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From SCADA to lifetime assessment and performance optimization: how to use models and machine learning to extract useful insights from limited data

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Abstract. A common challenge in the decision making process regarding operation and life extension of existing wind farms is the lack of accurate information about the actual dynamic states of the turbines in terms of its operation from inception. SCADA records normally contain limited number of channels, and are not necessarily kept for the entire operating period of the wind farm; design and site data may be outdated or inaccessible. Nevertheless, as long as a minimum amount of information is available, statistical analysis and augmentation with artificial intelligence based simulation can be used to supplement the information. In the present study, we delineate a combination of data analysis, physical modelling and machine learning, that produces a detailed assessment of the operating conditions experienced by a wind farm and establishes the corresponding power performance, loads and fatigue damage accumulation.

1. Introduction and purpose

The decision making process regarding operating strategy or end-of-life considerations requires characterizing the current state of the wind turbine structures, potentially combining several sources of information: 1) an overview of the wind turbine design assumptions and limitations, 2) recovering the operating and loading history of each turbine, and 3) visual or other form of non-destructive testing to determine the presence of other failure modes not captured by the standard modelling approaches used in the design calculations. In particular, the operating history in terms of dynamic states and loading history is necessary in order to determine whether any of the design assumptions has been violated during the wind farm lifetime. A common challenge in this process is the incompleteness of historical information. SCADA records [1] normally contain limited number of channels usually dealing with power production, rotor speed and other such system information, and are not necessarily kept for the entire operating period of the wind farm, but they have nevertheless been used for various applications. A commonly reported use of SCADA data is for predictive applications such as failure detections [1],[2],[3],[4]. Other common use is power output forecasting as shown in [5],[6]. In [7], SCADA data are used in combination with wake models for determining wind direction, wind speed, and for power output prediction. Operational wind farm data rarely include load measurements, therefore studies with such analysis are scarce and typically limited to a few turbines over a short-term load measurement campaign, as in e.g. [8],[9]. In a scientific field that previously has been dominated by power and fault prediction analysis, the present study aims at demonstrating how detailed fatigue load estimation can be obtained for each individual turbine in a wind farm, based on SCADA measurements supplemented with an aeroelastic model. The use of a combination of limited SCADA based measurements and wind turbine/farm simulations using a verified design basis of the turbines is



very appropriate to train an artificial intelligence system to forecast the future performance of the wind turbine and the fatigue life consumption of its components. The following sections elaborate on the process followed to establish this method.

