ECN

Energy research Centre of the Netherlands

Flight Leader Concept for Wind Farm Load Counting

Final Report

T.S. Obdam

L.W.M.M. Rademakers

H. Braam

ECN-E--09-068

we@sea

Acknowledgement/Preface

This report is written in the context of the project *'Flight Leader Concept for Wind Farm Load Counting and Performance Assessment'* which is carried out within research line 5 (RL5) of the Dutch research program We@Sea. The aim of this project is to develop a cost-effective method for estimating the load accumulation on all turbines in an offshore wind farm.

In addition to SenterNovem and We@Sea, who have partly financed this work also Nordex AG is thanked for supplying the required information of the Nordex N80 wind turbines. The project made use of the measurements on the Nordex N80 wind turbines located at the ECN Wind turbine Test site Wieringermeer (EWTW).

The Bouw Combinatie Egmond (BCE) consortium is acknowledged for making data from the OWEZ wind farm available for further evaluation and improvement of the Flight Leader concept and software.

This project was funded partly by We@Sea and partly by ECN (EZS).
ECN project nr.: 7.9501

Distribution

T.J. de Lange	1
L.W.M.M. Rademakers	2
H. Braam	3
T.S. Obdam	4
H. Korterink	5
Archives ECN Wind Energy	6-12
Central archives ECN	13
We@Sea	14-15

Summary

Within the We@Sea project *'Flight Leader Concept for Wind Farm Load Counting and Performance Assessment'* a cost-effective methodology has been developed for assessing the load accumulation of all turbines in an offshore wind farm.

Instead of equipping all turbines with mechanical load measurements only a few reference (Flight Leader) turbines are extensively instrumented. Using data from these turbines relations between standard SCADA parameters and load indicators, which are representative for the ageing or degradation of a certain wind turbine component, are established. Once such relationships are determined these can be combined with SCADA data from the other turbines in the wind farm. This enables the determination of the accumulated loading on all turbines in the farm.

A demo version of a software model has been developed in MATLAB®. The software includes all aspects of the Flight Leader concept and is intended to be used by operators of offshore wind farms and can be applied to process the SCADA data and mechanical load measurements from an (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 developed software model has been implemented at the ECN Wind turbine Test location Wieringermeer (EWTW). Several analyses have been performed where the main goal of the research was to assess if the Flight Leader principle can be accurately applied in practice. In addition to this the research had the goal to determine what method is best used for characterising the relation between SCADA parameters and load indicator, which is essentially the core of the Flight Leader principle. Furthermore it has been tried to identify the contributors to insecurities in the predictions of the flight leader software.

Finally a second analysis has been performed with the goal of evaluating whether the proposed Flight Leader principle can also be applied to make accurate estimations of the load accumulation for all turbines in a large offshore wind farm, where wave-induced loading and wake effects play an important role. For this purpose use has been made of data from the Offshore Wind farm Egmond aan Zee (OWEZ).

In this report the background regarding the project is explained. Furthermore details regarding the developed software model are presented. Next, the most important results from the onshore and offshore evaluation of the Flight Leader concept are discussed. Finally, the most important conclusions are summarised and an outlook for future research is given.

Contents

1. Introduction

In this chapter first the background of the project is explained. Next, the objectives are listed after which the followed approach for completing the listed objectives is presented.

1.1 Background

Previous research has shown that the power output of a turbine, and more importantly, the load fluctuations in a wind turbine blade, strongly depend on whether a wind turbine located in a farm is operating in the wake of other turbines or not. These observations imply that the loading of the turbines located in a large (offshore) wind farm is location specific; the turbines located in the middle of the farm operate more often in the wake of other turbines compared to the turbines located at the edge of the wind farm. Therefore, it is expected, that during the course of the lifetime of the wind farm certain components will degrade faster on the turbines experiencing higher loading, compared to the turbines subject to lower loading.

This kind of information could be a reason to adjust maintenance and inspection schemes according to the loading of turbines, instead of assuming similar degradation behaviour for all turbines in the farm. When a major overhaul of a certain component is planned the turbines on which the specific component has experienced higher load can be replaced first, whereas the replacement of the component on the turbines which have experienced lower loading can be postponed for a certain time. This approach can result in important O&M cost savings.

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. Such measurements are relevant for model verification or for the detection of (unexpected) high loads. The main reason for not measuring these effects is that an adequate measurement campaign is costly and time consuming, especially if all turbines need to be measured.

In this project the so-called 'Flight Leader concept' has been developed in order to make estimates of the accumulated loading on the critical components of all turbines in an offshore wind farm at acceptable costs. The basic idea behind the flight leader concept is that only a few turbines in an offshore wind farm are equipped with mechanical load measurements. These are labelled the 'Flight Leaders'. Using the measurements on these Flight Leader turbines relations should be established between load indicators and standard SCADA parameters (e.g. wind speed, yaw direction, pitch angle, etc.), which are measured at all turbines. Once such relationships are determined for the reference turbines in a wind farm (the flight leaders) these can be combined with SCADA data from the other turbines in the wind farm. This enables the determination of the accumulated loading on all turbines in the farm. This is illustrated in Figure 1.1.

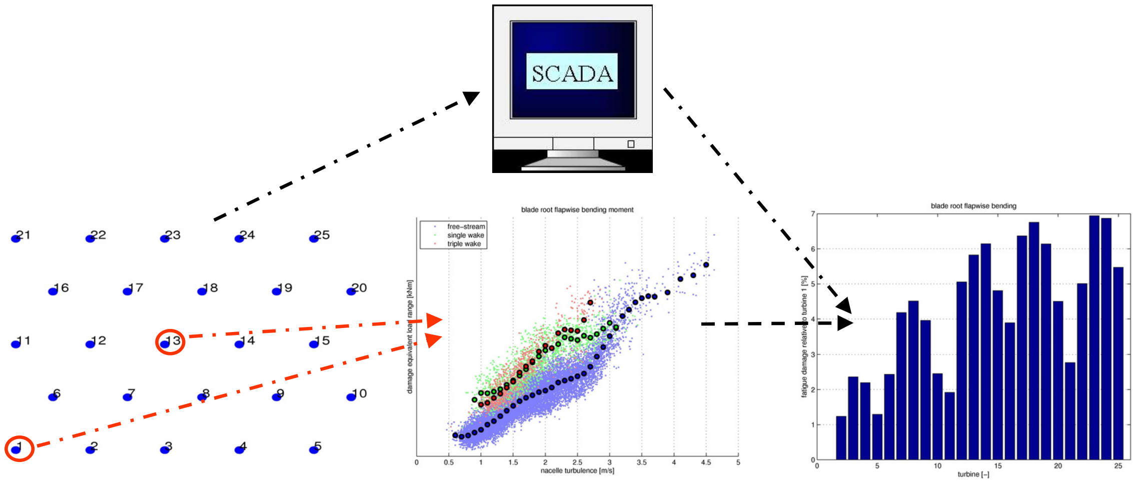

Figure 1.1 *Illustration of the flight leader concept; the load measurements performed on the flight leader turbines (indicated by the red circles) are used to establish relations between load indicators and standard SCADA parameters; these relations are combined with the SCADA data from all other turbines in the wind farm in order to estimate the accumulated loading of all turbines in the farm.*

1.2 Objectives

The main goal of this project aims at developing a cost effective method for the determining the mechanical loads on the different turbines in a wind farm. Sub goals of the project include:

- Development of a demo version of a software model should be developed which can be used process the data (both SCADA and mechanical loads) from an offshore wind farm and predict the total load accumulation of all turbines in the wind farm.
- Evaluation of the feasibility and accuracy of the Flight Leader concept using measured data from an onshore wind farm.
- Investigate the added benefit of including the results of aero-elastic simulations in the empirical Flight Leader model.

1.3 Approach

During the first months of the project firstly functional specifications for the Flight Leader software have been drafted [8]. In this document it has been described what functionality should be included in the software model and based on this information the actual development of the software could be started. Based on the functional specifications technical specifications have been written [9]. These describe the different processes in the software in detail and serve as a detailed guideline for the actual programming of the software.

Parallel to the drafting of the specifications for the Flight Leader software also the measurement infrastructure at the ECN Wind turbine Test site Wieringermeer (EWTW) has been greatly extended. Firstly, a measurement plan has been drafted [6] where a detailed description of all planned instrumentation work has been described. Based on this information the instrumentation work at two Nordex N80 turbines has been carried out. After instrumentation of the turbines was completed a comprehensive instrumentation report has been written, which describes the implemented measurement infrastructure in great detail. The report also includes information of the implementation of measured data in ECN's LTVM database (which contains all measured data on the five Nordex N80 turbines), including the formulae for calculating pseudo-signals [7].

In addition to this also a detailed wind turbine model has been programmed in ECN's aero-elastic code PHATAS [5]. Using measurements of the EWTW farm the model has been evaluated and tuned. Using ECN's wake analysis program FluxFarm and wind field generation software SWIFT various (both free-stream and wake conditions) 3-D wind fields have been generated, which cover the whole range of operation of a wind turbine. These wind fields then served as input for the aero-elastic simulation program. Using the output of the simulations relations between SCADA parameters and load indicator are derived and these have been compared with the corresponding relations derived from measurements. It is also investigated whether the simulations can be applied to accurately predict the load accumulation of a wind turbine.

Based on the detailed technical specifications a demo version of the Flight Leader software has been programmed in MATLAB®. After finishing the first version of the demo a start was made with evaluating the Flight Leader concept using data from ECN's EWTW wind farm [11]. Based on the experiences gathered while evaluating the Flight Leader concept some changes to the software were made [10]. Using the updated software an additional evaluation of the Flight Leader concept applied at the Dutch OWEZ offshore wind farm was made[1] [12].

During the course of the project the results of the performed research have been presented at various workshops and conferences [1, 2, 3, 4].

1.4 Structure of the report

In the following chapters an overview of the results achieved during the course of the project 'Flight Leader Concept for Wind Farm Load Counting and Performance Assessment' is given. In chapter 2 the Flight Leader software model is presented. Finally, in chapter 3 and 4 the results of, respectively, the onshore and offshore evaluation of the Flight Leader concept are discussed.

[1] It should be noted that the evaluation of the Flight Leader concept using data from an offshore wind farm was originally not foreseen within this project. However, due to good progress (with respect to both time and finance) and the possibility to use data from the OWEZ wind farm it was decided to also evaluate the Flight Leader software implemented at an offshore wind farm.

2. Flight Leader software

Developing an empirical software model has been one of the main goals of the Flight Leader project. A demo version of the software has been programmed in MATLAB [4, 5, 6]. The software includes all aspects of the Flight Leader concept and is intended to be used by operators of offshore wind farms and can be applied to process the SCADA data and mechanical load measurements from an (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 general structure for the flight leader computer model is shown in the flowchart in Figure 2.1.

