

Flight Leader Concept for Wind Farm Load Counting and Performance Assessment

T.S. Obdam

L.W.M.M. Rademakers

H. Braam

This report has been presented at the European Wind Energy Conference 2009,
Marseille, France, 16-19 March 2009

ECN-M--09-054

Flight Leader Concept for Wind Farm Load Counting and Performance Assessment

T.S. Obdam, L.W.M.M. Rademakers, H. Braam

Energy Research Centre of the Netherlands (ECN)
Wind Energy
P.O. Box 1
1755 ZG Petten
Tel. (+31) 224 56 4395
Fax. (+31) 224 56 8214
obdam@ecn.nl

Abstract

ECN is developing the Flight Leader model, which is based on a concept with which the accumulated mechanical loading of all turbines in an offshore wind farm can be estimated at acceptable costs. This information can be used to optimise and lower the cost of Operation & Maintenance (O&M), for example by prioritising inspections and replacements. In this paper the background and general concept of the Flight Leader model are presented. Key to the application of the Flight Leader concept are the relations between standard (SCADA) signals and load indicators. The more accurate these relations, the more reliable are the calculations of accumulated loading. Using measurements from ECN's EWTW wind farm it will be shown how artificial neural network (ANN) techniques can be used for accurately estimating load indicators using only 10-minute statistics of standard SCADA parameters.

Keywords: Load Monitoring, Offshore Wind Energy, Operation & Maintenance

1. Introduction

Operation & Maintenance (O&M) costs for offshore wind farms account for up to 30% of the kWh price [1]. Lowering these costs is an important prerequisite for the economical exploitation of large offshore wind farms. The adequate planning of condition based maintenance is one aspect that could decrease the O&M costs; instead of having similar maintenance and inspection schemes for all turbines, the O&M requirements for each turbine can be made more dependent on its accumulated mechanical loading [2].

The most obvious way to get insight in the loading of all turbines in an (offshore) wind farm is to instrument all turbines with load measurements on the critical components. However, in practice after a wind farm is built, the actual loads on components are measured in only very few occasions. This is mainly caused by the fact that an adequate measurement campaign is labour intensive, costly and time consuming, especially if all turbines need to be measured.

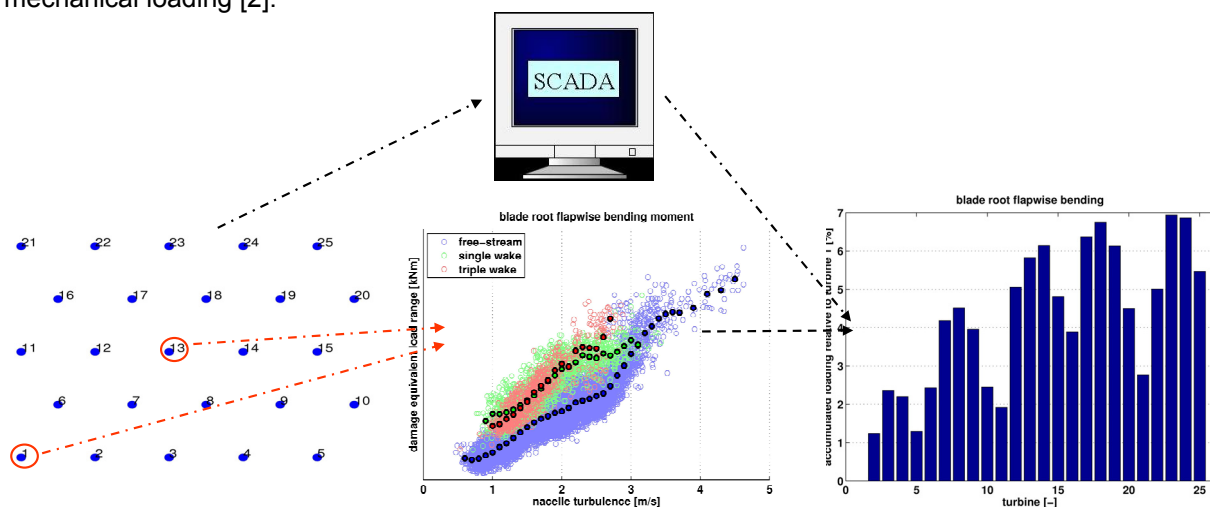


Figure 1: General structure of the flight leader computer model.

