Determination of wind farm life consumption in complex terrain using ten-minute SCADA measurements

Anand Natarajan¹, Leonardo Bergami²

¹Technical University of Denmark (DTU), Dept. of Wind Energy, Fredriksborgvej 399, Roskilde 4000, Denmark
²Suzlon - Blade Science Center, Havneparken 1, 7100 Vejle, Denmark

Email - anat@dtu.dk

Abstract. Measured ten-minute mean turbine performance characteristics are used to characterize the turbulence within wind farms. A neural network is trained to reproduce turbulence at each mean wind speed, given the ten-minute mean power production, blade pitch angle and rotor speed. The predicted turbulence from the neural network is verified using simulated wind turbulence that is input to aeroelastic simulations. The neural network is further trained to predict loads time series, given SCADA input time series. The load predictions are validated using an instrumented turbine. Based on the verified ability to predict wind turbulence and loads, the methodology is extended to reproduce loads on the blade and tower of wind turbines within wind farms in complex terrain. The input to the neural network is reduced to only the ten-minute mean measurements from the wind turbines, which are converted to 10-minute time series using Principal Component Analysis (PCA). The output of the neural network is the load time series, which are processed to damage equivalent loads. The standard deviation of measured power is used as a proxy for loads, to validate the predicted damage equivalent loads. The methodology is shown to provide a useful indication of relative fatigue life consumption within the wind farm, even when only mean SCADA measurements are available.

1. Introduction

Multi-year records of operational measurements from wind turbines in a wind farm may be obtained using the turbine Supervisory Control and Data Acquisition system (SCADA). The specific measured quantities may vary based on the wind farm, but usually comprise of the 10-minute mean values of individual wind turbine performance parameters, such as power production, rotor speed, wind speed, wind direction etc. It is also possible for the complete 10-minute statistics to be obtained, which includes minimum, maximum and standard deviations of the measurements.

Wind turbine structures are designed using partial safety factors applied to characteristic load values and material resistance values, as described in the basic design standard IEC 61400-1 [1]. These partial safety factors are determined based on assumed uncertainties in wind conditions, load simulation software and material test data. In reality these uncertainties may be different for each wind farm and are a function of the operational history. Further the IEC 61400-1 also mandates that the 90% quantile of wind turbulence is used in the design process, which value is assumed using IEC specified values, but is in reality site dependent. These factors imply that in practice the wind turbine structures may be able to withstand fatigue damage for a longer period of operation than originally planned in the design process. The specific period of extension of life of the wind turbines in farm beyond the originally planned design lifetime may be determined readily if the damage consumption on the wind turbines can be measured throughout the turbines lifetime. Therefore, along with ten-minute mean power, rotor speed etc., the ten-minute mean damage consumption of the major wind turbine structures need to be tracked continuously. This would also allow for planning specific inspections for the most loaded turbines within a wind farm, and where necessary, adjust accordingly the planned maintenance interventions. This approach can be directly applied also to wind farms located in complex terrains.
Wake models may not capture correctly the turbulence variation across turbines in complex terrain. Local increases in wind turbulence levels (ultimately responsible for increased fatigue damage) can in fact arise both from turbine wakes, but also from local terrain effects, which can be difficult to model in conventional tools. The fatigue damage is characterized in the design process using load cases, amongst which the normal power production load case (DLC 1.2), as described in the IEC 61400-1 is typically governing. The lifetime fatigue damage equivalent load as obtained in the turbine design conditions can be then compared with the actual damage consumed using site specific wind conditions that include wake and terrain effects. Fatigue load monitoring using SCADA and other sources has been explained in [2]. Further, quantifying life consumption using surrogate models derived from aeroelastic simulations has been published in literature widely [3,4]. Some of the published literature has used specific wake models inherent in aeroelastic software [4], others use the full statistics from SCADA signals alone to determine turbine loading conditions [5]. However these studies have been mainly focused on offshore wind farms or wind farms on flat terrain. Herein the procedure is delineated where wake models need not be applied to estimate the damage consumption quantification and which is applicable for wind farms in complex terrain. While literature such as [5] use the full ten-minute statistics from SCADA measurements to train neural networks to predict fatigue DEL, the main novelty herein is that only the 10-minute means from the SCADA measurements are shown to be needed to quantify the loads on the blade root and tower base for wind farms in complex terrain. This is a significant improvement over using the full 10-minute statistics because several old wind farms which may require life extension assessment possess only 10-minute mean records and not the full statistics. This article therefore shows that wind farms owners can quantify life consumption with simultaneous mean measurements from several SCADA signals, without requiring further detailed 10-minute statistics.