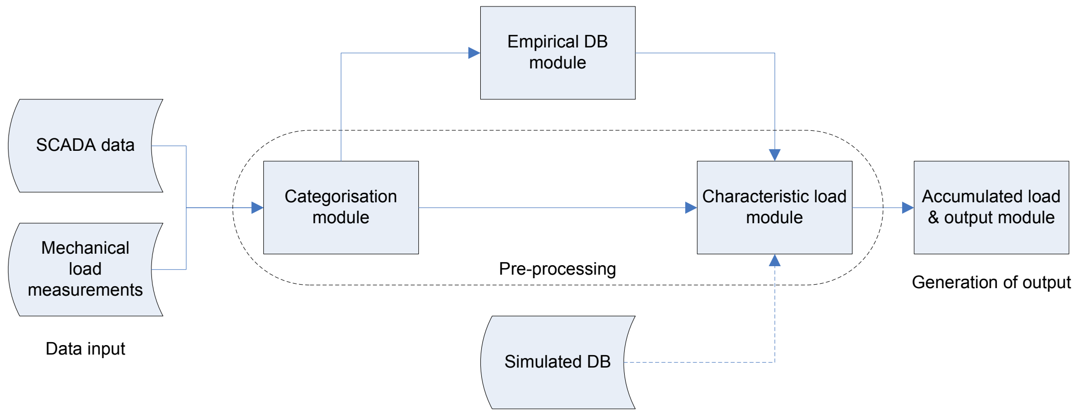

Figure 2.1 *General structure for the flight leader computer model.*

2.1 Data input

The most important input for the empirical flight leader model are the data collected from the offshore wind farm. Two types of data can be distinguished; (1) SCADA data, which is being collected from all turbines, and, (2) mechanical load measurements, which are being collected from the flight leader turbines.

Usually the SCADA data is delivered to the (offshore) wind farm owner/operator by the manufacturer of the wind turbines in the form of 10-minute statistics. The mechanical load measurements should be collected as time series. These time series need to be processed in order to calculate load indicators (10-minute statistics), which are representative for the degradation or ageing of a certain wind turbine component. Since the mechanical load measurement campaign is usually performed independently from the wind turbine manufacturer, the processing (including quality control/post-validation) of the mechanical load measurements should be done by either the wind farm owner/operator or the party performing the mechanical load measurement campaign. The resulting processed 10-minute statistics of the load signals, together with the 10-minute statistics of the different SCADA parameters subsequently serve as input for the Flight Leader model. This is indicated in Figure 2.2.

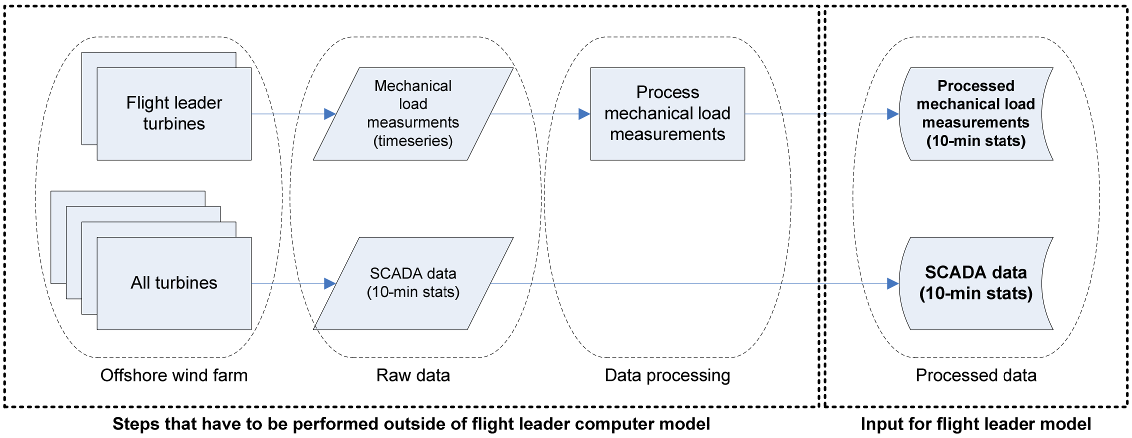

Figure 2.2 *Flowchart indicating the different steps for generating the (measured) input (SCADA and mechanical load measurements) data for the flight leader computer model.*

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*. The possible combinations are indicated in Table 2.1.

Table 2.1 *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	*Not Applicable*
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 2.1. 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. An example of the software's empirical database module is shown in Figure 2.3.

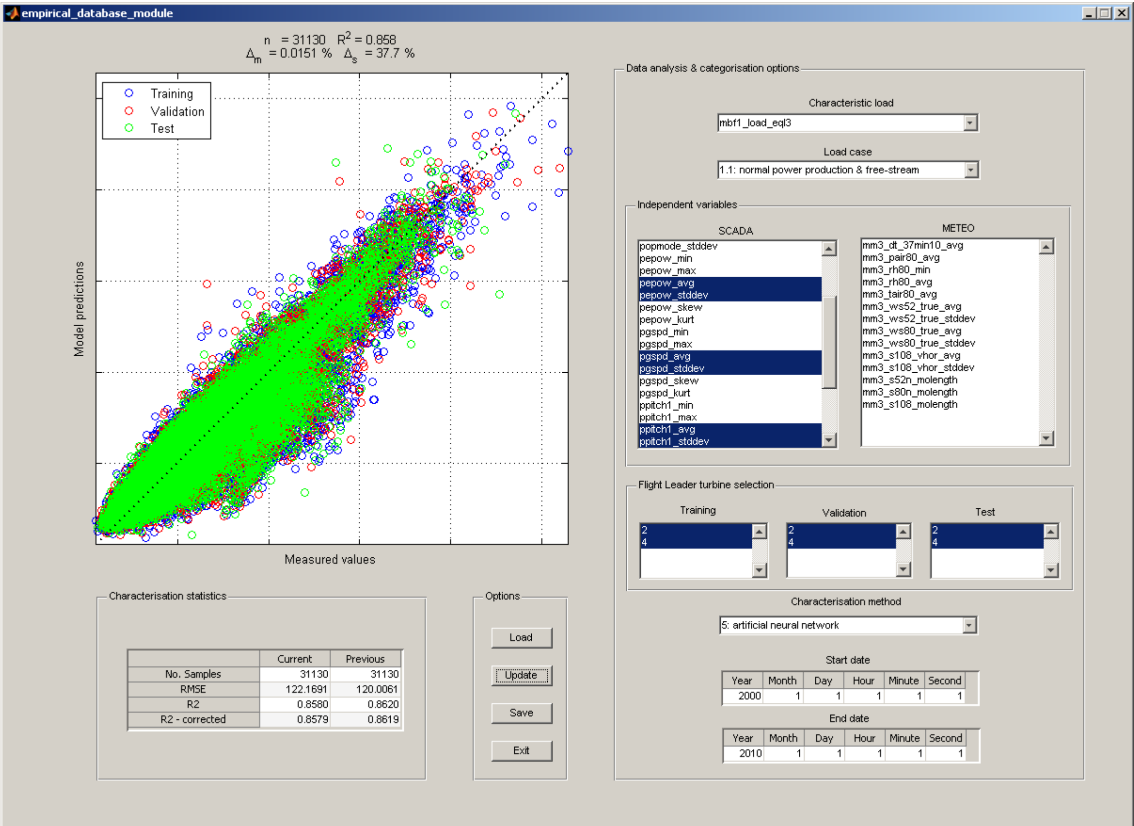

Figure 2.3 *The Flight Leader's empirical database module for establishing relations between SCADA parameters and load indicators.*

2.4 Simulation database

The Flight Leader concept is mainly an empirical concept. However, the software also offers the possibility to include results from aero-elastic simulations. This can be useful in case not (yet) enough data are available for establishing a solid relation between SCADA parameters and the load indicator. This is most likely to occur in the period directly after the commissioning of the offshore wind farm when little measured data are available. Furthermore, also for those situations with a low probability of occurrence, such as emergency shutdowns or extremely high wind speeds, including results from simulations might be beneficial.

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 simulation 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).

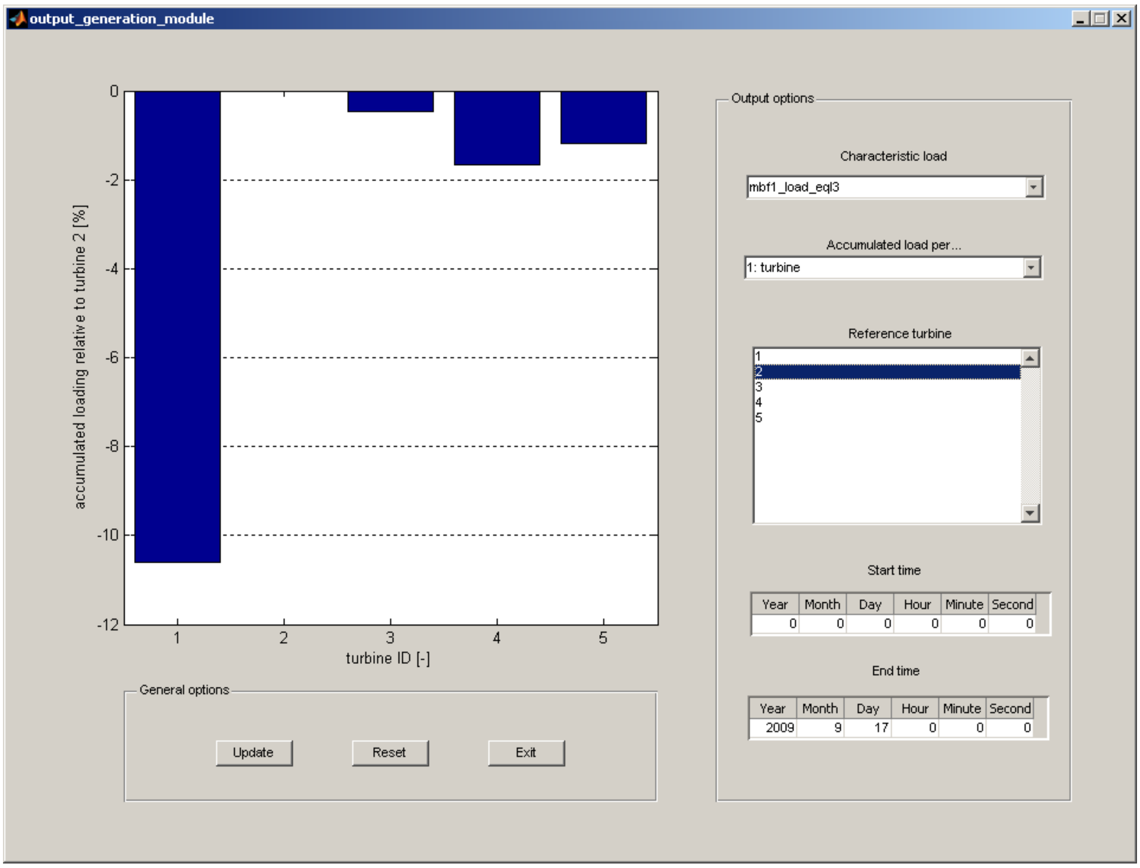

Figure 2.4 *Example of the output generation model of the Flight Leader software, where the relative (to turbine 3) load accumulation of all turbines is displayed.*

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. An example of such output is depicted in Figure 2.5.

