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Conmow Final Report

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Acknowledgement/Preface

This report has been written as part of the project "CONMOW", which was initiated to investigate whether a cost effective integral condition monitoring system can be realized in practice for wind energy application.

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Abstract

For offshore turbines the demand for high reliability and low operation and maintenance (O&M) costs is higher than for onshore turbines. Recent studies show that the O&M costs of offshore wind farms are too high, about 25 to 30% of the energy generation costs, and a considerable part is caused by unexpected failures leading to corrective maintenance.

In the CONMOW project it has been investigated whether online condition monitoring (CM-) techniques have added value for optimizing O&M strategies of large offshore wind farms and how these techniques can be improved.

Therefore first an inventory has been made of available and suitable state-of-the-art CM-techniques followed by a failure mode and effect analysis to select meaningful (applications for) condition monitoring systems and to identify useful developments.

Then a measurement campaign was carried out on a GE 1.5S turbine and on five Nordex N80/2.5 MW turbines to assess and improve the performance of CM-techniques. Results from five different drive train vibration monitoring systems have been analysed in combination with high-frequency data from “traditional” measurement systems and from the turbine PLC. By analysing the high-frequency electric power signal using wavelet transformations a shaft misalignment could be detected. This was confirmed by vibration measurements, which provided more detailed information on the origin and the effects of these vibrations.

Further large amounts of SCADA statistical data and inspection reports have been analysed. Several methods to process and present these data, such as de-trending and filtering, showed to reduce scatter and resulted in a simple and orderly presentation to the operator. This makes it easier to observe trends and abnormalities, which can improve early failure detection. However, due to the limited measurement time during which no failures occurred in the turbines, no proof was found that the methods indeed are useful to determine failures at an early stage.

The presently available drive train monitoring systems, supplied by Gram&Juhl and Prűftechnik performed well and reliable. It was demonstrated that the systems are able to detect component errors at an early stage as well as off-design conditions, such as shaft misalignment. Up till now, the response on abnormalities in the data is either more frequent inspections or an immediate shut down to avoid consequence damage, as yet insufficient knowledge is available to make prognoses how the failures will develop in order to change from *calendar based maintenance* to *condition based maintenance*. Such knowledge can only be obtained from a larger population of identical wind turbines and longer measurement periods during which faults occur.

In the project several improvements have been implemented in the vibration monitoring systems, including more accurate vibration measurements on the low-frequency stages, improved configuration and processing techniques and automated reporting via Internet.

All types of measurement systems and CM-systems produce large data amounts which are difficult to interpret by wind farm operators, although reporting has improved. Therefore one is dependent on dedicated experts to derive meaningful recommendations for O&M optimization.

Instead of the original ambition to implement the lessons learnt into a wind farm SCADA system and test these over a longer period of time, additional simulations have been performed. Simulations with GH Bladed showed that in some cases fault conditions and off-design conditions can be detected from measurements. A cost sensitivity study showed a clear effect of the quality of the CM-systems, e.g. percentage of false alarms or non-detected failures, on the potential O&M cost reduction. Both the ECN cost model as the Risø cost model clearly showed that significant cost benefits are possible when suitable CM-techniques are applied.

FINAL TECHNICAL REPORT

DETAILED FINAL REPORT

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PROJECT N° : **NNE5-2001-00804**

ACRONYM : **CONMOW**

TITLE : **Condition Monitoring for Offshore Wind Farms**

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PARTNERS :
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Gram&Juhl APS - DK
Prűftechnik CM GmbH – D

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Part 2. Detailed Final Report

1 Objectives and strategic aspects

This chapter provides an introduction to Operation and Maintenance (O&M) aspects of offshore wind farms, including a cost analysis. After describing Condition Monitoring and different maintenance strategies, it is explained why optimization of O&M is needed, especially offshore. Then it is explained what are the main requirements to apply Condition Monitoring techniques to optimize the maintenance strategy. Finally the project objectives and approach are discussed.

1.1 Why condition monitoring for offshore wind energy

Offshore wind turbines are located at remote sites under harsh conditions, with limited access is and high costs, e.g. of transport vessels. Therefore the demand for high reliability and low operational costs is higher than for onshore turbines. In this chapter, the need to reduce maintenance costs, especially for corrective maintenance, is discussed.

Condition based maintenance is often seen as one of the means to lower the costs for corrective maintenance. In that case appropriate condition monitoring systems and good diagnostics are essential. In this chapter it will be discussed how in general condition monitoring techniques could contribute to the optimization of any Operation and Maintenance (O&M) strategy and an overview will be given of the condition monitoring techniques that are presently available.

For wind turbines, it will be investigated if such a generic approach with the available techniques is applicable. Boundary conditions and constraints specific for wind turbine engineering will be considered.

1.2 O&M costs

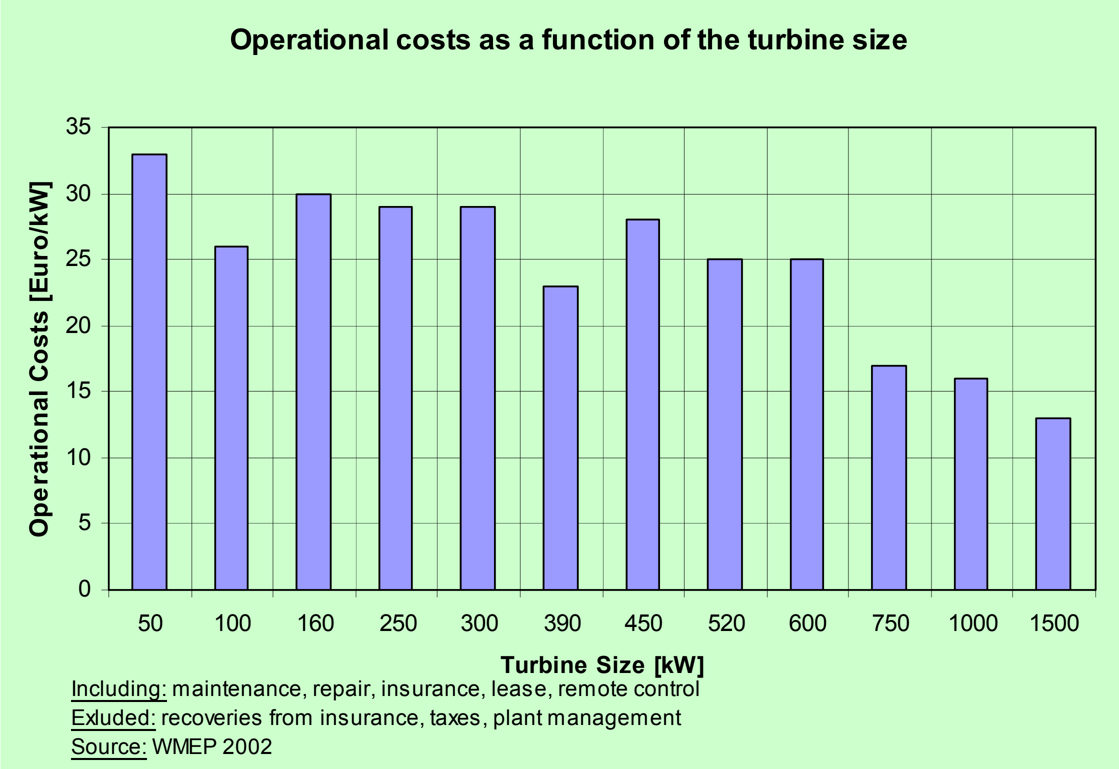
1.2.1 Onshore

For onshore wind turbines, a lot of operating experience has been collected and analyzed. Since onshore wind energy is a mature branch of industry, reliable data is available. In Table 1.1 some key figures are presented, mainly derived from [1], [2], and [3].

Table 1.1: Key figures for O&M onshore (Investment costs of turbine ≈ € 1000/ kW)

Failure rate	1,5 to 4 failures per year	
Availability	> 98 %	
Service contract	0,5 to 0,8 % of invest. costs per year;	5 to 8 €/kW
Service contract incl. warranty	1,0 to 1,6 % of invest. costs per year;	10 to 16 €/kW
Costs for corrective maintenance year 5	0,5 to 0,8 % of invest. costs per year;	5 to 8 €/kW
Costs for corrective maintenance year 15	4 to 6 % of invest. costs per year;	40 to 60 €/kW
Average O&M costs over lifetime	2 to 4 % of invest. costs per year	
Insurance costs	5 to 8 €/kW (machine damage, 3rd parties, revenue losses)	
LPC (O&M costs)	5 to 10% of kWh price (of which half due to maintenance) 0.5 (year 1) to 1.5 (year 10) €cent/kWh	

From the WMEP database 2002, [1], it is revealed that the O&M costs become lower per installed kW. Figure 1.1 shows the total operational costs. In Figure 1.2, an analysis has been made of the service contracts of nowadays available wind turbines related to their investment price [4]. The data has been compared with the figures presented in [1] and with the offers for four commercially available turbine types in the 2 MW range. It is clear that the figures presented in [1] and [5] do not include warranties, spare parts, consumables, 24 hours monitoring, etc.



Including: maintenance, repair, insurance, lease, remote control
Exluded: recoveries from insurance, taxes, plant management
Source: WMEP 2002

Figure 1.1: Operational costs as a function of turbine size [1]

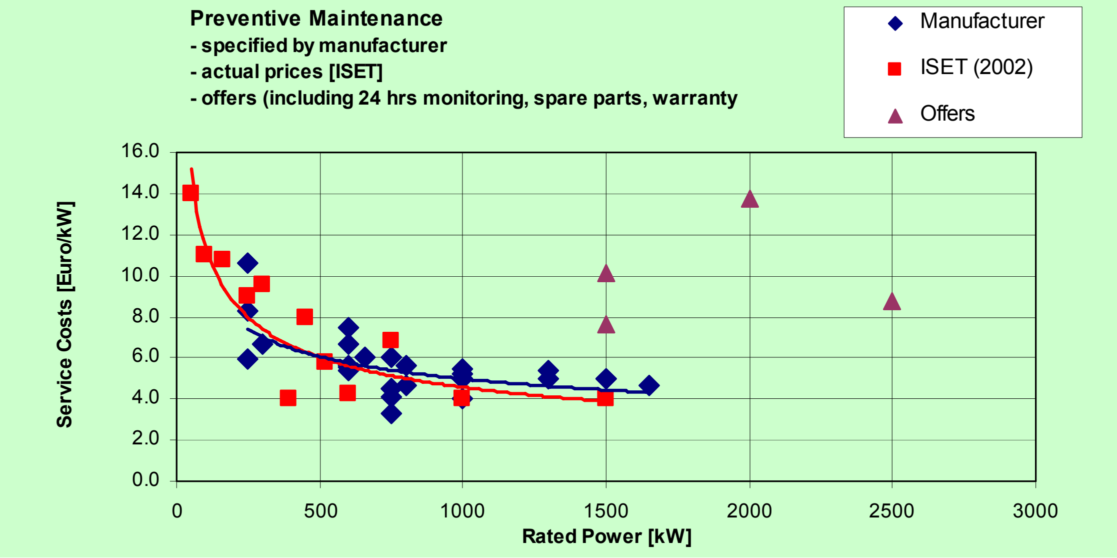


Figure 1.2: Prices of service contracts as a function of turbine size [1]

Figure 1.3 splits up the total maintenance costs into costs for preventive and corrective maintenance. As can be seen, these costs are more or less equal.

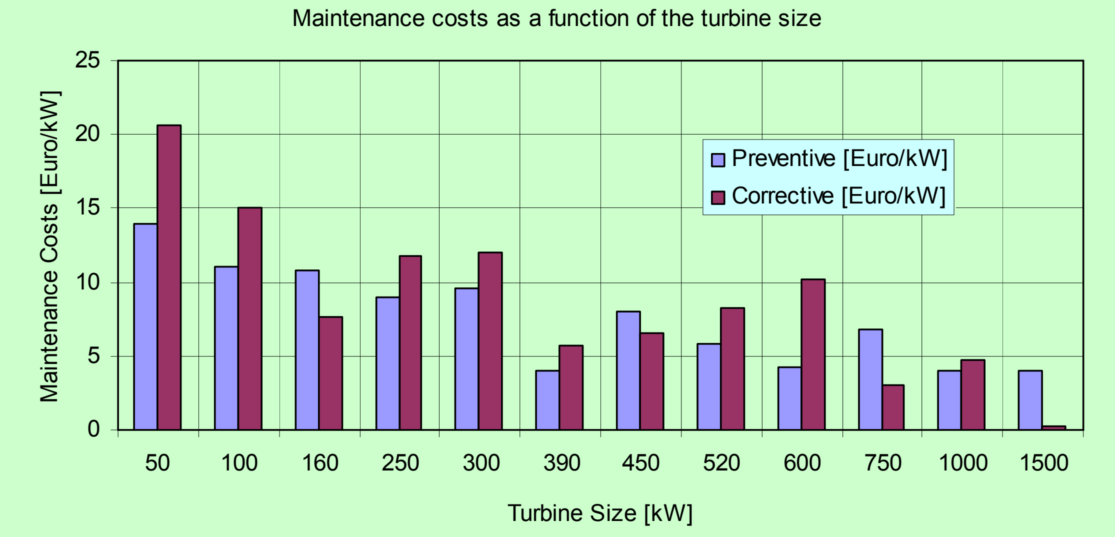


Figure 1.3: Costs for preventive and corrective maintenance as a function of turbine size [1]

A German study performed by DEWI [6] indicates that after twenty years lifetime, approximately 64 % of the investment costs should be made for spare parts. The study used data of smaller wind turbines. On average, this corresponds to more than 3 % of the investment costs per year. With an investment price of 1000 €/kW, this equals 30 €/kW which is higher than the numbers given in Figure 1.1.

1.2.2 Offshore

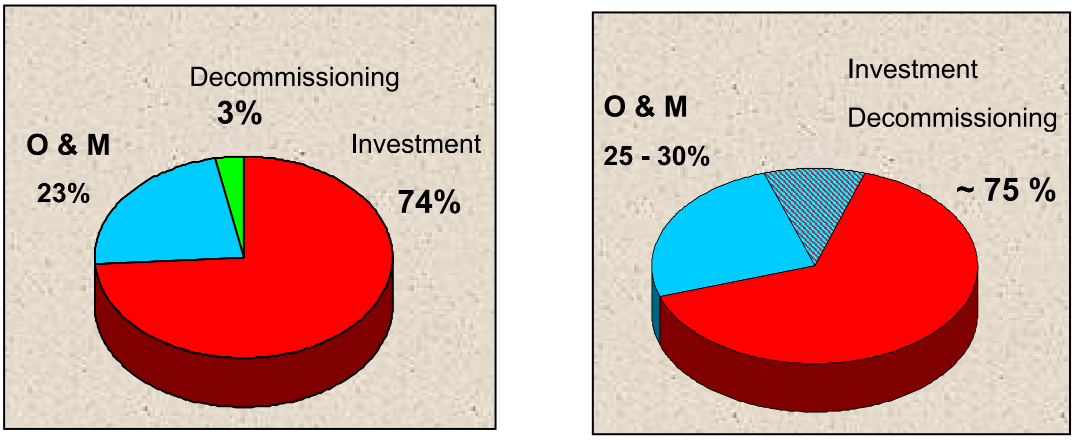
For offshore wind farms hardly any operating experiences are available and therefore the determination of operation and maintenance (O&M) costs could be done only by means of modeling (an example can be found in [7]). From recent studies for developing O&M plans for offshore wind farms, ECN has concluded that the costs for maintaining offshore wind farms are higher than for maintaining onshore wind farms. Typical figures (including costs for maintaining the park infrastructure, civil structures, etc.) are:

- preventive maintenance 0,003 to 0,009 (€/kWh)
- corrective maintenance 0,005 to 0,010 (€/kWh)

It is remarkable that the costs for *corrective* maintenance are a factor of 2 higher than for *preventive* maintenance, whereas for onshore turbines the costs for preventive and corrective maintenance are in balance. This is mainly caused by the expensive equipment that is needed such as crane ships. In addition to that, the costs for the revenue losses are substantially higher for offshore wind farms. The accessibility of onshore wind turbines is hardly influenced by the weather conditions whereas offshore, long downtimes do occur due to high waves and strong winds. Analyses revealed that the revenue losses are about 50 to 80 % of the costs for corrective maintenance. The figures are covered with great uncertainty, originating from a.o.:

- the failure rate of the turbines, indicating the demand for corrective maintenance;
- the equipment to use for access and lifting and their fluctuating prices;
- the influence of the wave height and wind speed on the operational windows for accessing and repairing the turbine
- the distance to the shore;
- logistic aspects (the crew size, stock control, contracts with equipment suppliers and offshore companies, etc).

ECN's studies also revealed that the contribution to the kWh price is approximately 25 to 30% [8], [9] whereas onshore, the contribution is in between 10 to 15 %. The results of the ECN studies have been compared with public data, e.g. [1], [4], [10], [11], [12], [13], and [14]. Figure 1.4 confirms that the O&M costs do contribute 25 to 30% of the total kWh costs.



1998 (Opti-OWECS study)

2001 (CA-OWEE)

Figure 1.4. The cost breakdown determined in (left) the Opti-OWECS study of Delft University of Technology [15] and (right) in the concerted action [9] carried out by various European wind turbine manufacturers, offshore companies and R&D institutes

In [13] the cost estimates are presented of a Danish offshore wind farm in the North Sea and in the Baltic Sea Figure 1.5. These figures match very well with the ECN figures.