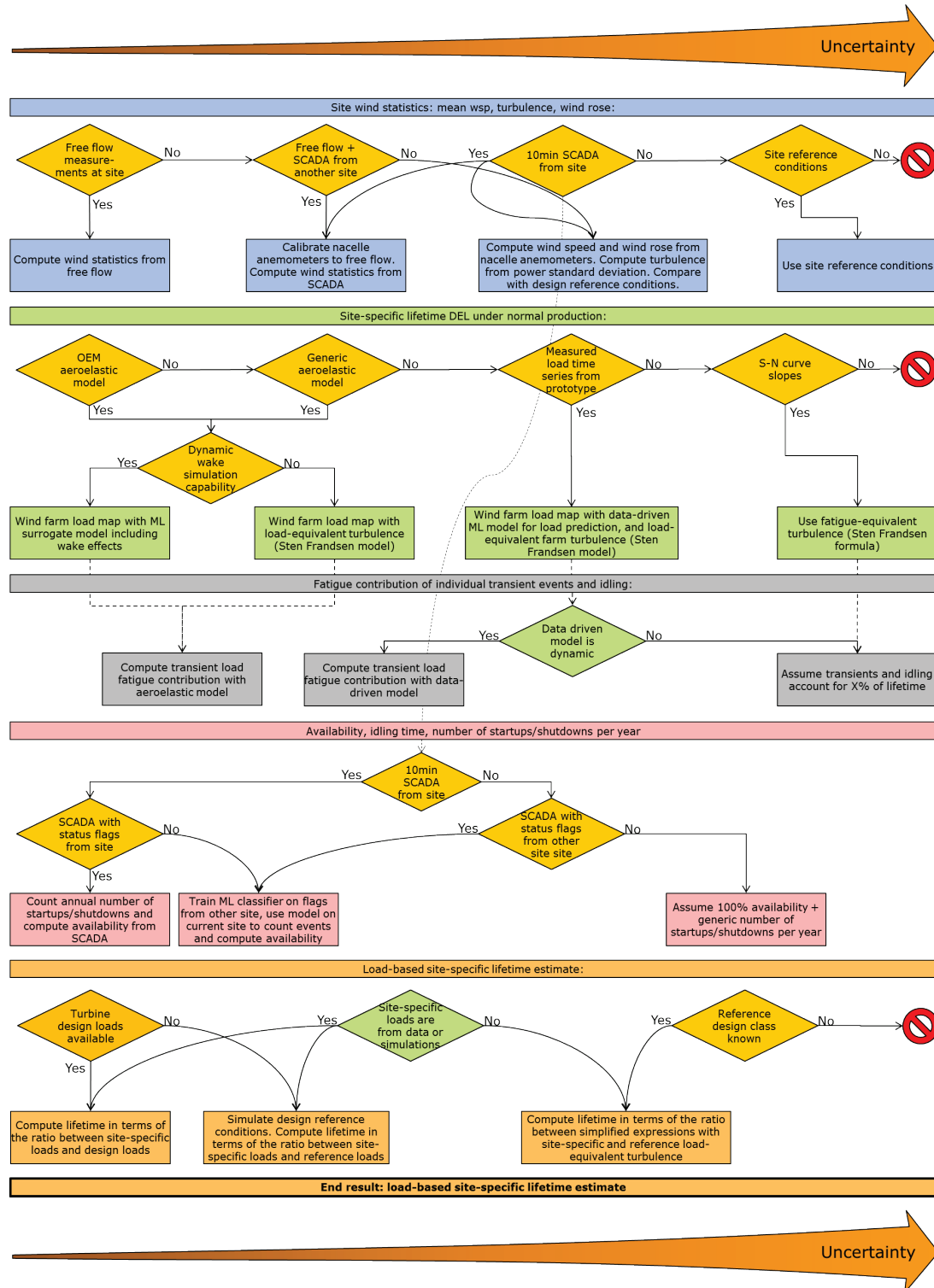


Figure 1. Chart describing a procedure for estimating load-based site-specific remaining lifetime, with different process alternatives depending on the type of information available.

2. Methods

Practically every wind farm in the world is unique as a project due to the varying environmental conditions, wind turbine technologies, project developers, owners, and operating history. As a result it is very likely that each project also comes with a unique combination of available data. Due to this data heterogeneity it is largely infeasible to define a fixed procedure for establishing the dynamic history of wind farms. Instead, we suggest a flexible procedure as shown on Fig.1. The procedure requires several predefined categories of information; however the numbers within each category can be obtained using a choice of different methods depending on the type of data and design information available. It is assumed that more detailed information will in general lead to lower uncertainty as indicated in Fig.1.

The SCADA data recorded by wind turbines typically contain information recorded by sensors mounted on the turbines such as nacelle anemometers. The wind speed measurements from a nacelle anemometer are potentially biased as the nacelle anemometers are operating in a disturbed flow downwind from the rotor. Therefore, in order to utilize the information available in SCADA, a transfer function between true wind speed and turbulence and readings from a nacelle anemometer needs to be established. It is expected that a few months of data on a site with met mast should be sufficient to establish the transfer function. Alternatively, the statistics of electrical power output (mean and standard deviation) can be used as proxies to rotor-equivalent wind speed and turbulence. The transfer function is calibrated by means of a machine learning (ML) regression model. Then, free wind speed and turbulence at farm level can be estimated by 1) correcting the nacelle anemometer readings using the abovementioned transfer function, and 2) averaging the corrected readings from turbines operating in free wind. Among the multiple potential choices for regression models, in the present study we use Artificial Neural Networks (ANNs)[10], due to their computational efficiency and versatility. By applying a series of simple operations (a weighted multiplication or convolution followed by a nonlinear activation function) ANNs provide a nonlinear mapping between inputs and outputs, which, given a network of sufficient size, can theoretically approximate any real-valued function [11]. Once the model has been trained, neural networks can make thousands of forward propagations (predictions) per second to simulate wind farm operational states that yield valuable information on fatigue lifetime. ANNs can also be trained to represent the dynamic behavior of a dynamic system where the approach is taken to map input-output responses that are a function of time. Response surface methodology and neural networks have been adopted in literature for nearly two decades to represent several types of aeroelastic systems[12],[13].

SCADA signals measured from wind turbines such as the rotor speed, blade pitch angle etc. can be mapped to corresponding mechanical loads on the turbine components during operation either using load measurements or aeroelastic simulations. If measured loads on the wind turbine are unavailable, then an aeroelastic design basis of the wind turbine can be set-up so as to successfully reproduce the operating conditions of the wind turbine and simulate the exact rotor speed, power output, blade pitch angle as measured on the actual turbine. Consequently a neural network can be trained to reproduce the loads on the blade root, tower top, tower base using a set of representative SCADA signals as the input.

