period study regarding the necessary use of 1 Hz wind speed signal to assess the actual WTB fatigue [3]. The industry standard is to work with 10 min aggregated signals (average, min, max, standard deviation) as recommended by the IEC standard 61400-12-1 [4]. The 10 min period has been proved to insure to keep the energetic content of the wind [4]. However, as mentioned above, the evaluation of WT fatigue requires data of higher frequency, which are not always archived in the SCADA systems. Figure 1 presents the difference in terms of data volume between different aggregations intervals.

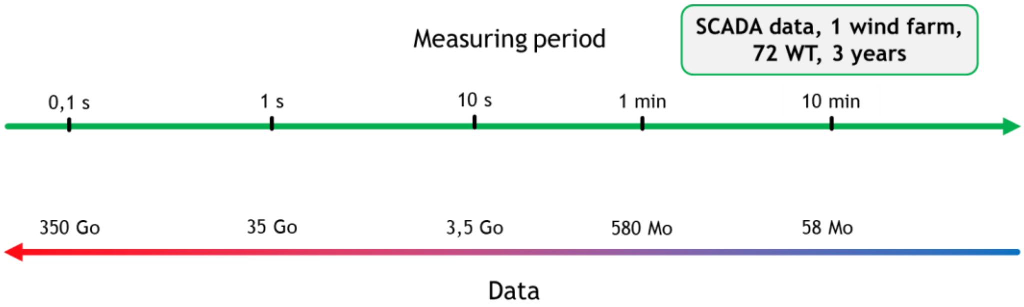


Figure 1. Schema showing the relation between data weight and the measuring period for a wind farm composed 72 WT for 3 years.

2. Resources and Methods

2.1. Resources

To carry out this study, we had access to 5 s measured wind speed signal from a wind farm composed of several 2 MW WT providing high frequency wind speed signal and then by resampling it, average mean wind speed for different period of time like classical 10 min SCADA data can be obtained (see Figure 2).

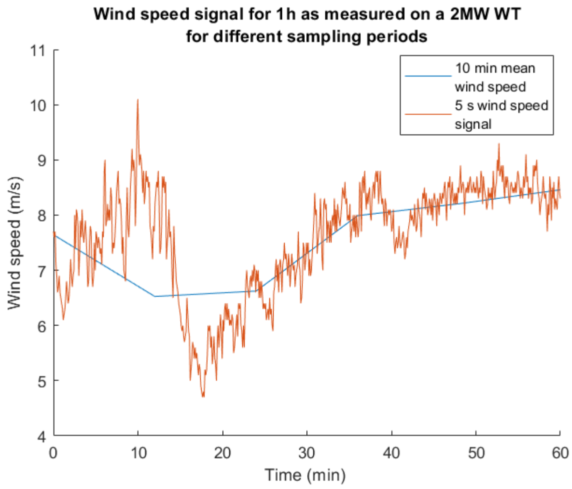


Figure 2. Wind speed signal with different sampling rate

Then, MATLAB programming language and FAST aeroelastic model have been utilized to estimate the aerodynamic loads leading to stress variations and hence the damage due to the wind speed fluctuations. However, to estimate the inner stress in the WTB, a detailed numeric model of the WTB must be used. Because the blueprints of those 2 MW WT are not available, a 5 MW WT numeric model in open access in the NREL library will be used as reference. To do this, it is assumed that both WT must obey to the same regulation contained in [5] in terms of life expectancy. So, it is expected that despite their output power capacity difference, they should have the same fatigue damage behavior.

2.2. Considered environmental effects

WTB fatigue are caused by different environmental factors like rain erosion [6], the gravity effect [7], the variation temperature can also affect the material fatigue strength [8]. But, according to the scientific literature, the main factor influencing on the WTB fatigue damage is the wind [9]. For reasons of simplicity, we will focus only on this aspect in the rest of this paper.

2.3. Standard Method

The standard methodology to evaluate the damage level of wind turbine blades is proposed by the International Standard IEC 61400-1 [5]. It relies on physical damage model based on the Palmgren-Miner linear damage accumulation rule and the Rainflow Counting algorithm (RFC).

The mean stress exerted on the WTB $|\sigma|$ estimated using the wind speed time series from the SCADA, the simulation tool FAST using the AeroDyn module and the 5 MW WT geometry from the NREL library and the extremum design load of the material σ_u, the RFC algorithm enable to estimate:

$$[\Delta\sigma_i, n_i] = \mathrm{RFC}(u(t), |\sigma|, \sigma_u) \quad (1)$$

Here, $\Delta\sigma_i$ is the stress range amplitude of the cycles, n_i corresponds to the number of cycles according to the cycle amplitude $\Delta\sigma_i$ and RFC represents the Rainflow counting method function as defined in Matlab [10] in our situation.