Operational year:	**1-2 year**	**3-10 year**	**11-20 year**	**Average O&M cost over lifetime (in 2001 value - not indexed)**
Location:	**DKK/kWh ($UScent/kWh)**			
The North Sea (20 MW)	0.047 (0.56 cent)	0.067 (0.79 cent)	0.10 (1.20 cent)	0.082 (0.98 cent)
The Baltic Sea (20 MW)	0.052 (0.62 cent)	0.075 (0.89 cent)	0.11 (1.31 cent)	0.090 (1.07 cent)
Assumptions: "State of the art" 2 MW wind turbines. Plant size 20 MW as integrated part in a +100 MW Offshore Wind Farm in Danish offshore location. Projected full-load hours are 3,700 hours and 3,300 hours for North Sea and Baltic Sea respectively. Exchange rate: 8.4 DKK = $US 1				

Figure 1.5: O&M costs for two Danish offshore wind farms

1.2.3 Summary and conclusions of cost analyses

If offshore wind farms will be built with state of the art technology of onshore turbines, with onshore failure rates, and maintained with methods used in offshore industry before 2003, it is expected that the O&M costs will be much higher and the availability will be approximately 85 to 95 %. From recent studies, [1][4][8][9], combined with [10][11][12][13][14], ECN derived the following generic key figures with respect to costs of offshore wind energy.

- the energy generation costs of offshore wind farms are approximately 72 €/MWh (in between 5 to 10 €cents/kWh);
- the investment costs for wind farms built of small units (< 2 MW each) are expected to be in the range of 2000 to 2500 €/kW;

- the investment costs for future offshore wind farms built of larger units (>3 MW each) are expected to be in the range of 1400 to 2000 €/kW with a most likely value of 1700 €/kW;
- the turbines (>3 MW each), including the tower but without the support structure are expected to contribute to the investment costs for approximately 40 to 50% which corresponds to 680 €/kW (= 0.4*1700) to 850 €/kW (= 0. 5*1700);
- the O&M costs form approximately 23 to 30 % of the energy production costs, which corresponds to 30 to 50 €/kW per year, or 1.2 to 3 €cents/kWh (see also Figure 1.4).
- approximately 2/3 of the O&M costs (say 20 to 45 €/kW installed capacity) are caused by corrective maintenance;
- the revenue losses are in the same order of magnitude as the costs for corrective maintenance.

These figures emphasize that there is a potential for optimization of the O&M procedures. Condition monitoring can play a role in this optimization process if:

- it is able to reduce the number of failures and thus the number of repair actions;
- it is able to reduce the severity and consequence damage of failures and thus reduce the cost of a repair action;
- it is able to reduce the downtime, and thus the revenue losses (a.o. through the integrated planning and scheduling of repairs);
- it is able to maximize component life by avoiding the conditions that reduce equipment life (for example, by ensuring ongoing precision alignment, minimal lubricant contamination etc.)
- the investment and operational costs of CM systems are at an acceptably low level.

1.3 How to apply CM-techniques for O&M optimization

1.3.1 Development of an O&M strategy

Before condition monitoring techniques can be applied to improve the effectiveness of an O&M strategy it should be recognized what the role of condition monitoring is in the entire O&M strategy. Therefore, briefly some general aspects of an O&M concept will be discussed first.

Before setting up an O&M concept for any component, some basic information should be available or otherwise assumptions need to be made:

1. The failure behavior of the system under influence of its loading and external conditions
2. The failure frequency (or failure rate, or mean time to failure)
3. The consequences if a failure occurs
4. The costs for preventive maintenance of the system

Furthermore, the lifetime of the component is assumed to be shorter than the lifetime of the entire system.

Some remarks need to be made here.

Ad. 1) In Figure 1.6 an example of failure behavior over the lifetime is given under ideal circumstances. The lifetime of a large number of identical components has been tested under constant loading and constant external conditions. The tests revealed that all components survived the first twelve months, the average lifetime is eighteen months, and after two years, all components failed. The distribution function in Figure 1.6 applies to the external conditions and loading pattern present during the tests. If the loading will increase it is likely that the lifetime will shorten and/or the distribution function may change, see for example Figure 1.7. In most applications it is not always clear (1) what the actual load pattern over the lifetime will be and (2) what the influence of different loading patterns is on the distribution function and the lifetime.

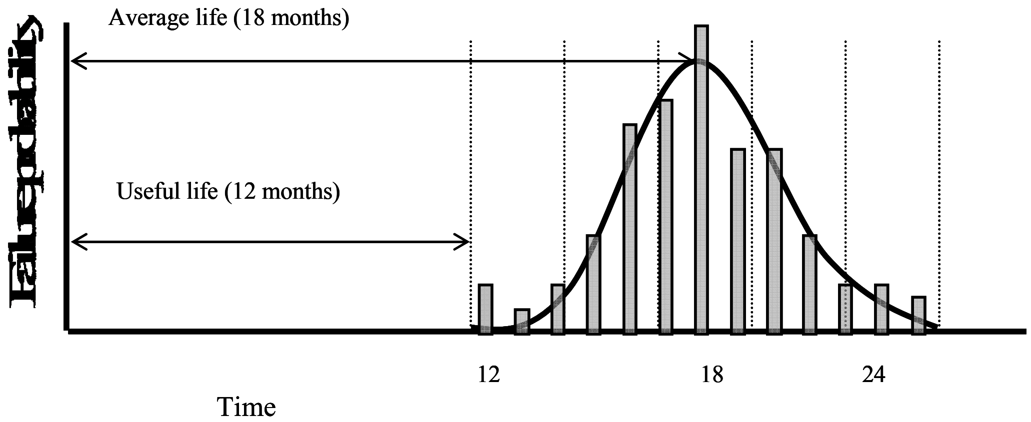


Figure 1.6: Failure probability as a function of the lifetime

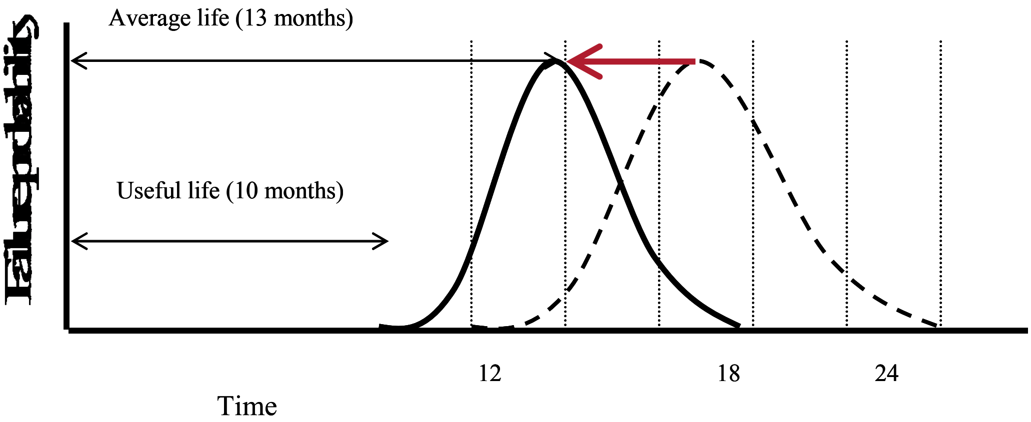


Figure 1.7: Failure probability under increased loading

Ad 2) The failure rates of components can be derived from reliability testing as is illustrated above. In practice, such information is hardly available. For electronic components reliability testing is sometimes carried out, but for mechanical and structural components this is not common practice. In many cases however, failure data is available from similar applications. The failure rates can then be determined roughly by dividing the number of failures by the (operational) time. When applying these data for new applications it should be kept in mind that the historical data are valid only under similar external conditions, similar loading, and a similar preventive maintenance strategy.

Ad 3) It should be assessed what the consequences of a failure are. If a failure does lead to severe damage, long machine outage, and expensive repairs it is recommended to prevent the failure from happening. If this is not the case (e.g. a light bulb in an office) corrective maintenance is acceptable. A structured approach to assess the consequences of a failure is the Failure Mode and Effects Analysis (FMEA). Usually the consequences can be determined in terms of costs. To further assess the consequences it is recommended to multiply them with the failure frequency. By doing so, the criticality is obtained which is usually expressed in the costs per year for corrective maintenance.

Ad 4) When looking at Figure 1.6, carrying out preventive maintenance every year (or even more often) would prevent any failure from happening. However, this strategy might be too expensive. Extending the service intervals will lead to lower annual service costs, but may lead to an increase of failures and thus of the annual costs for corrective maintenance. In practice, carrying out a risk analysis to find a good balance between preventive and corrective maintenance is usually difficult and covered with large uncertainties. Furthermore, practical boundary conditions do play a role in selecting the optimal interval for preventive maintenance. For instance a preventive maintenance action for the entire machine is planned at intervals that do not correspond with the optimal interval for a specific component. Clustering all actions at one point in time is usually cheaper than servicing all components at their optimal intervals.

Ad 5) Several components in a system are designed such that their lifetimes are longer than the lifetime of the entire system. In that case maintenance is not needed. Referring again to Figure 1.6: if the lifetime of the entire system is only 11 months, the probability of failure of the component is negligible and no maintenance is required. Inspection and maintenance might become relevant however if one is uncertain about the actual loading pattern and external conditions that will occur during the lifetime. In that case it is uncertain if the distribution of Figure 1.6 applies, probably the one in Figure 1.7 applies and the failure probability of the component is not negligible over the 11 months lifetime.

According to handbooks and publications on O&M (e.g. [16], [17]) preventive maintenance and corrective maintenance can again be split up into different categories. For the purpose of the CONMOW project the following categories seem appropriate, see also Figure 1.8.

Preventive maintenance	- scheduled maintenance, based on fixed time intervals, or a fixed number of operating hours or performance
	- condition based maintenance (sometimes called "predictive maintenance"), based on the actual health of the system
Corrective maintenance	- planned corrective maintenance, based on observed degraded failures (the component does not work properly but fulfills the system demands)
	- unplanned corrective maintenance, based on catastrophic failures (the component does not fulfill its specifications and is not able to fulfill its task anymore)

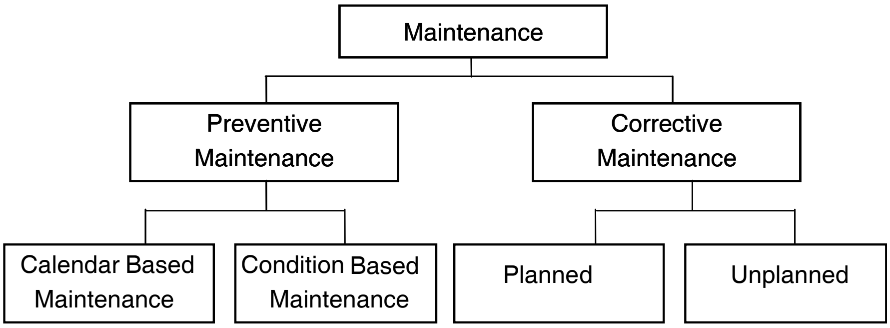


Figure 1.8: Preventive and corrective maintenance

The role of condition based maintenance and condition monitoring will be explained in the next section.

Example: What would be the best approach for servicing the component considered in Figure 1.6 for a lifetime of 40 months: preventive or corrective?

To answer this, the following is given:
1. Costs for Preventive Maintenance are € 1.100-- per action (including labor, traveling, revenue losses, materials, and consumables)
2. Costs for Corrective Maintenance are € 2.000,-- per action (including labor, traveling time, revenue losses, materials, consumables and consequence damage)

From in Figure 1.6 it is learned that preventive maintenance needs to be carried out every 12 months to avoid failures from happening, so during 40 months 3 preventive maintenance actions need to be carried out, in total € 3.300,--. Without preventive maintenance 2 failures can be expected on average during the 40 months lifetime, in total € 4.000,-- Euro. So for this case, preventive maintenance is preferred.

1.3.2 Condition Based Maintenance

For condition based maintenance it is necessary to determine the health of the system. This can be done by periodic inspections, analyzing offline measurements, periodic oil samples, or SCADA data, or by online analyzing measurements. This means that for implementing a condition based maintenance strategy one is not limited to using online condition monitoring systems! The systems health can also be determined from offline measurements, given that the degradation does not go too fast.

Furthermore it should be noted that condition based maintenance mainly makes sense if (1) the design life of the component is shorter than that of the entire turbine and if (2) it is clear that wear indeed is the cause of failure. Gearbox oil for instance will be replaced several times during the turbine lifetime. Condition based maintenance can then be applied to determine if the oil needs to be changed after say 4 years (calendar-based) or maybe after 7 years (condition based). This could save one oil change within the turbine lifetime. So called "safe life components" such as rotor blades for instance are designed for a lifetime longer than that of the turbine lifetime. If such components are replaced during the lifetime, the failure cause is usually not wear but e.g. too high loading, poor manufacturing, or unforeseen conditions.

A successful application of condition based maintenance using periodic inspections is schematized in Figure 1.9: at t = 5 a significant change in the condition is observed. At t = 6 a critical level ("yellow light") is exceeded and action should be taken. Repair is carried out during the next preventive maintenance at t = 7. Online measurements would make sense if the fault progresses faster than the time between two inspections, see also Figure 1.10. In the latter case it is possible to prevent catastrophic failure, e.g. by shutting down the system. Since the fault progresses so fast, there is no opportunity to better plan the preventive maintenance actions.

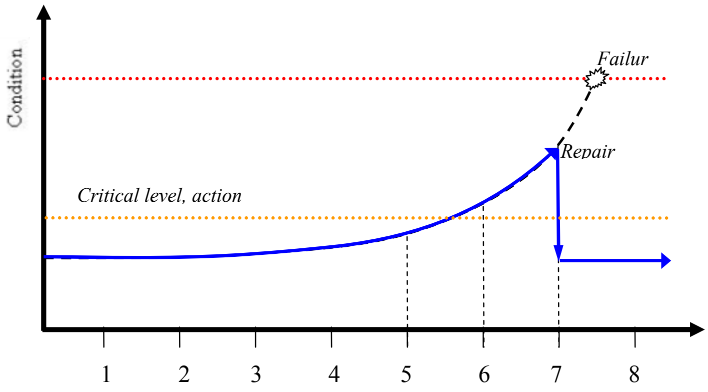


Figure 1.9: Example of periodic inspections for condition based maintenance

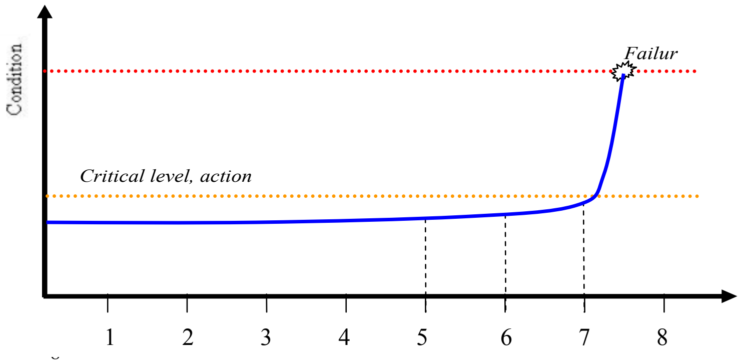


Figure 1.10: Since degradation develops too fast, online measurements could be useful to determine the component's health.

1.3.3 Online Condition Monitoring

A general definition of condition monitoring is the following:

> ***Condition monitoring*** *is the process of monitoring a parameter of condition in machinery, such that a significant change is indicative of a developing failure.*

From this definition the following three conditions can be derived[1].

1. Detection of failure mechanism

It needs to be clear what the failure mechanism is and which diagnostic means should be available to detect the failure mechanism and its development. Components can fail in different ways and a Failure Mode and Effects Analysis (FMEA) can be performed to determine all possible failure modes, conceive mitigating measures and, if possible, determine "early indicators" that represent the development of the failure and the system condition.

2. Detection on time

The use of condition monitoring allows maintenance to be scheduled, or other actions to be taken to minimize the consequences of failure, before the failure occurs. This means that change in the machinery condition needs to be detected on time and prognoses need to be made about future developments in order to take mitigating measures. This also means that condition monitoring is not applicable to avoid sudden failures.

3. Measurable criteria

In fact, just measuring the failure and its development is not enough; clear and measurable criteria should be developed before it can be decided that actions should be taken. Simply said: a *green*, *yellow*, and *red* light should be available to assess the condition monitoring results. It should be clear what level is acceptable to determine that the system is healthy and what level should be exceeded before one decides that the failure starts developing. To determine such criteria long term experiences, including measurements during situations with failures, need to be available. The situation becomes even more complex if (like in wind energy) the development of the failure is caused by stochastic loading.

Example: below, the possibilities of condition monitoring for a hydraulic pump unit are given as an example:

Failure Mode 1: Unit fails to run

The cause for this failure mode is a defective electrical power supply. Condition monitoring cannot play a role for O&M improvement. The failure will occur randomly and suddenly.

Failure Mode 2: Leakage of oil

By monitoring the oil pressure, severe damage of the hydraulic pump unit can be avoided if the pressure drops below a certain value. The three above mentioned conditions are fulfilled. A parameter can be measured (pressure), the failure develops slowly, and a clear criterion for assessing the health is available (minimum pressure level). Two actions can be taken: (1) consequence damage can be avoided by shutting down the pump unit, or (2) one can decide to let the pump unit run until the next preventive maintenance action. In the latter case unforeseen standstill can than be avoided and repair will be part of the scheduled maintenance. This can only be done if there is enough confidence that the failure does not develop too fast.

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[1] In [15], an Open System Architecture for Condition Based Maintenance (OSA-CBM) organisation is discussed. The three criteria have been split up further into seven layers or modules that should be available before applying CBM.

