Wind Turbine Structural Health Monitoring: A Short Investigation Based on SCADA Data

Evangelos Papatheou, Nikolaos Dervilis, Eoghan Maguire, Keith Worden

WIND TURBINE STRUCTURAL HEALTH MONITORING: A SHORT INVESTIGATION BASED ON SCADA DATA

E. Papatheou[1], N. Dervilis[1], A.E. Maguire[2] and K. Worden[1]

[1] *Dynamics Research Group, Department of Mechanical Engineering, University of Sheffield, Mappin Street, Sheffield, S1 3JD, UK*
[2] *Vattenfall Research & Development, New Renewables, The Tun Building, Holyrood Road, Edinburgh EH8 8AE, UK*

e.papatheou@sheffield.ac.uk

ABSTRACT

The use of offshore wind farms has been growing in recent years, as steadier and higher wind speeds can be generally found over water compared to land. Moreover, as human activities tend to complicate the construction of land wind farms, offshore locations, which can be found more easily near densely populated areas, can be seen as an attractive choice. However, the cost of an offshore wind farm is relatively high, and therefore their reliability is crucial if they ever need to be fully integrated into the energy arena. As wind turbines have become more complex, efficient, and expensive structures, they require more sophisticated monitoring systems, especially in offshore sites where the financial losses due to failure could be substantial. This paper presents the preliminary analysis of supervisor control and data acquisition (SCADA) extracts from the Lillgrund wind farm for the purposes of structural health monitoring. A machine learning approach is applied in order to produce individual power curves, and then predict measurements of the power produced of each wind turbine from the measurements of the other wind turbines in the farm. A comparison between neural network and Gaussian process regression is also made.

KEYWORDS : *wind turbine monitoring, SCADA, machine learning*

INTRODUCTION

It is perhaps well known that there has been a recent expansion in the use of wind energy, which is likely to continue with an accelerated pace over the coming years. Among the various forms of wind energy, offshore wind farms have become more popular, mainly due to the broader choice regarding their location and also the generally steadier and higher wind speeds that can be found over water, when compared to land. It is also understood that although offshore locations may be preferable to land sites, they can increase radically their maintenance costs, thus the monitoring of offshore wind farms becomes crucial if the expansion of their use continues to grow.

There have been several different approaches for the monitoring of wind turbines, from traditional non-destructive evaluation (NDE) and vibration approaches on the blades, to advanced signal processing and machine learning approaches in gearboxes. General reviews can be found in [1] and [2]. Most modern wind farms will contain some form of supervisor control and data acquisition (SCADA) system installed which can provide for the measurement and the recording of several different variables, such as wind speed, bearing and oil temperatures, voltage, and the power produced, among others. As the SCADA system records constantly and is primarily used to monitor and control plants, it forms an ideal basis for a complete online structural health monitoring approach. In addition, SCADA extracts are perhaps the most direct and potentially useful data obtained from wind turbines, except of course any direct measurements acquired on the turbines themselves (through accelerometers, laser vibrometry or any other sensor).

The use of SCADA data for monitoring has been shown in several studies, such as in [3, 4], and in most cases it aims at the development of a complete and automatic strategy for the monitoring of the whole turbine or wind farm, although sub-components (e.g. bearings, generator) may be individually assessed as well. Among the various approaches, power curve monitoring has been popular and successful. Wind turbines have been designed by manufacturers to have a direct relationship between wind speed and the power produced, and as they require a minimum speed to produce the nominal power, but limit the power generated from higher wind speeds, the power curve usually resembles a sigmoidal function. A critical analysis of the methods for modelling the power curve can be found in [5], but in general researchers have exploited the deviation from a reference curve to perform SHM on turbines. The use of machine learning approaches for the estimation of power generation can be seen as far back as in [6] and in [7], with more recent works appearing as well [8, 9]. In [10] a steady-state model of a whole wind farm with neural networks was shown to have fair results if the data used were pre-processed, while in [11] three operational curves, power, rotor and pitch were used for reference in order to produce control charts for the monitoring of wind turbines. The current paper explores the potential of using SCADA data for the monitoring of individual turbines, and of the whole farm, by constructing power curves for each turbine and then compare how well they predict for other turbines. The modelling is done with neural networks and Gaussian processes.

The layout of the paper is as follows. The next section contains a brief description of the wind farm and the SCADA data which are used. The third section presents the regression with the neural networks and the Gaussian processes on all the wind turbines of the farm, and how well each constructed power curve predicts the other turbines. Finally, the paper is rounded off with some overall conclusions in the final section.