ECN is developing the Flight Leader concept, which is a methodology where only a small number of turbines at strategic locations in the offshore wind farm are equipped with mechanical load measurements. Using the measurements at these so-called ‘Flight Leader’ turbines relations are established between standard (SCADA) signals and load indicators. Combining these relations with the standard signals of all other turbines in the wind farm, offers the possibility to keep track of the accumulated mechanical loading of all turbines in the offshore wind farm at low costs. This is illustrated in Figure 1.

ECN is currently developing a demo version of a software model [3, 4], which includes all aspects of the Flight Leader concept. The software is intended to be used by operators of offshore wind farms and is used to process the SCADA data and mechanical load measurements from the offshore wind farm. The main output of the model is a comparison of the accumulated mechanical loading of all turbines in the offshore wind farm. This information can subsequently be used to optimise O&M strategies, for example by prioritising the inspection or replacement of certain components on the heavier loaded turbines. The structure and functionality of the software model is explained in more detail in chapter 2.

Key to the application of the Flight Leader concept are the relations between standard (SCADA) signals and load indicators. The more accurate these relations, the more reliable are the calculations of accumulated loading. Using measurements from the ECN Wind turbine Test location Wieringermeer (EWTW), it will be shown how artificial neural network (ANN) techniques can be used for accurately estimating load indicators using only 10-minute statistics of standard SCADA parameters. First a short introduction on the EWTW wind farm and neural networks is given in chapter 3 and 4 respectively. In chapter 5 the approach is discussed and the actual results of the analysis are presented.

2. The flight leader model

In this chapter the structure of the flight leader model will be treated in more detail. The general structure for the flight leader computer model is shown in the flowchart in Figure 2.

In the following subsections the different parts of the flight leader model will be discussed in more detail.

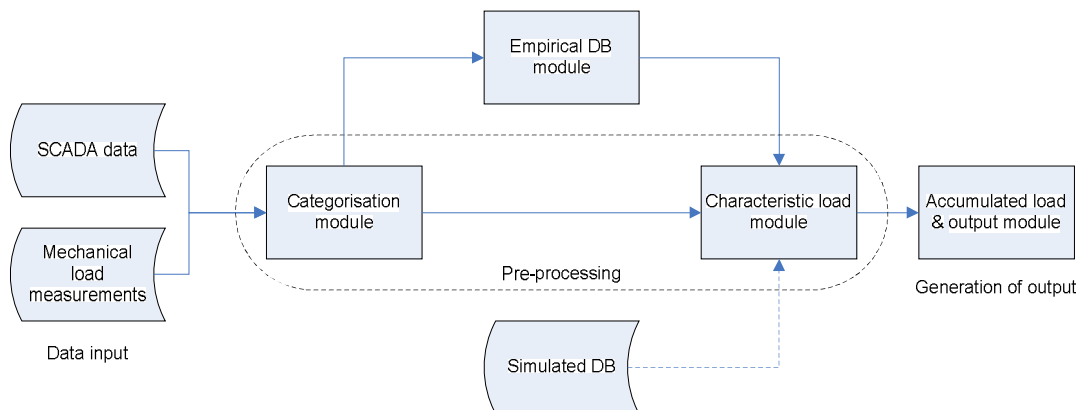


Figure 2: General structure of the flight leader computer model.

2.1 Data input

The input for the flight leader model is the data that are collected from the offshore wind farm. Two types of data can be distinguished; (1) SCADA data, which are being collected from all turbines and (2) mechanical load measurements, which are being collected only from the flight leader turbines. Both data should be collected as 10-minute statistics.

2.2 Data categorisation

Unfortunately a wind turbine does not always operate in normal power production mode.

Furthermore, when located in an (offshore) wind farm, wind turbines do not always experience free-stream wind conditions. Both mentioned conditions are expected to have an effect on the mechanical loading.

In order to take this into account the first step of the flight leader model is to categorise each timestamp in the dataset in one of the possible combinations of the five pre-defined turbine states j and three pre-defined wake conditions

k .¹ The possible combinations are indicated in Table 1.

Table 1: Possible combinations of turbine states & transitional modes and wake conditions.