(1) the Sensor module, Signal processing module, and Condition monitoring module to make sure a failure mechanism can be detected;

(2) the Condition Monitoring module, Health Assessment module , and Prognostic module to assess how the failure progresses over time, and

(3) the Decision Support module and Presentation module to assess if the failure exceeds certain criteria.

Failure Mode 3: Vibration of pump

A high vibration level of a pump is often a sign that internally failures are developing. (e.g. a pitting of a bearing or a wear of a piston). Vibration measurements could be a means to detect such failures. However, before this method can be used successfully to optimize the O&M procedures, the following should be noted. By using vibration measurements, only one condition is fulfilled: detection of the failure. However, it should also become clear if the failure can be detected at an early stage to avoid consequence damage, and measurable criteria should be defined such as the maximum allowable vibration level. Long term experience is often required to fulfill the last two conditions.

1.4 Application of condition monitoring techniques for wind farms

At present a number of condition monitoring techniques (CM-techniques) are available with successful applications in several branches of industry. Therefore it is expected that some CM-techniques have potential to lower the amount of corrective maintenance, including related costs and downtime of offshore wind farms.

However experience with CM-techniques in wind farms to date is limited and shows that it is problematic to realize successful application for a number of reasons, which are related to the conditions mentioned in 1.3.3:

1. First failure causes and mechanisms are often not very well understood, as wind turbines are subject to stochastic loading conditions, which vary per individual turbine and are very complex (e.g. wake effects, extreme events, system dynamics). Also for many types of failures no proper indicators are known, e.g. blade degradation.

   Therefore new data analysis techniques are needed to improve the detection and of premature failures, to identify the failure causes and mechanisms.

2. Adequate configuration of CM-systems, such as proper settings of alarm- and warning levels, should be based on experience from a large number of installations as well as on behavior of the individual turbine. However little operating experience is available as turbine designs have changed rapidly over time and larger differences exist between different farms or even individual turbines, because of different wind conditions, changes in component specifications, etc.

   Therefore CM-techniques have to be improved, in order to obtain a more accurate configuration, thereby requiring less time and effort. This should lead to results (e.g. warning messages, alarms, failure diagnosis and prognosis) that are more reliable and easy to interpret. This will enable operators to take effective well-planned O&M actions that could lead to lower O&M costs.

Apart from this more room for improvement is expected, as in most types CM-systems operate independently from the SCADA systems and other monitoring systems (apart from rpm measurement and power measurement to determine the operating state). Therefore a lot of valuable information as temperatures, pressures and status signals are not used, unless there is a clear alarm from the SACADA system. It is expected that integration of CM-systems with the SCADA system will not only save costs but will also lead to more effective monitoring.

1.5 CONMOW Project

The CONMOW project has been defined to investigate whether online condition monitoring techniques do have added value for optimizing the O&M strategies of large offshore wind farms. Existing CM-techniques should be improved using newly developed new diagnostic techniques and a number of selected techniques should be demonstrated on a wind farm scale.

Secondly, it was the objective to find out if the already available data (often offline) such as SCADA data, PLC measurements or inspection reports can be used to make better use of condition based maintenance strategies. If both objectives could be achieved, the CONMOW project also had the ambition to implement the lessons learnt into a wind farm SCADA system and test it over a longer period and to contribute to newly developed wind turbine communication standards: IEC61400-25.4.

Therefore the following set of objectives was defined:

1. Development of new algorithms for data processing by a case study of a turbine with variable speed and pitch control.
2. Improvement of currently available condition monitoring techniques and SCADA systems to the specific wind turbine needs and to make sure that they will meet the newly developed wind turbine communication standards as being developed for instance in IEC TC88 WG 25.
3. Investigating and demonstrating the benefits of condition monitoring techniques and generic SCADA systems in a wind farm and assessing the added value in the operation of large wind farms at remote (offshore) locations.
4. Implementing the selected procedures and techniques for condition monitoring into the O&M plan for the offshore wind farm with the aim to change from preventive and corrective maintenance to condition based maintenance.

1.5.1 Contribution to the goals of EU Program

The results of this project will make better diagnostics and condition monitoring techniques available for use, not only the turbine manufacturer, but also by the operator, specialized service companies, and suppliers of components. They can be implemented in one of the generic SCADA systems that have been developed recently or that are under development.

The following benefits from these developments are expected, leading to increased availability of the wind farm as well as to lower O&M costs. The remaining lifetime of e.g. oil filters, gearbox oil, bearings and gearboxes can be estimated in advance. The number of unplanned visits for corrective maintenance can be reduced. Moreover, better diagnostics will also lead to more efficient preventive maintenance. If the condition of most systems and components is known before visiting the turbine, problems can be fixed during the visit and sufficient spare parts can be transported to the turbine on time. Usually, a service visit leads to additional visits because of some pending actions.

So wind energy becomes more competitive, as the main indicator of the competitiveness of an energy source is the cost per kWh of produced energy. This contributes to other EU policies, as CO_2 reduction, diversification of supply and increases the share of renewable energy sources.

1.5.2 Consortium and project structure

A project team has been established representing:

- suppliers of vibration monitoring systems:
  Gram & Juhl A/S, DK and Prűftechnik CM GmbH, D;
- suppliers of online oil monitoring systems:
  Pall Europe Ltd., E;
- wind turbine manufacturers:
  Nordex Energy GmbH (D)
- suppliers of SCADA systems:
  Risø National Laboratory, DK, and Garrad Hassan and Partners Ltd., UK;
- R&D institutes:
  Energy research Centre of the Netherlands, ECN, NL and
  Loughborough University, CREST, UK.

The project has been separated into two main phases.

The first phase comprised the extensive instrumentation of a single turbine, not only with online condition monitoring techniques but also with the "traditional" measurement systems like load measurements. The objective of this phase was to carry out an extensive measurement campaign on a pitch controlled turbine with variable speed under normal operating conditions. With data from this campaign, inter-relationships can be determined between various turbine parameters and condition monitoring results and if turbine parameters could provide the same information as additional condition monitoring systems.

In the second phase the methods should be applied on a larger scale in a wind farm. The systems had to be tested over a longer period of time and continuously improved. Also a sensitivity study had to be performed to assess the potential cost benefits of applying condition monitoring in a typical offshore wind farm at the North Sea.

The work for phase 1 is divided in 5 technical work packages (WP1 – WP5) and the second phase in 3 technical work packages (WP6 – WP8), as stated in Table 1.2.

Table 1.2: List of Work Packages

Work package	**Work package title**
WP1:	Summarizing and selection of CM-techniques
WP2	Extensive instrumentation and measurement of single turbine
WP3	Signal processing and Development of Fault Prediction Algorithms
WP4	Reporting generic conclusions on single turbine
WP5	Implementing new algorithms in and adaptation of SCADA system
WP6	Instrumentation of 5 turbines in farm
WP7	Long-term measurements, data collection, assessment, and analyses
WP8	Further improvement of SCADA system
WP9	Reporting

1.5.3 Project execution

As introduction to the detailed description of the project activities and results in Section 2, the main activities per work package are briefly described below.

Preparations

As a basis for setting up a measurement campaign aiming to evaluate, improve and demonstrate CM-techniques, an inventory was made of the condition monitoring techniques that are presently available and could be applicable for wind turbines. This inventory has been compiled into a State Of the Art Report (SOAR) on condition monitoring techniques [18].

Then a Failure Mode and Effect Analysis (FMEA) analysis has been carried out in which the possible failure modes and their impact on O&M were categorized. Subsequently the potential for improving O&M using CM-techniques was assessed for each of these failure modes. This analysis not only provides a basis for selecting CM-techniques for the measurement campaign, but also for the need for development or improvement of CM-techniques and for the analyzing the potential cost benefits when applying these techniques [30].

Measurement campaign on a single turbine (phase 1)

A measurement campaign on a single turbine was started in 2003 on a GE1.5S turbine of Siemens, which is located in Zoetermeer in the Netherlands. In this turbine two vibration monitoring systems were installed and a number of other turbine signals have been measured during normal operation as part of WP2.

However, this campaign had to be terminated after 1 year and the planned measurement campaign in phase 2, also foreseen on GE 1.5S wind turbines, could not start at all. As a result a new campaign was started in 2005 with five Nordex N80/2.5MW turbines at ECN Wind turbine Test site Wieringermeer (EWTW) in the Netherlands.

Measurement campaign on 5 turbines (phase 2)

The measurement campaign on a wind farm scale, aiming to demonstrate selected CM-techniques resulting from phase 1, has been combined with the measurements in phase 1 for reasons of time.

This joint campaign included extensive measurements on the Nordex turbines included SCADA data and high frequent data from online condition monitoring systems on all five turbines as well as data from load measurements on a single turbine.

Signal processing algorithms

All measurement data have been analyzed in various ways to detect degradation of components and to describe the new algorithms, which resulted in the development of several signal processing algorithms (WP3), both for high-frequency time series data and for statistical data.

Consequences of switch to new measurement campaign on Nordex turbines

The switch to a new measurement campaign on the Nordex turbines led to a significant delay, so that the time for proper evaluation of developed algorithms in phase 1 was too short. Furthermore it was not possible to introduce fault situations in the turbines and only two relevant random failures were observed in this project during the measurements at the GE1.5S turbine, and one off-design condition at the N80 turbine. Therefore the knowledge gained on failure mechanisms during phase 1 was insufficient for implementing new algorithms in a wind farm SCADA system, as was planned for phase 2.

Simulations and cost analysis studies

As an alternative for introducing fault situations in the turbines, several simulations were made to determine the relationship between the failed situation (e.g. rotor mass imbalance) and several "measurable parameters" (e.g. nacelle vibrations).

Finally, an economic assessment has been made of the added value of condition monitoring techniques for wind turbines. Several O&M cost studies have been carried out in which the potential of these systems to predict faults and remaining lifetimes has been investigated.

2 Scientific and technical description of the results

This chapter provides a detailed description of the project results, starting with the inventory and selection of CM-techniques in section 2.1. The measurement campaigns in which selected CM-techniques have been applied combined with traditional measurements and acquisition of SCADA data is described in Section 2.2. Section 2.3 presents the results from the measurement campaign and is subdivided into analysis results and related signal processing algorithms derived form high-speed measurements 2.3.1, results from statistical (SCADA) data 2.3.2, results from CM-systems Gram&Juhl 2.5.1 and Prűftechnik 2.5.2. Simulation results using GH Bladed are presented in Section 2.4 and two cost analyses studies are reported in Section 2.6.

2.1 Identification of CM-techniques

As a first step to identify CM-techniques that have potential to improve O&M of wind turbines, which can then be selected to be applied in the measurement campaign, an inventory was made of the condition monitoring techniques that are presently available. This inventory has been compiled into a State Of the Art Report (SOAR) on condition monitoring techniques.

2.1.1 State of the art CM-techniques

There is a wide number of condition monitoring techniques used throughout industry [18], [19]. To date, techniques such as vibration and process parameter analysis have been applied to wind turbines. As part of WP1 the state of the art on condition monitoring techniques for wind turbines and wind farms has been reviewed by CREST in [20]. This includes background information on maintenance practices and wind turbine maintenance practices, an introduction to the basic techniques used in condition monitoring, examples of current and state of the art techniques as applied in industry, typical wind turbine failures and an appraisal of CM techniques that have been and could be applied to wind turbines. The report also includes an appraisal of data analysis and interpretation techniques.

In the following subsections the most promising areas for the application of condition monitoring of wind turbines, particularly moving offshore, are briefly described.

2.1.1.1 Blades

Strain, vibration and acoustic analysis

Risø have carried out research on strain, vibration and acoustic analysis in their evaluation of the suitability of blade condition monitoring in terms of cost-benefit and technical potential, [23], [24]. Through laboratory experimentation and full scale testing three sensor types were found to perform adequately. The tests performed were:

- stress wave detection using acoustic emission
- modal shape change measurement using accelerometers and
- fiber optic detection of crack openings

Process parameter techniques: time and frequency domain analysis of the electrical power

In 1996 Jeffries researched a technique for monitoring wind turbine blades using electrical power output [25]. The early results published from this work indicated that imbalances in blade mass and stiffness were detectable in the spectral density and coherence and bi-coherence estimations and suggested that these techniques could be used for condition monitoring purposes. A significant advantage of this type of technique is the simplicity, as it relies solely on process parameters and no extra instrumentation is required.

2.1.1.2 Pitch mechanism

Process parameter techniques: analysis of the electrical current of pitch servos

Another example of monitoring via process parameters is for the condition of bearings of electrical pitch drives. This can be implemented by means of measuring and recording the electrical current required to rotate the blades; large peaks in the signal are then indicative of jerking movements due to the bearings sticking.

2.1.1.3 Drive train and generator

Acoustic and vibration analysis of selected drive train components

It is the components making up the drive train assembly (low speed shaft, gearbox, high speed shaft and generator) that have probably seen the most commercial-style condition monitoring. Gearboxes and bearings are widely used in many branches of industry and as a result condition monitoring of these components is quite common practice.

A number of firms offer commercially available vibration analysis products that have been used for the monitoring of wind turbines. In most cases the products have been used 'as-is' but in come cases these products have been rebadged and possibly adapted for specific use with wind turbines. Some systems include vibration monitoring of the bearings, gearbox and transmission, while others also include vibration analysis on the tower, blades and generator.

Vibration analysis has been applied elsewhere on low speed bearings using both acoustic emission and velocity based sensors and this may have implications for monitoring the low speed shaft bearings and rotor components.

Acoustic analysis at the ultrasonic level has been used to assess the health of the wind turbine drive-trains (generator, brake-disk and gearbox). The stress waves caused by friction and shock events on the moving parts of the machinery are detected using a piezoelectric crystal. The signals are then amplified and filtered using a high frequency band pass filter thus removing the low frequency noise set up in the bearing housing. The stress wave pulses are processed to determine the highest amplitude and total energy content of each shock event. These characteristics can be used to determine the depth and size of spalling in a spalled bearing. Acoustic analysis can be used to detect the very early stages of damage where the energy released between the contact surfaces is too small to excite gearbox or engine structures to levels significantly above background vibration levels, until catastrophic failure or extensive secondary damage occur.

Analysis of oil quality: tribology

Debris detection in lubricant oil is a most promising technique for use in wind turbine condition monitoring. It can be fitted on- or in-line and is one of the simplest techniques for detecting the onset of a wear failure. The characteristics of wear debris will follow the trends outlined in Figure 2.1. Initially there is a high rate of wear as the component in question 'wears in' and any swarf or particles from the manufacturing process are removed as polishing of the contact surfaces occurs. There is then a period of steady but low 'benign' wear. Finally as the component reaches its service life or if a particle in the lubricant oil has caused a bearing element failure the wear rate accelerates and both the amount and size of the wear particles increases significantly.

Similarly on- or inline lubricant oil analysis can also yield important information on the condition of the gearbox. Trend analysis of the wear particles would appear to offer a suitable condition monitoring technique, with alarm limits derived from knowledge of the particular gearbox and the general recommendations [25]. In order to fully benefit from this type of analysis, on and inline devices will require a move away from the traditional splash lubricated gearboxes to pressure fed systems.

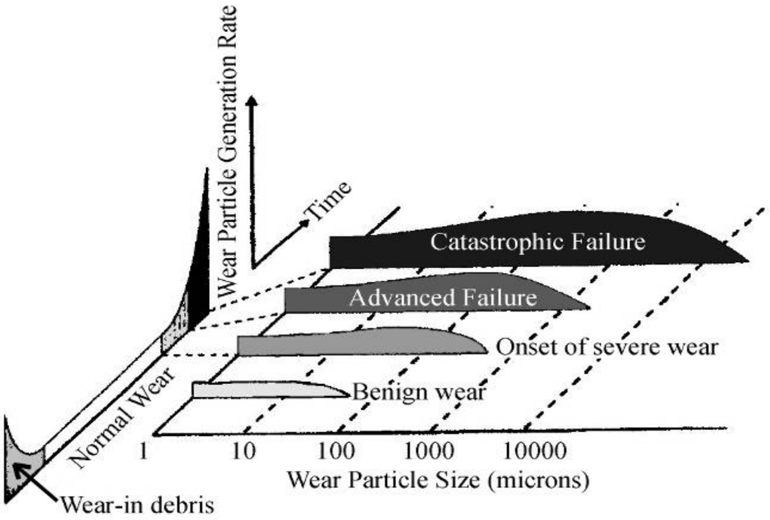


Figure 2.1: Characteristics of wear debris over time

Laser-optic alignment techniques

When two shafts are misaligned in their normal operation and that can be either a parallel or offset misalignment or an angular misalignment there will be some undesired forces generated. These stresses can cause problems such as increasing vibrations, increase in bearing wear and fatigue of the seals. Traditionally shaft alignment is an offline condition monitoring technique carried out at regular intervals but more online systems are entering the market place based predominantly on laser-optic alignment techniques.

Process parameter techniques: time and frequency domain analysis of the electrical power

Using spectral analysis of the power output signal as a monitor for not only rotor imbalances but also for gearbox and bearing analysis was suggested in [27]. A novel approach, which is described in [28], is used to process parameters to detect certain gearbox and clutch faults (as well as anemometry failures, pitch mechanism failures and general power deterioration). This approach was developed for use in wind farm situations as the condition of a particular turbine is based up on the variation between its output signals and a predicted output based on the output signals of the other turbines making up the wind farm. Different output signals were used to detect particular groups of faults as shown in Table 2.1.

Table 2.1: Variables used to detect specific faults, from [28]

Fault situation	**Output signals used**
anemometer degradation	average wind speed
wind direction misalignment	average nacelle angle
pitch setting	average pitch angle and pitching quality (standard deviation/average)
general power deterioration	average power
gearbox faults	power variability (average/standard deviation)
clutch faults	power turbulence (standard deviation/average)

The gearbox faults were identified with a gradual increase in power variability prior to the changeover between low and high shaft speeds along with a small decrease in the power curve and increase in the power standard deviation curve. Clutch faults were characterized by a slight deterioration in the power curve and increased scatter on the power standard deviation and power turbulence curves. There was also an increase in power turbulence above rated wind speed.