Neural Networks [6] have been used in the modeling of wind turbine response [5] and the response of aeroelastic systems [7]. Since they are shown to reproduce the fluid-structure coupling inherent in aeroelastic systems [7], it implies that they are capable to model wind turbine design loads. In this article, the blade root and tower base bending moments are analyzed. The use of aeroelastic simulations combined with limited SCADA based measurements on a wind farm is very useful in training artificial intelligence systems to map the common turbines operational measurements (power, rotor speed, wind speed) to the corresponding loads on its components. The following sections elaborate the methods followed to establish this.

2. Methodology

Load time series at the blade root and tower base of wind turbines within a wind farm are reproduced from simultaneous 10-minute average SCADA measurements using a neural network. The following steps are required to be completed in order to achieve this:

1) Run several 10-minute load simulations with varying normal turbulence levels over all operational mean wind speeds with the manufacturer’s aeroelastic model of the turbine in a commercial aeroelastic software used by the manufacturer.

2) Show that it is possible to reproduce wind turbulence at the hub height using a neural network from simultaneous mean signals of rotor speed, blade pitch, electrical power and wind speed, as inputs, based on load simulation results from an aeroelastic software.

3) Train another neural network to reproduce load time series at the blade root and tower base given the time series of rotor speed, blade pitch, electrical power and wind speed.

4) Validate the neural network based load predictions using measured SCADA time series and measured load time series on a single turbine.

5) Reproduce the time series of rotor speed, blade pitch, electrical power and hub height wind speed.
when using measured simultaneous mean SCADA signals by using principal component analysis and simulated variations of SCADA signals.

6) Apply the trained neural network to wind farms in complex terrain using measured simultaneous mean SCADA signals to predict the load time series at the blade root and tower base.

The above process relies on the ability of the neural network to identify local wind conditions variations from simultaneous mean SCADA measurements, and thereafter return corresponding variations on the components loads. This also implies that the wind turbulence can be estimated across the wind farm from mean SCADA measurements. Wind turbulence is defined as the standard deviation of the measured wind time series over a fixed duration, usually ten minutes. This assumes the wind time series is a stationary process with a fixed mean and standard deviation. The measured power curve of the wind turbine is a mean power curve typically given by the 10-minute average power over each mean wind speed bin. However, since the power is proportional to the cube of the wind speed, the power averaging at each mean wind speed is heavily influenced also by the wind turbulence level. The mean power can be thus described by Eq. (1) as:

\[ P = \frac{1}{2} \rho A c_p (u^3 + 3u \sigma_u^2) \]  

where \( \rho \) is the air density, \( A \) is swept area, \( c_p \) is the coefficient of power, \( u \) is the mean wind speed and \( \sigma_u \) is the wind turbulence conditional on the mean wind speed.

From Eq. (1), it can be readily seen that conversely, knowing the mean power and mean wind speed, as well as the air density and turbine power coefficient, it is possible to derive the turbulence over a ten-minute period. This inverse problem is numerically challenging and requires further inputs to predict turbulence. It is solved by training a neural network with input mean values of wind speed and power, along with the mean values of rotor speed and blade pitch angle, which affects the turbine power coefficient; the neural network output is the estimated wind turbulence over a ten-minute period. The input to the neural network are averages of the wind speed, rotor speed, electrical power and blade pitch angle as obtained with Flex5 [8,9] aeroelastic simulations, where the objective is to reproduce the input turbulence intensity.

Once reproduction of wind turbulence from mean SCADA signals is verified, the next step is to use the corresponding input time series to train a neural network reproduce the blade root and tower moment time series. Here in addition to the ten-minutes series of the above mentioned signals, the tower top acceleration time series is also used as an input to the neural network. The output of the neural network is ten-minutes time series of the tower base for-aft moment, side-side moment and blade root flap moment. As earlier, Flex5 based simulations are used to train the neural networks. In order to utilize these neural networks in a wind farm scenario, it is required to be able to convert the measured ten-minutes average values into ten-minutes time series. This is achieved using Principal component analysis (PCA), which involves linear transformations of datasets based on the correlation between the samples [10]. This is done by solving an eigenvalue problem,

\[ [R][X] = \lambda X \]  

where \( R \) is the correlation matrix of the data vectors \( q \) and \( X \) is the eigenvector that diagonalizes the correlation matrix.

Based on the magnitude of the eigenvalues, \( \lambda_1 > \lambda_2 > .. > \lambda_M > .. > \lambda_N \), the first \( M \) significant eigenvalues and eigenvectors are selected, so that a reduced order model of the dataset is obtained, as
Thus the principal components of the signal comprising of the [power, wind speed, rotor speed, pitch, tower top accelerations] can be used to generate a time series of the corresponding signals, given their mean signal and an estimate of its variation. The reconstructed SCADA time series using the significant principal components is seen to reduce noise in the neural network output and improves the loads prediction. The following sections demonstrate the viability of the described method.