ID	Turbine state or transitional mode j	Wake condition k
1.1	Normal power production	Free-stream
1.2		Partial wake
1.3		Full wake
2.1	Parked/Idling	Free-stream
3.1	Start-up	
4.1	Normal shutdown	
5.1	Emergency shutdown	

2.3 Empirical database

After all available data have been categorised the measurements from the flight leader turbines can be used to establish relations between (standard) SCADA parameters and load indicators, which are representative for the damage, aging or degradation of a certain component.

As mentioned in the previous section, these relations are expected to differ for the identified turbine states & transitional modes and wake conditions. Therefore the relations between SCADA parameters and load indicators have to be determined for each of the possible combinations shown in Table 1.

The software model offers the possibility to characterise the relations using more traditional methods such as interpolation or multivariate regression but also using artificial neural network techniques.

2.4 Simulated database

In the period directly after the commissioning of the offshore wind farm little measured data are available. Therefore it might be beneficial to incorporate the results of aero-elastic simulations into the flight leader model. This is particularly interesting for those situations with a low probability of occurrence, such as emergency shutdowns or extremely high wind speeds.

2.5 Estimating load indicators

Next step is estimating the load indicators at all turbines in the offshore wind farm. This is achieved by combining the SCADA data, collected at all turbines, with the relations between SCADA parameters and load indicators as stored in the empirical database. Optionally, for this process also results from aero-elastic simulations can be incorporated.

¹ It is assumed that wake conditions are only relevant in case a wind turbine operates in normal power production.

The situation might occur that for a certain turbine for a certain amount of time no SCADA data are available. For these periods the load indicators cannot be estimated neither with the empirical nor the simulated database. In order to ensure a fair comparison of the total accumulated loading the software also contains a procedure for handling missing data.

2.6 Output

Finally, the last part of the model is the process of generating and displaying the desired output of the flight leader model. The main output consists of a comparison of the accumulated mechanical loading of all turbines in the offshore wind farm. This output needs to be shown for the several load indicators (e.g. blade root bending, tower bottom bending or main shaft torque).

Besides the main output the software model can calculate and display various breakdowns of the accumulated loading. For instance the contribution of each turbine state or transitional mode or wake condition to the total accumulated loading can be displayed. Furthermore the load accumulation per time period can be studied. These outputs can be used to get more insight in the performance of the offshore wind farm and what operating conditions have the largest impact on the loading of the turbines in the offshore wind farm.

3. The EWTW wind farm

In this chapter some brief information regarding the EWTW wind farm is presented.

3.1 Location

The ECN Wind turbine Test location Wieringermeer (EWTW) [5, 6, 7] is located in the Wieringermeer, a polder in the northeast of the province Noord-Holland, 3 km north of the village of Medemblik and 35 km east of ECN Petten. The test location and its surroundings are characterised by flat terrain, consisting of mainly agricultural area, with single farmhouses and rows of trees. The lake IJsselmeer is located at a distance of 2 km east of EWTW.

3.2 Layout

The EWTW contains two rows of wind turbines; a row of five research Nordex N80 turbines and a row of four prototype turbines. For wind speed measurements three meteorological masts are located at the EWTW; meteorological mast 3 just south of the row of research turbines and meteorological masts 1 and 2 just south of the row of prototype turbines.

An overview of EWTW is shown in Figure 3.

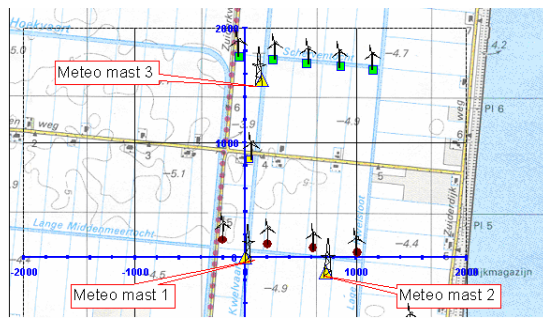


Figure 3: Overview of the ECN Wind turbine Test location Wieringermeer (EWTW).