Temperature monitoring / thermo graphic analysis

Temperature measurements are usually taken in the gearbox and can be used to trend defects. Faulty bearings, inadequate lubricant, misalignment and normal wear can cause excessive heat and gears, shafts and couplings can all fail from overheating. Infrared thermography could also be used to pin point the area that is overheating.

With respect to generator and electrical faults associated with over/under parameter trips, wiring problems and component damage, analysis of component temperatures possibly using online thermography is a possible method for detecting and predicting imminent failures

Inclusion of visual/aural examination to enhance maintenance planning.

It is widely accepted that a skilled operator can detect the onset of problems from changes in pitch or characteristic noises generated from particular components. Systems for visual examination of blades, which are also applicable for monitoring within the nacelle, use a remote video camera [28] to check internal parts where alerts or alarms have been triggered and an internally mounted microphone can allow the service engineer to listen for any unusual noises.

Thermo graphic analysis of electrical components

With respect to faults associated with over/under parameter trips, wiring problems and component damage, analysis of component temperatures using online thermography is a possible method for detecting and predicting imminent failures.

2.1.1.4 Yaw system

Process parameters

Condition monitoring of the yaw system is problematic in that it only sees intermittent use with the only periods of, somewhat short, continual use occurring when the cables are untwisted, in which instance the operational conditions (e.g. the loads seen) are not representative. Nevertheless, trending of the yaw error could pick up degradation of the operation of the yaw mechanism.

Monitoring the performance of the turbine may give an indication of yaw misalignment, in that the turbine will underperform in these conditions. However, there are other problems that will cause a similar response. Monitoring the yaw error will give an indication of either a problem with the wind vane sensor or with the yaw mechanism if the yaw misalignment continually falls outside the acceptable limits. Temperature measurements of the motors may well detect problems developing with the small yaw motors, as may motor current analysis. A combination of analysis of yaw error over time and the power signal could be used to detect a causal link between degradation of power output and increasing yaw error.

2.1.1.5 Hydraulics

Tribology

The oil analysis techniques described above may equally be applied to hydraulic oil, which is subject to far stringent standards than the lubricating oil.

Process parameters

Using suitable pressure sensors, trending of the pressure in the hydraulic oil may be carried out to detect problems such as blocked filters. Leaks may be detected with hydraulic oil level measurements.

2.1.1.6 Structural components

Vibration monitoring

Vibration monitoring has been applied to wind turbine tower monitoring by Gram & Juhl. Some of the difficulties involved in monitoring the structural movements of the wind turbines that they have overcome include:

- structural movements are very low-frequency (down to 0.1Hz),
- components such as transient events caused by blade-passing (also low-frequency) and high-frequency components originating from e.g. the gear and the generator need to be separated from the tower's structural movement,
- both single- or omni-directional monitoring may be called for.

2.1.2 Failure Mode and Effect Analysis

In order to be able to produce meaningful algorithms to predict failure, it is necessary to identify the key failure modes that can be identified by condition monitoring and it is necessary to analyze how these failure modes are likely to manifest themselves.

The methodology of Failure Mode and Effect Analysis (FMEA) has been applied, which is generally intended to identify all possible failure modes of a system, their likelihood, and their consequences in terms of costs, downtime, safety, etc. The FMEA results in a list with the most vulnerable items and recommendations on how to reduce their criticality. A possibility is to reduce the likelihood, e.g. by choosing components with a lower failure rate or limiting the consequences. This can be done for instance by design changes towards more effective maintenance.

The FMEA, which was reported in [30], provides a generic overview of frequently occurring failure modes and preventive maintenance tasks typical for wind turbines, based on experiences from previous projects. A turbine-specific analysis could not be performed, as the required information, such as turbine design parameters and failure rates, could not be obtained.

The objective of the FMEA in the CONMOW project was to identify those failure modes that show up gradually and which can be detected in an early stage by (online) health monitoring. For those failures, the maintenance action might become easier and cheaper, and the production losses can be reduced. For this reason, a *Failure Repair Class* (F-1 through F-7) has been assigned to each failure mode, see Table 2.2 and the explanations below.

Table 2.2: Classification of Repair Classes

Failure Repair Class
F-1: Alarm with remote reset
F-2: Alarm with repair
F-3: Alarm with replacement
F-4: Service with repair
F-5: Service with replacements
F-6: Failure of large components
F-7: Lightning strike

F-1: Alarm with remote reset

This is an alarm generated by the WT control system, which can be reset remotely by the operator. Frequent occurrences of such an alarm can be followed by service activities to be performed during regular maintenance. The costs are limited to the production losses.

F-2: Alarm with repair

The turbine will shut down due to the alarm and a remote reset is not the appropriate means to restart the turbine. A visit from a technician is required. In this failure class, a toolbox with small spare parts and consumables is sufficient to carry out the repair.

Offshore, the response time depends strongly on the weather conditions and will probably be long. The efficiency of such a maintenance action could be improved by CM because of better diagnostics. In some cases, where early fault detection is possible, the immediate presence of technicians can be avoided. (F-2==>F-4)

F-3: Alarm with replacement

As in class 2, the turbine will be shut down and the visit of a technician is required to repair and restart the turbine. The small spare parts and consumables that are either in stock in the turbine or in the toolbox are not sufficient. Other (larger) spare parts should be transferred to the turbine. For this kind of activities it is essential to know which parts have to be transferred. This might make an additional visit necessary for local inspection. With improved diagnostics by CM additional visits for inspection could be avoided. Apart from this, early fault detection might result in a reduction of replacements (F-3 ==> F-2 or F-5).

F-4: Service with repair

In this case, failure or degradation of a component has been noticed during a service visit or as a result of CM. It does not necessarily lead to a shutdown of the turbine but the failure should be repaired very soon. One can think of an oil filter that is full, a cable that hits the tower or wear of a bearing.

As in class 2, the toolbox with small spare parts and consumables and the stock in the turbine are sufficient to carry out the repair. During the time span between the failure diagnostic and the execution of the repair action, the turbine is in operation. During this time span, CM offers additional possibilities to monitor the system and to intervene when necessary.

F-5: Service with replacements

This class is similar to class 4. However, the sizes of the components to handle are equal to those of class 3. Similar to class 3, CM might result in smaller repair action (F-5==>F-4) and improved possibilities for watching the turbine during the preparation phase.

F-6: Failure of large components

This class includes failures of components that need to be hoisted outside the tower. One can think of the gearbox, generator, blades, hub, or entire nacelle. These large repair actions could be avoided in certain cases by application of CM, especially with respect to gearbox, main bearing and generator due to the early detection of the fault developing (F-6==>F-5).

F-7: Lightning strike

If a turbine shuts down after a lightning strike, or in case that a turbine is damaged after a lightning strike, an inspection is needed before the actual repair can be carried out. CM of the rotor blades might be helpful to get an indication of the damage and avoid immediate visits. This information can be helpful in making decisions about the urgency of inspection and continuation of operation.

As a second step in the FMEA is to make a classification of CM-systems. This classification is not based on different technologies, but on their applicability, state of development and potential for reduction of maintenance costs. This classification is defined in Table 2.3.

Table 2.3: Classification of CM-systems

	Early fault detection possible	**Detection tools / instruments available**	**Potential for maintenance cost reduction**	**Remarks**
CM-1	+	+	++	E.g. vibration based CM-systems, available on the market
CM-2	+	+	+	
CM-3	+	-	++	E.g. blade CM-systems, currently under development
CM-4	+	-	+	
CM-5	-	-	-	

Note: Visual inspection or normal safeguarding functions are not considered as Condition Monitoring

One of the aims of Condition Monitoring is to shift failures from the severe classes, e.g. F-5 or F-6 to the less severe classes, such as F-3 or F-2. Table 2.4 illustrates this with some examples.

For the generator bearing it shows that a failure of large components (F-6) can be shifted to a less severe class (F-5) and the potential to apply CM-systems for this purpose is good (CM-1). The same holds for failures within the oil system concerning insufficient lubrication. However for two other failures mentioned for the oil system no potential reduction is seen. For the electrical pitch system some failures can be made less severe and some potential for cost reduction exist, however condition monitoring techniques are not available yet (CM-4).

Table 2.4: Classification of CM-potential

Failure mode	**Failure Class**	**Potential for early fault detection**
Generator bearing		
Surface fatigue failure	F-6 ⇒ F-5	CM-1
Fretting	F-6 ⇒ F-5	CM-1
False brinelling	F-6 ⇒ F-5	CM-1
Wear	F-6 ⇒ F-5	CM-1
Oil circuit		
Insufficient lubrication	F-6 ⇒ F-5	CM-1
Insufficient cooling	F2	N/A
Filter full	F5	N/A
Electrical pitch system		
Failure of motor controller or motor / reduction box	F-3 ⇒ F-2	CM-4
Failure of battery charger / Insufficient battery capacity	F-3	
Damage of bearing	F-6	CM-5

From this FMEA it can be concluded that with respect to conventional condition monitoring techniques, which are available on the market large benefits can be expected on the longer term. These systems all focus on the main bearing, the gearbox and the mechanical parts of the generator. Developments for this kind of systems should be focused on improvement of fault detection algorithms specific for wind turbines.

Apart from these applications, there are several other components, for which condition monitoring can be attractive from economical point of view. However, for these applications, no standard instrumentation is available. Special developments are necessary. Especially with respect to the rotor blades, early detection can reduce maintenance costs to a large extent.

2.2 Measurement campaigns

Based on the results of the SOAR and the FMEA a selection has been made of CM-systems and other measurement systems to be applied in the measurement campaign, which was planned on a solitary GE 1.5S turbine, owned by Siemens and located in Zoetermeer in the Netherlands. Other considerations for this campaign were which data analysis methods could be applied to detect and identify developing failures. Obviously also a number of turbine and site characteristics and limitations have influenced the setup of the measurement campaign.

Section 2.2.1 describes the instrumentation in the solitary GE 1.5S turbine, owned by Siemens and located in Zoetermeer in the Netherlands.

After one year of measurements this campaign had to be terminated and the planned measurement campaign in phase 2, which was foreseen on a wind farm with GE 1.5S wind turbines, could not start at all. As an alternative a campaign was started in 2005 with five Nordex N80/2.5MW turbines at ECN Wind turbine Test site Wieringermeer (EWTW) in the Netherlands. As the project faced a delay of about 1.5 years, the measurement campaigns of phase 1 and 2 were combined for reasons of time. This campaign is described in section 2.2.2.

The results of these measurement campaigns are reported in section 2.3.

2.2.1 Instrumentation of GE 1.5S turbine, Siemens Zoetermeer

Figure 2.2 shows a schematic of the planned instrumentation in the GE 1.5S turbine.

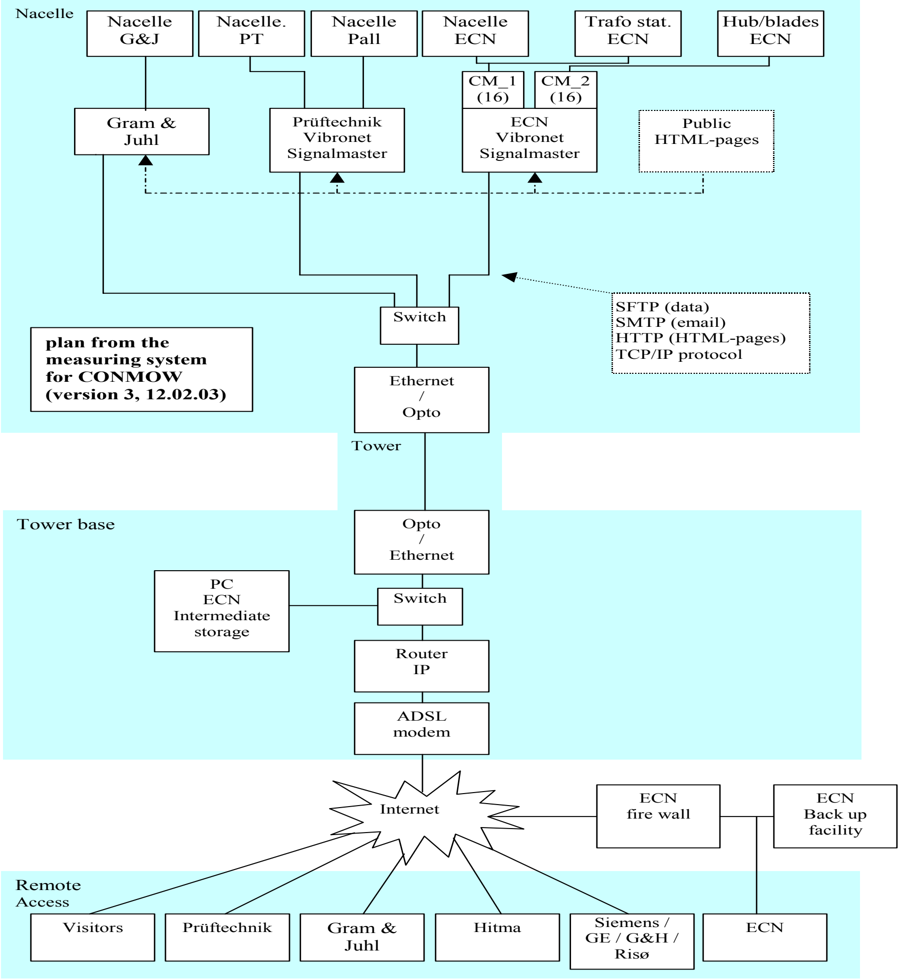


Figure 2.2: Instrumentation in the GE 1.5S turbine

The instrumentation comprises 4 types of measurement systems:

1. *ECN measurement system*

The ECN system comprises measurements from the turbine control system as well as from additional sensors. Table 2.5 lists the available measured signals from this measurement system.

Table 2.5: List of measured signals vial ECN system.

Signal description	**Source**	**Frequency**	**Remarks**
Turbine			
Blade flap moments	ECN	32 Hz.	
Blade edge moments	ECN	32 Hz.	
Temperatures pitch motors	ECN	32 Hz.	
Measured pitch angles	GE	1 Hz.	
Requested pitch angle	GE	1 Hz.	
Rotorspeed	ECN	32 Hz.	
Rotor azimuth	ECN	32 Hz.	
Rotor shaft torque	ECN	32 Hz.	Available from April 2004
Acceleration nacelle (X / Y-direction)	ECN	32 Hz.	
Yaw angle	GE	1 Hz.	
Yaw misalignment	ECN	32 Hz.	
Electrical power	GE	1 Hz.	
Meteo			
Precipitation detection	ECN	4 Hz.	
Wind speed Nacelle	GE	1 Hz.	
Air pressure	ECN	4 Hz.	
Ambient temperature	ECN	4 Hz.	

The installation of the ECN measurement systems was completed in the 1st half of 2003 without modifications to the turbine. After several tests the system was fully operational in July 2003 and from that time on every 10 minutes the data is stored at the tower base PC.

In addition a torque measurement system of Astech Ltd. (TX20D/1/IFM digital transmitter, IH2 inductive antenna head, and RE2D/IFM/1 decoder) was installed by ECN and Bienfait BV. This system has been operational since April 2004 and the data were stored on the tower base PC.

To measure the pitch motor currents hall-effect clamp sensors have been applied. Since these type of sensors proved to be inadequate to monitor the pulse-width modulated currents and no measurement resistor was allowed instead for reasons of safety, these measurements could not be made available.

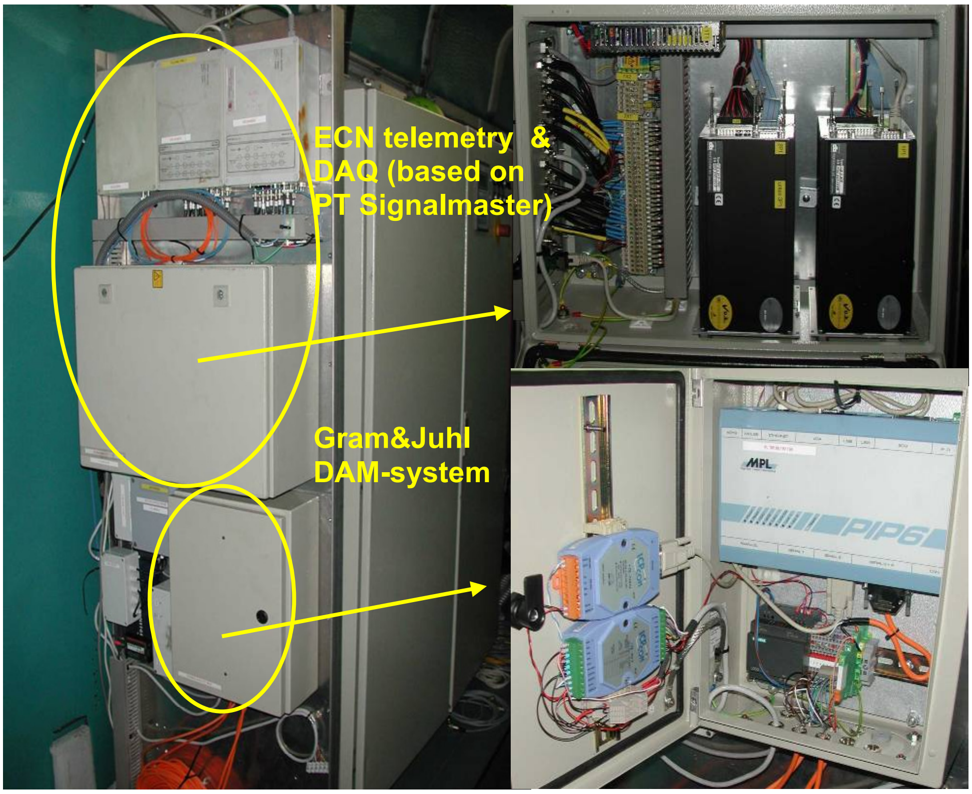


Figure 2.3: Measurement cabinet in GE 1.5S turbine showing systems of ECN and Gram&Juhl.

