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Flight Leader Concept for Wind Farm Load Counting: First offshore implementation

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Flight Leader Concept for Wind Farm Load Counting:
First offshore implementation

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Abstract

ECN has developed a demo version of 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. Furthermore, the results of the evaluation (using data from ECN's wind farm EWTW) of the accuracy and reliability of the Flight Leader software are discussed. Finally the first results of the Flight Leader software, implemented at an offshore wind farm, are presented.

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.

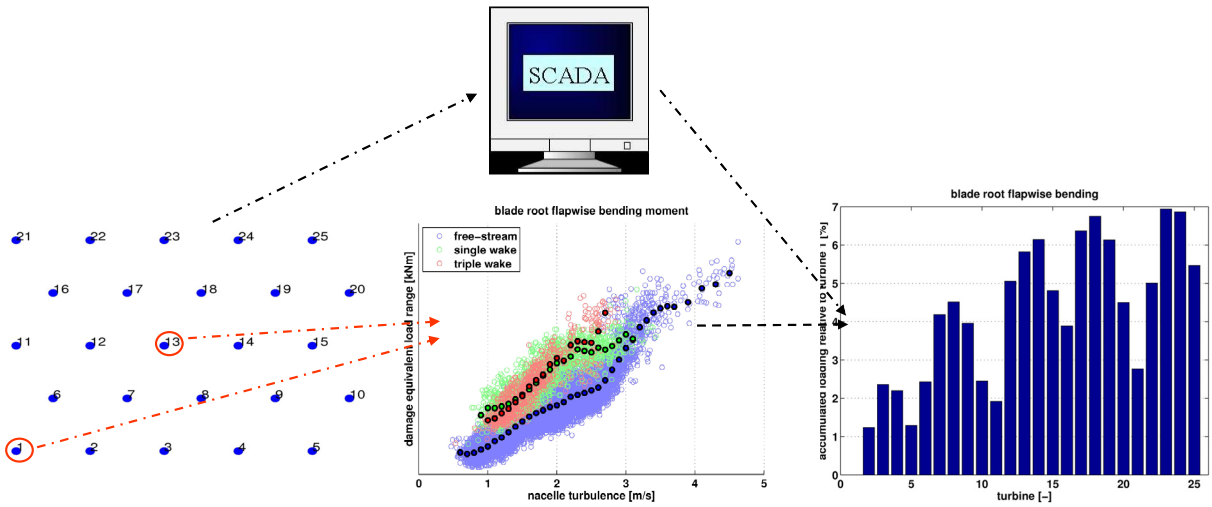


Figure 1.1: General structure of the flight leader computer model.

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 1.1.

ECN has developed a demo version of a software model [3, 4, 5], 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 and results for the evaluation of the Flight Leader are presented. Finally, in chapter 6 the first results of the Flight Leader software, implemented at an offshore wind farm, 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 2.1.

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

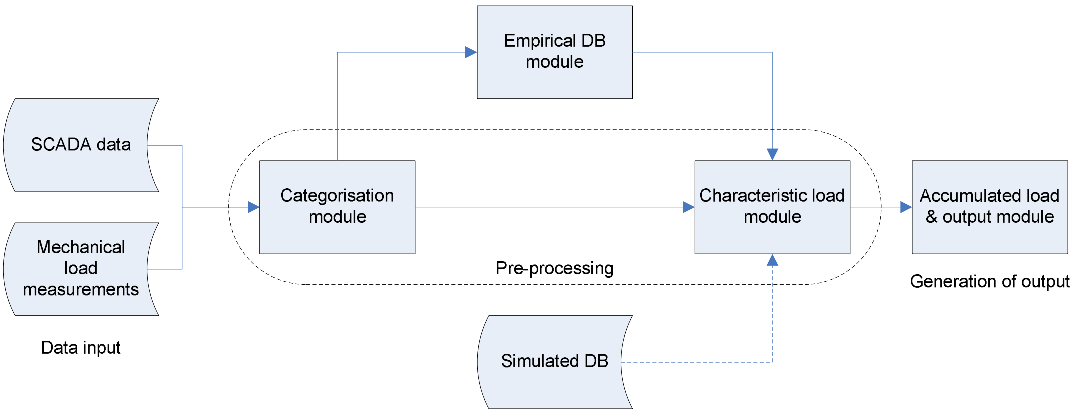


Figure 2.1: General structure of the flight leader computer model.