3.3 Measurement campaign

Since October 2004 various measurements campaigns have been carried out at the EWTW find farm. The data collected from the five research Nordex N80 turbines include:

- Maintenance sheets;
- SCADA data (134 signals, 10-minute statistics) for all five Nordex N80 turbines. The data are obtained from Nordex on a daily basis;
- Measured SCADA data (25 Hz) from all five Nordex N80 turbines;
 - Turbine operational mode;
 - Wind speed;
 - Wind direction;
 - Electrical power output;
 - Generator speed;
 - Yaw direction;
 - Pitch angle.
- Mechanical load measurements at 2 Nordex N80 turbines (N6 & N8):
 - Blade root bending moments;
 - Tower bottom bending moments;
 - Tower top torsion;
 - Main shaft torque and bending moments;
 - High speed shaft torque.

The measurements at the Nordex N80 turbines have been used for various types of research. Examples are wake analyses, characterising failure behaviour, evaluating condition monitoring techniques and developing and evaluating new (wind farm) control strategies.

4. Artificial neural networks

Besides the more 'classical' techniques of interpolation and regression so-called 'artificial neural networks' can also be applied to model the relationship between two or more variables.

4.1 General description

A neural network in fact represents a mathematical model, where a number of (transfer) functions are connected in parallel and, possibly, also in series. Based on the weighted sum of multiple input signals each transfer function calculates a value, which subsequently serves as input for the next transfer function. The transfer function, including the weighted summation of multiple input signals, is labelled as neuron. A neural network with a sufficient number of neurons is, in theory, able to approximate every possible function.

A schematic representation of a neuron and a neural network (consisting of two 'hidden' layers of neurons) is shown in Figure 4.

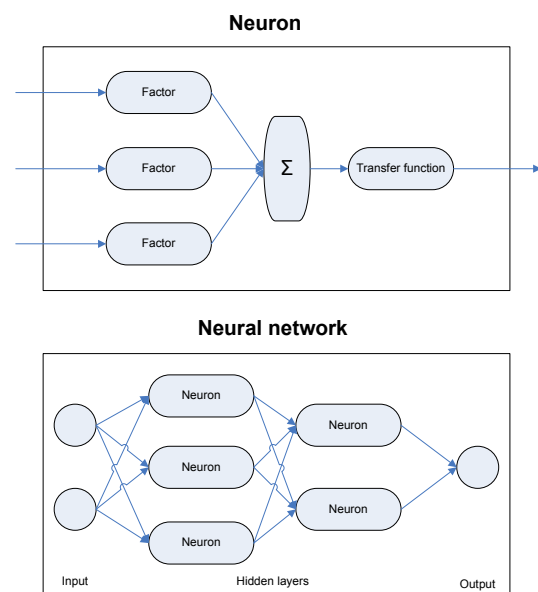


Figure 4: Schematic representation of a neuron and a neural network.

4.2 Application

For the analyses that will be described in chapter 5 the MATLAB[®] Neural Network Toolbox[™] has been used. The neural networks are trained using the Levenberg-Marquardt back-propagation algorithm. In order to prevent overfitting the early stopping technique is used.

5. Estimating load indicators using neural networks

In this chapter it will be discussed how the relations between SCADA parameters and load indicators can be accurately characterised using artificial neural network (ANN) techniques.

5.1 Previous work

Some previous work in this field has already been performed. Using prototype measure-

ments Germanischer Lloyd [8] showed that neural networks can be applied to accurately estimate fatigue load distributions of different components. A similar study has been performed at the SWE group at the University of Stuttgart [9], where based on simulations with an aero-elastic code neural networks have been applied to estimate fatigue load distributions.

Although this previous research has proven that neural networks are an excellent measure for estimating mechanical loading using standard signals, some important questions have to be answered:

- Are the results obtained on a single turbine applicable to the same turbine type placed at a different location?
- Are the results that have been determined using only free-stream data also applicable for estimating the loads on a turbine that operates in wake conditions?

5.2 Approach

The analysis, of which the results will be presented in this chapter, has been performed for two load indicators.

The first step in developing an empirical neural network model is preliminary identifying which standard signals could be used as independent variables in the neural network. This has to be done for each of the identified load indicators.

Next a representative dataset should be selected where it is essential that the mechanical load measurement data are pre-processed in order to remove measurement errors such as spikes.

After selecting the representative dataset the artificial neural network should be trained to fit the relation between the independent variables and the load indicator. A validation dataset should always be used in order to halt network training at the point where generalisation stops improving.