Then, using the Palmgren-Miner rule, it is possible to have an estimation of the damage evolution $D \in [0,1]$ in the WTB:

$$D = \sum_i \frac{n_i}{N_i} \quad (2)$$

With N_i the maximum number of cycles before rupture of the material for the equivalent stress amplitude $\Delta\sigma_i$:

$$N_i = \left(\frac{\sigma_u - |\sigma|}{0.5\gamma\Delta\sigma_i}\right)^m \quad (3)$$

Here m is the slope of the S-N curve for the corresponding material and γ is a safety coefficient [11].

Next, the damage evolution is expressed as a function of cycles. Therefore, it is necessary to convert the damage into a time-dependent value. The standard method is summarized in Figure 3.

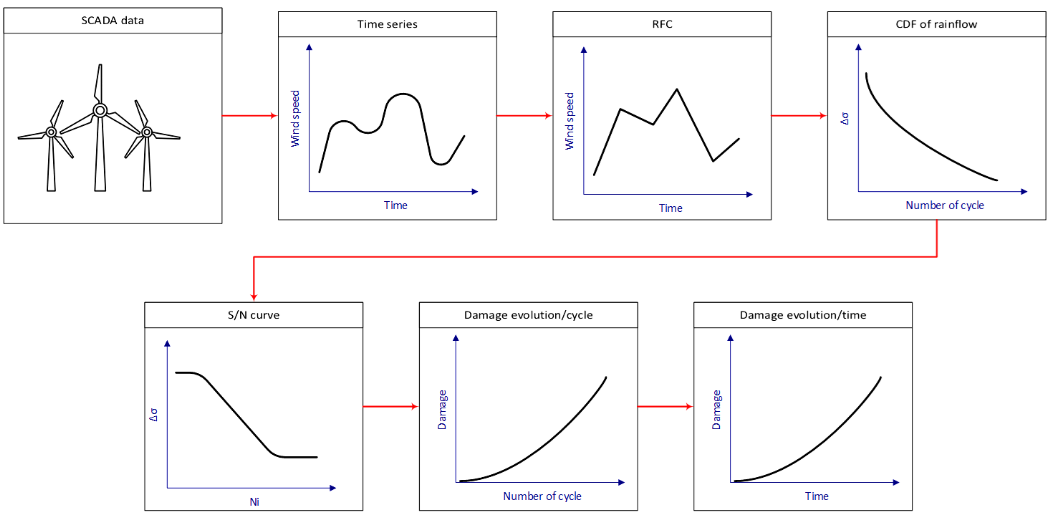


Figure 3. Standard methodology for fatigue estimation

2.4. Stress and damage estimation:

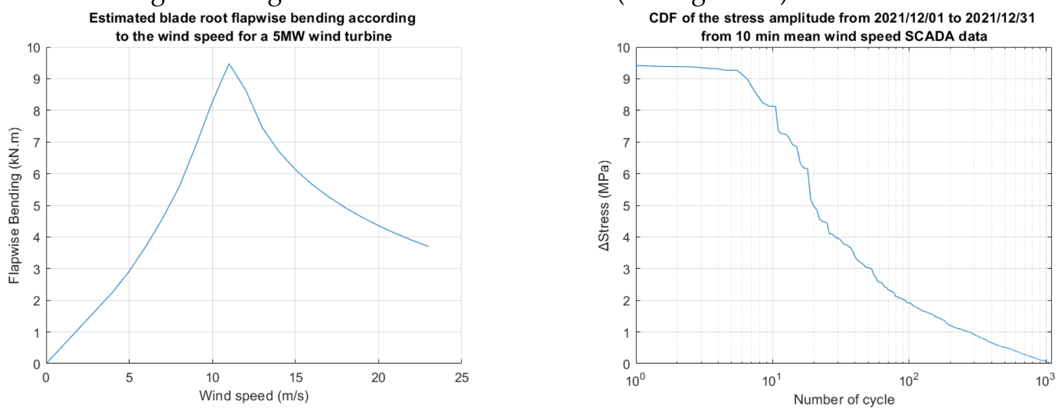
The blade root is a hot spot of the blade [12], and the flapwise bending is expected to be the main source of damage in normal working condition [13]. Hence, we will focus on the damage caused by the flapwise bending at the root of the blade

Using FAST software and a 5 MW WT model from the NREL library, it has been possible to estimate the flapwise bending moment at the blade root according to the wind speed (Figure 4a).