In the following, we demonstrate examples of several of the potential solutions outlined in Fig.1 for specific combinations of real-world data. In Section 3, we show how the lifetime-equivalent fatigue loads under normal operation at the Horns Rev 1 wind farm can be estimated based on approx. 3 years of basic SCADA (nacelle wind speed, yaw direction, power and status flags) supplemented with load simulations as well as mast measurements synchronized with SCADA from a single turbine. In Section 4, two additional solutions are shown for situations where 1) some load measurements are available for at least one turbine, e.g. a prototype, and 2) if the wind turbine operating status flags are not available in the wind farm SCADA, but may be available on a smaller data set, e.g. a prototype of from a dedicated campaign.

3. Case study: lifetime estimation for the Horns Rev 1 wind farm

3.1. Overview of available data

In this example, we use the Horns Rev offshore wind farm in western Denmark (Figure 2) consisting of 80 Vestas V80 turbines with 2MW power rating. The following data types are available:

- Ten-minute SCADA statistics (power, nacelle wind speed and yaw direction, including mean values, standard deviations and status flags) for 3 years;
- Wind speed, turbulence and wind direction at close to hub height (70m) from 3 met masts;
- A generic aeroelastic model of the V80 turbine using the DTU Wind Energy controller [14].

As no load measurements from the wind farm are available, we need to use a load model to estimate the accumulated fatigue damage. The aeroelastic load model requires inputs in terms of the free wind conditions, and this information can be obtained from the SCADA. As discussed earlier, the SCADA data are not guaranteed to be representative of the free wind conditions due to various disturbances. However, as data from a nearby met mast are also available, they are used to calibrate transfer functions which map the SCADA readings to the reference free wind conditions. The transfer functions are calibrated based on comparing data from the met mast and from a single turbine in the farm. With this approach we aim at also covering a scenario where there is no mast at the wind farm location but measurements could be available from another site with e.g. a single prototype turbine. Prior to analysis, the SCADA and met mast data are filtered based on the status signals. For a ten-minute period to be considered valid for analysis, at least one turbine in an outer row facing the incoming wind direction needs to be available and producing power. To enable comparison with met mast data, an additional condition is that mast wind speed and wind direction have to be available. This results in approximately 150,000 data points valid for analysis.

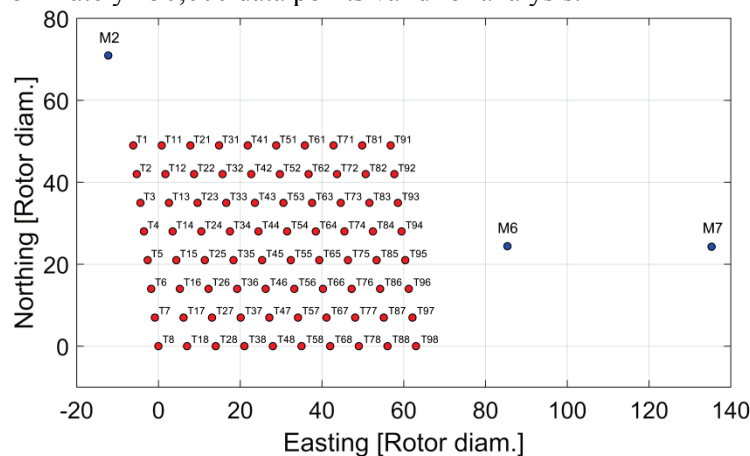


Figure 2. Horns Rev 1 wind farm layout and met mast locations.

3.2. Computing wind direction, ambient wind speed and ambient turbulence from SCADA

The yaw records of individual turbines can be unreliable – for example, in the SCADA data set used in the present study, the availability of yaw information for some turbines is as low as 30%. It is therefore not sufficient to calculate wind direction statistics for individual turbines. Instead, farm-average wind direction is calculated based on the yaw directions of turbines operating in free wind using the following algorithm:

- For a given 10-minute period, a preliminary average direction is estimated as the median of the yaw angle readings of all operational turbines in the farm;
- The preliminary wind direction combined with the farm geometry is used to estimate which turbines are operating in free wind conditions (no turbines upwind within a $\pm 20^\circ$ sector);

- Final wind direction is estimated as the median of valid yaw readings from the turbines operated in free wind conditions.