The accuracy of the relations is judged by comparing the predicted outputs by the model with the measured values (targets). The coefficient of determination R^2 and the mean difference between output and target Δ_m are used to characterise the accuracy.

5.3 Load indicators

The approach discussed above will be followed for two load indicators; the 1 Hz damage equivalent load range of (1) the blade root

flapwise bending moment, and (2) the tower bottom for-aft bending moment.

The damage equivalent load range ΔF_{EQ} is the load range that for some arbitrarily chosen number of cycles N would, in theory, produce the same damage as all actual load ranges (which follow from rain flow counting) combined:

$$\Delta F_{EQ} = \sqrt[m]{\frac{\sum_i n_i \cdot \Delta F_i^m}{N}} \quad (1)$$

where m is the Wohler coefficient, n_i the actual number of cycles and ΔF_i the actual load range for each occurring case i .

5.4 Independent variables

The measured SCADA data parameters, as described in section 3.3, are possible input candidates for the artificial neural network. Initially only the first two statistical moments (arithmetic mean and standard deviation) of the nacelle wind speed, electrical power output, generator speed and pitch angle will be used as independent variables in the neural network.

5.5 Dataset

For both turbine 6 and 8 at EWTW both a ‘free-stream’ and a ‘wake’ dataset are selected. The respective turbines should be in normal power production. For the ‘free-stream’ set only data are considered with timestamps between 2008-01-01 and 2008-10-01. Since wake conditions at EWTW occur less frequently for the ‘wake’ set data are considered with timestamps between 2007-01-01 and 2008-10-01 in order to ensure a dataset of sufficient size is available. Furthermore, all independent variables and load indicators should have a valid value.

5.6 Results

In this section the results from the analyses, as have been described in section 5.2 will be presented.

5.6.1 Generalisability free-stream conditions

The first goal is to determine whether an accurate relation between SCADA parameters and both load indicators can be established for a turbine in normal power production and under free-stream conditions. In addition to this the generalisability of this relation is assessed.

The neural network is trained using only data from turbine 6. Data from turbine 8 is used as

validation set, which is a measure for network generalisation. The training is halted as soon generalisation stops improving. The results for blade root flapwise and tower bottom for-aft are shown in Figure 5 and Figure 6 respectively.

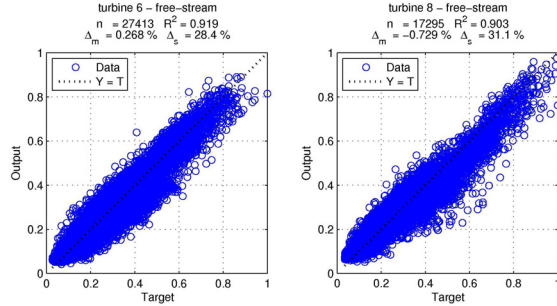


Figure 5: Blade root flapwise bending. Left: Relation between output (prediction by ANN trained at turbine 6 in free-stream conditions) and target (measured values at turbine 6 in free-stream conditions). Right: Relation between output (prediction by ANN trained at turbine 6 in free-stream conditions) and target (measured values at turbine 8 in free-stream conditions).

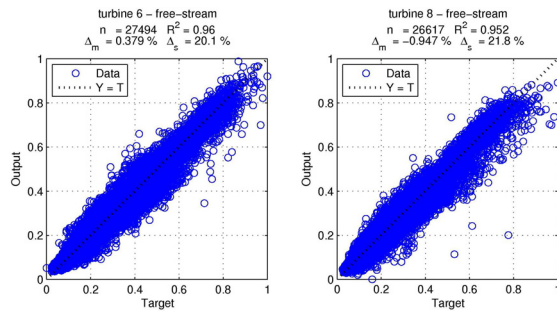


Figure 6: Tower bottom for-aft bending. Left: Relation between output (prediction by ANN trained at turbine 6 in free-stream conditions) and target (measured values at turbine 6 in free-stream conditions). Right: Relation between output (prediction by ANN trained at turbine 6 in free-stream conditions) and target (measured values at turbine 8 in free-stream conditions).

The results (left graph in the figures) indicate that it is possible to accurately estimate the load indicators of both blade root flapwise bending and tower bottom for-aft bending ($R^2 = 0.92$ and $R^2 = 0.96$ respectively) using the independent variables as listed in 5.4. Furthermore, the generalisability of these relations (right graph in the figures) is encouraging as is indicated by $R^2 = 0.90$ and $R^2 = 0.95$ for blade root flapwise and tower bottom bending respectively.