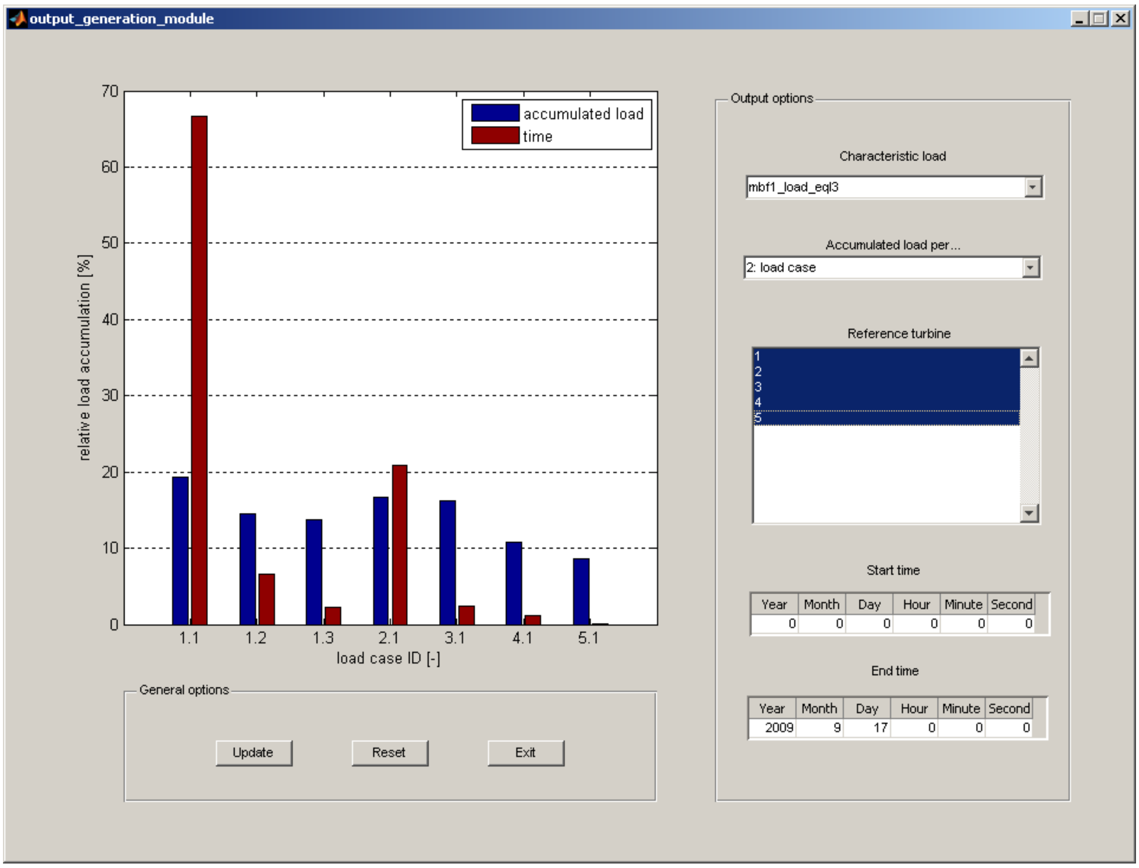

Figure 2.5 *Example of the output generation model of the Flight Leader software, where the contribution of each load case to the total load accumulation is shown.*

Besides calculating and comparing load accumulation the Flight Leader software also offers the opportunity to validate the accuracy of its predictions, by comparing the measured load accumulation with the predicted load accumulation for the Flight Leader turbines. This can be done for each individual load indicator and load case.

3. Flight Leader concept evaluation (onshore)

In this chapter the approach and results of the first (onshore) evaluation of the Flight Leader concept are discussed. The main goal of the research was to assess if the Flight Leader principle can be accurately applied in practice. In addition to this the research had the goal to determine what method is best used for characterising the relation between SCADA parameters and load indicator, which is essentially the core of the Flight Leader principle. Furthermore it has been tried to identify the contributors to insecurities in the predictions of the flight leader software.

In the following subsections first some information regarding the measurement infrastructure on ECN's EWTW wind farm is provided. In section 3.2 some brief information on artificial neural networks is given. Next, in section 3.3 the most important results of the analysis are presented. Finally, in section 3.4 the conclusions are summarised.

3.1 Wind farm description

During the course of the project a lot of use is made of the data collected from the five Nordex N80 turbines at ECN's EWTW wind farm. In this chapter some background information of the location and layout of the wind farm is given. Furthermore, the measurement infrastructure, which has been greatly expanded during this project, is presented [13, 14, 15].

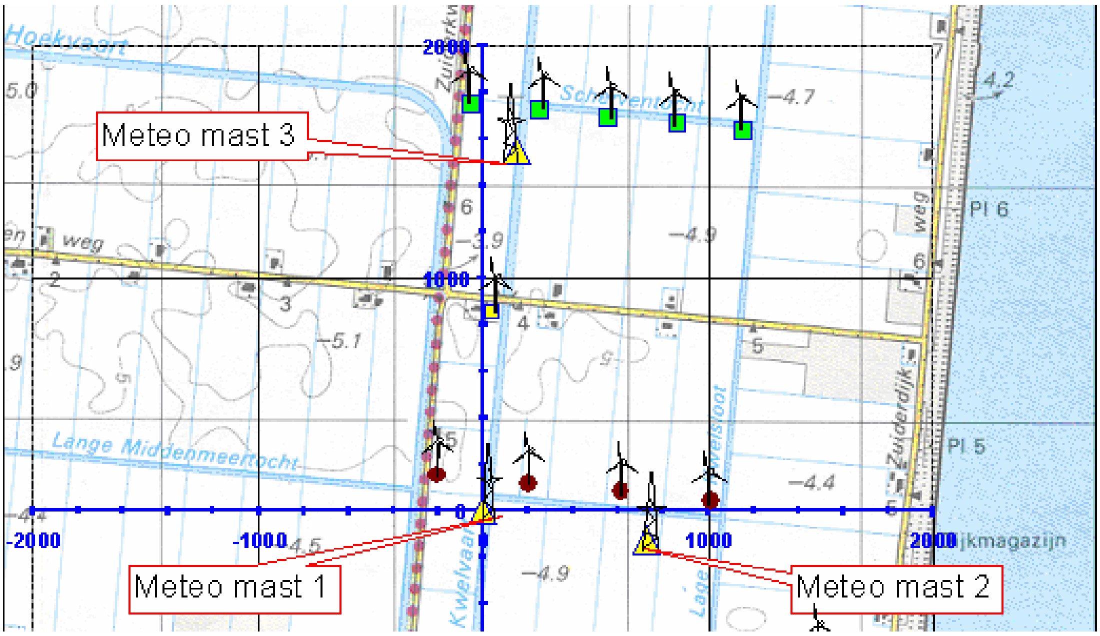

Figure 3.1: *Overview of the ECN Wind turbine Test location Wieringermeer (EWTW).*

3.1.1 Location

The ECN Wind turbine Test location Wieringermeer (EWTW) 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.

3.1.2 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. The layout of the EWTW farm is shown in Figure 3.1.

3.1.3 Measurement campaign

Since October 2004 various measurement campaigns have been carried out at the EWTW wind 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):[2]
    - 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.

3.2 Artificial neural networks

Characterising the relationships between load indicators and SCADA parameters is an essential part of the Flight Leader concept. Within this project it has been investigated what characterisation technique is most accurate and reliable.

3.2.1 General description

Besides the more ‘classical’ techniques of regression and interpolation so-called ‘artificial neural networks’ can also be applied to model the relationship between two or more variables. 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 [16, 17]

[2] During the course of this project turbine 8 has been full equipped with mechanical load measurements, whereas the measurements on turbine 6 have been extended with tower top torsion, main shaft bending and torque and high speed shaft torque mechanical load measurements.

A schematic representation of a neuron and a neural network (consisting of two 'hidden' layers of neurons) is shown in Figure 3.2.

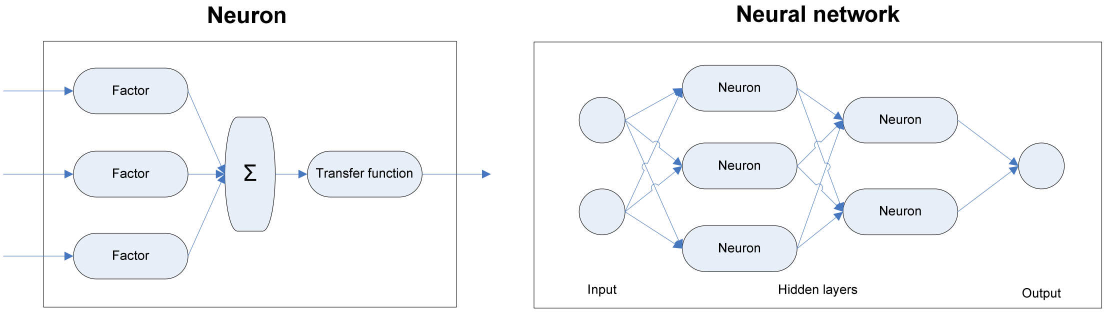

Figure 3.2 *Schematic representation of a neuron and a neural network.*

The main advantage of a neural network is the fact that the network can be trained, using suitable algorithms, to approximate the relation between input and output variables. As mentioned earlier, if the neural network is of sufficient size complex non-linear relations can be approximated. An obvious disadvantage of using neural networks is the fact that additional software is required for designing and training the network. It might be difficult to incorporate this software in the actual flight leader software.

3.2.2 Application

For all analysis performed during the course of this project the MATLAB® Neural Network Toolbox™ has been used. The neural networks are trained using the Levenberg-Marquardt backprogagation algorithm. In order to prevent over-fitting the early stopping technique is used.

3.3 Results

In the following subsections the results from the first (onshore) evaluation are presented. In order to keep this report at an acceptable size only a small selection of the full results will be shown[3]. In section 3.4 the most important conclusions of the full analysis are listed.

3.3.1 Selection of load indicator and SCADA parameters

The evaluation of the Flight Leader software has been performed for four load indicators; the 1 Hz damage equivalent load range ΔF_{EQ} of:[4]

- 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:

[3] Note that all results shown in the following subsections have been derived using artificial neural networks as characterisation method (hence also the description of neural networks in section 3.2. An important part of the first evaluation of the Flight Leader concept was to determine the differences between different characterisation methods. The results of this comparison are listed in the conclusions in section 3.4.

[4] For the sake of compactness only the results for blade root flapwise bending are discussed in detail in this chapter.

$$\Delta F_{EQ} = \sqrt[m]{\frac{\sum_i n_i \cdot \Delta F_i^m}{N}} \tag{3.1}$$

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 3.1.3, are possible input candidates for the artificial neural network. A trial-and-error approach has been adopted in order to assess which signals should be in- and excluded in the artificial network. The selected SCADA parameters are listed in Table 3.1 for each load case.

Table 3.1 *SCADA signals used to estimate the load indicator for blade flapwise bending for each load case.*

Load case	*Rotor speed*				*Pitch angle*				*Power*			
ID	avg	std	skew	kurt	avg	std	skew	kurt	avg	std	skew	kurt
1.1	o	o	o	o	o	o			o	o	o	o
1.2	o	o	o	o	o	o			o	o	o	o
1.3	o	o	o	o	o	o			o	o	o	o
2.1	o	o			o	o						
3.1	o	o			o	o			o	o		
4.1	o	o			o	o			o	o		
5.1	o				o				o			

3.3.2 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 2.1). The results of the data categorisation step are displayed in Figure 3.3.

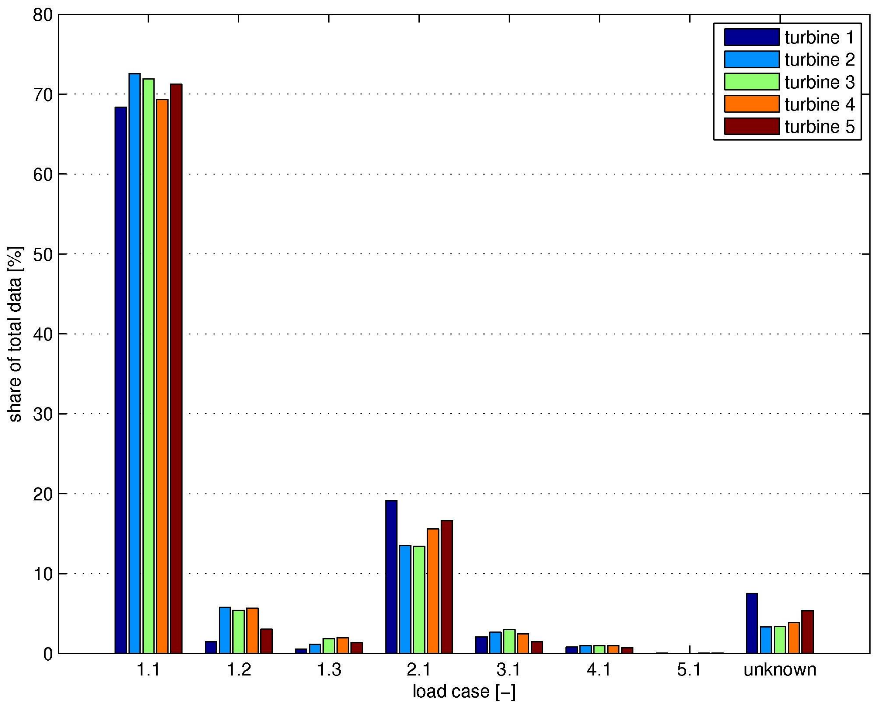

Figure 3.3: *Results of the data categorisation step.*

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.