In the above, the median is preferred instead of the mean, because the mean would be affected by outliers such as erroneous yaw readings. Alternatively, the mean can be used together with a filter which eliminates all yaw readings which are certain number of standard deviations away from the mean [7]. The SCADA-based estimate of the wind direction computed with the above procedure shows very high correlation ($r^2 = 0.973$, Table 1) with the wind direction measured by met mast 6 (M6). There is a constant bias of approx. 9deg, which can be due to bias in the reference (true north) orientation of either the met mast or the wind turbines. When the bias is subtracted from the wind direction estimated from SCADA, the resulting time series show excellent agreement with the wind direction measured from the mast, Fig.3. This also results in a close resemblance between the wind roses estimated from the mast and from SCADA, as shown on Fig.4.

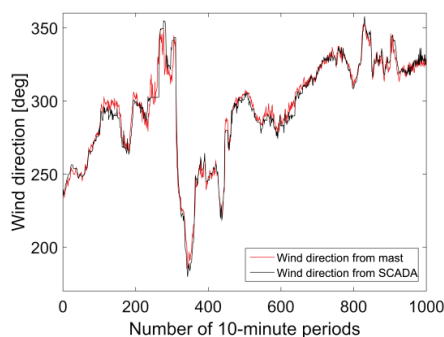


Figure 3. Comparison of the wind direction prediction from SCADA data with measurements from met mast M6.

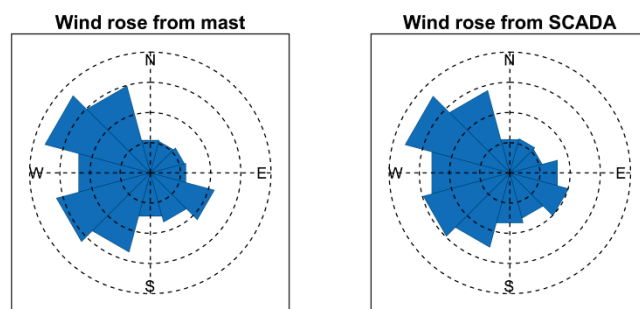


Figure 4. Comparison of the wind roses at Horns Rev 1 derived from M6 mast measurements and from SCADA.

Having determined the wind direction, it is straightforward to identify the turbines which are operating in free wind conditions. The criterion applied is that there should be no wind turbines upwind within a sector of $\pm 20^\circ$ from the mean wind direction. Using the same approach as with the wind direction, the free wind speed and turbulence can be estimated as the median of the nacelle wind speed and turbulence recorded by the turbines in free wind conditions. However, due to the influence of the rotor, the nacelle wind speed readings show a nonlinear behavior with respect to the free wind speed, with a change of slope at around rated wind speed. On Figures 5 and 6 the raw nacelle wind speed readings are plotted against the readings from M6 (black circles), for a single turbine and for the average from free-wind turbines, respectively. The change of slope around rated wind speed can be best observed on Figure 6 where the raw nacelle wind speed is lower than the mast wind speed for wind speeds above rated. In order to eliminate some of the nonlinearity, a transfer function is calibrated between the nacelle wind speed reading of a single turbine and the wind speed measured by M6. The transfer function used is a simple ANN regression model with a single hidden layer with 5 neurons and hyperbolic tangent (\tanh) activation functions. The transfer function is calibrated for wind turbine 81 which is in the northeast corner of the wind farm. This choice maximizes the availability of data where both the turbine and the met mast are in free wind conditions. The transfer function is then applied on the nacelle wind speed readings of all wind turbines in free wind, and a corrected farm wind speed is estimated. Shown with blue dots on Figures 5 and 6, the correction almost completely eliminates the bias for the turbine where the function is trained on, while for the wind farm there is a noticeable reduction in bias while the coefficient of determination remains practically unchanged. A similar corrective approach is also applied to the turbulence (standard deviation of wind speed) from the nacelle anemometers, however with four input variables to the neural network model: nacelle wind

speed, nacelle turbulence, mean power production, and standard deviation of power production. Due to the larger number of inputs the model used is also slightly larger, with 10 neurons in the hidden layer. The correlation between the nacelle readings and mast data is shown on Figure 7 for a single turbine and on Figure 8 for all turbines in free wind. There is significantly more uncertainty than with the wind speed estimation; nevertheless applying the correction noticeably improves the correlation.

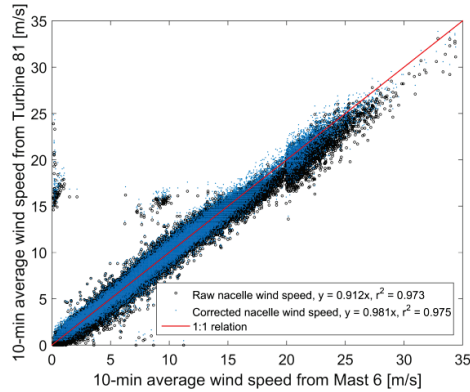


Figure 5. Mean wind speed estimation from the nacelle anemometer of a single turbine, compared to data from M6.