5.6.2 Validity for wake conditions

In order to assess whether the neural network, trained using only free-stream data, can also be applied to a turbine operating in wake conditions, a dataset is selected where turbine 6 operates in (partial and full) wake conditions. This dataset is now used as a validation set which is used to halt training when the gener-

alisation capacities of the neural network (which is trained using data where turbine 6 operates in free-stream conditions) stop improving. The results for blade root flapwise and tower bottom for-aft bending are indicated in Figure 7 and Figure 8 respectively.

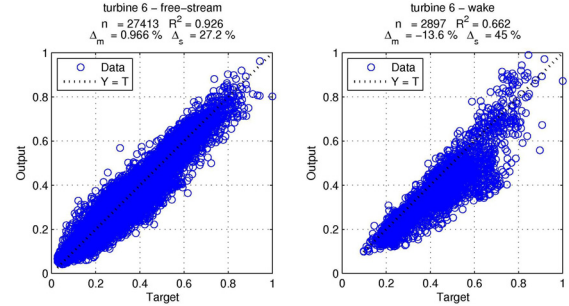


Figure 7: Blade root flapwise bending. Left: Relation between output (prediction by ANN trained at turbine 6 in free-stream conditions) and target (measured values at turbine 6 in free-stream conditions). Right: Relation between output (prediction by ANN trained at turbine 6 in free-stream conditions) and target (measured values at turbine 6 in wake conditions).

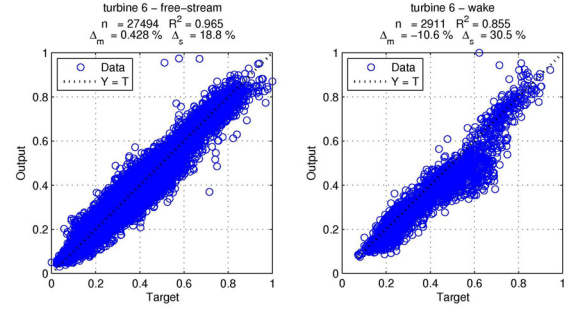


Figure 8: Tower bottom for-aft bending. Left: Relation between output (prediction by ANN trained at turbine 6 in free-stream conditions) and target (measured values at turbine 6 in free-stream conditions). Right: Relation between output (prediction by ANN trained at turbine 6 in free-stream conditions) and target (measured values at turbine 6 in wake conditions).

The results shown in Figure 7 and Figure 8 clearly indicate that the neural network trained using only free-stream data cannot be applied to estimate the load indicators of a turbine operating in wake conditions. If this would be done the value of the load indicators of the blade root flapwise bending and tower bottom bending would, on average, be underestimated by 13.6% and 10.6% respectively.

5.6.3 Generalisability wake conditions

The results presented in the previous section indicate that a neural network trained using only free-stream data cannot be applied to estimate the values of the load indicators of a turbine operating in wake conditions. Therefore it will be necessary to train a separate neural network for both free-stream conditions and wake conditions.

In this section the same approach as in section 5.6.1 is followed with the only difference being the fact that instead of only free-stream conditions now only wake conditions are considered. The results are presented in Figure 9 and Figure 10.

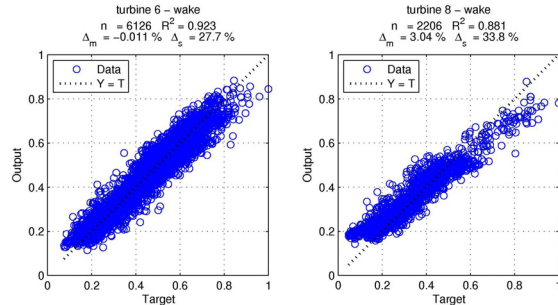


Figure 9: Blade root flapwise bending. Left: Relation between output (prediction by ANN trained at turbine 6 in wake conditions) and target (measured values at turbine 6 in wake conditions). Right: Relation between output (prediction by ANN trained at turbine 6 in wake conditions) and target (measured values at turbine 8 in wake conditions).