2. Vibration systems of Prűftechnik

In October 2003 a drive train vibration monitoring system based on a Prűftechnik Signalmaster was installed with sensors located on the main bearing in two directions, on all three gearbox stages and the high-speed bearing as well as on the generator bearings, both radial and axial.

Wherever possible existing boreholes were used, but other sensors were glued, as no permission was given to drill any extra holes, however this is a less preferred option with respect to sensor response and reliability.

The vibration measurements system had to be configured according to the kinematics of equipment they are mounted on. For this purpose detailed kinematical data of the gearbox and bearings was required but could not be provided by GE timely. Although the system of Prűftechnik has been fully installed, it could not be properly configured due to lack of kinematical data.

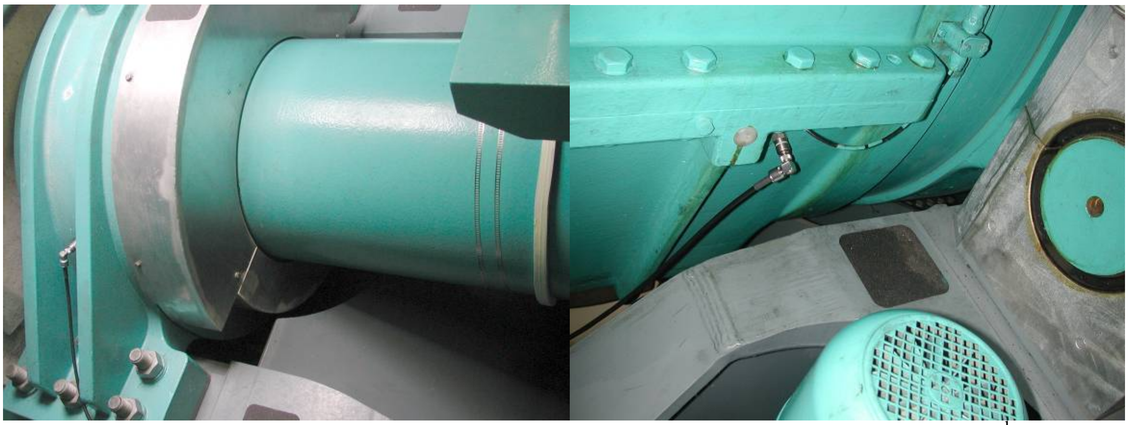


Figure 2.4: Vibration sensors of Prűftechnik system mounted on main bearing and 2nd gearbox stage

3. *Vibration system Gram&Juhl*

The installation of the DAM-system of Gram&Juhl was completed in November 2003 and included intelligent Dynamic.Accelerations Modules on the main bearing and the different gearbox stages. Because of space limitations these sensors had to be mounted (also glued) on locations which were less optimal than those of the Prűftechnik sensors, resulting in a signal quality that was even worse.

The configuration of this vibration monitoring system was also troubled by the lack of kinematic data. However, to avoid further delays, Gram&Juhl configured their system based on a drawing of a gearbox of which it was not clear whether this drawing is the right drawing for the WT in Zoetermeer. The measurements have been running since February 2004 and the results were stored on the tower base PC.

4. *Oil monitoring system of Pall*

The installation of the oil monitoring system of Pall required several hardware modifications, such as redesign of piping and a change of the oil filter type. As for these modifications no alternative was possible and no permission was granted, the Pall system was not installed.

2.2.2 Data availability

Figure 2.5 shows the monthly data availability, which was 91% on average.

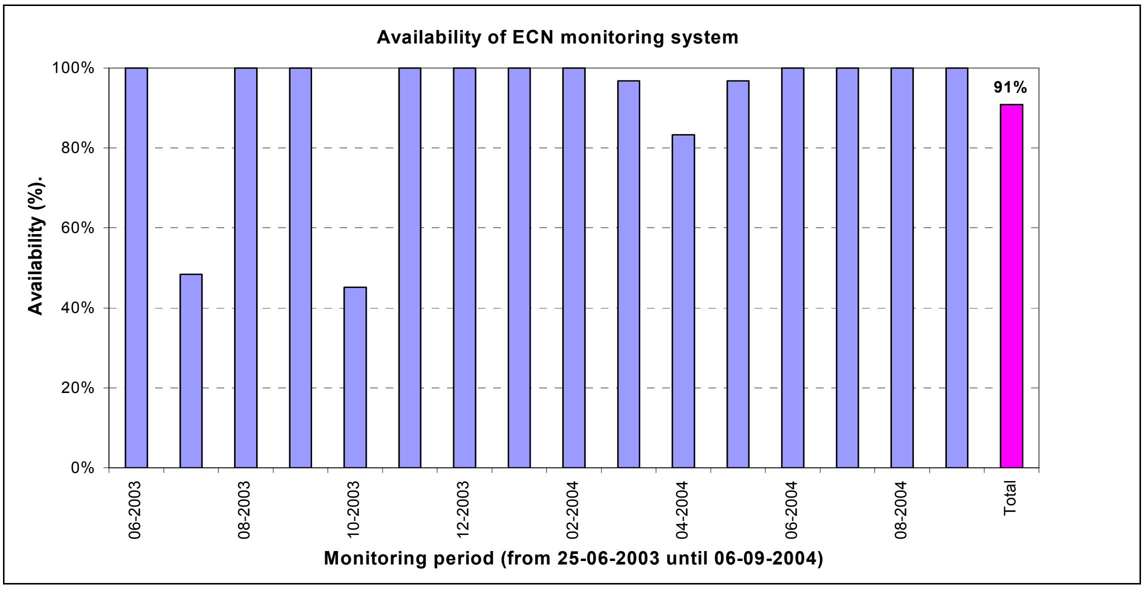


Figure 2.5: Availability of the ECN monitoring system.

In July 2003, there was an interruption of the measurements due to communication problems in the local network. No relevant data has been missed since the wind speeds were very low.

In October 2003 there was again an interruption of measurements due to failure of the yaw sensors, which disturbed 16 input channels. In the same period, due to changes in IP-addresses, the measurement systems were not remotely accessible, which resulted in loss of measurements.

2.2.3 Occurrences during measurement campaign on GE 1.5S turbine

In March 2004 a generator bearing failed and was therefore replaced. Results from data analysis on the detection of this failure are reported in section 2.2.4.

On August 13th, 2004 a major gearbox failure occurred in the WT in Zoetermeer, which lead to standstill on August 17th, 2004. After inspection the WT was put in operation again with the power reduced to 800 kW until the gearbox was replaced in September 2004. The failure was detected by the PLC, but unfortunately not by the Conmow measurement system, as the vibration monitoring system of Prűftechnik was not configured yet and the sensors of the Gram&Juhl system were mounted at very insensitive locations. Just before the gearbox replacement the measurement system was partly dismantled in order to minimize damage to the sensors, although it is to be expected that the strain sensors in the blades and on the main shaft will be damaged as the rotor has been detached.

After the start-up no further instrumentation was allowed and after considering several options it was decided to set up a new measurement campaign with Nordex on the ECN Wind turbine Test park Wieringermeer (NL) instead, which is described in section 2.2.4.

2.2.4 Instrumentation of Nordex N80/2.5MW turbines, ECN Wieringermeer

It was decided by the consortium to start a new measurement campaign for phase 1 and phase 2 on five Nordex N80/2.5 MW wind turbines, which are part of the ECN Wind turbine Test site Wieringermeer in the Netherlands. The operation of these turbines is primary focused on energy production. Apart from this, the turbines are also used by ECN for several long-term experiments. The yearly average wind speed at hub height (80 m) is about 8 m/s. The turbines are in operation since the summer of 2004 and are numbered 5 up to 9, see Figure 2.7. Figure 2.6 shows the turbine nr. 6 with the meteo mast nr. 3.

In September 2005 instrumentation of the single turbine in phase 1 as well as the other four turbines of the wind farm in phase 2 started. A brief overview of the instrumentation is given below.

Figure 2.6: Nordex N80 turbine nr. 6 with meteo mast nr. 3 at ECN Windturbine Test site Wieringermeer (EWTW)

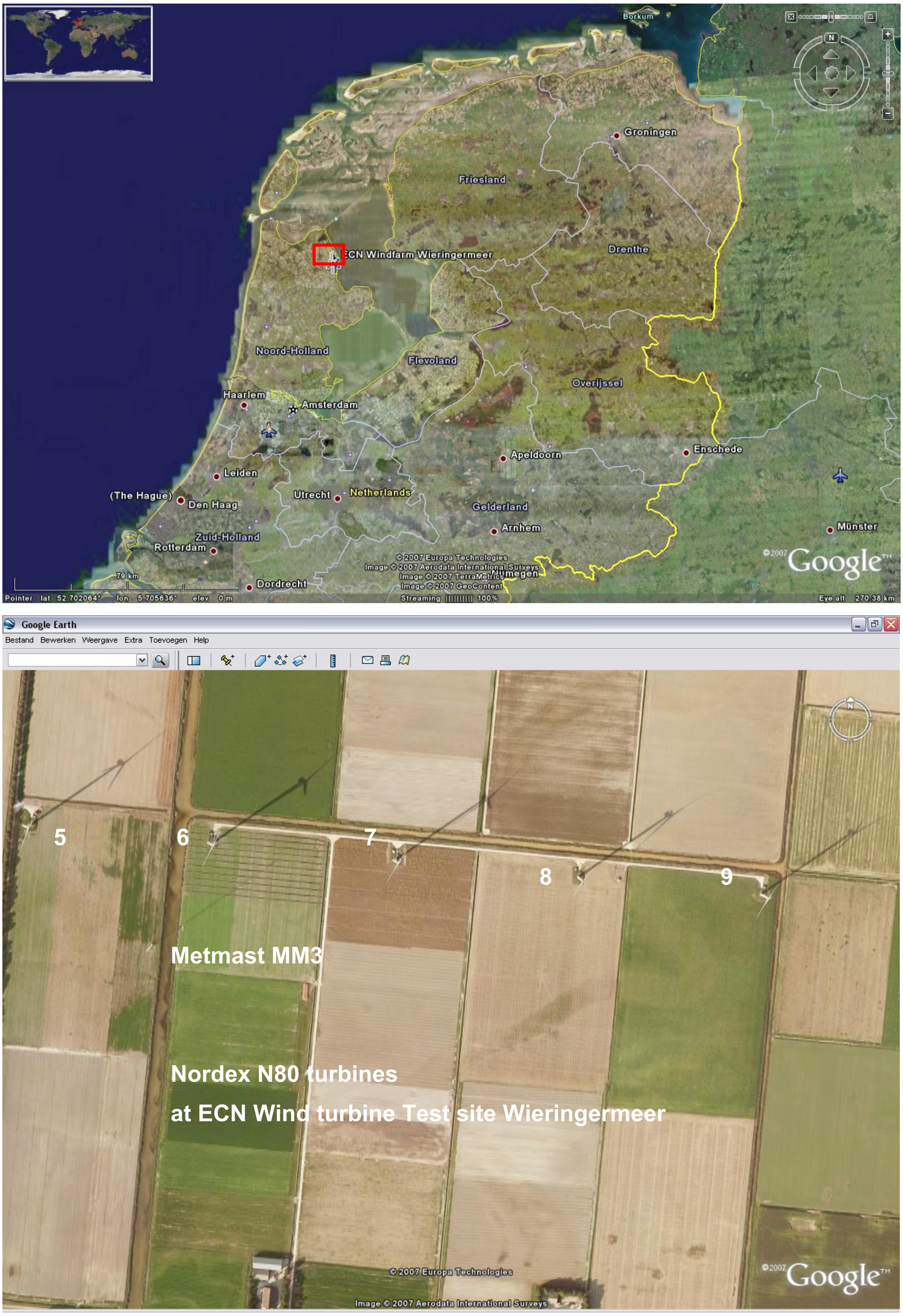


Figure 2.7: The location of the ECN test wind farm as seen with Google Earth. In the detailed picture, the sea is seen at the far right.

Instrumentation of single turbine in phase 1

In one of the five turbines in the ECN test farm, turbine nr. 6, blade and tower load measurements were already running for several months together with measurements of meteo signals from the nearby meteo mast number MM3. Part of these data are available for the Conmow project, cf. Table 2.7.

For this turbine also high-frequency measurements were made available from a selected number of PLC channels as well as statistics of all PLC channels via the Nordex SCADA system.

For the CONMOW project a VIBROWEB XP® vibration monitoring system of Průftechnik was installed. This is a certified CM-system with acceleration sensors located on the main bearing in two directions, on all gearbox states, on the high-speed axis gearbox bearing and on the generator bearings.

In this way condition monitoring data and other operational data as well as load measurements and meteo data from a single turbine was made available for data analysis and algorithm development.

Instrumentation of wind farm in phase 2

For phase 2, the other four turbines are equipped with drive-train vibration monitoring systems as well, all with a different setup, cf. Table 2.6.

Table 2.6: Overview of installed CM-systems.

Turbine	**CM-system**	**Description**	**Installation date**
5	Gram&Juhl DAM system	Previously installed in GE1.5S in Zoetermeer	Oct. 2005
6	Průftechnik VIBROWEB XP®	Certified CM-system	Sept. 2005
7	Gram&Juhl TCM® system	Certified CM-system	Oct. 2005
8	Průftechnik VIBNODE®	Low-cost CM-system	Nov. 2005
9	Průftechnik VIBNODE®	Low-cost CM-system, with improved DAQ resolution	Dec. 2006

The Gram&Juhl TCM® system in turbine 7 is also a certified system, which analyses measured accelerations on all gearbox stages, on the high-speed shaft bearing (axial) and structural vibrations using an intelligent X-Y sensor.

Both Průftechnik VIBNODE® systems apply acceleration measurements on the main bearing, on two gearbox stages and the high speed bearing (axial) as well as on the gearbox bearings. Further an axial displacement sensor is applied on the gearbox 1st planetary stage. This system has been developed for constant speed turbines. Therefore no rotational sampling is implemented, so for application on variable speed turbines some other solution had to be chosen, which is that frequency bands are being analyzed rather than discrete frequency peaks.

As for the single turbine, PLC signals high-frequency measurements and statistics were made available for all four other turbines.

Most of this instrumentation has been realized in parallel with that of phase 1. Therefore most of the data from the other four turbines could also be used for algorithm development within phase 1, e.g. by comparing the behavior of the neighbouring turbines.

Table 2.7: Overview of available high-speed signals.

Signal description	**Source**	**Supplier**	**Frequency**	**Details**
Turbine				
Rotor in plane torque	T6	ECN	32 Hz.	Calculated from measured blade root moments
Rotor thrust	T6			
Electrical power	T5 and T6			3-phase power transducer at low-voltage side machine trafo
Turbine (from PLCs)				
Electrical power	T5 - T9	ECN/Nordex	32 Hz.	Signal update freq. 25 Hz.
Generator speed				
Wind speed nacelle				
Wind direction nac.				
Yaw angle				
Pitch angles				
Operating mode				
Meteo				
Wind speed	MM3	ECN	4 Hz.	Calculated from 3 sensors on @80m, in directions: 0° (N), 120° (SE) and 240° (SW)
Wind direction				
Air pressure				@80m
Relative Humidity				@80m
Ambient temperature				@80m
Precipitation detect.				

From other sources the following data were available:

- operational statistics of all turbines from Nordex SCADA system, 10-minutes statistics;
- maintenance reports (up to October 2005) and alarm logs (Nordex), available to ECN;
- simulation data of fault conditions with GH Bladed (GH).

High frequency measurement data and statistics from CM-systems and from the traditional measurements have been collected since November 2005. The partners have been given online access to measurement data and analysis results via the web interfaces on the websites of ECN, Prűftechnik and Gram&Juhl. Prűftechnik has produced draft templates for a baseline report, a trend report and some other diagnostic reports of the CM-systems and has provided access to their database and WebReport reporting tool via the Prűftechnik website.

Compared to the original instrumentation plan the following was modified:

- As the preparations to install the Pall online oil quality monitoring system took much more time than foreseen, it was decided to install only a single system instead of two. It was planned to combine this with the installation of the third Prűftechnik VIBNODE system in turbine nr. 9 in December 2006. However, after the technical issues had been solved Nordex Central Engineering and the equipment was available on site, a legal agreement could not be established before the end of the project, so no oil monitoring system was installed after all.
- Access to the data from the CM-systems for the partners has been arranged via the websites of Prűftechnik and Gram&Juhl instead of supplying this to the data on the ECN server.

2.2.5 Data quality and availability

The data availability and data quality have been checked on daily basis and monthly overviews of the data availability were issued. Time series and statistical data have been made available starting from 1 January 2005 until 31 January 2007.

The average availability of the data was 98.8% for the meteo signals. The average availability of the load signals (rotor thrust and torque) was only 60%. This is because both signals are calculated using six blade load measurements and the measured rotor azimuth. In the end of 2005 the strain measurements in turbine 6 have been recalibrated after repair. In June 2006 one of the strain measurements failed twice, due to different causes, which was repaired by ECN. In 2005 disturbances showed in the measured rotor azimuth. As an example Figure 2.8 shows the availability of the following statistics: wind speed, rotor azimuth and the two calculated load signals. Figure 2.9 shows a high availability of the measured electrical power (from power transducers in turbines 5 and 6) and PLC signals from the Messboxes in all five turbines.