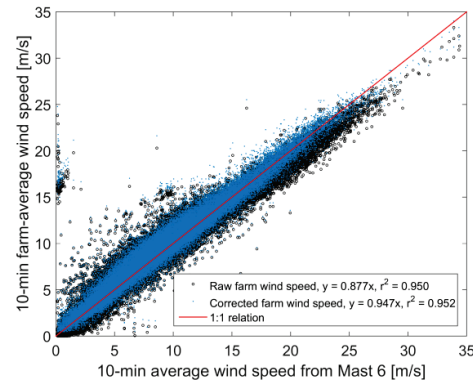


Figure 6. Mean wind speed estimation from all wind turbines in free wind conditions, compared to data from M6.

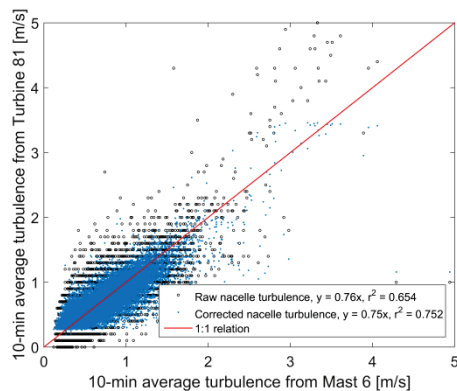


Figure 7. Turbulence estimation from the nacelle anemometer of a single turbine, compared to data from M6.

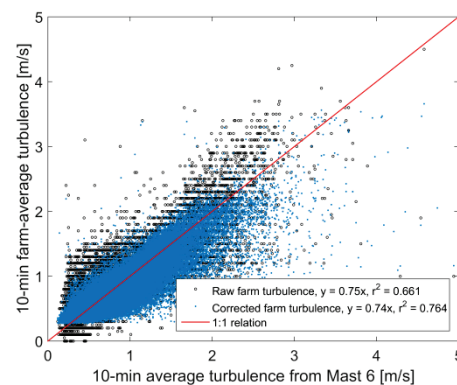


Figure 8. Turbulence estimation from all wind turbines in free wind conditions, compared to data from M6.

3.3. Load prediction including wake-induced effects

The SCADA records in existing wind farms usually do not include reliable and extensive load measurements. This is also the case for Horns Rev 1. Instead, a model can be trained that maps the mechanical loads on major mechanical components as function of the inflow conditions. If a certain amount of SCADA measurements (e.g. a few months on a turbine prototype) in terms of measured power production, wind speed and rotor speed, are available, the load mapping can be realized by training a data-driven regression model using e.g. artificial neural networks (ANN). This is feasible both in terms of load time series and in terms of 10-minute load statistics. An alternative is to use an aeroelastic model of the turbine which can be used to generate a synthetic data set, and the ML model is then trained on the synthetic data set [15],[16]. The use of the aeroelastic model can be beneficial in most cases also as a supplement to measured loads, as it is unlikely that a single load measurement campaign can provide enough information about the full range of possible operating conditions. In the present study, we use a generic aeroelastic model of the Vestas V80 wind turbine developed in the Hawc2 aeroelastic simulation software [17]. As the OEM-installed turbine controller is confidential, the model features the DTU Wind Energy controller [18] tuned to reproduce the known power, pitch

and rpm curves of the V80 turbine. The model includes a monopile foundation with variable water depth between 7 and 15m. The model mass and stiffness are tuned so that it reproduces the natural frequencies of the real structure, including the variation of the frequency with water depth.