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

10-minute 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.

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) [6, 7, 8] 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; meteoro-

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

logical 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 3.1.

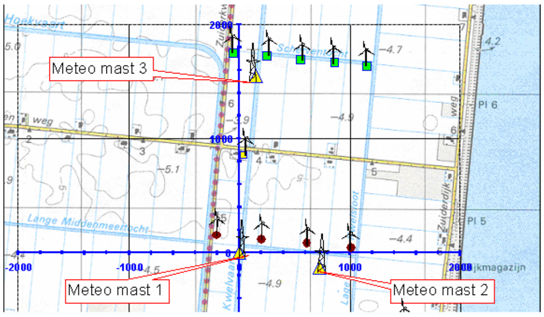


Figure 3.1: Overview of the ECN Wind turbine Test location Wieringermeer (EWTW).

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 [9, 10]

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 4.1.

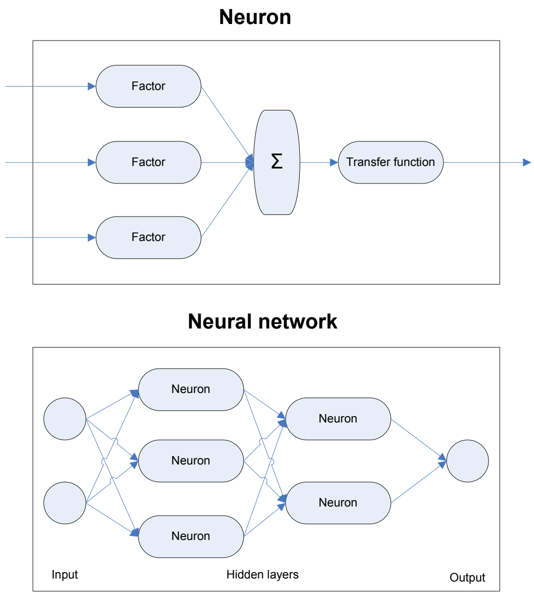


Figure 4.1: Schematic representation of a neuron and a neural network.

4.2 Application

For the analyses that will be described in chapter 5 and 6the MATLAB® Neural Network Toolbox™ has been used. The neural networks are trained using the Levenberg-Marquardt backprogagation algorithm. In order to prevent overfitting the early stopping technique is used.

5. Evaluation of the Flight Leader at EWTW

In this chapter the results of the evaluation of the Flight Leader software at the EWTW wind farm are presented. The evaluation has been performed using 24 months of measured data from all five turbines.

In the following subsections the results from all steps in the evaluation process are discussed.

5.1 Selection of load indicator and SCADA parameters

The evaluation of the Flight Leader software will performed for four load indicators; the 1 Hz damage equivalent load range ΔF_{EQ} of:

- Blade root flapwise bending;
- Tower bottom for-aft bending;
- Main shaft bending;
- High speed shaft torque.

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:

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

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.

The measured SCADA data parameters, as described in section 3.3, are possible input candidates for the artificial neural network. For the evaluation the first four statistical moments (arithmetic mean, standard deviation, skewness and kurtosis) of the electrical power output, generator speed and pitch angle have be used as independent variables in the neural network.[2]

5.2 Data categorisation

As discussed in chapter 2 the first step of the analysis is to categorise the data for each turbine i and 10-minute timestamp t in one of the pre-defined load cases (see Table 1). The results of the data categorisation step are displayed in Figure 5.1.

The figure illustrates that most of the time the turbines operate in normal power production and in free-stream conditions. As expected turbines 2, 3 and 4 operate more often in wake conditions compared to turbines 1 and 5 as these turbines are located in the middle of the row configuration (see Figure 3.1). Furthermore, all five turbines are in parked/idling condition for a significant part of time. This occurs in case of too low wind speeds or when the turbine is stopped for maintenance. Finally, also around 5% of the data could not be categorised in one of the defined load cases. This can be caused by (1) the unavailability of the SCADA signals which are used to categorise the data or (2) by the fact the data does not meet any the categorisation criteria for each of the seven defined load cases.