3.3.3 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 2.1). As an example in Figure 3.4 the characterisation result is shown for blade root flapwise bending for the load case power production under free-stream conditions. The scatter plot shows the predicted values of the load indicator (output) versus the measured values of the load indicator (target).

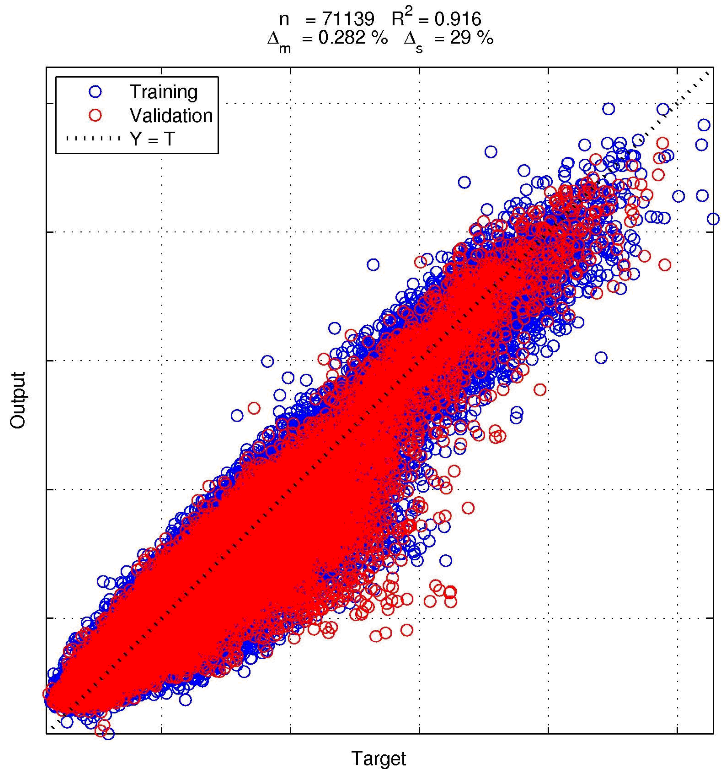

Figure 3.4 *Performance of the neural network trained for estimating the blade root flapwise bending load indicator for a turbine in power production under free-stream conditions. Data from turbine 2 (blue) are used to train the neural network, whereas data from turbine 4 (red) are used to validate the network's performance.*

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.

The results (number of data points and coefficient of determination) for all five load cases are summarised in Table 3.2.

Table 3.2 *Number of data points and coefficient of determination for the established relations between SCADA signals and the load indicator for blade flapwise bending.*

Load case	*Data points*	R^2
1.1	71139	0.9162
1.2	5766	0.8922
1.3	1141	0.8599
2.1	12355	0.8805
3.1	2475	0.9563
4.1	958	0.9411
5.1	16	0.9222

3.3.4 Load indicator estimation

In the previous section it has been described that for each of the seven load cases a relation between the selected SCADA signals and load indicator has been determined and stored in the empirical database of the Flight Leader software. Next step is to combine these relations with the SCADA collected from all five Nordex N80 turbines in the EWTW wind farm in order to make an estimate of the values of the load indicators for each turbine *i* and timestamp *t*.

After the load estimation has been executed two post-processing procedures are performed. Firstly, outliers are identified using the criteria that the calculated value of a load indicator can never be smaller or larger than a certain factor β multiplied with, respectively, the minimum and maximum measured value of the load indicator. Timestamps *t* which do not meet this criteria have been classified as *NaN* in the dataset.

$$(1-\beta)\cdot \min\left(\Delta F_{EQ,i\,FL}\right) \le \Delta F_{EQ,i} \le (\beta+1)\cdot \max\left(\Delta F_{EQ,i\,FL}\right) \tag{3.2}$$

The initial analysis has been performed for different values of β. However, it was found that this did not have a significant influence on the number of corrected outliers. The analyses described in this report have been performed using β = 0 (no extrapolation possible).

Next step is to ensure that for all turbines an equal amount of data is available. If for a certain turbine *i* at a certain timestamp *t* the value of the load indicator is unknown the value will be estimated by taking the average value of load indicator *c* at all turbines in the farm for which at timestamp *t* the value of load indicator *c* is known.

$$\Delta F_{EQ,c,i_{unavailable},t} = \frac{1}{n}\cdot \sum_{i_{available}}^{n} \Delta F_{EQ,c,i_{available},t} \tag{3.3}$$

where $\Delta F_{EQ,c,t}$ is the value for characteristic load *c* at timestamp *t*, $i_{available}$ and $i_{unavailable}$ represent turbine *i* for which SCADA data are, respectively, available and unavailable, and *n* is the number of turbines for which the value of load indicator *c* is known.

3.3.5 Output

Now the values of the load indicators have been estimated for each turbines *i* for each 10-minute time period *t* it is possible to calculate the total load accumulation for each turbine *i*. Total load accumulation $\Delta S_{total,i}$ for each turbine *i* is calculated as follows:

$$\Delta S_{total,i} = \sqrt[m]{\sum_{t=1}^{N} \Delta S_{i,t}^{m}} \tag{3.4}$$

where $\Delta S_{i,t}$ is the value of the load indicator for turbine i and 10-minute timestamp t.

Subsequently, the relative difference in load accumulation is calculated according:

$$Difference = \frac{\Delta S_{total,i} - \Delta S_{total,iref}}{\Delta S_{total,iref}} \tag{3.5}$$

where $\Delta S_{total,i}$ and $\Delta S_{total,iref}$ are the total load accumulation for turbine i and reference turbine i_{ref} respectively.

In Figure 3.5 a comparison of the load accumulation for the blade root flapwise bending moment is shown. The load accumulation of each turbine i is shown relative to the load accumulation of turbine 2.

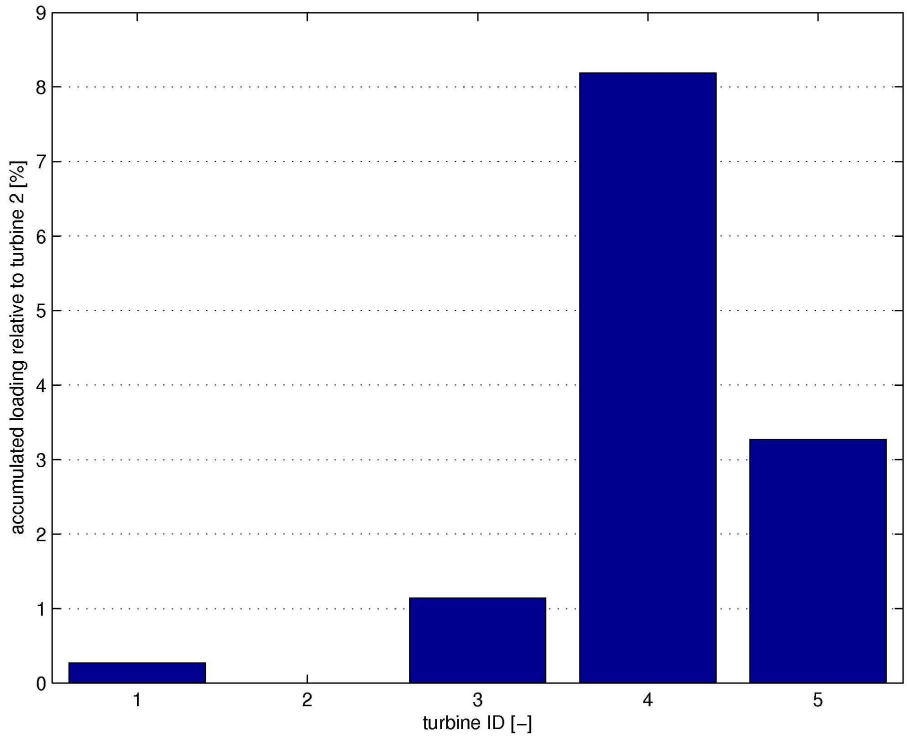

Figure 3.5 *Load accumulation of all five turbines relative to load accumulation of turbine 2 for the load indicator for blade root flapwsie bending.*

According to the flight leader software the blades of turbine 4 have accumulated most loading (8% more than turbine 2), whereas the load accumulation for turbine 1 and 2 is about equal. Turbines 3 and 5 have accumulated slightly more load compared to turbine 2 (about 1% and 3% respectively).

In order to be able to explain the results shown in Figure 3.5 several breakdowns of the output have been generated. This is shown in Figure 3.6, for the results presented in this figure data from all five turbines have been used.

In the top graph the accumulated loading for each defined turbine state and transitional mode is displayed. It can be seen that, according to the flight leader software, normal power production accounts for about 60% of the total load accumulation. During the parked/idling turbine very little load accumulation occurs. For start-up, normal shutdown and, especially, emergency shutdown the load accumulation is larger compared to the time the turbine operates in these transient events.

The middle graph indicates that load accumulation for all three wake conditions (free-stream, partial- and full wake) the load accumulation is proportional to the time the turbine operates in the respective wake condition.