3. Validation of the Neural Network

The neural network is designed to be a feed-forward network with 3-hidden layers consisting of 14 to 28 neurons each. The validation of the neural network is done in two parts: the first part is the ability to reproduce wind turbulence based on mean inputs and in the second part, the ability of the neural network to reproduce loads time series given input SCADA based time series is validated.

3.1. Reproduction of Turbulence

The neural network is trained using several load simulations with the widely used Flex5 loads simulation software at four wind turbulence levels, as specified in the IEC 61400-1. The mean values of wind speed, power, rotor speed and blade pitch angle are considered as inputs required to determine the wind turbulence at the rotor center over a ten-minutes period. The Flex5 simulations for training the neural network are made for mean wind speeds from 7m/s to 25m/ and over IEC Class A+, A, B and C turbulence levels. Test cases with different turbulence levels than used in the training set are also simulated in Flex5. The neural network is tested thereby to determine its ability to reproduce the turbulence at each mean wind speed, given the corresponding mean turbine inputs. Figure 1 shows that the neural network satisfactorily reproduces the wind turbulence level even outside the training set, given the corresponding mean SCADA input parameters.

![Figure 1: Verification of Neural Network predicted wind turbulence with Flex5 Simulations](image-url)
3.2. Reproduction of Load Time Series

In order to validate the capability of the neural network to reproduce dynamic loads given SCADA input signals, measurements from an instrumented turbine are used. Load time series measurements on a single instrumented wind turbine are considered along with corresponding measured SCADA time series on the same turbine to train the neural network. The SCADA signals used are the times series of the wind speed, power, rotor speed, blade pitch angle and tower top accelerations. The loads measured are the blade root flap moment and tower base moments. The neural network is trained using the measured SCADA time series as input with the measured load time series as output. Figure 2 provides the validation of the neural network output blade root flap moment and tower base resultant moment using the corresponding load measurements on a single wind turbine.

![Figure 2: Validation of the predicted loads from the neural network with the measured loads.](image)

Based on the comparisons shown in Figure 2, it can be reasonably concluded that for normal operating conditions of a wind turbine, the major variations in loads at the blade root and tower base can be
satisfactorily predicted using neural networks that use SCADA based time series of the blade pitch angle, power, rotor speed, wind speed and tower top accelerations.

4. Reproduction of damage consumption in a wind farm

The neural network is further trained to predict blade and tower loads using the results from Flex5 simulations of the turbine at different mean wind speeds and turbulence levels as can be observed in complex terrain conditions. This trained neural network is now utilized to predict the damage equivalent loads (DEL) on a wind farm in complex terrain. The site is situated in the United States and features 29 wind turbines of 2+ MW each. Figure 3 shows the pictorial details of the complex terrain, and the wind farm layout. Ten minute mean SCADA measurements from all 29 wind turbines over several months are used to generate corresponding time series of the SCADA signals using PCA as input to the trained neural network to predict the corresponding blade root and tower base moment time series. The combined mean SCADA inputs is matched to the nearest corresponding combined set in the simulated SCADA conditions that were obtained during training. The corresponding principal components and simulated variation are used to generate ten-minute time series of inputs signals. The resulting neural network output load time series is post-processed to determine the corresponding DEL on each wind turbine in the wind farm.

In order to validate the predicted DELs across the wind farm, they are compared against the measured Weibull weighted standard deviation of power, which is considered indicative of the fatigue load variation within the farm. It should be noted that the power std. deviation is more useful as a proxy for wind driven loads at means wind speeds below rated. The neural networks do not use any measured std. deviations of SCADA signals, whether power or otherwise as input. The validation is intended to be qualitative since the main objective is to identify the critically loaded wind turbines in the wind farm which have the highest life consumption.
Figure 4 displays the comparison of the predicted DEL of the blade root flap moment, the tower base fore-aft moment and the tower base side-side moment with the measured power std. deviation power over all 29 turbines in the wind farm. As expected, the rows of turbines towards the rear of the wind farm show greater damage than the front. However there are specific turbines in the rear rows that show much higher damage than at other points of the row. This may be due to local terrain effects due to the complex terrain of the farm. The power standard deviation distribution corresponds reasonably well with the predicted tower base fore-aft damage equivalent moments over the wind farm, wherein five highly loaded wind turbines can be clearly identified.

The prediction of damage consumption is further examined on another site in the U.S. with even higher degree of complex terrain than presented in Fig. 3. The site comprises 10 wind turbines, on two lines as shown in Fig. 5. The prevailing wind direction at the site is south-east; a large mountainous terrain is located south-west from the site.
The accumulated DEL estimation is based on two years of SCADA data, consisting for each turbine of 10-minute averages of commonly available sensors: power, rotor speed, pitch angle, nacelle based wind speed. The data are filtered so to exclude any instance where the turbine minimum power in any 10 minute period is below cut-in. In addition, the 10-minute power standard deviation signal is now also included in the analysis. The power standard deviation signal is again used as a check for correlation with load variations on the turbine.