After which, knowing the flapwise bending moment and the geometry of the WTB it is possible to estimate the stress at the blade root thanks to the following equation [14]:

$$\sigma_{flap} = \frac{M_{flap} c}{I} \tag{4}$$

With σ_{flap} the stress linked to the flapwise bending, M_{flap} the flapwise bending moment, c the half of the airfoil thickness at the root and I the moment of inertia of the WTB root section. The next step is to carry out a RFC of the stress amplitude to estimate the fatigue damage as described in Section 2.2 (see Figure 4b).



(**a**) (**b**)

Figure 4. (a) Estimated blade flapwise bending according to the wind speed for a 5 MW WT; **(b)** Stress amplitude CDF obtained from 10 min SCADA data

Then, using the previous stress amplitude RFC, the WTB damage evolution has been estimated through the equation (2) (see Figure 5).

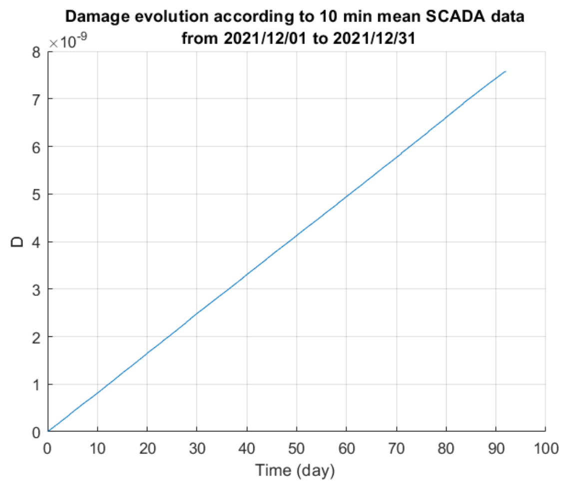
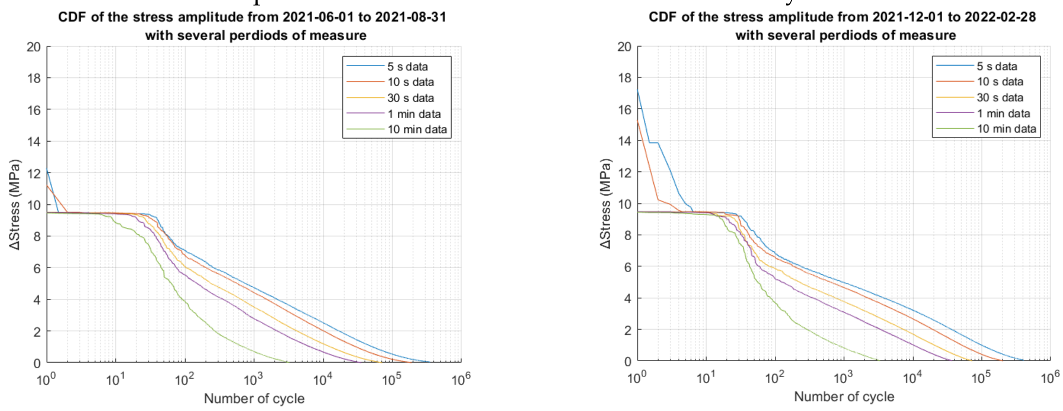


Figure 5. Evolution of the WTB damage from 10 min mean wind speed SCADA data

3. Results and discussion

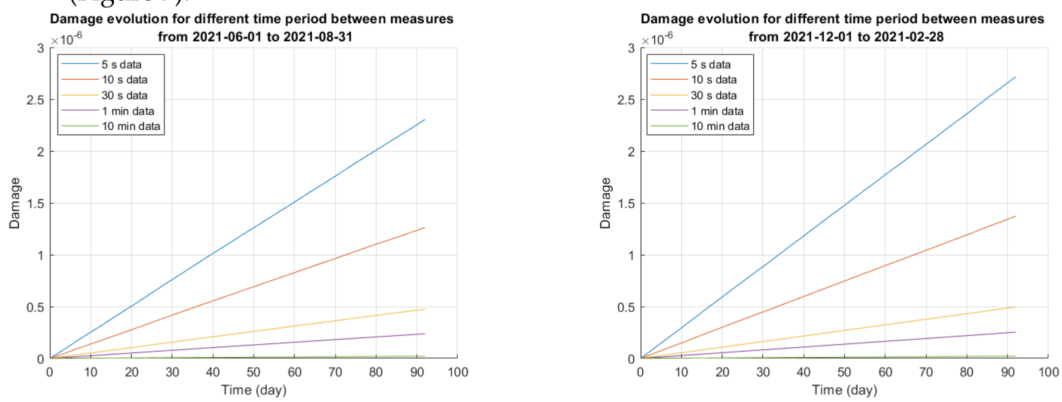
First, the CDF of the stress amplitude has been calculated for different wind speed sampling intervals or frequency: 5 s samples, 10 s mean; 30 s mean, 1 min mean and 10 min mean wind speed on the same wind turbines for the summer and winter seasons of 2021 (Figure 6). This allows a better understanding of the signal properties for different sampling periods compared to the one with 5 s direct measure taken as reference. Summer and winter have been chosen because they generally possess the wide differences in terms of mean wind speed. According to [15] in winter the mean wind speed seems to be higher than in summer nevertheless with approximately the same turbulence intensity. So, it is expected to obtain wider extrema wind speed amplitude and hence stress amplitude in winter than in summer in this study.