Wake effects are a major load driver in wind farms and a fatigue life prediction model needs to take wakes into account. In the present study, we use the approach described in [16] and [19], where the wake-induced effects are accounted for by introducing three variables describing the relative location of upwind turbines: R_D , the distance in rotor diameters to the closest turbine upwind, θ , the relative angle between the wind direction and the direction of the upwind turbine (or row of turbines), and N_{rows} , the number of turbines upwind in case there is an aligned row of turbines. A random sample of 30,000 combinations of these variables with other external conditions (wind speed, turbulence, wind shear, and water depth) is generated, and aeroelastic load simulations are carried out using the Hawc2 aeroelastic simulation tool[17], where wake effects are simulated with the Dynamic Wake Meandering model [20]. In order to reduce the statistical (realization-to-realization) uncertainty due to using random turbulent realizations, six simulations with random turbulence seeds are carried out for each sample point, resulting in a total of 180,000 simulations. A regression model is trained on the results using an ANN with 3 hidden layers with 24 neurons each, and with tanh activation functions. The process of training the model and its performance are discussed in details in[16]. As there are no load data available, it is not possible to directly validate the load predictions with measurements. However, the same ANN model can be used to predict the power output, and the results can be directly compared to the SCADA records. The prediction is carried out on each individual turbine, and the values are summed to also estimate the total power output of the wind farm. Figure 9 shows a comparison of the predicted total power output time series vs. the one recorded from SCADA, while Figure 10 shows the correlation between measured and predicted power outputs at individual turbines. Both the total and individual turbine power output predictions show high correlation with measurements. From some differences visible on Figure 9 it may be argued that the power curve of the aeroelastic model may not be fully accurate at close to rated wind speeds. This is to some extent expected as the load and power predictions are based on a generic model and not on one provided by the OEM.

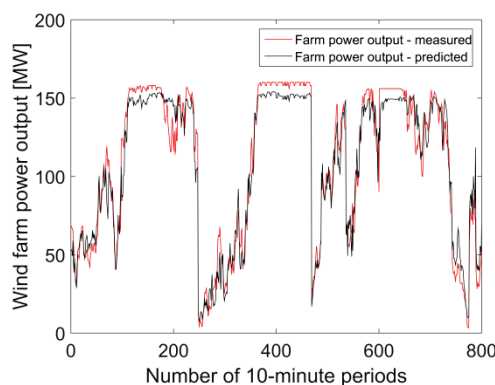


Figure 9. Comparison of measured and predicted time series of total electrical output from the Horns Rev 1 wind farm.

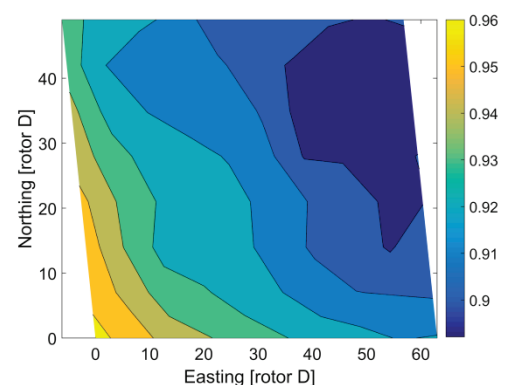


Figure 10. Correlation (r-square) between measured and predicted power output at individual turbines.

Damage-equivalent fatigue loads (DEL) are predicted simultaneously with the power predictions, based on the same input data. Based on these results, ten-minute fatigue damage increments are computed for individual turbines, thus establishing their fatigue damage accumulation history. The fatigue damage is computed relative to an assumed 20-year design lifetime under IEC 1A reference conditions. Figure 11 shows the estimated damage accumulation history for main shaft torsion, while Figure 12 provides a map of the accumulated blade root flapwise fatigue damage over the wind farm based on approximately 3 years of operation. These estimates are based on directly applying the load

prediction model on the free wind time series obtained from SCADA and the prediction length is limited to the amount of data available. In order to estimate the damage accumulation over the entire operating period, inflow statistics (wind rose, wind speed and turbulence probability distributions) need to be established from the data. Afterwards the lifetime-equivalent loads can be estimated by numerically integrating the load model outputs over the joint distribution of inflow conditions.

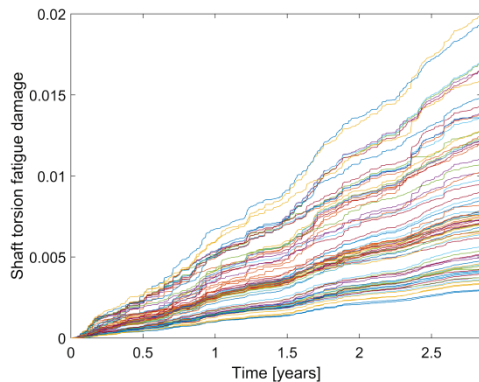


Figure 11. Time series of accumulated shaft torsion fatigue damage for all individual turbines in Horns Rev 1.

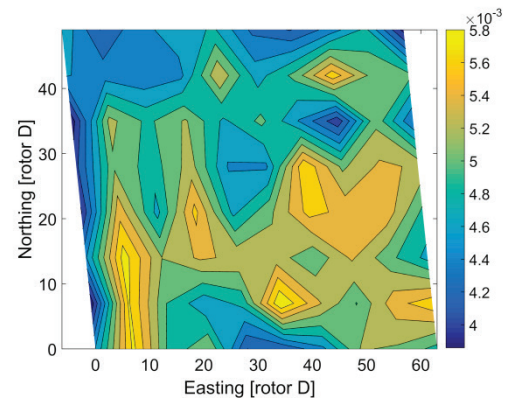


Figure 12. Map of blade root flapwise lifetime fatigue damage estimates for all individual turbines in Horns Rev 1.