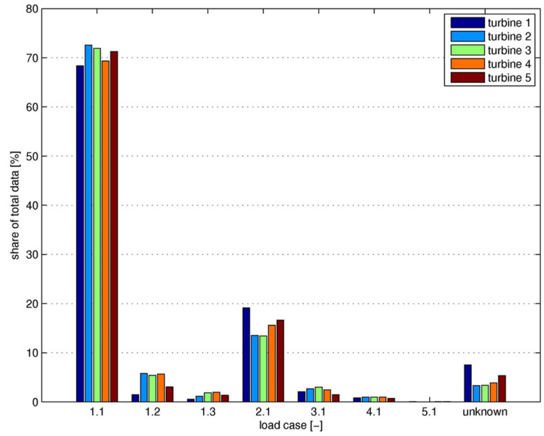


***Figure** 5.1: Results of the data categorisation step.*

5.3 Relation SCADA parameters and load indicator

Next step in the analysis is to establish the relation between the selected SCADA parameters and load indicator. A separate relation has to be determined for each of the seven defined load cases (see Table 1). As an example in Figure 5.2 the relation is shown for tower bottom for-aft bending for the load case power production under free-stream conditions.

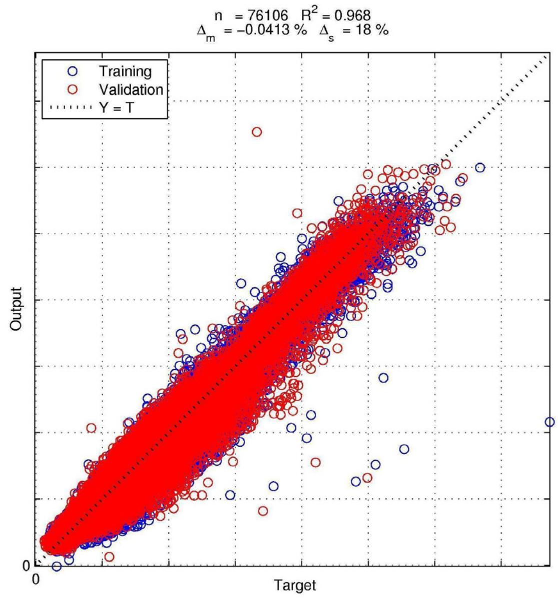


Figure 5.2: Performance of the neural network trained for estimating the tower bottom for-aft bending load indicator for a turbine in power production under free-stream conditions. Data from turbine 2 (blue) are used to train the neural network, whereas data from turbine 4 (red) are used to validate the network's performance.

[2] This applies for the normal power production load cases. For the other load cases some slight variations in SCADA parameter selection exist.

The results presented in the figure indicate that when applying neural networks as characterisation method the relation between the selected SCADA parameters and load indicator can be determined (turbine 2, see blue data) in a fairly accurate manner. When applying the trained network to data from turbine 4 (see red data) it can be seen that the established relation is also accurate for the same turbine type placed at a different location.

5.4 Output

After similar relations (between SCADA parameters and load indicator) have been determined for the other six load cases it is possible to combine these relations with the relevant SCADA data for all five turbines in order to estimate the value of the load indicator for each turbine *i* and timestamp *t*. Subsequently for each turbine the total load accumulation is determined and the turbines are ranked. This is shown in Figure 5.3.

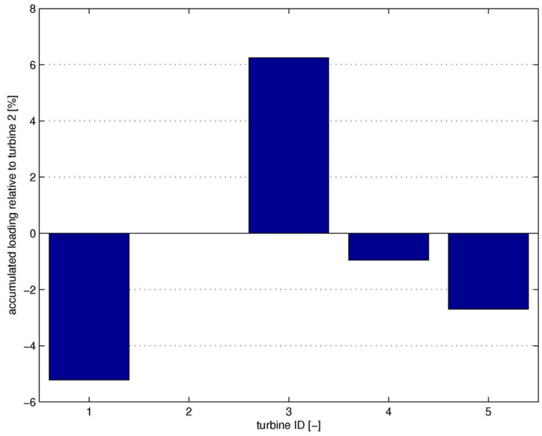


Figure 5.3: Load accumulation of all five turbines relative to load accumulation of turbine 2.

According to the flight leader software the tower of turbine 3 has accumulated most loading (6% more than turbine 2); whereas turbine 1 has accumulated about 5% less load. Turbines 4 and 5 have accumulated slightly less load compared to turbine 2 (about 1% and 2%).

In order to be able to explain the results shown in Figure 5.3 several breakdowns of the output have been generated. This is shown in Figure 5.4, for the results presented in this figure data from all five turbines has been used.