(**a**) (**b**)

Figure 6. (a) Estimated stress amplitude CDF for different measuring period in summer; **(b)** Estimated stress amplitude CDF for different measuring period in winter.

It is worth noting that in summer 2021, the maximum stress amplitude observed for the different sampling frequency are close to each other even if the corresponding cycle amount decreases as the sampling period rise. While in winter, the observed maximum stress amplitude rises with the sampling frequency. Then, concerning the total number of cycles, it is approximately proportional to the sampling frequency in both cases. Concerning the damage estimation, the one obtained via 10 min mean wind speed SCADA data is widely underestimated compared with the 5 s sampled wind speed signal (Figure 7).



(**a**) (**b**)

Figure 7. (a) Blade root damage estimation for different measuring period in summer; **(b)** Blade root damage estimation for different measuring period in winter.

Those observations suggest that valuable information concerning the stress history could be lost with 10 min mean wind speed SCADA data compared to the 5 s wind speed signal, in terms of stress amplitude as well as the total number of cycles, leading finally to a wide underestimation of the damage evolution. The results are summarized in Table 1 and Table 2.

Table 1. Results for summer 2021

Sampling period	Relative maximum stress	Relative total number of cycles	Relative blade root damage	Relative computing time
5 s	1	1	1	1
10 s	9.17×10^{-1}	5.55×10^{-1}	5.57×10^{-1}	4.03×10^{-3}
30 s	7.92×10^{-1}	2.08×10^{-1}	2.06×10^{-1}	1.23×10^{-3}
1 min	7.92×10^{-1}	1.04×10^{-1}	1.03×10^{-1}	6.76×10^{-4}
10 min	7.92×10^{-1}	9.44×10^{-3}	9.62×10^{-3}	8.30×10^{-5}

Table 2. Results for winter 2021

Sampling period	Relative maximum stress	Relative total number of cycles	Relative blade root damage	Relative computing time
5 s	1	1	1	1
10 s	9.11×10^{-1}	5.02×10^{-1}	5.05×10^{-1}	3.13×10^{-3}
30 s	6.47×10^{-1}	1.83×10^{-1}	1.83×10^{-1}	1.01×10^{-3}
1 min	6.18×10^{-1}	9.45×10^{-2}	9.31×10^{-2}	5.24×10^{-4}
10 min	5.59×10^{-1}	7.86×10^{-3}	8.14×10^{-3}	1.34×10^{-4}

According to the results summarized in Table 1 and Table 2, it appears that apart from the damage accuracy issue, using 10 min SCADA signal seems to be a time-saving way for damage estimation, reducing the computing time to a fraction of the one obtained with 5 s data. Moreover, 10 min SCADA data are the most common time frame in the wind turbine industry. These points arise the interest for a method allowing to estimate the wind turbine blade damage evolution with 10 min SCADA combining the associated timeliness with the accuracy of a higher frequency one. This topic might be the subject of a future study.

4. Conclusion

The current work showed the wind speed sampling period impact on the resulting stress history of a given wind turbine. In fact, as the sampling period increases, the extreme stress amplitudes diminish (peak shaving) along with the total number of stress cycle, in a proportional way for the last one. As result, the damage estimation according to the common 10 min SCADA is widely underestimated compared to that one obtained from 5 s wind speed data. Hence, direct estimation of the damage evolution from 10 min SCADA data cannot perform well in terms of accuracy. In future work, it would be interesting to check if some interesting results could be extracted from 10 min SCADA data despite their deficiencies like the classification of the most damaged WT in order to prioritize the maintenance efforts on the most sensitive WT within a wind farm. Then, proposing a method allowing estimating the equivalent 1 s wind speed WTB damage (as recommended by the scientific community) from common 10 min SCADA data would be an interesting contribution to the WT predictive maintenance domain and also for the evaluation of lifetime extensions.

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