Finally, Table 1 provides a summary of the accuracy of the various ML models presented above. The measures used are the coefficient of determination (R-square), and normalized root mean squared error (NRMSE).

Table 1. Overview of the accuracy of the estimations based on SCADA and ML models.

Variable names	R-square	NRMSE
Wind direction	0.973	0.075
Free wind speed	0.952	0.085
Ambient turbulence	0.764	0.256
Individual turbine power output	0.919	0.229
Total wind farm power output	0.956	0.188

4. Examples of alternative analysis approaches

In the previous section we showed a particular case study for the Horns Rev 1 wind farm, where a generic load model, and a certain amount of mast and SCADA data were available. In the following, we present further alternative steps which can be implemented when more information is available from the SCADA signals.

4.1. Load time series

While the last section described the ability to successfully reproduce mean wind farm performance using neural networks, similar models will be utilized here to reproduce component loads time series given SCADA based measurement time series. Based on measured time series from the SCADA system of electrical power, wind speed, blade pitch angle, tower top accelerations and rotor speed, a 3-layer feed-forward neural network is trained to output the corresponding time series of blade root flap moment and tower base fore-aft moment. The training is based on a selected sample of measured loads on a selected turbine within a wind farm over various mean wind speeds and time periods. The trained neural network is subsequently simulated using a different set of measured SCADA inputs not used in the training process. The result of simulation of loads using this neural network for such an arbitrary

10-minute SCADA input is shown in Figure 13, which demonstrates that a reasonable fidelity of the structural loading can be reproduced using measured SCADA signals.

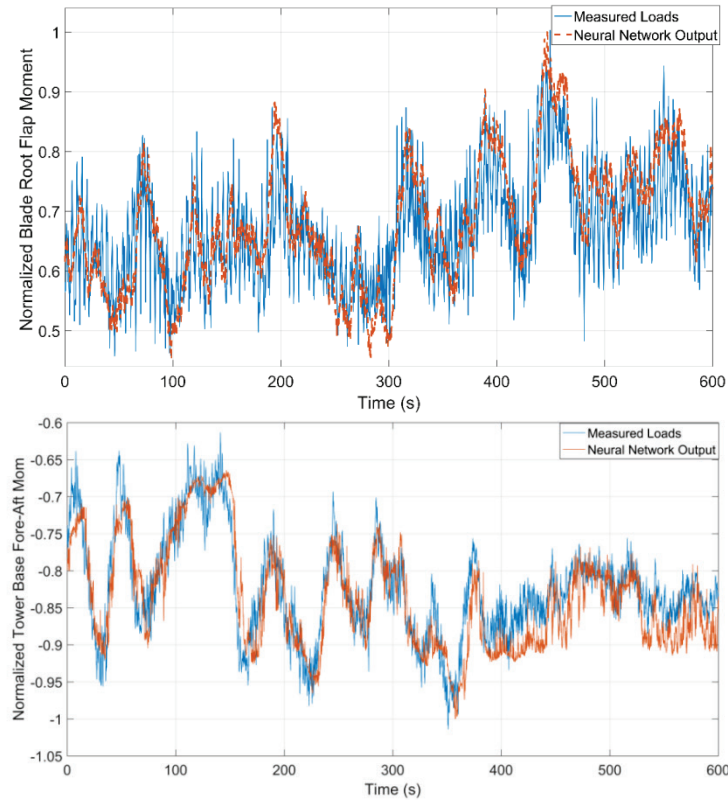


Figure 13. Mapping of wind turbine load time series to wind speed, rotor rpm and power by means of a Neural Network model.

Based on the neural network load simulation shown in Fig. 13, the corresponding load time series can be processed to yield damage equivalent loads or damage. The ANN model appears to act as a low-pass filter. However, due to the exponential relationship between load amplitude and fatigue damage, the large load cycles are predominant and the ANN model is capable of tracking the fatigue life consumption of the corresponding wind turbine structure within a wind farm. A comparison of the normalized damage equivalent blade root flap moments between measurements and simulations shows that difference is of the order of 10%-15% for some of the operating wind speeds as shown in Fig. 14.