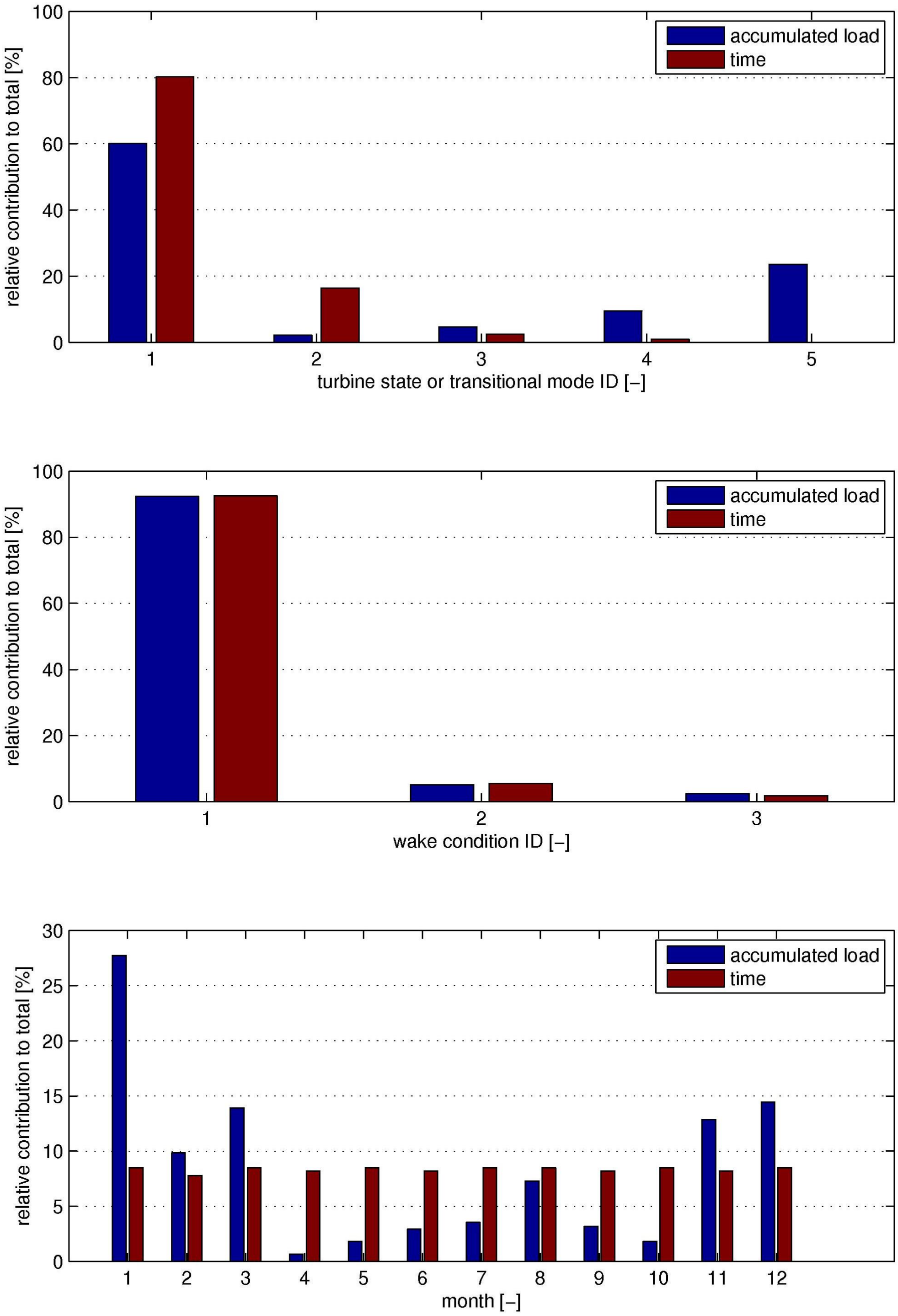

Figure 3.6 *Different breakdowns of the load accumulation: (1) per turbine state and transitional mode, (2) per wake condition and (3) per month. The red bars indicate the amount (relative to total) of data available for each category.*

Finally, the bottom graph indicates that, according to the flight leader software, in January almost 30% of all load has been accumulated. Furthermore, in February, March, November and December load accumulation is also higher than average.

3.3.6 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 3.3.3) have all been derived using data from turbine 2 only[5]. 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 (see equation 3.6). This comparison is shown in Figure 3.7 for all four load indicators.

$$Error = \frac{\Delta S_{total,pred} - \Delta S_{total,meas}}{\Delta S_{total,meas}} \tag{3.6}$$

where $E_{total,pred}$ and $E_{total,pred}$ are the predicted and measured total electricity production subsequently.

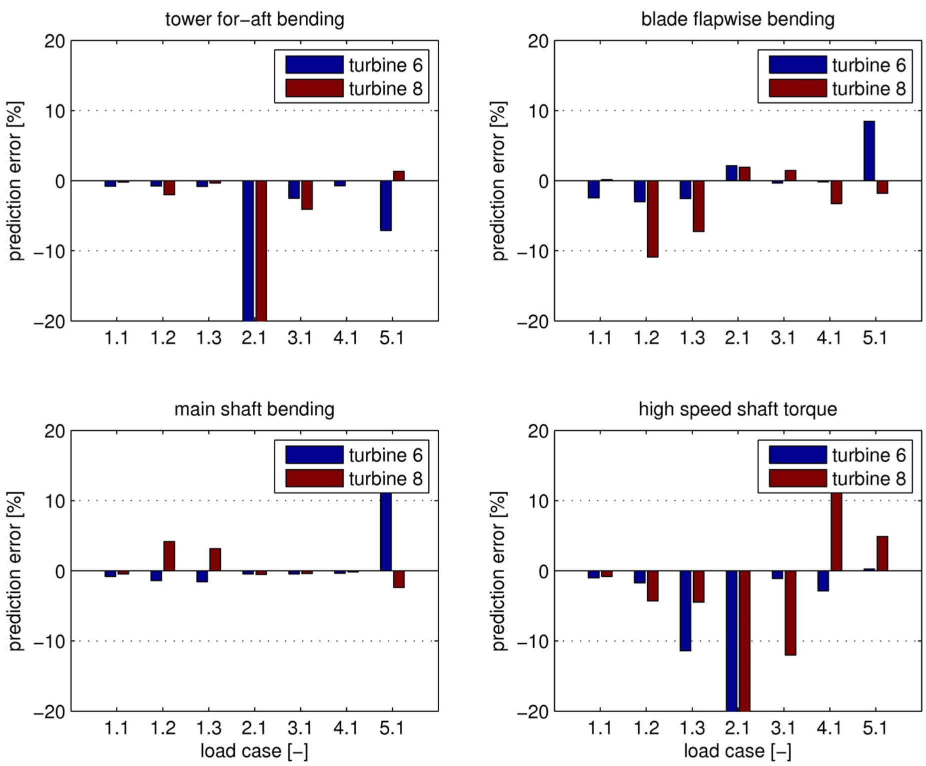

Figure 3.7 *Prediction errors of the Flight Leader software for four different load cases. An artificial neural network has been used for characterising the relation, where data from turbine 2 have been used to 'train' the network and data from turbine 4 for validating its performance.*

When studying the top left 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 3.6 it was shown that close to zero load accumulation takes place during a parked/idling turbine state and

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

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 right 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 3.5.

3.4 Conclusions

For the first (onshore) analysis the feasibility and accuracy of the flight leader software has been evaluated using data from ECN's wind farm EWTW. The main goal of the research was to assess if the flight leader principle can be accurately applied in practice. In addition to this the research had the goal to determine what method is best used for characterising the relation between SCADA parameters and load indicator, which is essentially the core of the flight leader principle. Furthermore it has been tried to identify the contributors to insecurities in the predictions of the flight leader software.

The evaluation of the flight leader software has first been performed for the load indicator electrical power production. Power production is not a true load indicator in the sense that it is not meant as a measure for the degradation of a certain component. However, since power production is measured at all five Nordex N80 turbines it is an excellent measure for evaluating the feasibility and accuracy of the flight leader principle. The results have shown that for one particular turbine a large prediction error of the flight leader software occurred. After performing a detailed investigation into the causes for this error it has been found that the nacelle anemometer is the most likely source of the error. This illustrates that calibrated nacelle anemometers are an absolute prerequisite for the reliable application of the flight leader principle. Therefore, for the analysis of the four other load indicators the nacelle wind speed has not been used.

The original plan was to investigate three different characterisation methods (second order polynomial, partial least squares relationship and an artificial neural network). However, the prediction errors, when using the partial least squares relationship, were found to be much larger compared to when the other two methods were applied. In order to keep this document at an acceptable size the results for the partial least squares relationship are not displayed.

For the four other load indicators (blade flapwise bending, tower for-aft bending, main shaft bending and high speed shaft torque) in general the results have been encouraging. When comparing the two characterisation methods the artificial neural network gives the best results. Usually the second order polynomial relationship gives accurate results for turbine 2 (whose data is used to derive the polynomial). However the prediction errors for turbine 4 are generally larger. When a neural network is used (which is trained on data from turbine 2) the prediction accuracy for turbine 4 is much better. This can be partly attributed to the fact that during the training of the neural network data from turbine 4 is used to determine the point where the training should be halted (in order to ensure the generalisability of the relation).

When evaluating the accuracy of the flight leader predictions it was found that for the load cases parked/idling and emergency shutdowns often large prediction errors occur. For the former this can be contributed to the fact that during the parked or idling the mechanical loads are often very low and show little variation and as a result cannot be correlated with the selected SCADA parameters. For the latter these large prediction errors are a consequence of the fact that only very few emergency shutdowns have occurred. Therefore not enough data are available to establish a solid relation between SCADA parameters and load indicator. A solution here would be to use the results of aero-elastic simulations in order to estimate the values of the load indicator for a 10-minute time series where an emergency shutdown occurs.

4. Flight Leader concept evaluation (offshore)

The first evaluation of the Flight Leader software showed that in principle the Flight Leader concept can be used to estimate the load accumulation of all turbines in a wind farm based on load measurements of only a few reference turbines (see chapter3).

The Flight Leader concept is mainly intended to be used for offshore wind farms since here O&M costs are high and the benefits of tailor-made maintenance are expected to be larger compared to onshore. Therefore it also has to be shown that the Flight Leader concept is also feasible to be applied to turbines placed offshore, where wake effects play a more significant role. In addition to this offshore turbines also face additional wave-induced loading.

In addition to this main goal some additional analyses have been performed during the second evaluation of the Flight Leader concept. The first evaluation showed that artificial neural networks are most suited for characterising the relation between load indicator and SCADA parameters (see section 3.4). During this second evaluation it has been investigated how the performance of a neural network can be further improved by comparing different methods for training the neural network.

Another conclusion that was drawn from the first evaluation was the fact that for the emergency shutdown load case the Flight Leader predictions were less accurate. It was stipulated that this was caused by the fact that very little data points were available for this load case and that including results from aero-elastic simulations could possibly improve the performance of the Flight Leader software for seldom occurring load cases. This has also been investigated during the second evaluation discussed in this chapter.

In this chapter the approach and results of the evaluation of the Flight Leader software at the Offshore Wind farm Egmond aan Zee (OWEZ) are presented. In the first two subsections some information of the wind farm and the dataset is given. In the following subsections the results from all steps in the evaluation process are discussed. The last section of this chapter summarises the most important conclusions from the performed evaluation.

4.1 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.

4.2 Dataset

The evaluation has been performed using 9 months of measured data from all 36 turbines. Available SCADA signals include nacelle wind speed, rotor rotational speed, pitch angle, 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.

4.3 Results

In the following subsections the results of the offshore evaluation of the Flight Leader concept are presented in a similar fashion as has been done in chapter 3. It should be noted that again only a small selection of the total results is presented were the focus lies on the main goal of proving the feasibility of the Flight Leader concept for a large offshore wind farm. The most important conclusions from the additional research are summarised in section 4.4.

4.3.1 Selection of load indicator and SCADA parameters

The evaluation of the Flight Leader software has been performed for two load indicators[6]; the 1 Hz damage equivalent load range ΔF_{EQ} of (see equation 1):

- Blade root flapwise bending;
- Tower bottom for-aft bending;

Similar as for the onshore analysis (see section 3.3.1) a trial-and-error approach has been adopted in order to assess which signals should be in- and excluded in the artificial network. It has also been chosen to, at first, not to include any signals from the meteorological mast or wave buoy. The selected SCADA parameters are listed in Table 4.1 for each load case (for both load indicators the same set of SCADA parameters has been used).

Table 4.1: *SCADA signals used to estimate the load indicator for tower for-aft bending for each load case.*

Load case	*Wind speed*		*Rotor speed*		*Pitch angle*		*Power*	
ID	avg	std	avg	std	avg	std	avg	std
1.1			o	o	o	o	o	o
1.2			o	o	o	o	o	o
1.3			o	o	o	o	o	o
2.1	o		o		o			
3.1	o	o	o	o	o	o	o	o

4.3.2 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 2.1). It should be noted that instead of the original seven load cases for the OWEZ wind farm only five load cases have been used since it has not been possible to distinguish between the different transient events. Therefore all transient events are categorised as load case 3.1.