1. Description of the wind farm

The Lillgrund wind farm is situated in the sea area between Denmark and Sweden and consists of 48 identical wind turbines of rated power 2.3 MW [12]; their distribution can be seen in Figure 1. The original labelling of the turbines made use of a combination of letters and numbers (rows A to D, see again Figure 1), but for convenience the turbines were simply numbered from 1 to 48. In this paper, only the pure number labelling is going to be used. It is important to note that the spacing between the turbines in the specific wind farm is significantly closer than most conventional farms [12], and this is generally expected to affect their performance.

The available data used in this study correspond to a full year of operation. All the SCADA extracts consist of 10 min averages, with the maximum, mean, minimum and standard deviation of the 10 min intervals being recorded and available. The actual sampling frequency is less than 10 mins, but it is not disclosed here.

2. Power curve monitoring of wind turbines

2.1 Neural Networks

Artificial Neural Networks (ANNs) are algorithms, or to be more specific, mathematical models which are loosely based on the way the human brain and biological neurons work. They have been extensively used for regression and classification, and they have been very successful in modelling data originating from various different sources. In the current work the multi-layer perceptron (MLP), the most common neural network, is used. All the modelling was done with the help of the Netlab [13] package in MATLAB, and the optimisation algorithm used was scaled conjugate gradients [13]. Since neural networks have been successfully used for nonlinear regression, they seem ideal for learning the power curve of wind turbines. The wind speed is available, in 10 min averages, from the SCADA extracts for each turbine (there is an anemometer in each tower). In addition, the SCADA data provide a status for the operation of the turbines, usually in the form of an ‘error code’. For the creation of the

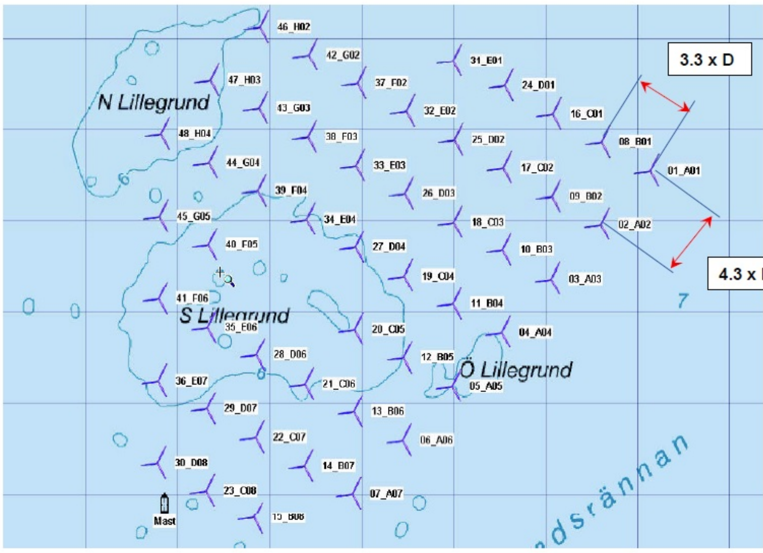

Figure 1 : Lillgrund wind farm and the distribution of the wind turbines [12].

healthy power curve (the reference curve), data from the whole year were used, but only when they corresponded to time instances with a status code equal to ‘0’, which means ‘no error’ in the turbines. The one-year healthy data were separated into training, validation and testing sets. The training set is primarily used for the training of the networks, while the validation is used to identify the best structure for the network. Different numbers of training cycles are applied, and in the end the finally selected network is tested with fresh data with the help of the testing set. The search for the network structure here went from 1 up to 10 hidden units, and the finally selected number of training cycles used was 300. The measure of the goodness of the regression fit was provided by the normalised mean-square error (MSE) shown in equation (1),

$$MSE(\hat{y}) = \frac{100}{N\sigma_y^2} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \qquad (1)$$

where the caret denotes an estimated quantity.

In total, 48 different networks (same as the number of turbines) were finally selected to create a power reference curve for the turbines. After that, each network was provided with wind speed data from the rest of the turbines and was asked to predict the power produced. In Figure 2 the MSE errors of each trained network, when tested with wind speed data for the turbine for which they were trained, and subsequently the remaining turbines, is shown. Each axis of the confusion matrix shown in Figure 2 corresponds to 1 up to 48 turbines, where on the y-axis is the number of the trained turbine and on the x-axis the number of the tested turbine. In general, an MSE error below 5 is considered a good fit and below 1 excellent.