The correlation of power std. deviation (termed syn. Power std. in Fig. 6) to predicted blade root flap DEL is made as a function of the mean wind speed (colour coded). Figure 6 displays the results of this analysis and it outlines two clusters of points: at below rated wind speeds (with higher power variance), and above rated (with lower power variance but higher flap loads). Within each cluster of points, there is indeed a positive correlation between power standard deviation and blade root flapwise fatigue loads.

![Figure 5: Turbine Layout and terrain of site-2](image1)

![Figure 6: Comparison of blade root flapwise 10-minute DEL versus the corresponding 10-minute power standard deviation. The colouring of the points indicates the mean wind speed during the 10 minutes.](image2)
As the wind distribution at the site favours above rated wind speed, higher fatigue loads could be here associated to relatively lower power standard deviation.

Figure 7 plots the relative blade root flap DEL and tower base fore aft DEL across the wind farm. The turbines that are located on the first line of the wind farm, the southern end, appear much more loaded than the turbines on the second line. This may be attributed to the first-line turbine operating more often in high-above-rated wind speed conditions, and hence with lower power standard deviation, but higher fatigue loading. This verification therefore brings out the different behaviour of the std. deviation of power below and above rated wind speed and how they correlate with the DEL behaviour.

5. Conclusions

It was clearly shown that feed-forward neural networks can be used to determine multiple output quantities from input mean SCADA signals of rotor speed, power production and blade pitch angle. The neural networks were shown to be able to reproduce the wind turbulence, blade root moment and tower base moment time series. The turbulence reproduction using neural networks was validated using aeroelastic simulations, whereas the load time series reproduction from a neural network was validated with a single instrumented turbine using measured loads. The complete setup was further validated in two wind farms in complex terrain using measured mean SCADA signals as inputs to the neural network, wherein the validation of the damage equivalent load prediction was made using the measured standard deviation of power.

While the prediction of fatigue damage consumption at the blade root and tower base showed very good correlation with the measured std. deviation of power on one wind farm with complex terrain, it was not so evident in another wind farm also in complex terrain. The reason for the potential lack of good correlation of damage equivalent loads with the standard deviation of power was determined to be due to longer durations of operation of the wind farm above rated wind speed wherein fatigue loads increase but power std. deviation reduces. In wind farms where the pre-dominant operation is at mean wind
speeds below rated wind speed, the correlation of power std. deviation to fatigue loads will be more evident.

Acknowledgments
This work has been supported by the Danish Energy Agency through the EUDP LifeWind project (Grant Number 64017-05114). The support is greatly appreciated.

References
[1]. IEC 61400-1 2019 International Electro technical Committee, IEC 61400-1: Wind Turbines Part 1: Design Requirements Edition 4 Geneva.
[2]. Cossack N and Kühn M, 2009, An approach for fatigue load monitoring without load measurement devices, Proceeding of the European Wind Energy Conference and Exhibition, EWEC-2009, Vol. 1, 513-522
[3]. Dimitrov, N and Natarajan, A, 2019 From SCADA to lifetime assessment and performance optimization: how to use models and machine learning to extract useful insights from limited data, Journal of Physics: Conference Series 1222, 012032
[4]. Galinos C, Dimitrov N, Larsen T J, Natarajan A, Hansen K S, 2016 Mapping Wind Farm Loads and Power Production - A Case Study on Horns Rev 1. Journal of Physics: Conference Series 753(3), article number 032010.
[5]. Vera-Tudela, L and Kühn, M, 2017, Analysing wind turbine fatigue load prediction: The impact of wind farm flow conditions, Renewable Energy Journal, Volume 107, 352-360.
[6]. Goodfellow, I, Bengio, Y and Courville A, 2016 Deep Learning. MIT Press, http://www.deeplearningbook.org.
[7]. Natarajan, A, Kapania, R K, Inman, D J 2004 Aeroelastic Optimization of Adaptive Bumps for Yaw Control, Journal of Aircraft, Vol. 41(1), 175-185.
[8]. Øye, S, 1996 FLEX4 Simulation of Wind Turbine Dynamics. Proceedings of 28th IEA Meeting of Experts on State of the Art of Aeroelastic Codes for Wind Turbine Calculations, Lyngby.
[9]. Øye, S, 1999 FLEX 5 User Manual, Technical University of Denmark, Lyngby.
[10]. Natarajan, A and Verelst, D R, 2012 Outlier Robustness for Wind Turbine Extrapolated Extreme Loads, Wind Energy Journal, Vol 15(5), 679-697.