4.3.3 Relation SCADA parameters and load indicator

After identifying the load indicators and relevant SCADA parameters the next step is to establish the relation between the selected SCADA signals and the load indicator. A separate relation has to be devised for each of the five identified load cases. The relations are characterised by an artificial neural network, which is trained using data from both Flight Leader turbines.

Half of the total amount of data is used for training the network. Another 25% is used to validate the network's performance for every iteration step and to halt training at the point where generalisation starts decreasing. The final 25% is used as an independent measure (has no influence on the network's training process) of the network's performance when fed with new data.

[6] For the sake of compactness only the results for blade root flapwise bending are presented in the following pages.

The performance of the trained artificial neural network for the load case power production & free-stream conditions is shown in Figure 3.4.

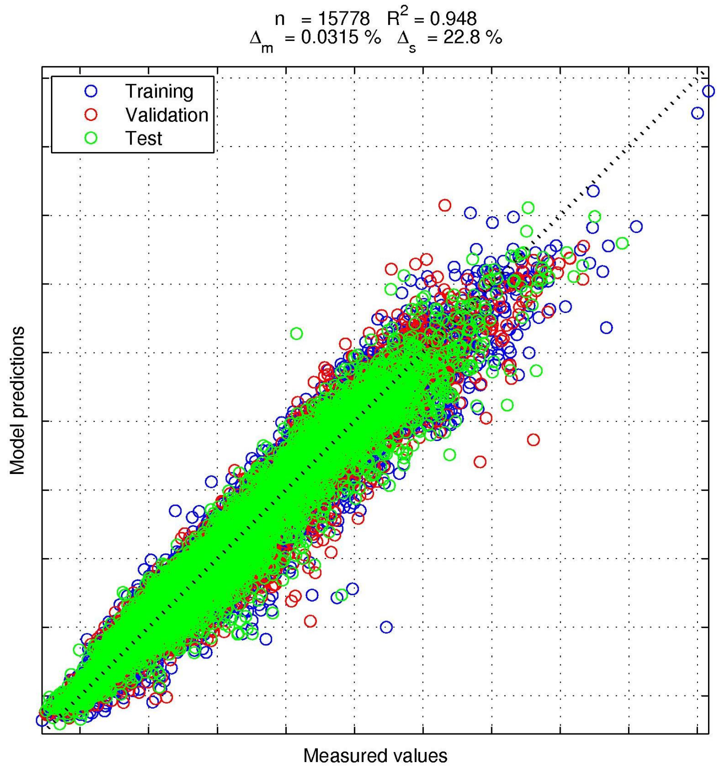

Figure 4.1 *Performance of the neural network trained for estimating the blade root flapwise bending load indicator for a turbine in power production under free-stream conditions.*

The results presented in the figure indicate that a good relation exists between the selected SCADA parameters (see Table 4.1) and the load indicator for the tower bottom for-aft bending moment (see equation 1). This is confirmed by the value of the coefficient of determination (R^2 = 0.95). When studying the green data points, which represent the 'test' dataset (which has had no influence on the network's training), it can be seen that here also a good performance is achieved. This is an important indicator for the generalisability of the neural network (its ability to make accurate predictions when fed with new data). Therefore it can be expected that the trained neural network will also make accurate predictions for the other turbines in the same wind farm for this load indicator.

The results (number of data points and coefficient of determination) for all five load cases are summarised in Table 4.2.

Table 4.2 *Number of data points and coefficient of determination for the established relations between SCADA signals and the load indicator for tower for-aft bending.*

Load case	*Data points*	*R^2*
1.1	16174	0.9507
1.2	3266	0.9439
1.3	1669	0.9593
2.1	12987	0.6812
3.1	1193	0.9530

The table indicates that for all load cases but parked/idling a good accuracy (of around R^2 = 0.95) is achieved. This might be unexpected, since no wave-describing parameters are included as independent variables in the artificial neural network (see Table 4.1). However, wave height and direction are, in general, strongly correlated with wind speed and direction. As a result the fluctuations in the tower bottom for-aft bending for an offshore turbine can be accurately estimated without information on the wave conditions.

The main reason why for parked/idling more scatter is observed is the fact that no wave-describing SCADA signals are included as independent variables in the relation. When the turbine is not in operation it also generates no thrust force, which means that the fluctuations in the tower bottom for-aft bending are solely caused by wave-induced loading. In case the 10-minute significant wave height, direction and period are included as independent parameters a significantly improved accuracy is achieved ($R^2 \approx$ 0.80-0.85). However, since the data from the wave buoy is missing for large chunks of time, only about 3000 data points are available. Including these parameters in the relation also has the consequence that the Flight Leader software cannot make any predictions of the value of the load indicator for the periods where no wave data are available. This would lead to a significant error when estimating the total load accumulation and therefore it is decided to establish the relations without including wave-describing parameters.

4.3.4 Load indicator estimation

In the previous section it has been described that for each of the five load cases a relation between the selected SCADA signals and load indicator has been determined and stored in the empirical database of the Flight Leader software. Next step is to combine these relations with the SCADA collected from all 36 turbines in the offshore wind farm in order to make an estimate of the value of the load indicator the tower for-aft bottom bending moment for each turbine i and timestamp t.

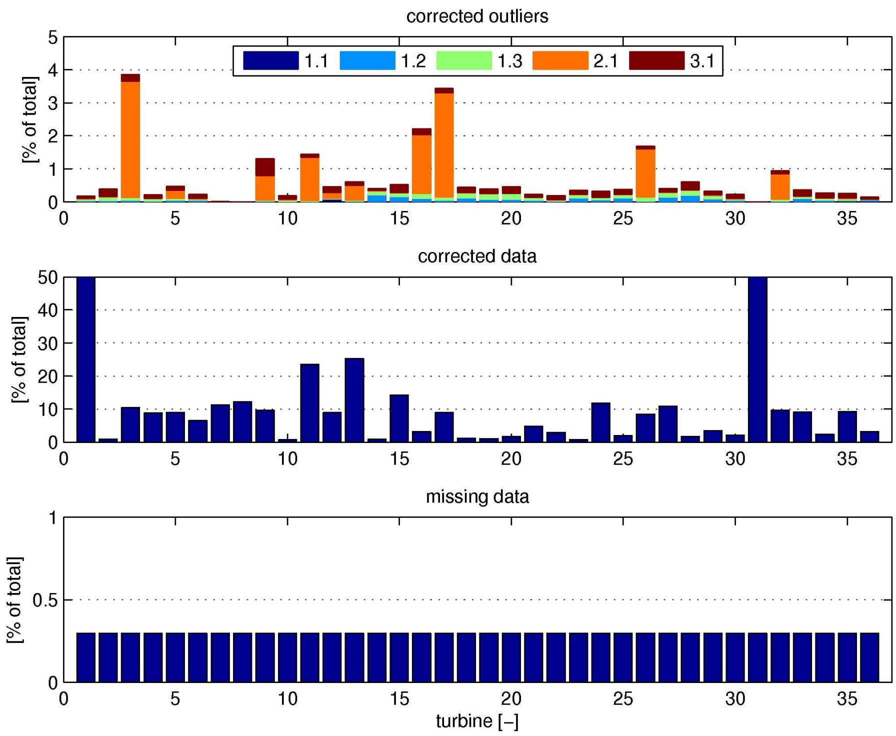

Figure 4.2 *Results of the post-processing steps for estimating the values of the load indicator for tower for-aft bending.*

The results of the post-processing are shown in Figure 4.2. The top graph indicates the number of data points classified as outliers, the middle graph shows the amount of corrected data for each turbine and the bottom graph indicates the percentage of missing data after all post-processing steps have been performed.

It can be seen that for most turbines the number of outliers is quite low (less than 0.4%) for all turbines. However, for some turbines about up to 4% of the estimated values of the load indicator have been classified as outlier. It can also be observed that for these turbines most outliers occur for the load case parked/idling. As can be seen in Table 4.2 this is also the load case where a less accurate relationship between the selected SCADA parameters and load indicator has been established.

Furthermore, the results of post-processing indicate that the amount of corrected data varies greatly over the different turbines. For a number of turbines only about 2% of all load estimations had to be done using data from other turbines. Subsequently also a number of turbines has had around 10% of their load estimations corrected. Finally, for four turbines more than 20% of the estimated values of the load indicator have been derived from other turbines. This should be considered when comparing the load accumulation of these turbines with the other turbines as will be described further on in this report.

The bottom graph indicates that after both post-processing steps have been completed the amount of missing data is identical for all 36 turbines and is equal to less than 0.5% of the total amount of data.

4.3.5 Output

Now the values of the load indicator for tower bottom for-aft bending have been estimated for each turbines i for each 10-minutetime period t it is possible to calculate the total load accumulation for each turbine i using equations 3.4 and 3.5. The results are for the tower bottom for-aft bending are presented in Figure 3.5 where the load accumulation of each turbine i is shown relative to the load accumulation of turbine 18.

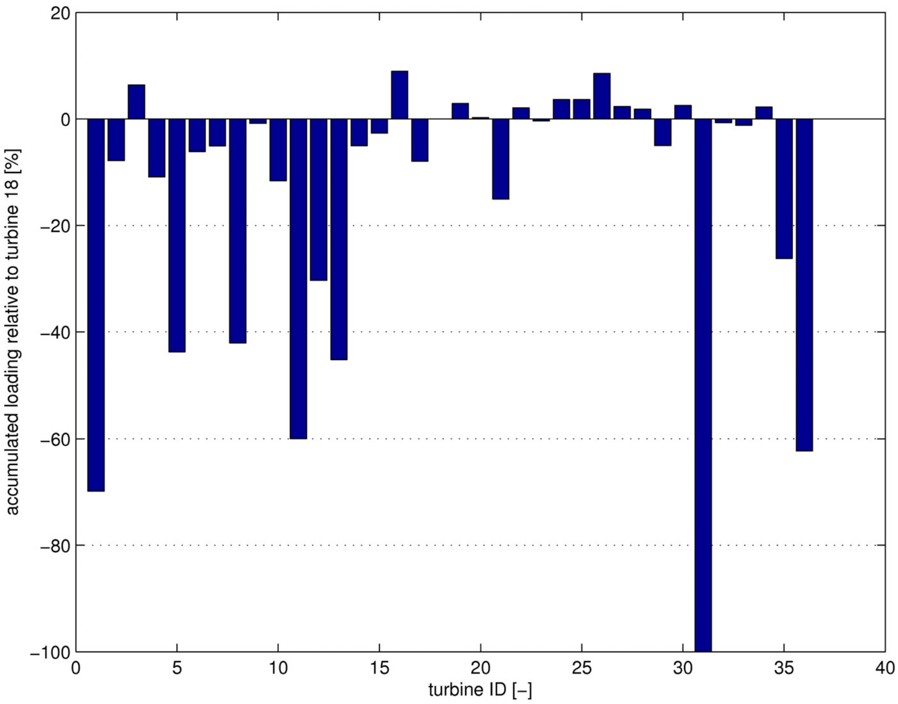

Figure 4.3 *Load accumulation of all five turbines relative to load accumulation of turbine 18.*

The figure indicates that most turbines have suffered a load accumulation which is roughly within about 10% of the load accumulation of turbine 18. However, also about 10 turbines have accumulated significantly less load. When interpreting these results the outcome of the load estimation post-processing steps should be kept in mind (see Figure 4.2). It was shown that for turbines 1, 11, 13 and 31 more than 20% of all estimated values of the load indicator have been derived by averaging the data from the other turbines. This procedure is necessary to ensure that for all turbines an identical amount of data is available for calculating load accumulation but also leads to an inaccurate calculation of load accumulation for the mentioned turbines.