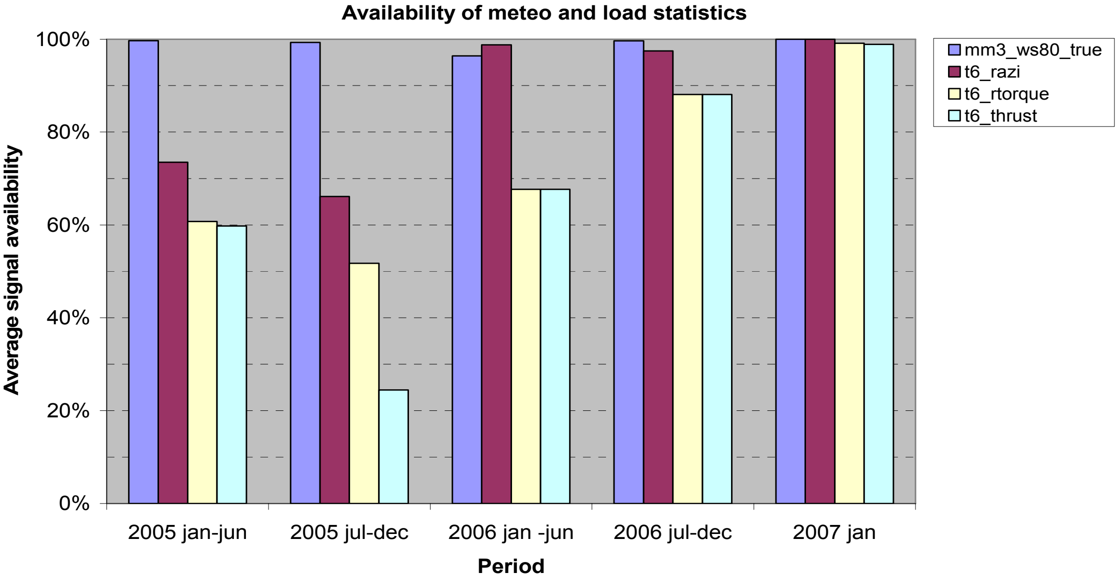


Figure 2.8: Availability of load and meteo statistics from measured time series

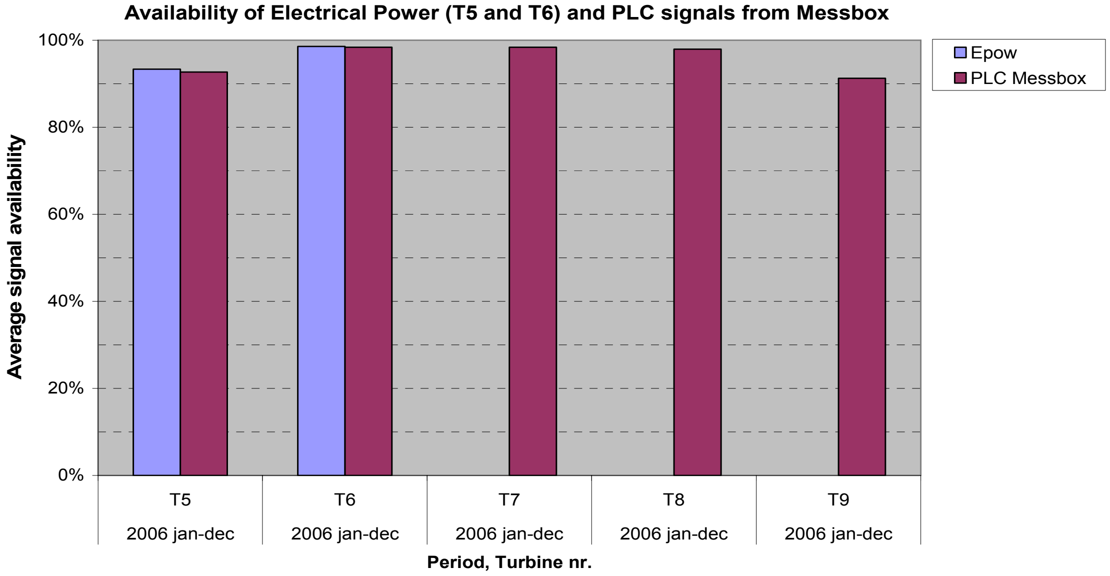


Figure 2.9: Availability of Electrical power and PLC statistics from measured time series

The availability of the 32Hz. time series is higher compared to the statistics, because the statistics over a 10-minute period are only calculated if all measurements within this interval are available and valid.

In October 2006 the two transducers for active power measurement in turbine 5 and 6 have been replaced by other types, which resulted in a more accurate measurement.

2.2.6 Occurrences during measurement campaign on Nordex turbines

During the measurement campaign on the five Nordex turbines no major failures have occurred.

Turbine 8 showed increased vibration levels due to misalignment of the generator shaft. This was detected by the Prűftechnik VIBNODE system as well as by CREST from analyzing the electrical power measurements. After the detection maintenance actions were taken by Nordex, however these did not provide an effective solution to decrease the vibration levels.

2.3 Signal processing and development of fault prediction algorithms

2.3.1 Analysis of high speed measurements

The analysis of the high speed measurement data has focused on the electrical power output and on the pitching and yawing mechanism. The aim of the analysis of the electrical power signal was to trace vibrations at certain frequencies, which indicate mechanical abnormalities or even premature faults.

2.3.1.1 Signal analysis of high-frequency measurements and simulations

Both theory [31], [32] and practice [33] suggest that some vibration frequency components caused by faulty mechanical elements could appear in electrical signals. As the electrical and mechanical signals produced by faulty elements in wind turbines are irregular and non-stationary and the measurements cannot be easily controlled, [34], [35] a particular algorithm has been developed at CREST that employs both discrete and continuous wavelet transforms. A certain wavelet type is used to extract a particular signature in the wind turbine power output sampled at 32Hz. To discriminate the difference between healthy and damaged elements, the maximum amplitude of the wavelet coefficients are estimated by a fast Fourier transform (FFT) and the root-mean-square (RMS). We take the RMS values to monitor the mechanical elements, because results show that the maximum amplitude of the wavelet coefficients has a similar trend to the RMS values. A theoretical basis and detailed description of the algorithm are reported in [20].

2.3.1.2 Results from signal processing algorithms

Using the algorithms outlined above, it was possible to detect evidence of damage by analysis of the wind turbine power signal. An example is given in Figure 2.10. The amplitude of the Fourier transformed wavelet component in the frequency range 2.5 to 3 Hz of the power output of the GE1.5S wind turbine shows an increase in November 2003. In January 2004, a generator misalignment was noted and an attempt made to correct this. This attempt was not successful and in March 2004, the generator bearing failed. When the bearing was replaced the amplitude was reduced. It can be seen that this technique detected the misalignment at least three months before failure occurred.

The same analysis technique has been applied on the high speed electrical power measurement on the Nordex turbines. In the period from January to May 2006 high amplitudes were observed for Nordex 8 within a frequency range corresponding to twice the generator slip frequency, as shown in Figure 2.11. This indicated a bearing misalignment problem, as this would generate a fluctuation in the permeance of the air gap, resulting in a pulsating torque of twice the slip frequency.

The diagnosis for shaft generator misalignment was confirmed by the Průftechnik VIBNODE system, also providing more details, as well as by trend analysis of the shaft bearing temperature cf. Sections 2.5.2 and 2.3.2.1 respectively.

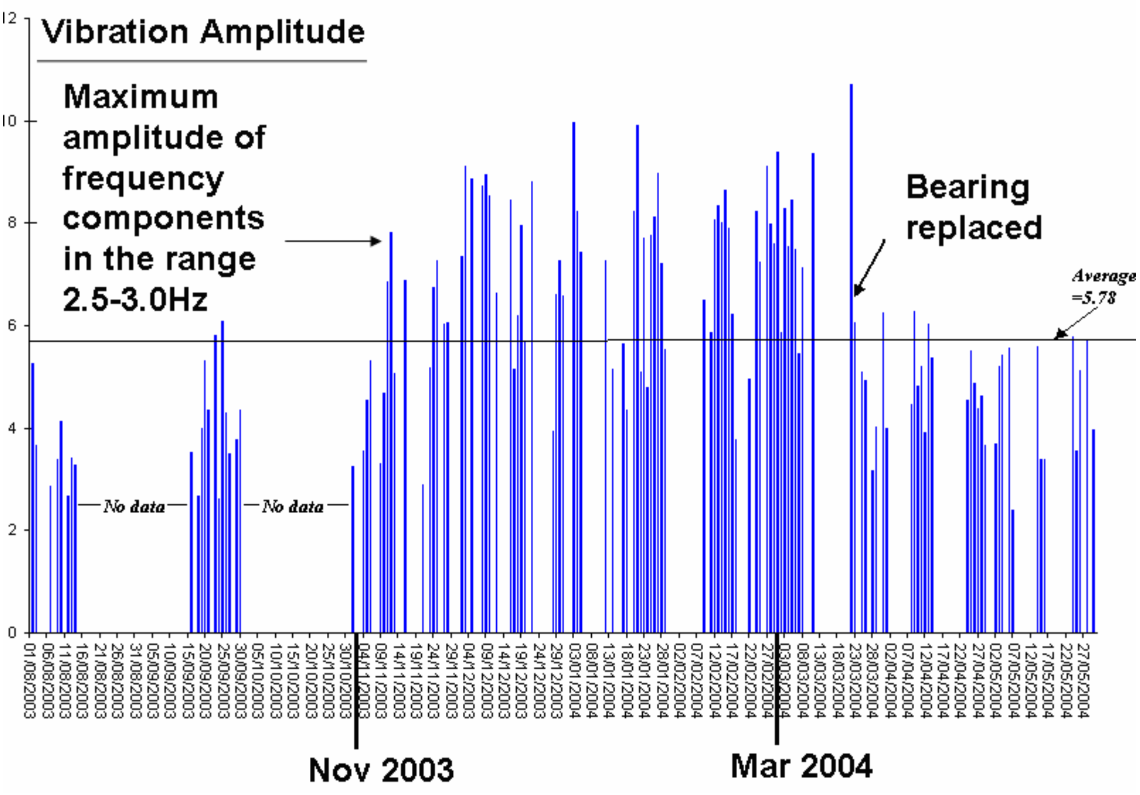


Figure 2.10: Maximum daily amplitude of the wavelet FFT filtered GE 1.5S wind turbine power output within the frequency range 2.5 and 3.0Hz.

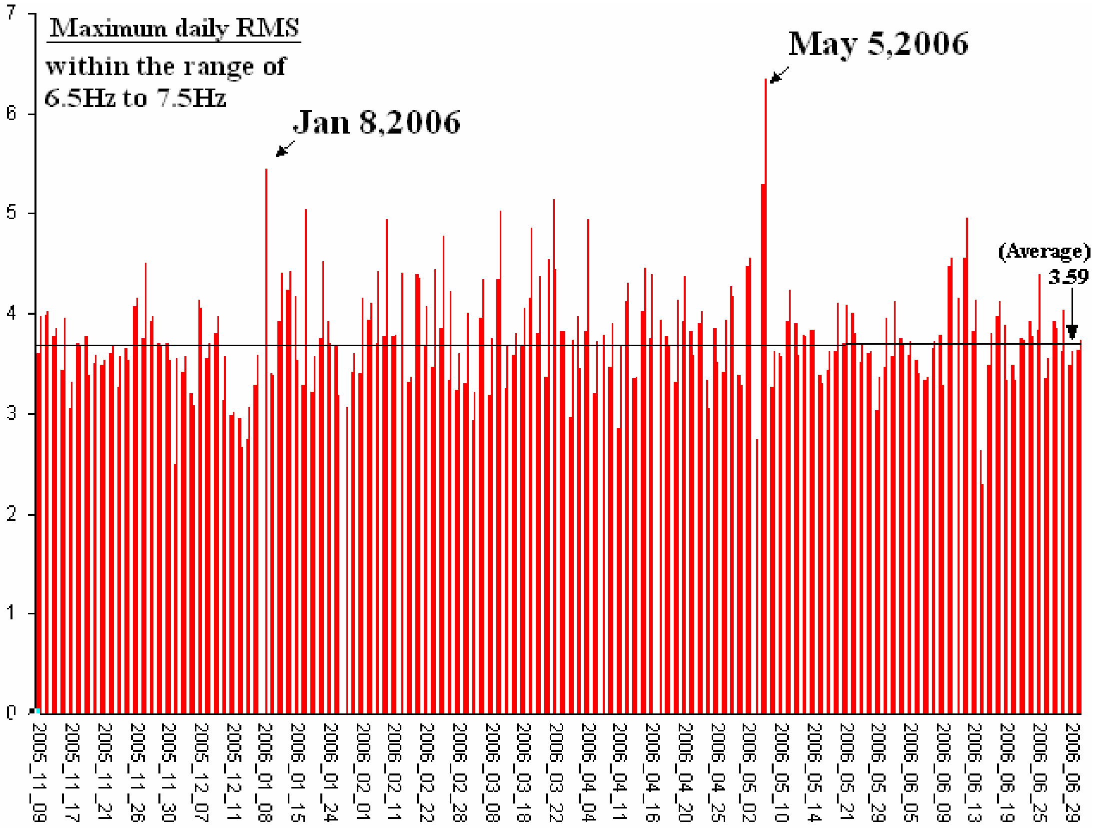


Figure 2.11: Maximum daily RMS of one of the wavelet filtered Nordex N80 wind turbine power outputs within the frequency range 6.5 and 7.5Hz.

2.3.2 Analysis of statistical data from SCADA systems

A selected number of statistical data from the SCADA system and the from the other measurement systems have been analyzed using data reduction techniques as well as filtering and regression techniques.

2.3.2.1 De-trending of 10-minute averages

De-trending of wind turbine SCADA data has been looked at as a way of picking out potential deviations from ‘normal’ behavior. Figure 2.12 shows an example of ten-minute averaged temperature measurements on a generator bearing of one of the Nordex N80 turbines as a function of power output. To enhance the trend, the data have been linearly corrected for ambient temperature (using data over a small rotational speed range) and the values plotted have been averaged in bins corresponding to increments of 0.1m/s. In practice, monitoring of this trend would compare values against normal bounds determined from historic data. An increase in bearing temperature due to bearing wear or possibly shaft misalignment could then manifest itself by observations being consistently above the maximum level of the set normal bounds as a function of power output. The advantage of this approach over standard alarm levels is that it allows a larger degree of sensitivity, as disturbing variations due to changing ambient temperature and power output being suppressed by means of compensation and binning.

Figure 2.13 shows a similar plot showing 10-minute averaged nacelle accelerometer (z-direction) vibrations as a function of the square of the wind speed (as a proxy for thrust).

In both cases, clear trends are seen and the value in terms of condition monitoring is to establish acceptable bounds for the trend lines which may be determined from the standard deviation of points around the trend lines during periods of known ‘normal operation’. Subsequent measurements outside these bounds would trigger an analysis of the data point and comparison with other measurements (e.g. high frequency vibration measurements) to confirm possible operational problems. An example of abnormal behavior in this case might be an increasing drive train misalignment resulting in points significantly and consistently above the normal operating envelope about the straight line fit in Figure 6.

Although the effectiveness of these methods could not be demonstrated in the project because no major failures had occurred, it is already clear that the processed signals are limited within narrower bounds and are presented orderly. This makes it easier to detect coming failures of the turbines. This will help operators to analyze their SCADA data more accurately and quickly. Obviously more experience with these methods is needed, e.g. in order to define proper bounds for normal operation of each signal.

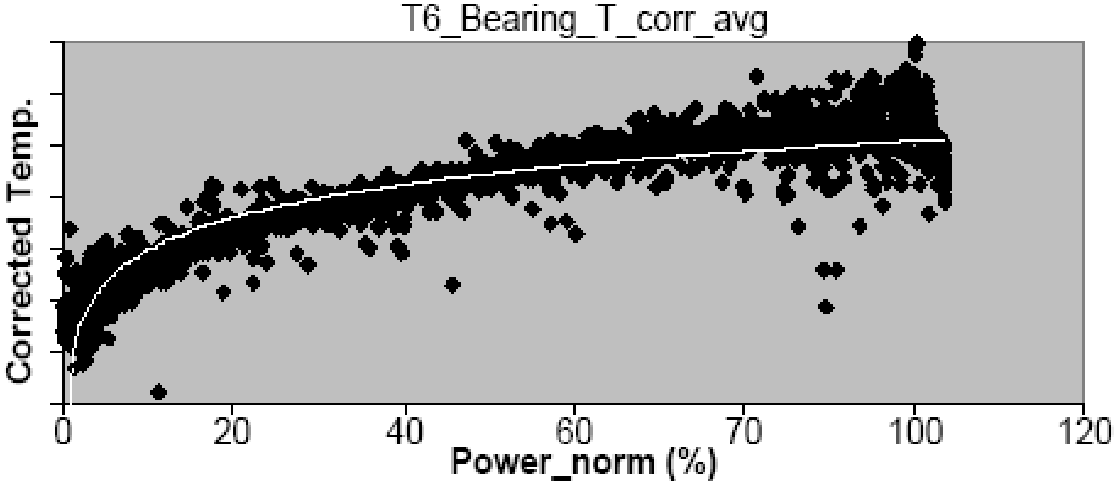


Figure 2.12: Nordex N80 generator bearing temperature (corrected for ambient temperature) as a function of power output.