From the results it is clear that almost all the trained networks are very robust and the maximum MSE error is around 5, which mainly occurs in turbines 3 and 4 which are located in the outside row of the wind farm. It can also be seen that in the diagonal of the confusion matrix (which corresponds to the testing set of the trained turbines when tested with data from themselves), the MSE error is very low, with the maximum appearing in turbine 39 (MSE=1.4708), and the minimum in turbine 31 with MSE at 0.5408. When the trained networks for an individual turbine were fed data originating from the same network, but which did not correspond to ‘no error statuses’, the MSE error was everywhere larger as can be seen in Figure 3, the lowest was 4.7991 which appeared in turbine 12 and it was still larger than the 0.8262 of the healthy data. In turbine 4, for example, the MSE increased from 0.768 to

149.033 and the standard deviation of the regression error from 0.0593 to 0.3685. Subsequent scanning of the data revealed that the majority of the instances where the regression error becomes high (in turbine 4) happened when the turbine was not working, either from emergency stops or manual stops. The emergency stops are associated with faults, but as these results derive from actual working data, the types of faults are limited to what was present during the recording period. Essentially, Figure 2 shows a map of potential thresholds, which can be used for the monitoring (in a novelty detection scheme) of the turbines individually or as a population.

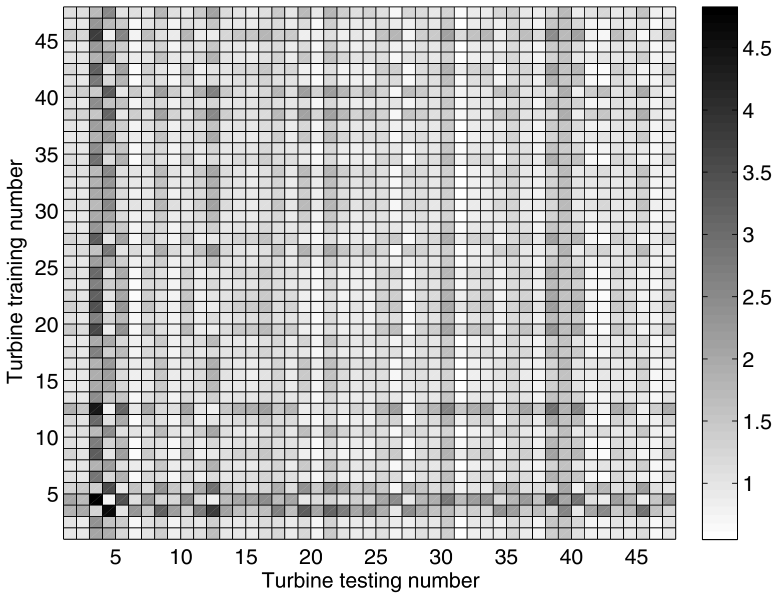

Figure 2 : Confusion matrix with MSE errors created from the neural networks - testing set.

2.2 Gaussian Processes

The power curve regression was also performed and compared with another algorithm, Gaussian processes (GPs). This is a research area of increasing interest not only for regression but also for classification purposes. For more details readers are referred to [14]. The use of GPs is a stochastic nonparametric Bayesian approach to regression and classification problems. These Gaussian processes are computationally very efficient and the nonlinear learning is relatively easy. Gaussian process regression takes into account all possible functions that fit to the training data vector and gives a predictive distribution of a single prediction for a given input vector. As a result, a mean prediction and confidence intervals on this prediction can be calculated from this predictive distribution.

The initial and basic steps in order to apply Gaussian process regression is to obtain a mean and covariance function. These functions are specified separately, and consist of a specification of a functional form and a set of parameters called hyperparameters. Here, a zero-mean function and a squared-exponential covariance function are applied [14]. When the mean and covariance functions are defined then the inference method specifies the calculation of the exact model and in simple terms describes how to compute hyperparameters by determining the minimisation of the negative log marginal likelihood. The software used for the implementation of GP regression was provided by [14].

In Figure 4, a similar confusion matrix to that produced for the MLPs is shown. The results appear to be very good again, with the same level of robustness and similar levels of MSE error, with the worst being again in turbines 3 and 4. In terms of the comparison between neural networks and