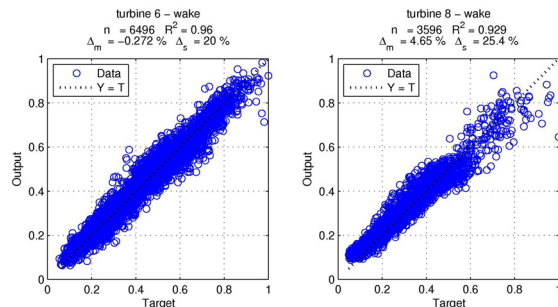


Figure 10: Tower bottom for-aft bending. Left: Relation between output (prediction by ANN trained at turbine 6 in wake conditions) and target (measured values at turbine 6 in wake conditions). Right: Relation between output (prediction by ANN trained at turbine 6 in wake conditions) and target (measured values at turbine 8 in wake conditions).

The left graphs in Figure 9 and Figure 10 indicate that both load indicators can be estimated equally well for a turbine operating in wake conditions as for a turbine operating in free-stream conditions. However, the load indicators at turbine 8 are, on average, slightly over-predicted by the neural network trained at turbine 6. Therefore it can be said that the generalisability of the relation between independent variables and load indicators for wake conditions is slightly less compared to free-stream conditions.

More research is required in order to determine the cause for the lesser generalisability of the network trained in wake conditions compared to the network trained in free-stream conditions.

5.7 Conclusions

The analyses have shown that artificial neural networks are an excellent method for estimating the values of load indicators using just 10-minute statistics of standard SCADA parameters. For free-stream conditions the relations determined are very accurate and when applying the trained network to another turbine encouraging results are obtained.

Furthermore the research has shown that a network trained using data of a turbine operating in free-stream conditions cannot be applied to accurately estimate the values of the load indicators for a turbine operating in wake.

When training a separate network for wake conditions an excellent accuracy is found, although the generalisability of these relations appears slightly less compared to the network for free-stream conditions.

6. Status and future work

Functional and technical specifications for the Flight Leader software model have been completed. On the basis on these detailed specifications a demo version of the Flight Leader software model has been programmed in MATLAB®.

Using the demo software model further analyses of the EWTW data will be performed, where the same approach (as has been presented in this paper) will be applied for load indicators relevant for other wind turbine components. The accuracy of the Flight Leader concept will be evaluated and, if necessary, the software model will be adjusted.

Finally, the demo version of the Flight Leader software model will be applied to the Offshore Wind farm Egmond aan Zee (OWEZ).

Acknowledgements

This study is carried out and co-financed by the Bsik programme 'Large-scale Wind Power Generation Offshore' of the consortium We@Sea (<http://www.we-at-sea.org>).

References

- [1] L.W.M.M. Rademakers, H. Braam, M.B. Zaaijer, G.J.W. van Bussel; *Assessment and Optimisation of Operation and Maintenance of Offshore Wind Turbines*; Proceedings European Wind Energy Conference 2003.
- [2] L.W.M.M. Rademakers, H. Braam, T.S. Obdam; *Estimating Costs of Operation & Maintenance for Offshore Wind Farms*; ECN-M--08-027; Presented at the European Wind Energy Conference 2008, Brussels.
- [3] T.S. Obdam, L.W.M.M. Rademakers, H. Braam; *Functional Specifications for the Flight Leader*; ECN-X--08-049; June 2008.
- [4] T.S. Obdam; *Technical Specifications and Model Description for the Flight Leader*; ECN-X--08-098, October 2008.
- [5] P.J. Eecen, J.P. Verhoef; *EWTW Meteorological database; Description June 2003 - May 2006*, ECN-E-06-004; September 2006.
- [6] P.J. Eecen, et. al.; *Measurements at the ECN Wind Turbine Test Location Wieringermeer*; ECN-RX--06-055; February 2006.
- [7] P.J. Eecen, et. al.; *LTVM statistics database*; ECN-CX--05-084; September 2005.
- [8] S. Schwarz, R. Dittmar, A. Anders; *Determination of Actual Fatigue Loading on Wind Turbines Based on Neural Networks*; 2005.
- [9] N. Cosack, M. Kühn; *Prognose von Ermüdungslasten an Windenergieanlagen mittels Standardsignalen und neuronaler Netze*; Presented at the Dresdner Maschinenelemente Kolloquium, Dresden; December 2007.