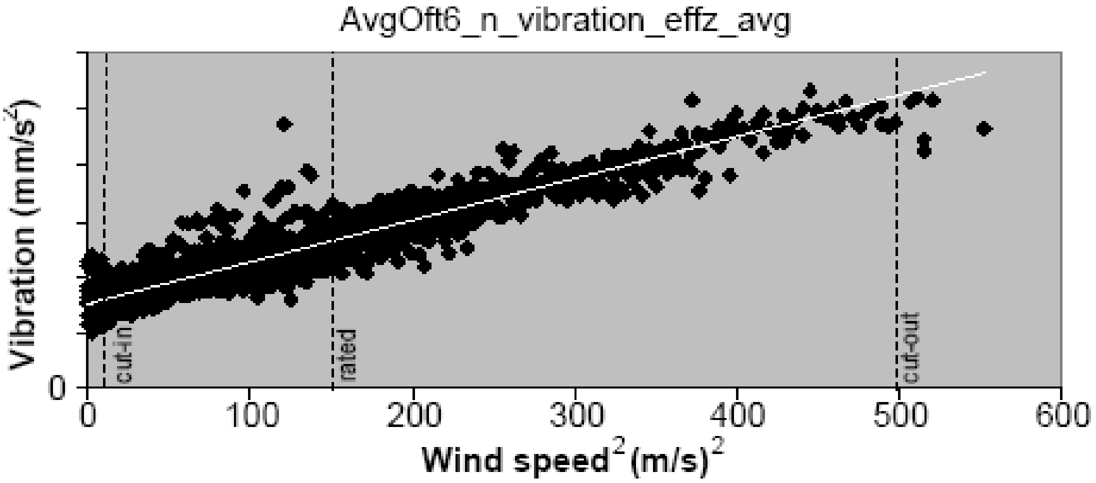


Figure 2.13: Nordex N80 nacelle accelerometer axial vibration as a function of the square of wind speed.

Example – Generator bearing temperature Turbine 8

Refining this analysis by looking at the deviation in temperature from a long-term trend line and analyzing this in time can help to better pinpoint potential changing in temperature. This has been done for a number of the components including each of the generators of the five Nordex N80 turbines. No significant deviation was seen except for turbine T8. Figure 2.14 shows the deviation from the normal heating trend line with time for T8 at location L2 on the generator (location was not defined by Nordex, but is assumed to be close to the main bearing). The same trend is seen at location L1. It can be seen that around the 16th October 2005 a significant jump (increase) in operating temperature is seen which does not return to a normal level until the 26th May 2006. The results are consistent with both the high frequency power spectral analysis using the wavelet/FFT methodology and the vibration measurements made by Prűftechnik and support the hypothesis of an increase in shaft misalignment for a period resulting in increased vibration, generator torque fluctuations and bearing heating.

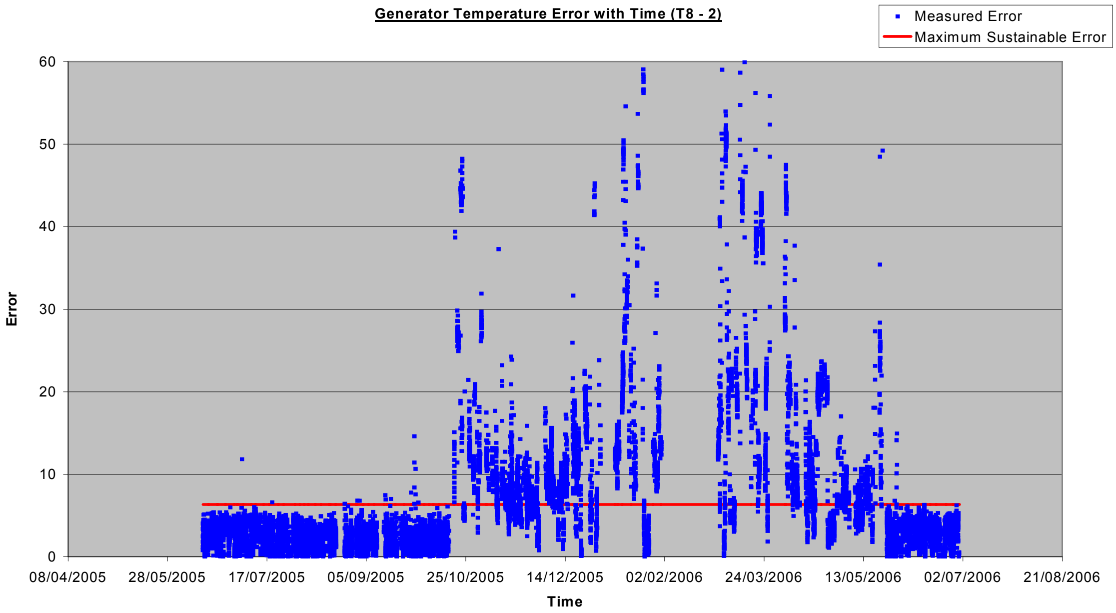


Figure 2.14: Nordex N80 Turbine 8 generator bearing temperature deviation from long-term trend line with time

2.3.2.2 Monthly mean values

It has been found that statistical characteristics for many parameters against rotor speed or electrical power, e.g. temperature vs. rotor speed have the same characteristics and are more or less independent on the averaging period. This is because a physical system can be described by a fixed model. Therefore it is possible obtain an extreme reduction of the data amounts and to reduce scatter, by calculating monthly averaged values, e.g. of SCADA signals. For this the following regression algorithm has been applied.

The proposed regression algorithm fits the data with a polynomial p(x) of degree n and finds optimal coefficients of the polynomial. As measured data exhibit scatter for a number of reasons, centering and scaling transformation are used to improve the numerical properties of the algorithm. The polynomial is of the form:

$$p(x) = p_1 x^n + p_2 x^{n-1} + \ldots + p_n x + p_{n+1}$$

The centering and scaling transformation of x is written as:

$$\hat{x} = \frac{x - \mu_1}{\mu_2}$$

where:

μ_1 is the mean of x

μ_2 is the standard deviation of x.

Changing x to $\hat{x}$, we have the polynomial:

$$p(x) = p^*{}_1 \hat{x}^n + p^*{}_2 \hat{x}^{n-1} + \ldots + p^*{}_n \hat{x} + p^*{}_{n+1}$$

Using the proposed algorithm, we have processed the data measured from 5 Nordex turbines. Figure 2.15 presents the normalized nacelle accelerometer values from one of the turbine 6 and 8, showing that high vibration levels can be detected by monthly statistical mean data and their regression fitting. Like turbine 6 the turbines 5, 7 and 9 show vibration levels around the normalized unity level, while turbine 8 shows levels which are about four times higher, which indicates some problem. In fact it has been confirmed by Nordex that the high vibration level is related to a generator shaft misalignment. The rightmost plot as well as the frequency analysis in Figure 2.11 and the temperature trend analysis in Figure 2.14 indicate that the problem was solved in May 2006.

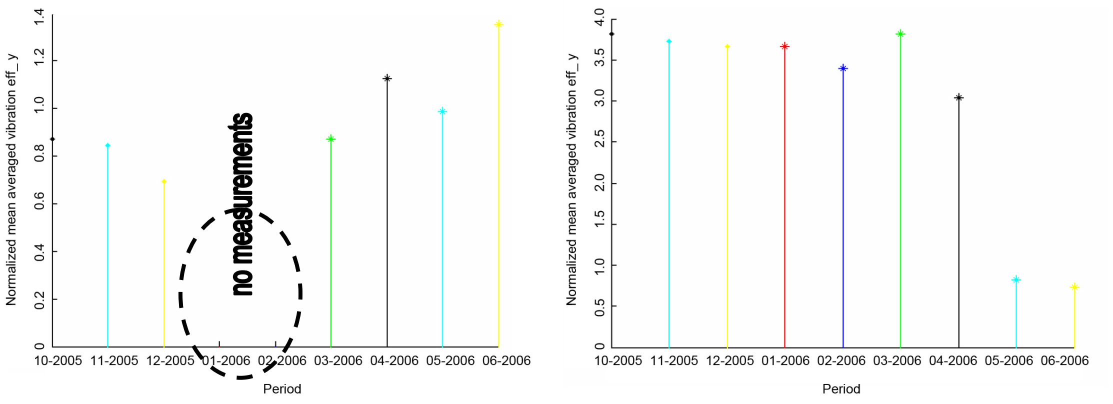


Figure 2.15: Monthly averages of sideways nacelle acceleration of turbine 6 (left) and 8 (right)

2.3.2.3 Normalization and de-trending

In addition to the de-trending as explained above, de-trending and normalization functions for wind farms have been derived, based on power and ambient temperature of individual turbines. This is applied in combination with the moving average (MA) filtering to account for long physical time constants, e.g. cooling down of large components. For standardized presentation an automated reporting tool is presented in [36].

Fitting trends to the data

For wind farm operators, it will be necessary to have a single de-trending function for a signal that can be applied to all turbines (of the same type). Otherwise, there will be too much specialized effort and, in addition, comparisons between individual turbines will be more difficult. As a result, a fit through the SCADA data must be defined that is applicable to all (or at least most) turbines. From the raw SCADA data it is observed that the measured values of the turbines may deviate from each other. There may be several causes, of which the sensor is the most probable, since these are seldom calibrated. On the other hand, the shapes of the fitted curves are more or less similar. In addition to the analyses of SCADA data from the Nordex turbines, in other projects SCADA data from other turbine types have been analyzed. For one of these projects the turbines in the wind farm were equipped with different gearboxes. It has been concluded for that case, that different normalization algorithms should be applied for the different gearboxes.

The normalization functions ordinarily are defined to be based on 10-minute averaged data. First, the SCADA data are binned for both power as ambient temperature, where the power is divided in 100kW intervals between 0kW and rated power and ambient temperature is divided in 5° intervals between -10°C and 30°C, or other limits that are typical for the local climate. For proper de-trending at least one year of data is required to include the seasonal effects on the ambient temperature. After binning the SCADA data as described for each turbine, per bin the median value over all turbines is determined. The median is used to determine the average of the most common behavior of the turbines in the wind farm, disregarding the outliers.

Through the median values, a polynomial is fitted. The polynomial is a second order, two parameter polynomial. The choice of this function has the advantage that it extrapolates relatively smoothly and reliably to bins without data. For the N80 turbines it is found that higher order polynomials are not required to catch the trends in the data.

Example - temperature of the gearbox bearing

As an example of the method described in the previous section, here the data are shown of the temperature of the nacelle. The temperatures are binned according ambient air temperature and turbine power. The averages over the five turbines per bin are presented in Figure 2.16, where the median values for the temperature of the gearbox bearing are presented in blue circles. Through these data a second order, two-parameter polynomial is fitted. The fitted plane is also shown. In this case, the normalization function that is found is:

Temperature Gearbox Bearing at high speed shaft - Moving Average:

$$-2.4208\text{e-}006\ P^2 - 0.00012938\ P\ T_a + 0.011343\ P + 0.0016984\ T_a^{\ 2} + 0.44467\ T_a + 41.6087$$

where:

T_a Ambient Temperature [°C]
P Active Power turbine [kW]

From the data it is clear that the temperature of the gearbox bearing is dominated by ambient temperature and is only slightly depending on the turbine power.

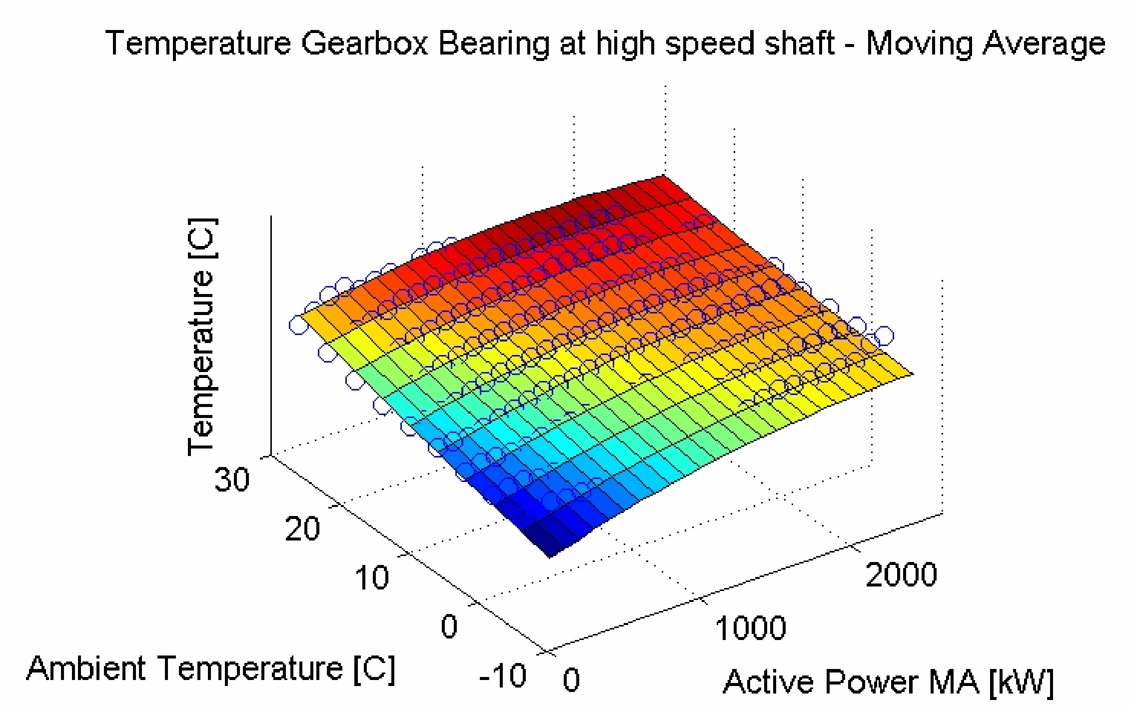


Figure 2.16: The median values per bin are indicated with blue circles. The second order, two parameter polynomial fit is indicated with the plane.

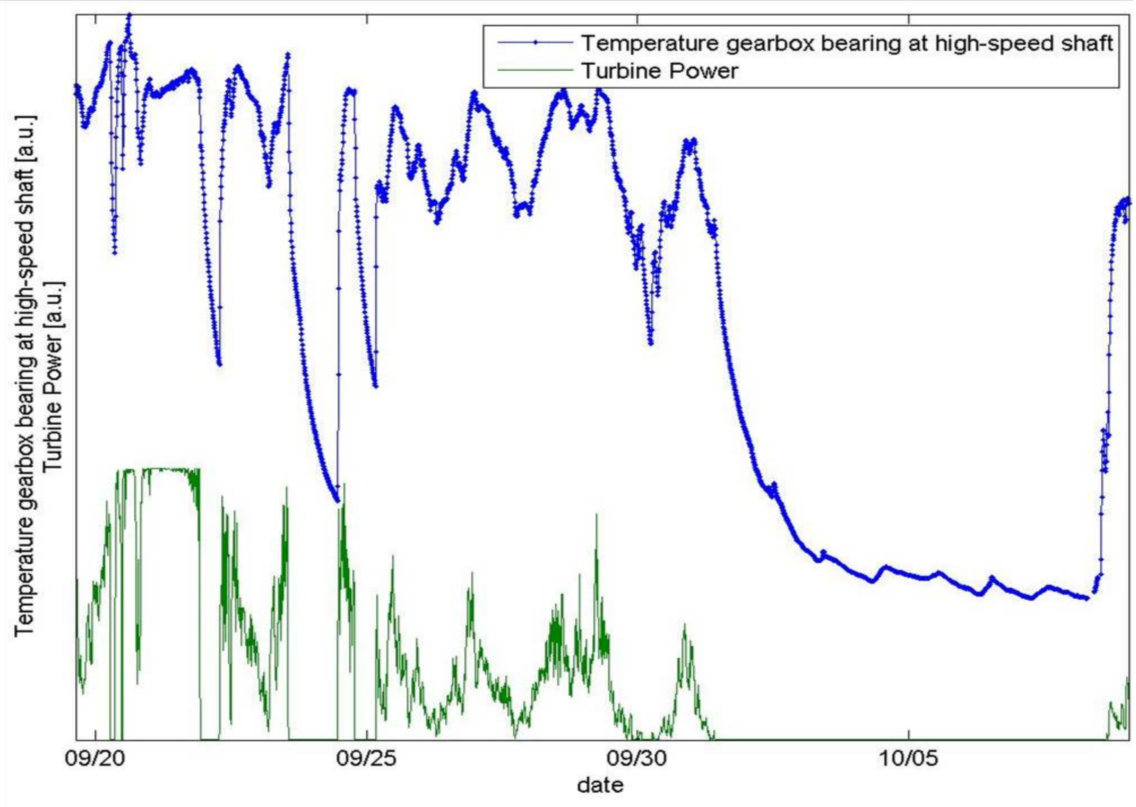


Figure 2.17: The temperature of the gearbox bearing at the high-speed shaft. It is clear to see that the temperature drops relatively slowly (when the turbine does not operate) and increases significantly faster when it starts operating. Note that each dot indicates a 10-minute period.

Moving Average filtering

For many parameters, the correlation between turbine power, ambient temperature and the parameter is strong. However, some parameters respond more slowly on changing turbine power than others, for example, bulky components that respond more slowly to heating or cooling than the smaller components. This is illustrated in Figure 2.17, where the temperature of the gearbox bearing at the high-speed shaft is plotted as function of time (blue line). At the same time, turbine power is indicated in a different scale (green line). As is obvious, the temperature of the gearbox bearing slowly decreases when the turbine power is reduced from full power to lower values. Equally, when turbine power quickly increases, the temperature of the gearbox bearing increases relatively slowly (in about 120 minutes). The decrease in temperature is even slower (up to a day). The effect of using moving average turbine power for the normalization has been tested for four different averaging times, 60, 120, 180 and 240 minutes. The averaging time most appropriate for the temperature of the gearbox bearing is found to be 180 minutes.