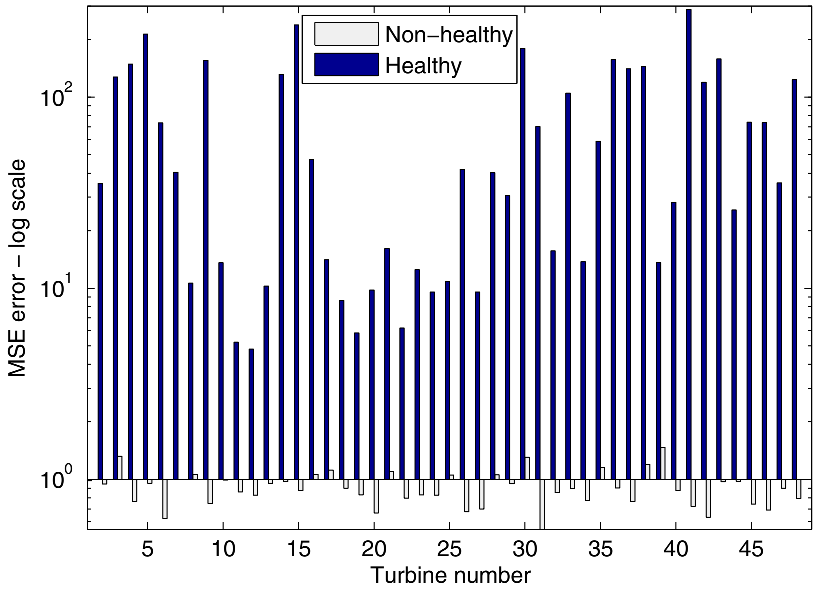

Figure 3 : MSE error of the neural network models when presented with data not corresponding to error code '0'.

Gaussian processes, it appears that the results are very similar with the networks performing with a slightly lower MSE error. It should be noted that the GPs are trained with about a third of the data that the neural networks were provided, but the testing sets are everywhere the same.

Figures 5 to 8 simply show the average MSE errors contained in the confusion matrices shown in Figures 2 and 4. In Figures 5 and 7 it is shown how well each trained (reference) power curve predicts the power produced in the rest of the turbines. In Figures 6 and 8 it can be seen how well the power produced in each turbine is predicted by the rest of the trained curves (corresponding to the rest of the turbines). From all those figures, it can be seen again that the worst turbines are 3 and 4 which predict, and are also predicted by the rest of the turbines with a greater error than the rest. The very low MSE errors show that the power curves have the potential of being used as a feature for the monitoring of the whole farm, as they were shown to be generally robust to the individual differences that the turbines inevitably present (location, different sensors, different generators etc).

CONCLUSION

This paper presented a preliminary exploration of the suitability of SCADA extracts from the Lillgrund wind farm for the purposes of SHM. Artificial neural networks and Gaussian processes were used to build a reference power curve (wind speed versus power produced) for each of the 48 turbines existing in the farm. Then, each reference model was used to predict the power produced in the rest of the turbines available, creating thus a confusion matrix of the MSE errors for all combinations. The results showed that nearly all models were very robust with the highest MSE error to be 4.8291, and this was happening when the model trained in turbine 4 was predicting power from turbine 3. Both turbines 3 and 4 are located in the outside row of the wind farm. It was shown that when wind speed data which did not come from time instances where the error status was '0' (meaning healthy data), were used as an input to the trained neural networks, the MSE error was significantly larger. Although, it was seen that in some cases the very large MSE was due to emergency stops or manual stops, and it is currently not known whether there was scheduled maintenance, this result, still shows the potential for novelty detection in the turbines. In this spirit, the confusion matrices that were presented earlier

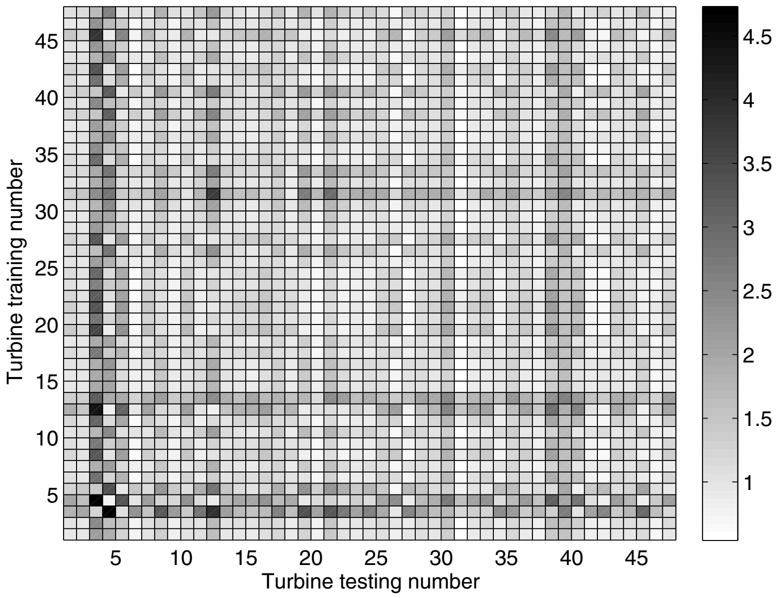

Figure 4 : Confusion matrix with MSE errors created from the Gaussian processes - testing set.