In the top graph the accumulated loading for each defined turbine state and transitional mode is displayed. It can be seen that most load accumulation is achieved during the turbine state normal power production. Interestingly, the flight leader software predicts that about 15% of the load accumulation can be contributed to emergency shutdowns. This is a very large share considering that these emergency shutdowns occur only few times per year. During the parked/idling state hardly any load accumulation occurs, whereas for start-up and normal shutdown the load accumulation is proportional to the amount of data where the turbines operate in these transient events.

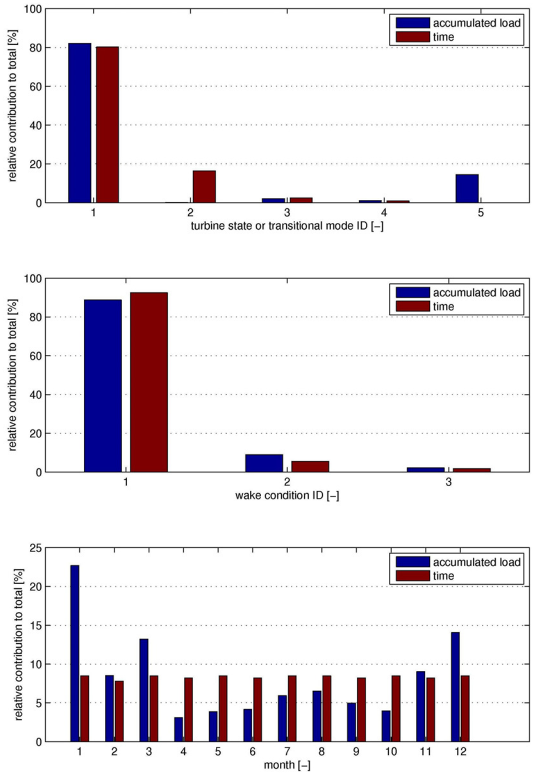


Figure 5.4: Different breakdowns of the load accumulation: (1) per turbine state and transitional mode, (2) per wake condition and (3) per month. The red bars indicate the amount (relative to total) of data available for each category.

In the middle graph the accumulated power production for each defined wake condition is shown. When the turbines operate in partial wake conditions the relative load accumulation is slightly larger compared to the situation where the turbines operate in free-stream conditions.

In the bottom graph the accumulated power production during each month is depicted. The bar plot indicates that during the months January, March and December most energy has been produced. During April, May, June and October relatively little load accumulated took place.

5.5 Validation

The output shown in the previous graphs is purely based on the calculated output by the flight leader software. In order to be able to ensure that the calculated results are reliable it is important that the output of the flight leader software is validated. The relationships between SCADA parameters and load indicator (see section 5.3) have all been derived using data from turbine 2 only[3]. By comparing the predicted load accumulation with the measured load accumulation at turbine 2 and 4 it is possible to evaluate the accuracy and reliability of the flight leader predictions. This comparison is shown in Figure 5.5 for all four load indicators.

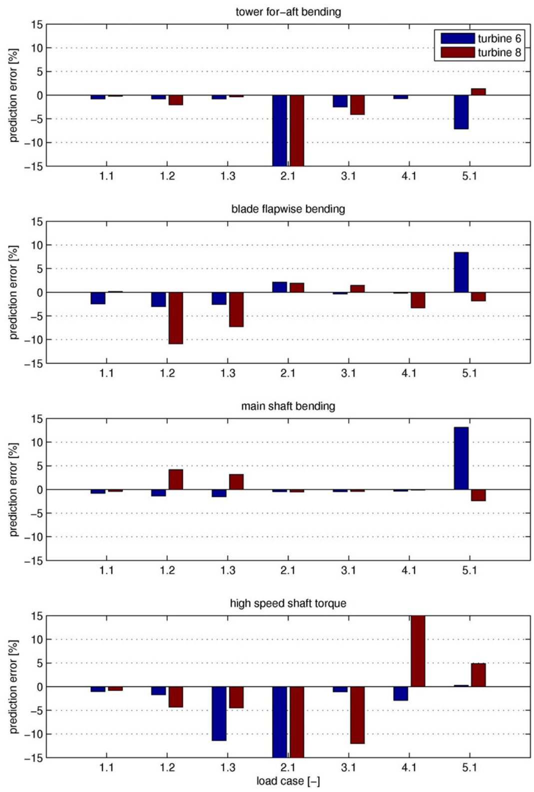


Figure 5.5: Comparison of predicted and measured accumulation for all seven load cases.