In order to get more insight in the presented results a breakdown of the total load accumulation has been calculated (see Figure 3.6). The graph shows the contribution of three of the five load cases to the total load accumulation (blue bars). In order to interpret the results in both graphs the amount of data is also illustrated (red bars). Data from all 36 turbines have been used.

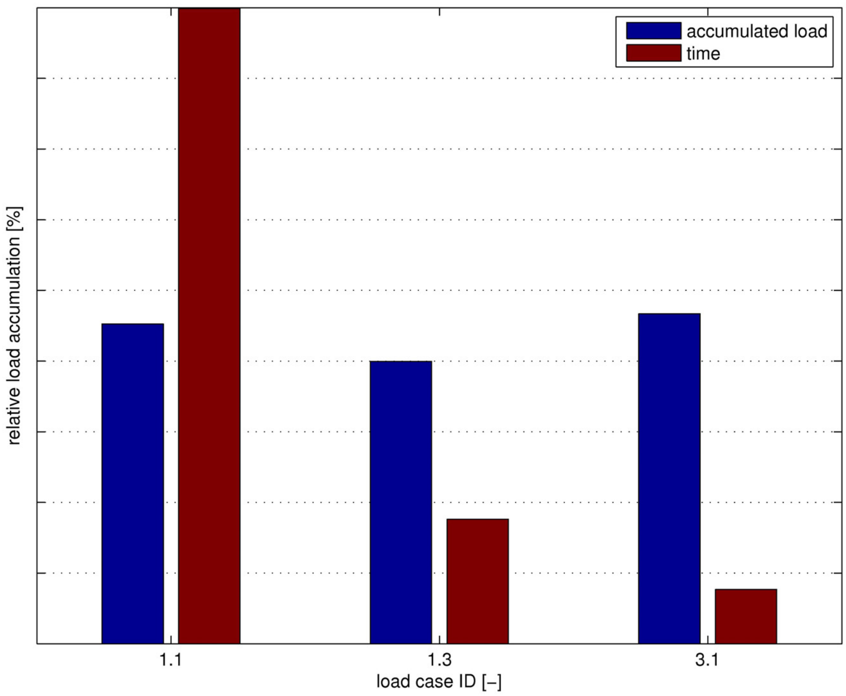

Figure 4.4 *Breakdowns of the load accumulation per load case. Note that the results of only three of the five load cases are displayed.*

The graph shows that on average the 36 turbines operate in power production and under free-stream conditions for most of the time. However, the total load accumulation for this load case is a much smaller part of the total. The opposite is found in case the turbine operates in wake conditions. Especially if the turbines are facing full wake conditions the load accumulation is more than two times as large compared to the amount of time the turbines operate in these conditions. Although, not shown in the figure it has been found that when the turbines are in parked or idling condition still a significant amount of load accumulation occurs. For onshore turbines this was not the case (see Figure 3.6), which indicates that for this load case the wave-induced loading is dominant. Finally, relatively the largest load accumulation occurs during transient events. This load case accounts for a very small part of the total data but still the load accumulation during this load case is similar to the one for power production under free-stream conditions for which a staggering 10 times as many data are available.

4.3.6 Validation

Last step in the analysis is the validation of the accuracy of the Flight Leader predictions. In order to do this the predicted and measured load accumulation for each load case are calculated for both Flight Leader turbines. The prediction errors are subsequently calculated using equation 3.6. The resulting prediction errors are shown in Figure 4.5.

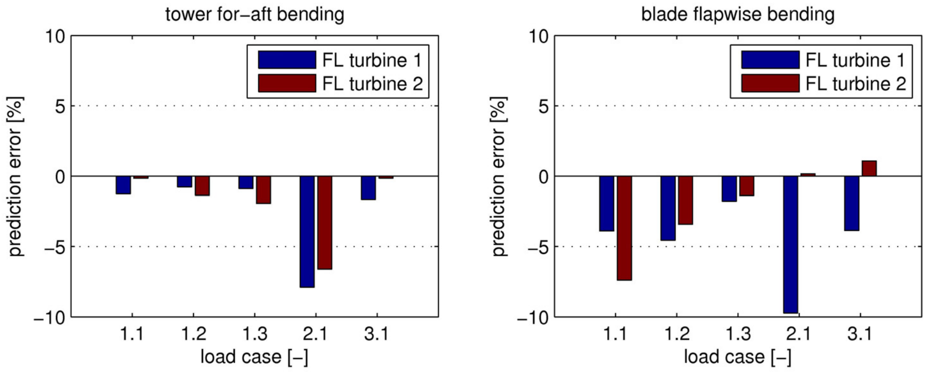

Figure 4.5 *Prediction errors of the Flight Leader software for the load indicators for tower bottom for-aft bending and blade root flapwise bending.*

The results in left graph show that the Flight Leader predictions of load accumulation are very accurate for the load indicator for tower for-aft bending. For the power production and transient event load cases the prediction errors are smaller than 2%. For the parked/idling load case the errors are slightly larger, which can be contributed to the fact that for this load case the relation between SCADA parameters and load indicator showed significantly more scatter compared to the relation for the other load cases.

The results in the right graph show that for blade root flapwise bending the Flight Leader gives larger prediction errors compared to the errors found for tower bottom for-aft bending. Almost all errors are smaller than 5%. For normal power production under free-stream conditions the Flight Leader software underestimates the load accumulation of turbine 8 by more than 7%, whereas for the parked/idling load case the load accumulation for turbine is underestimated by almost 10%. The most likely explanation for the observed higher prediction errors is the fact that the load accumulation is calculated using a Wöhler coefficient of $m = 10$. This has the result that outliers have a very dominant effect of the load accumulation calculation.

In order to prove this the total load accumulation has been calculated again but now using a Wöhler coefficient of $m = 4$ (similar as for tower bottom for-aft bending). When evaluating the prediction accuracy of the Flight Leader software with these settings it is found that for the power production load cases all prediction errors are smaller than 2%. For the transient events the error for both turbines is less than 3%, whereas for parked/idling the error is smaller than 5% for both turbines. These accuracies are at the same level as was found for tower bottom for-aft bending (see left graph), which indicates that the high value of the Wöhler coefficient causes the lower accuracy of the Flight Leader software when predicting the load accumulation for blade root flapwise bending.

4.4 Conclusions

A full Flight Leader analysis has been performed using data from the OWEZ offshore wind farm. The analysis has been performed for mechanical loading on both tower bottom for-aft bending and blade root flapwise bending. For both loads the damage equivalent load range is used as load indicator. The analysis has shown that the results for both load indicators are very similar. This can be explained by considering that during power production the load fluctuations in both blade flapwise and tower for-aft bending are mainly caused by fluctuations in rotor thrust. As a result the most important findings and conclusions will not be listed separately for each load indicator.

A trial-and-error approach has been adopted in order to determine what SCADA parameters are relevant for estimating the values of the load indicator. It was found that for both load indicators the same SCADA parameters should be included as independent variables in the artificial neural network. For each load indicator a relation between the selected SCADA signals and the values of the load has been determined. This has been done separately for each of the five identified load cases. For almost all load cases an accurate relation is established. Only for tower for-aft bending the relation for the parked/idling load case is surrounded by more scatter, which is caused by the fact that no wave-describing parameters are included in the relation.

After establishing all required relations the values of the load indicators are estimated for all 36 turbines in the offshore wind farm. Subsequently, the 10-minute load indicator values have been summed in order to calculate total load accumulation of each turbine in the farm. After comparing the total load accumulation of all turbines it has been found that the difference in total load accumulation is smaller than 20% for most of turbines. A few exceptions exist, mainly for the turbines that have been in parked of idling state for large periods of time.

It has also been analysed what load cases contribute most to total load accumulation. The most striking observation is the very high contribution of transient events to the total load accumulation. Despite its low frequency of occurrence for both tower for-aft and blade flapwise bending the load accumulation during this load case is about equal to the load accumulation during power production in free-stream conditions. Furthermore, also load accumulation during wake operation is relatively high. In contradiction to what has been observed onshore, during the parked/idling load case still significant load accumulation occurs. For tower for-aft bending this is caused by the wave-induced loading, whereas for blade flapwise bending the most likely cause is the fluctuating gravitational force acting on the blades during idling.

Finally, also the output of the Flight Leader software has been validated by comparing the predicted and measured total load accumulation for both Flight Leader turbines. For tower for-aft bending very small prediction errors are found for all load cases but parked/idling. The lower accuracy of the Flight Leader software here can be explained by the lower accuracy of the relation between SCADA parameters and load indicator for this load case. The prediction errors for blade flapwise bending are found to be larger. After some additional research it was found that this is caused by the high value of the Wöhler coefficient ($m = 10$) for calculating the total load accumulation. This has the consequence that outliers have a huge impact on the load accumulation.

5. Status and future research

Within this project the Flight Leader software has been developed, tested and evaluated using data from both an onshore and offshore wind farm. Based on the results of this research it is advised that in the future the following aspects should be investigated or developed further.

5.1 Online implementation

The evaluation of the Flight Leader using data both an onshore and offshore wind farm have been performed in an 'offline' way; where a dataset is retrieved from an already existing wind farm, where the measurement infrastructure is not optimised for the application of the Flight Leader. In the future the Flight Leader concept should be evaluated using 'online' implementation. During the construction of the wind farm the location of the Flight Leader turbines should be carefully selected. Furthermore, all turbines should be equipped with calibrated sensors in order to ensure accurate Flight Leader predictions.

After commissioning of the wind farm at regular intervals (every week or month) data should be retrieved and fed to the Flight Leader software. The software should be applied in order to update the prediction of load accumulation for all turbines in the farm. This information should be combined with results from inspections or condition monitoring systems in order to assess the health of the components and adjust the maintenance schemes accordingly.

The offline analysis has shown the Flight Leader concept is a cost-effective method for assessing the load accumulation at all turbines in a wind farm. By using the online implementation the practical application of the Flight Leader can be assessed.

5.2 Automated SCADA parameter selection

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. Before the relations can be established it has to be decided which standard signals should be used to estimate the load indicators. Until now this has been done using a trial-and-error approach. This however is not ideal, especially since a wind farm operator might not have detailed knowledge about the behaviour of the wind turbine. Therefore an automated procedure should be implemented in the software which uses some statistical method in order to select the set of SCADA parameters that should be used to estimate the values of a certain load indicator. If it turns out that no automatic procedure can be developed at least a library should be constructed which contains for a number of load indicators a preferred set of SCADA input signals.

In addition to this it will also be worthwhile to use aero-elastic simulations for assessing the importance of the different SCADA parameters for estimating the values of a certain load indicator. The benefit of using simulations is the fact that a large number of input signals are available in the simulations, which are not currently measured at the turbines at the EWTW site. Using the simulations it can be identified if certain parameters (which are not currently measured) can be used to estimate the values of a load indicator with greater accuracy. If this is found to be the case the next step would be to investigate if and how it is possible to measure these parameters on a modern multi-MW wind turbine.

5.3 Selecting relevant load indicators

For the research done so far relatively simple fatigue-based load indicators have been used. It is commonly accepted that for a wind turbine blade and tower fatigue is the most important degradation mechanism. However, the degradation of drive train components is much less well understood. This is a topic subject to further research.

5.4 Impact assumptions

During the development of the Flight Leader software several assumptions have been made. It needs to be verified whether these assumptions are correct or not. Furthermore, their influence on the output of the Flight Leader software should be assessed.

6. References

In the following subsections the references used in this document are listed. A distinction between public and confidential reports is made. Furthermore, literature that has been consulted during the course of this project is listed.