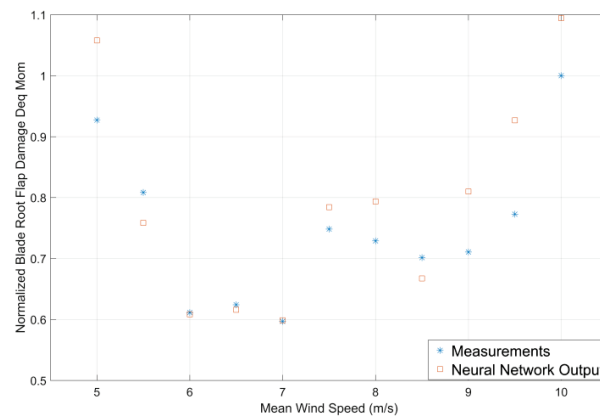


Figure 14: Mean flapwise damage equivalent moments on the blade root.

It is therefore possible to forecast a large fraction of the damage in the future based on a sufficient database of neural network simulation of loads based on SCADA inputs, which enables wind farm control to either diminish fatigue damage using de-rating or increase production.

4.2. Turbine operating status

SCADA data will often contain information about the operating status of the turbine, in terms of status flags (e.g. grid availability, available for production) and also system level information such as power, rotational speed etc. This information should be enough to establish statistics regarding the prevalence of different operating regimes of the turbine. In case the status flags are not available, a similar result can be obtained using basic operating data variables (power, rpm, nacelle wind speed and pitch low-order statistics), by training a ML classifier which predicts the turbine operating status and uses the basic variables as inputs. Training the classifier requires a reference data set with status flags for at least one turbine.

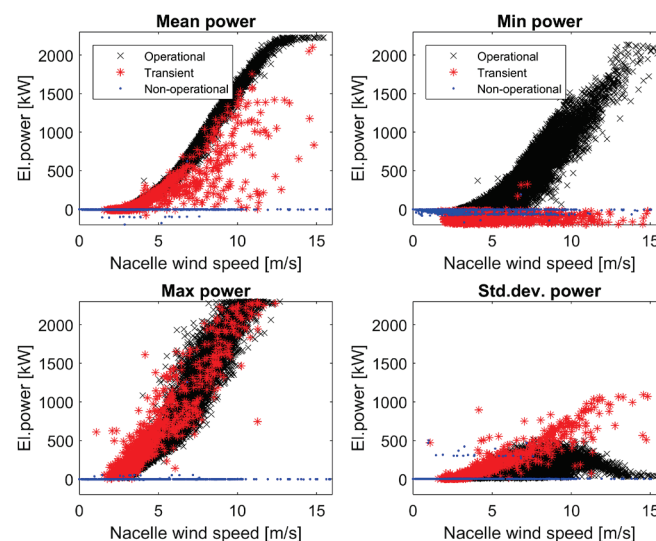


Figure 15. Illustration of the effect of turbine operational status on 10-minute power statistics from SCADA. Top left: mean power, top right: minimum power, bottom left: maximum power, bottom right: standard deviation of power.

Figure 15 shows the outputs of a ML classification model based on the random forest algorithm, for predicting the operating status of an onshore wind turbine. For training the model, 2 months of SCADA records on a single turbine including operational status flags (grid availability, turbine availability) are used. The trained model has an average precision score of 99.8%, with just 21 out of 10306 points being mislabeled. The outcome is a classification tool which can distinguish between three classes of operating conditions (operational, non-operational and transient) based on information about power, rotor rpm, nacelle wind speed, and blade pitch angle – all of which are basic variables typically present in SCADA records.

5. Conclusions.

The present study charted a flexible procedure for obtaining a load-based site-specific remaining lifetime estimate, where different alternatives are suggested based on the type and amount of information available. A particular case study on the Horns Rev 1 wind farm was shown, where free wind conditions were derived from SCADA, and the results were fed to a load prediction surrogate model trained on load simulations. The model predictions were validated against available SCADA data. It can be concluded that SCADA data can be used to derive an estimate of free wind conditions which is sufficiently good for carrying out load predictions. Furthermore, it was shown that a

simulation-based surrogate model where wake-induced effects are taken into account can perform well in predicting power output at wind farm as well as at wind turbine level.

Given measured load time series of rotor speed, power production, wind speed, pitch angles and tower top accelerations, it was determined that a neural network can reproduce the blade root and tower base load time series sufficiently well. If only 10-minute statistics of the SCADA signals are available, then an aeroelastic design basis of the wind turbine can be used to reproduce the 10-minute measured statistics and subsequently use the simulated time series to train the neural network.

Acknowledgements

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