When studying the top graph it can be seen that for tower bottom for-aft bending for all load cases except for parked/idling and, to lesser extent, emergency shutdowns, the predicted and measured load accumulation match extremely well (difference < 5%). In Figure 5.4 it was shown that close to zero load accumulation takes place during a parked/idling turbine state and therefore the large prediction error for this load case can be accepted. However, load accumulation during emergency shutdowns is significant and therefore it is necessary to increase the prediction accuracy of the Flight Leader software for this load case.

The second graph shows that for blade root flapwise bending for most load cases the difference between predicted and measured load accumulation is relatively small (< 5%). The only larger difference between prediction and measurements is for power production in wake conditions for turbine 4. At this moment the exact reason for these larger prediction errors is unknown. One possible explanation could be the fact that turbine predominantly operates in the wake of one turbine, whereas turbine 4 faces the wakes of three turbines most of the time. Not being able to measure the amount of wind shear in the rotor plane (which is significant when a turbine operates in partial wake conditions) could be another factor contributing to the lower accuracy of the Flight Leader prediction. In addition to this, similar as was found for tower for-aft bending, the prediction error for emergency shutdowns is also slightly larger compared to the other load cases.

The results for main shaft bending, as presented in the third graph, indicate that for almost all load cases a very good prediction accuracy is found (difference < 5%). The large difference between predicted and measured load accumulation for emergency shutdowns can be explained by the fact that very little data points were available, which causes the determined relation to have a lower accuracy.

Finally, in the bottom graph, which depicts the results for the high speed shaft torque load indicator, it can be seen that with a few exceptions the prediction errors by the Flight Leader software are relatively small. The largest difference is again found for the parked/idling case but since this load case hardly contributes to the total load accumulation the prediction error is expected to have a negligible influence on the results presented in Figure 5.3.

5.6 Conclusions

In the previous sections the results procedure for applying the Flight Leader software to data from ECN's EWTW wind farm have been discussed.

The most important conclusion that can be drawn from the analysis is the fact that in general the prediction accuracy of the Flight Leader software is relatively high. The largest prediction errors are found for the parked/idling and emergency shutdown load cases.

For the former this error does not have a significant influence on the comparison of the total accumulation, since hardly any load is accumulated when the turbine is in parked or idling condition.

However, for the latter the prediction error can have a significant effect since for some load

[3] Note that for artificial neural networks data from turbine 4 have been used to prevent 'over-fitting' of the data.

cases emergency shutdowns can have an important contribution to the total load accumulation. Since the errors are mainly caused because very little data are available for emergency shutdowns it might be beneficial to incorporate the results of aero-elastic simulations in the Flight Leader software in order to increase the prediction accuracy for this load case.

6. Implementation of the Flight Leader at an offshore wind farm

Compared to wind turbines placed on land offshore turbines suffer from additional wave-induced loading. Furthermore, offshore wind farms usually consist of a large number of turbines, which implies that wake effects are much more significant.

Although the results for an onshore wind farm look encouraging (see chapter 5), it is important that the accuracy and reliability of the Flight Leader predictions are also verified using data from an offshore wind farm.

In this chapter the first results of the Flight Leader software applied at an offshore wind farm are presented. In the following subsections a brief description of the wind farm is given, the data set used is discussed and the results from the preliminary investigation are presented.

6.1 Wind farm description

OWEZ is the first Dutch offshore wind farm, located 10-18 km from the village Egmond aan Zee. The farm consists of 36 Vestas V90 turbines, which are pitch-controlled variable-speed machines with a rated power output of 3 MW.

Two turbines in the farm are equipped with mechanical load measurements on blades and tower and will therefore act as Flight Leader turbines.

6.2 Data set

For the analysis described in the next section 6 months of data have been used. Available SCADA signals include nacelle wind speed, rotor rotational speed, pitch angle and electrical power output and nacelle yaw direction. Mechanical load measurements are performed on blade (flapwise and edgewise) and tower (north-south and east-west). Additionally, data from the meteorological mast and nearby wave buoy are available.

6.3 Preliminary results

Since the accuracy of the relations between SCADA parameters and load indicator hold the key for an accurate and reliable application of the Flight Leader concept the preliminary analysis of the offshore data will focus on this part.