6.1 Public reports and conference papers

[1] Eecen, P.J.; Garrel, A. van; Obdam, T.S.; Schepers, J.G.; Peeringa, J.M.; Snel, H.; Engelen, T.G. van; Wouters, D.A.J.; Ozdemir, O.; Bulder, B.H.; *ECN - Wind energy presentations of the Dutch Wind Workshops 2008*; ECN-M--08-082; November 2008; 241 pages; Presented at the Dutch Wind Workshops 2008, Delft, The Netherlands, 27-28 October 2008.

[2] Obdam, T.S.; Rademakers, L.W.M.M.; Braam, H.; *Flight Leader Concept for Wind Farm Loading Counting and Performance Assessment*; ECN-M--09-054; March 2009; 10 pages; Presented at the European Wind Energy Conference 2009, Marseille, France, 16-19 March 2009.

[3] Obdam, T.S.; Rademakers, L.W.M.M.; Braam, H.; *Flight Leader Concept for Wind Farm Load Counting: First offshore implementation*; ECN-M--09-114; August 2009; 13 pages; Presented at the OWEMES 2009 Conference, Brindisi, Italy, 21-23 May 2009.

[4] Obdam, T.S.; Rademakers, L.W.M.M.; Braam, H.; *Flight Leader Concept for Wind Farm Load Counting: Offshore Evaluation*; ECN-M--09-122; Presented at the European Offshore Wind Energy Conference, Stockholm, Sweden, 14-16 September 2009.

6.2 Confidential reports

[5] Korterink, H.; Peeringa, J.M.; *PHATAS Model Nordex N80*; ECN-X--07-139; December 2007; 72 pages.

[6] Korterink, H.; Kaandorp, F.A.; *Flight Leader Measurements EWTW: Measurement Plan*; ECN-X--08-013; February 2008; 87 pages.

[7] Korterink, H.; Kaandorp, F.A.; Werff, P.A. van der; Flight Leader Measurements EWTW - Instrumentation Report; ECN-X--09-056; July 2009; 204 pages.

[8] Obdam, T.S.; Rademakers, L.W.M.M.; Braam, H.; *Functional Specifications for the Flight Leader*; ECN-X--08-049 June 2008; 33 pages.

[9] Obdam, T.S.; *Technical Specifications and Model Description for the 'Flight Leader'*; ECN-X--08-098; October 2008; 99 pages.

[10] Obdam, T.S.; *Flight Leader Software Description*; ECN-X--09-101.

[11] Obdam, T.S.; *Evaluation of the Flight Leader Using EWTW Measurements*; ECN-X--09-027; April 2009; 81 pages..

[12] Obdam, T.S.; Korterink, H.; *Evaluation of the Flight Leader: Part II*; ECN-X--09-100.

6.3 Literature

[13] P.J. Eecen, J.P. Verhoef; *EWTW Meteorological database; Description June 2003 - May 2006*, ECN-E-06-004; September 2006.

[14] P.J. Eecen, et. al.; *Measurements at the ECN Wind Turbine Test Location Wieringemeer*; ECN-RX--06-055; February 2006.

[15] P.J. Eecen, et. al.; *LTVM statistics database;* ECN-CX--05-084; September 2005.

[16] S. Schwarz, R. Dittmar, A. Anders; *Determination of Actual Fatigue Loading on Wind Turbines Based on Neural Networks*; 2005.

[17] N. Cosack, M. Kühn; *Prognose von Ermüdungslasten an Windenergieanlagen mittels Standardsignalen und neuronaler Netze*; Presented at the Dresdner Maschinenelemente Kolloquium, Dresden; December 2007.

Appendix A Justification work packages

In this appendix the work performed during the course of the project is split up for each of the defined work packages in the original project proposal. This makes it easy to understand how the originally planned work is performed and where the different results are documented.

6.4 WP1: Development of initial model at the EWTW

Using the developed Flight Leader software relations between SCADA parameters and load indicators for several wind turbine components have been determined. Separate relations have been established for each of the seven defined load cases (which are a combination of turbine state and wake condition). Three different characterisation methods have been evaluated where it was found that artificial neural networks are the best method for establishing the mentioned relations.

6.5 WP2: Structural dynamic analyses for N80 turbine

A detailed aero-elastic wind turbine model of the Nordex N80 has been developed in ECN's aero-elastic software simulation tool PHATAS. The model has been tuned and validated using measured data from turbine 2 at the EWTW wind farm [5].

6.6 WP3: Wake analyses for five Nordex N80 turbines

Using ECN's wind farm wake analysis program FarmFlow has been applied to calculate the effects of wakes on the five Nordex N80 turbines at the EWTW site. For both a partial and full wake situation the added turbulence intensity and wind speed reduction (wake deficit) have been calculated for the whole operational range of the turbine. These data have subsequently been fed to ECN's WakeSWIFT code in order to generate 3-D wake wind fields which can be used as input for the aero-elastic simulations.

6.7 WP4: Specification of equivalent loads model

During the first months of the project firstly functional specifications for the Flight Leader software have been drafted [8]. In this document it has been described what functionality should be included in the software model and based on this information the actual development of the software could be started. Based on the functional specifications technical specifications have been written [9]. These describe the different processes in the software in detail and serve as a detailed guideline for the actual programming of the software.

6.8 WP5: Programming of equivalent loads computer code

Based on the detailed technical specifications a demo version of the Flight Leader software has been programmed in MATLAB® [10]. The software includes all aspects of the Flight Leader concept and is intended to be used by operators of offshore wind farms and can be applied to process the SCADA data and mechanical load measurements from an (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.

6.9 WP6: Verification of equivalent loads computer code

Extensive analyses have been performed using data form ECN's wind farm EWTW [11]. The performance and accuracy of the Flight Leader software has been evaluated for different load indicators. In general the results have been encouraging, where most of the larger errors could be explained by the fact that the (SCADA) sensors used at the Nordex N80 turbines are not calibrated. Based on the experiences gathered while evaluating the Flight Leader concept some changes to the software were made [10].

Although not originally foreseen in the project plan additional analyses have been performed using data from an offshore wind farm. The goal of this research was to assess whether the encouraging results found for the onshore analysis could also achieved when the Flight Leader concept is applied to an offshore wind farm where wave-induced loading and large-scale wake effects play an important role. Using data from the OWEZ offshore wind farm it has been confirmed that the Flight Leader concept is also valid for large offshore wind farms [12].

Appendix B Neural network training procedure

In this appendix the training procedure for a neural network is described in more detail. The complete procedure is indicated by the flowchart in Figure B.1. In the following subsections a description of the different parts are provided.

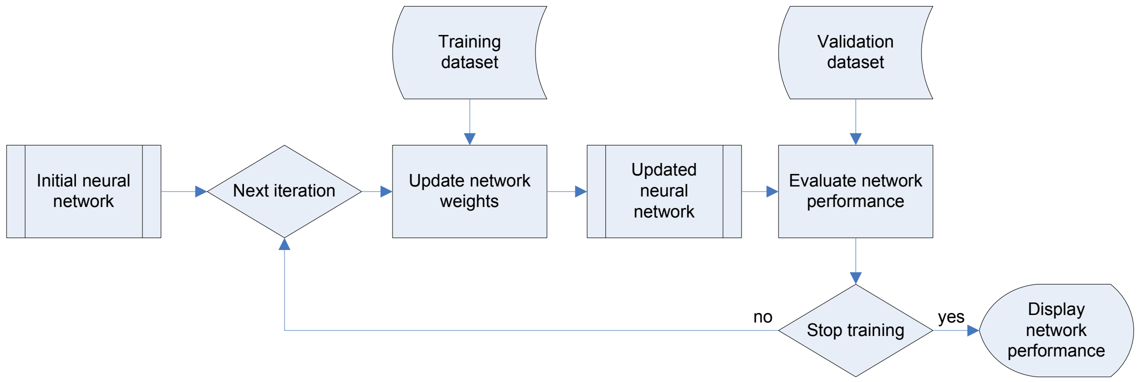

Figure B.1 *Flowchart indicating the procedure of neural network training and output visualisation.*

B.1 Initial neural network configuration

As mentioned already in section 3.2 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.

To start with the network architecture has to be specified. It has to be decided how many neurons are included in the network. In general it can be said that the more input signals are used the more neurons the network should contain. After the architecture is defined the network is initialised by randomly choosing a value for each connection weight in the network.

B.2 Updating network weights

After the initialisation is completed the 'training' process of the neural network is started. The goal of the training process is to adjust the network weights in such a way that it is able to estimate the values of the output variable as accurately as possible. During the training process the following steps are repeated:

1. Present the training dataset to the neural network. The dataset contains multiple samples (10-minute values) of both inputs (SCADA parameters) and output (load indicator).
2. Compare the network's output to the desired output from the 'training' dataset. Calculate the error in each output neuron.
3. For each neuron, calculate what the output should have been, and a scaling factor, how much lower or higher the output must be adjusted to match the desired output. This is the local error.
4. Adjust the weights of each neuron to lower the local error.
5. Assign 'blame' for the local error to neurons at the previous level, giving greater responsibility to neurons connected by stronger weights.

6. Repeat from step 3 on the neurons at the previous level, using each one's 'blame' as its error.

B.3 Evaluate network performance (early stopping)

Common practice in neural network analysis is the fact that 'over-fitting' of the trained network should be prevented at all times. Over-fitting is the phenomenon where the network is more accurate in fitting known data (hindsight) but less accurate in predicting new data (foresight). Over-fitting mainly occurs when too little training data are available or when the network is trained for a too long time. In order to prevent an over-fitting network the early-stopping technique is usually applied.

The neural network is trained using a 'training' dataset. Subsequently, for each iteration, the network's performance is evaluated using a 'validation' dataset. Naturally the networks' prediction error for the training dataset decreases with every iteration. Usually, for the first number of iterations, this is also the case for the validation dataset. At the point where the neural network's performance starts decreasing the training is halted. The early-stopping technique is shown graphically in Figure B.2 .

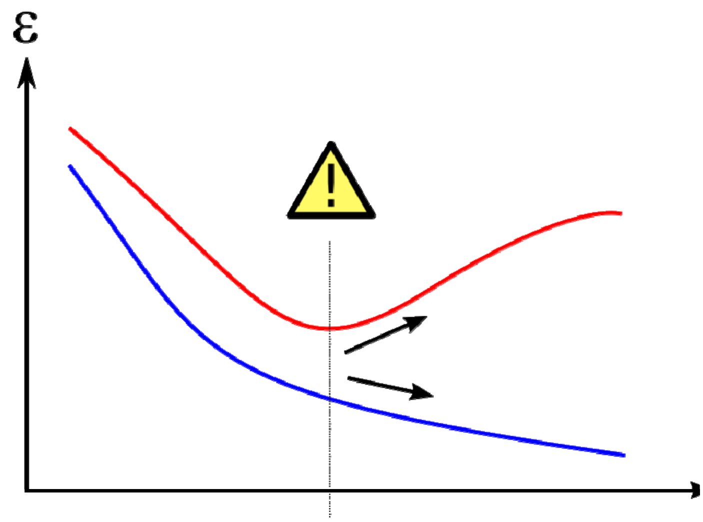

Figure B.2 *Early-stopping technique for preventing over-fitting of a neural network. The prediction error (y-axis) for both the training (blue line) and validation (red line) data sets are plotted as function of the number of performed iterations (x-axis). At the point (number of iterations) where the prediction error for the validation dataset starts increasing training should be halted.*

B.4 Display network performance

After the training of the neural network is completed the performance of the trained network can be visualised. Usually this is done by drawing a scatter plot which shows the desired output (in this case the measured values of a certain load indicator) on the x-axis versus the predicted output (values of a certain load indicator) on the y-axis. The amount of scatter in this graph is a good measure for the accuracy of the neural network: The more accurate the network the less scatter will be observed in this graph.