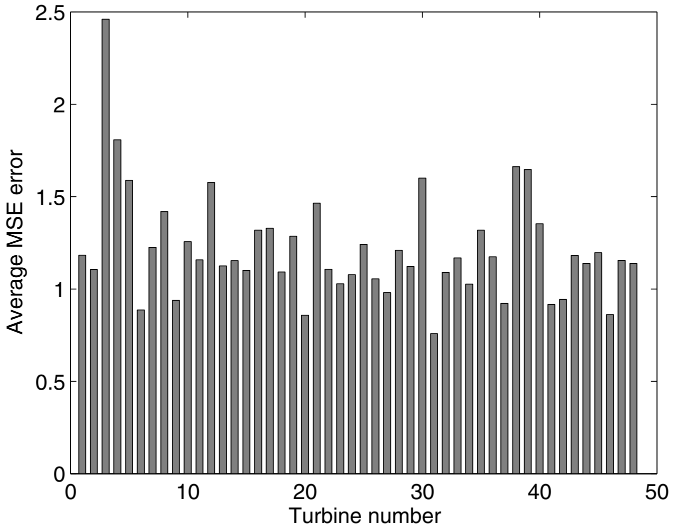

Figure 5 : Average MSE error showing how well neural networks trained to predict the power produced in each turbine, predict the produced power in the rest of the turbines.

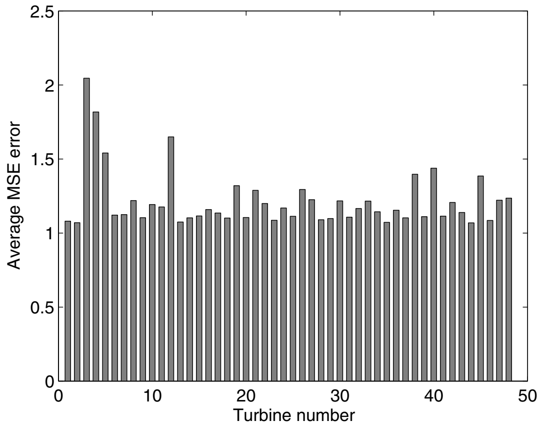

Figure 6 : Average MSE error showing how well the power produced in each turbine is predicted by the networks trained in the rest of the turbines.

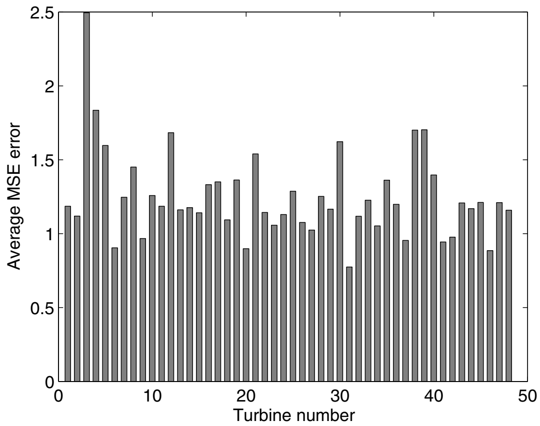

Figure 7 : Average MSE error showing how well each turbine predicts the produced power for the other turbines - Gaussian processes.

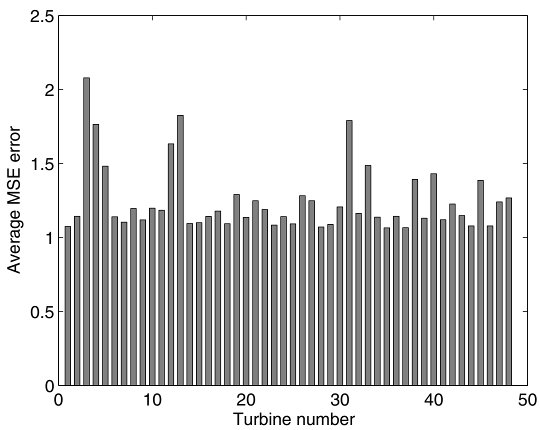

Figure 8 : Average MSE error showing how well each turbine (power produced) is predicted by the others - Gaussian processes.

can form the baseline for thresholds for a population-based SHM of the whole farm. It is anticipated that the power curve, and possibly other similar features, will be adequate to be used in future work in the construction of control charts for the monitoring of the whole wind farm and of the potential interaction or influence of the turbines with one another during their normal operation. Future work will also focus on the full analysis of the error statuses that were presented during the recorded time. In the comparison of the regression between neural networks and Gaussian processes, it was shown that there were no significant differences, with the networks performing with slightly lower MSE error.

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