The approach followed here is the exact same as has been described in section 5.3. Data from the first Flight Leader turbine is used to train the neural network and simultaneously the network's performance is validated using data from the second Flight Leader turbine.

The first part of the analysis focuses on the performance of a neural network trained to estimate the load indicator (see section 5.1) for flapwise bending for a turbine in power production under free-stream conditions. The results are presented in Figure 6.1.

Another network is trained for the same load indicator but for the situation where the turbine is operating in partial wake conditions. The network's performance is shown in Figure 6.2.

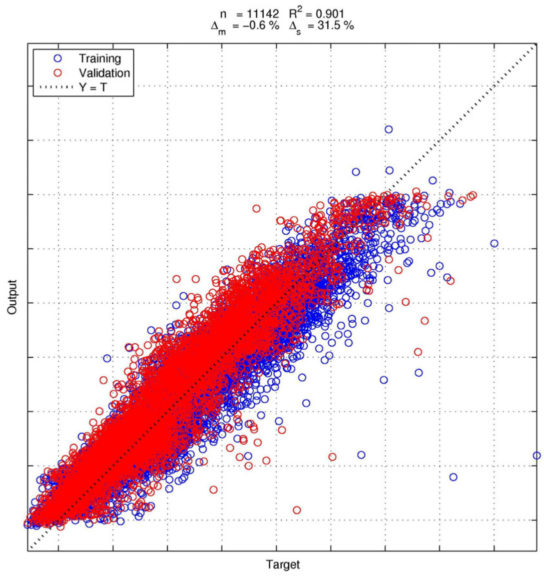
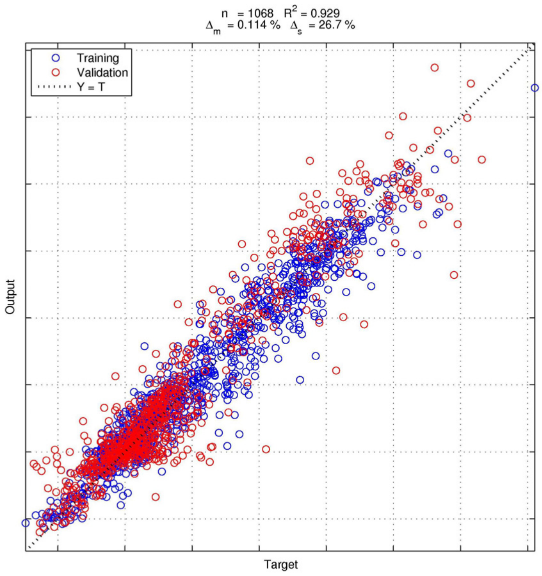


Figure 6.1: Performance of the neural network trained for estimating blade root flapwise bending load indicator for a turbine in power production under free-stream conditions. Data from turbine 2 (blue) are used to train the neural network, whereas data from turbine 4 (red) are used to validate the network's performance.

For free-stream conditions the trained neural network seems to be able to predict the values of the load indicator for Flight Leader 1 with reasonable accuracy. However the values of the load indicator for Flight Leader 2 appear to be slightly over-predicted.



<u>Figure 6.2:</u> Performance of the neural network trained for estimating the blade root flapwise bending load indicator for a turbine in power production under partial wake conditions. Data from turbine 2 (blue) are used to train the neural network, whereas data from turbine 4 (red) are used to validate the network's performance.

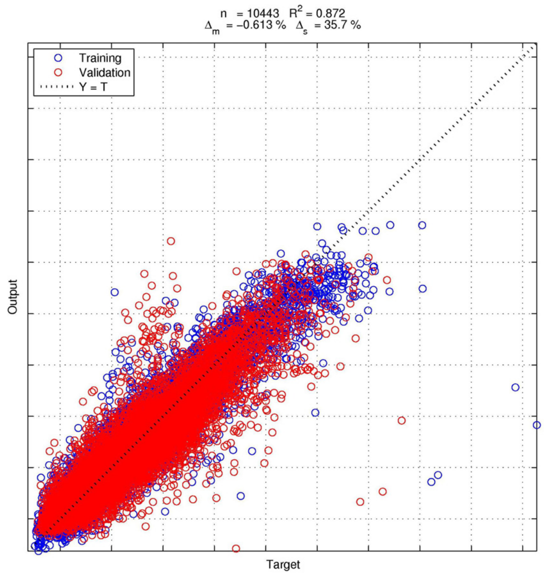
The neural network trained for partial wake conditions shows an encouraging performance; where the accuracy of the predictions is high for both Flight Leader turbines.

The second part of the analysis has the goal to determine if it is necessary to include parameters that characterise the sea state (wave height and direction) in order to accurately estimate the load indicator for tower bottom north-south bending.

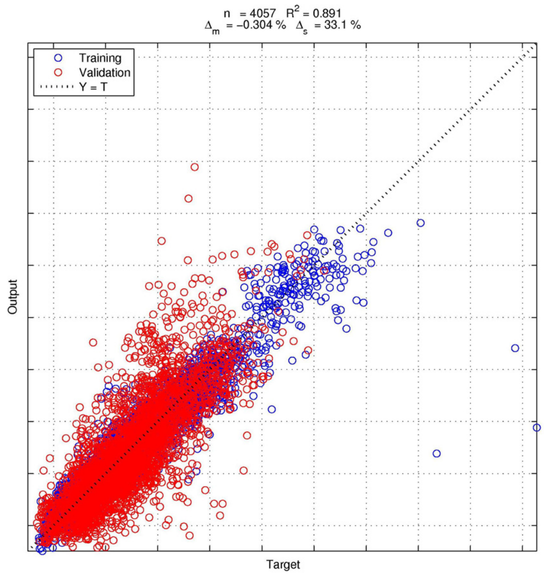
In Figure 6.3 the performance of a network trained using only the 10-minute average and standard deviation of nacelle wind speed, power output, rotor speed and pitch angle are used is shown. In Figure 6.4 the performance of a network trained with these SCADA parameters plus wave height and wave direction is depicted.

When only SCADA parameters are used (Figure 6.3) the network's performance for both Flight Leader 1 and Flight Leader 2 appears to be reasonable, although the accuracy (R^2 = 0.872) is significantly lower compared to the EWTW wind farm (R^2 = 0.968, see Figure 5.2).

In case the wave height and direction signals are included in the neural network model, the performance of the network (see Figure 6.4) slightly increases for Flight Leader 1 (which is used to train the network). However, a significant amount of scatter is observed for Flight Leader 2, which implies that the generalisability of the network is not very encouraging.



<u>Figure 6.3:</u> Performance of the neural network trained for estimating the tower bottom north-south load indicator for a turbine in power production in free-stream conditions. Data from turbine 2 (blue) are used to train the neural network, whereas data from turbine 4 (red) are used to validate the network's performance. Only standard SCADA parameters have been used as independent variables.



<u>Figure 6.4:</u> Performance of the neural network trained for estimating the tower bottom north-south bending load indicator for a turbine in power production in free-stream conditions. Data from turbine 2 (blue) are used to train the neural network, whereas data from turbine 4 (red) are used to validate the network's performance. In addition to the standard SCADA parameters also wave height and direction signals have been used as independent variables.

6.4 Conclusions

The demo version of the Flight Leader software has been implemented in an offshore wind farm and a start of the evaluation has been made.

Since the relations between SCADA parameters and load indicator hold the key for a reliable application of the Flight Leader concept the preliminary analyses were focussed on this part of the Flight Leader software.

Since wake conditions in a large offshore wind farm will occur frequently it is important that the flight leader software can make accurate load predictions in both free-stream and wake conditions It has been shown that for free-stream, and even more for partial wake conditions, the network's performance for estimating the blade root flapwise load indicator is encouraging.

Furthermore, the preliminary analyses have indicated that including wave characterising parameters in the neural network model does not significantly increase the performance of a neural network trained for estimating the tower bottom north-south load indicator. Possibly this can be contributed to the fact that the tower load is measured in north-south direction whereas the largest load fluctuations occur in the direction aligned with the nacelle yaw direction of the turbine.

7. 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 OWEZ data will be performed, where the same approach (as has been presented in this paper for the analysis of EWTW data) will be followed. The accuracy of the Flight Leader concept will be evaluated for an offshore wind farm and, if necessary, the software model will be adjusted.

Furthermore, results of aero-elastic simulations will be incorporated in the Flight Leader software with the target of (1) comparing the empirical and simulated relations between SCADA parameters and load indicator, and (2) to ensure that sufficient data is available for load cases for which little empirical data is available (e.g. emergency shutdowns).

Acknowledgements

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