Another way to plot this is to show the hysteresis in the oil temperature for increasing and decreasing wind, as shown in Figure 2.18.

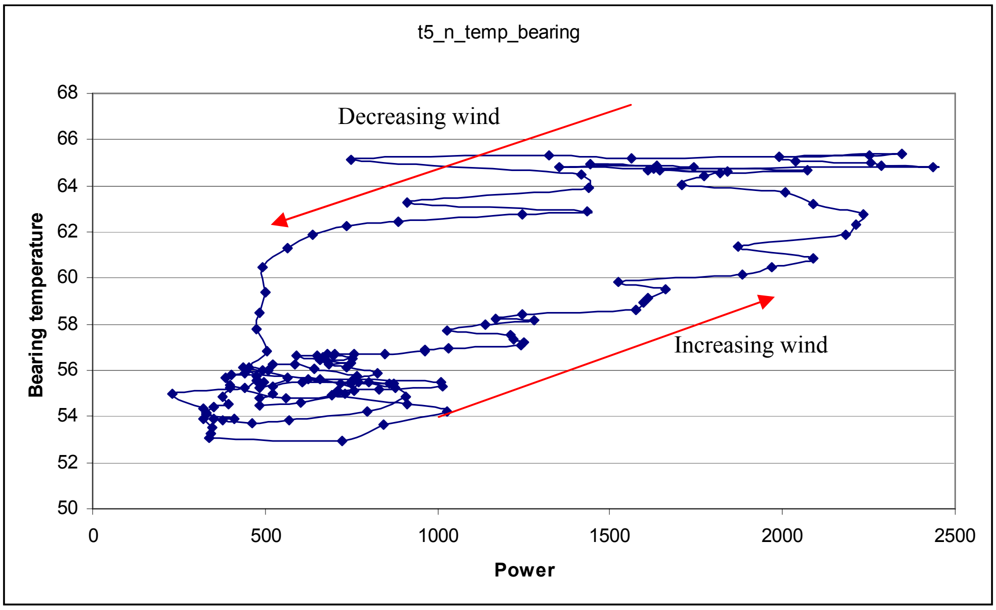


Figure 2.18: Bearing temperature showing the delay in heat transmission during 24 h of measurements. First the wind speed increased from about 6 to about 14 m/s, then it decreased again to below 8 m/s.

Normalization of SCADA data

The SCADA data should be normalized to smaller bandwidths so that operators can detect or observe abnormal behaving turbines in a relatively easy manner. The method of applying normalization to the SCADA data is the following:

1. Bin average the SCADA signal according ambient air temperature and turbine power for each turbine;
2. Determine for each bin the median value (of the above bin averages) over all turbines;
3. Fit a polynomial plane through the median-bin-averaged data.
4. The normalization function (as function of ambient temperature and turbine power) is used to normalize the 10-minute averaged data, resulting in values around one. Where moving averaged turbine power is indicated, the binning is based on moving average turbine power.

Daily averaged values

Since the method aims to analyze extensive sets of turbine data over long periods of time, it has been experienced that daily averaged data could have advantages. The amount of data is reduced drastically, as is the scatter. This makes for instance that daily averaged signals of several turbines can easily be compared within a single plot. Besides, turbine operators are most often interested in information that can support their day-to-day planning of necessary actions, for which not too much detail (such as hourly data) is required.

Tool for monthly reporting

To facilitate the operator with predicting wind turbine failures that could occur within a short period of several months ahead, it is important to provide a well-structured and easily accessible presentation of the processed SCADA data. Therefore a tool has been developed that performs the necessary de-trending, normalization and filtering functions and generates reports according to the format as shown in Figure 2.19. In the left graph the daily averages for the three preceding months are shown to get an impression of the general trend of the normalized signal. The right graph shows the normalized 10-minute averages (green dots) and the daily averages (blue dots) of the SCADA signal. Finally in both graphs a polynomial fit through the daily averages of the four months is shown.

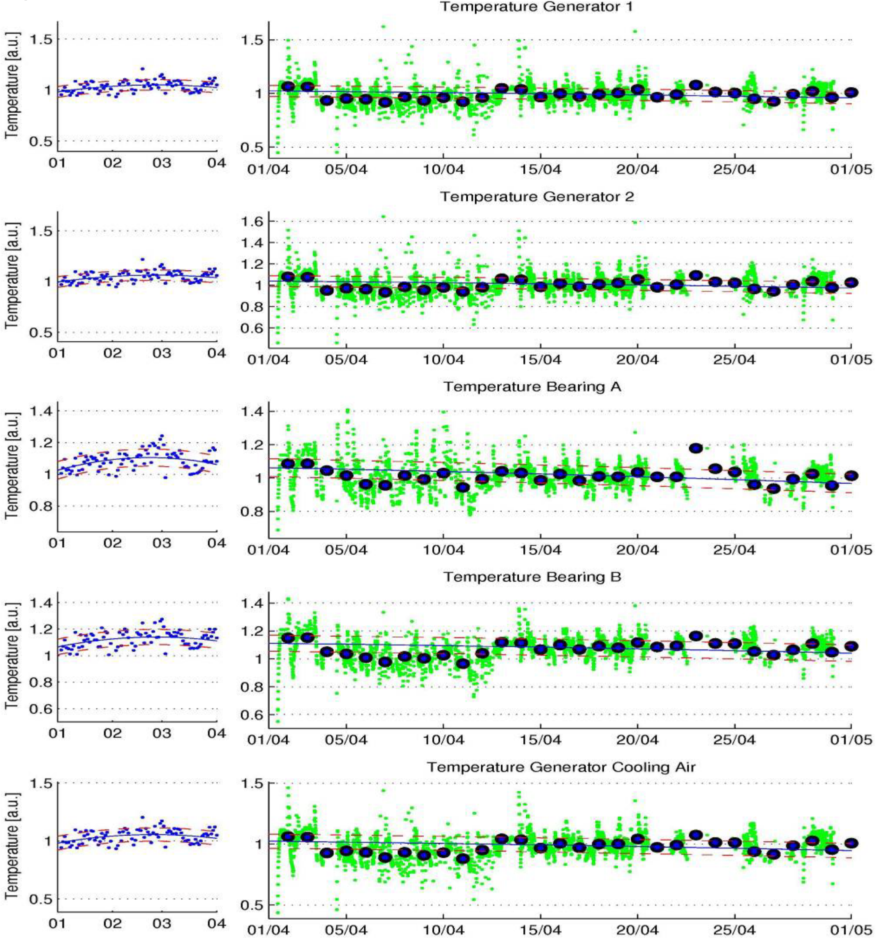


Figure 2.19: Example of a monthly report of the SCADA data of turbine 5 in April 2006. In the left plots the daily averages for the three preceding months are shown to get an impression of the general trend of the normalized signal during this time. The right graph shows the normalized 10-minute averages (green dots) and the daily averages (blue dots) of the normalized SCADA signal. Finally in both graphs a polynomial fit through the daily averages of the four months is shown to guide the analyst.

2.3.2.4 Correlating SCADA data with maintenance reports

As one of the several possible methods to detect premature failures, the maintenance reports of the wind farms are used in order to correlate the findings of the methods using SCADA data with actual maintenance visits and replacements of components. A problem with this analysis however is the limited availability of the maintenance reports. For example for the EWTW maintenance reports are available up to October 2005. Furthermore in the maintenance reports not that many replacements of components are described. However advantageous for the operator, it makes the analysis harder.

Presenting of alarm logs

In the format of the monthly reports, all alarms that have occurred during a month are presented to the operator. Only plots of those alarms are included that have generated alarm events during the reporting period. Therefore the report is quite small whenever the turbine has been in normal operation, since then no alarms have been generated. An example is presented in Figure 2.20.

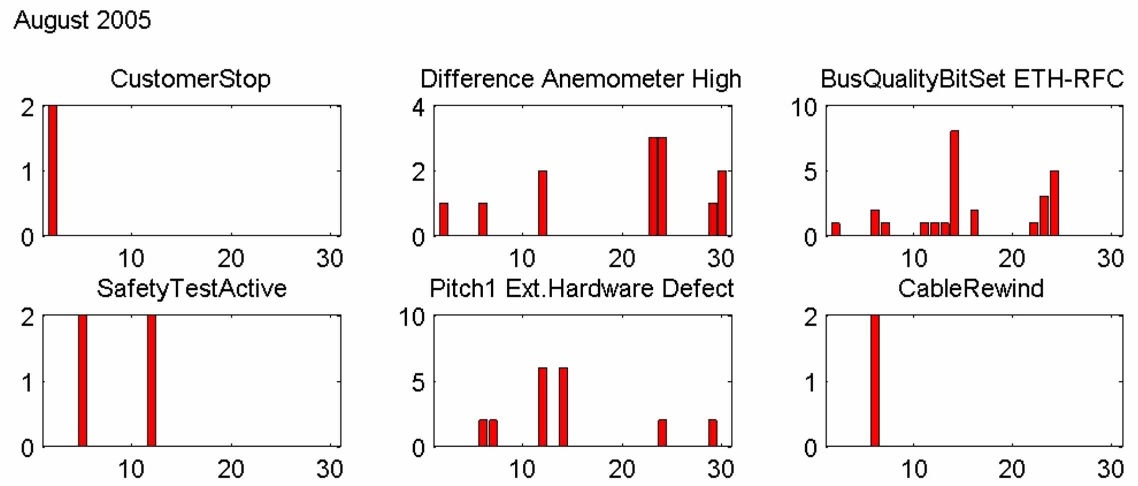


Figure 2.20: Example of presentation of alarms during in a monthly report. The number of alarms per day over one month is presented.

However, as soon as alarms occur it is common practice that either from remote operation the turbine is checked or a maintenance team is sent. From the data that are available an example is shown for the case where a pitch converter has been replaced. As can be seen, there have been many alarms during a period of a month prior to the replacement. From the service reports it is found that during January 2005 the pitch system needed several visits of maintenance teams, while during February no visits were made. The number of alarms was substantial and on March 10th of 2005 the pitch converter was replaced. This example shows the benefit of monitoring the internal alarm logs produced by the wind turbines. The method of presenting the alarms to the operator gives much better insight than a listing of the alarms would produce.

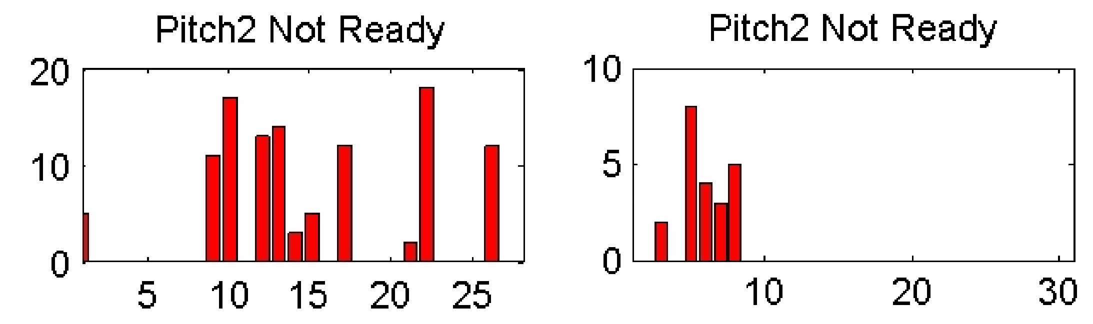


Figure 2.21: The number of alarms per day for the Pitch 2 system for February 2005 (left) and for March 2005 (right). On March 10th, 2005 the pitch converter was exchanged.

Example – gearbox replacement (from other wind farm)

Since no major components have been replaced on the Nordex turbines at EWTW, other datasets have been analyzed in the same way. From a completely other wind farm and other wind turbine type (>1MW) data is presented before and after a gearbox replacement. In the following figure the daily averages of the normalized gearbox and gearbox bearing temperature are plotted for the period from 2005 to 2007.

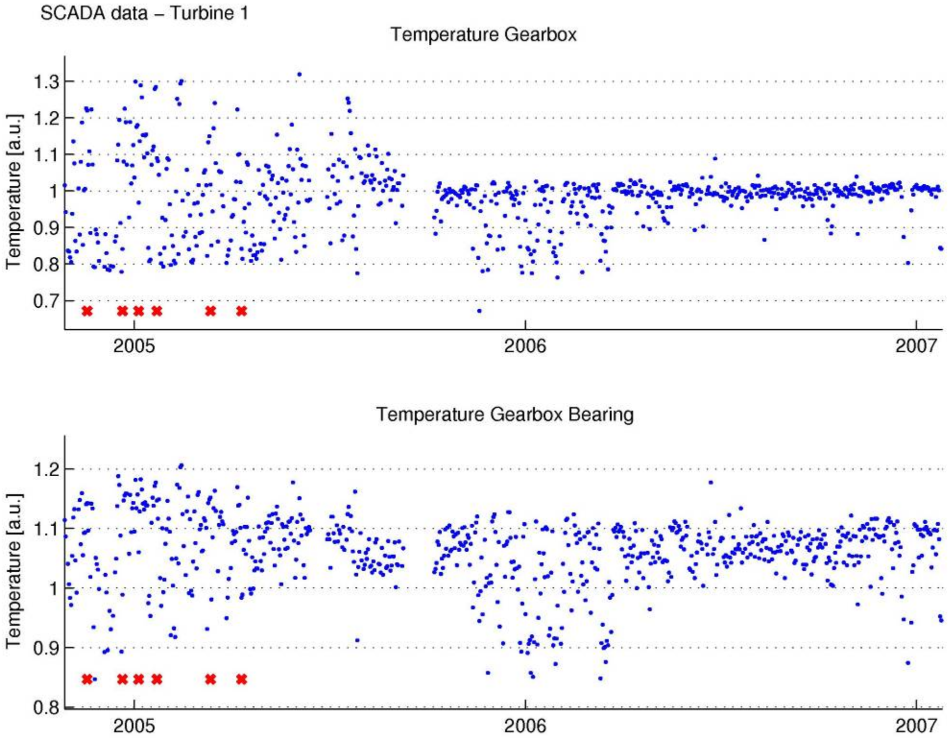


Figure 2.22: Analysis SCADA data turbine 1, where the blue dots indicate the daily averages of the normalized SCADA signals of gearbox and gearbox bearing temperature and the red crosses represent the gearbox oil filter replacements.

Analyzing the data presented in Figure 2.22, the oil filter replacements (that are indicated by the red crosses) occur in a period where the temperature of the gearbox has a relatively large scatter. Although there is not a trend observed that the temperature deviates over time, the scatter indicates a non-standard behavior. The non-standard behavior is illustrated by the regular oil filter replacements. Looking at the analysis it can be seen that at the end of 2004 and in the beginning of 2005 six oil filter replacements have been made. The daily averages of the normalized data in this period show quite a large amount scatter. After the last oil filter change the normalized data show no decrease of the amount of scatter. From the maintenance reports it is found that this turbine has undergone a gearbox replacement in the autumn of 2005. This is clearly visible in the graph by the period without data. After the gearbox change the normalized gearbox temperature has a smaller scatter compared to the period before the gearbox change.

2.3.3 Discussion

High frequency measurements

Using the methodology of analyzing the electrical power signal using wavelets certain drive train faults can be detected. This is shown by the results from a Matlab-based algorithm that has been developed and applied to both the GE1.5S and five Nordex N80 wind turbines. It is interesting to note that a particular fault was detected three months before actual failure occurred.

This methodology has an advantage over other methods by its simplicity, at least for offline implementation, that can reduce the cost of a condition monitoring system. This is particularly useful for offshore wind turbines.

An interesting new option of a methodology for modeling of fatigue life of drive train components is by estimating a so-called torque transfer function from measurements has been proposed by Risø. This transfer function should describe the dynamical interaction of mechanical parts of the drive train, enabling to estimate the rotor torque from high-frequency measurements, such as the power output signal. A comparison of this derived or “virtual” mechanical torque favours understanding of the interaction between the mechanical and electrical system, at least on certain types of wind energy conversion system. As from the current measurement campaign not all required measurements, e.g. individual blade loads, were available, this could not yet be elaborated further.

Statistical data

From the available statistical data, research has been carried out by CREST [19], ECN [36] and Risø [37] in order to find correlations between observed trends and malfunctioning turbine (component)s. With the use of these methods the shaft misalignment problem could be detected, although for diagnosis of the exact cause and assessing the severity and component degradation other methods, e.g. vibration monitoring, visual inspection need to be applied.

Due to several reasons it is complicated to detect premature failures from analyzing statistical data. Firstly, it has been observed that as soon as a trend shows up, in most cases a maintenance crew is sent to the turbine to investigate it and correct it. In several cases deviations were caused by the measurement itself. Secondly, the wind farms that have been investigated did not experience failures of main components. Thirdly, as always, after correcting for obvious errors, such as outliers, the data still contains errors, e.g. due to sensor offsets and drift. Also the exact sensor locations and types were unknown, which made interpretation even more difficult.

As a result only a few examples have been presented that demonstrate the benefits of the developed analysis methods. Although it is already clear these methods will facilitate analysis of SCADA data and improve the quality of the failure detection, obviously more experience with these methods is needed. For example, proper bounds for normal operation of each signal can be defined and the added value of these methods can be assessed in practice.

2.3.4 Integration aspects of algorithms

Besides the methods described above for algorithms based on general turbine data, trend analysis has been performed on the power curve as well as on the response of the yaw and pitch systems. The techniques often show rather poor indications of changes in system health. A possibility to improve the practical applicability of these algorithms is to integrate them so that the symptoms can be recognized from different approaches.

As a starting point for integrating the developed algorithms as described above as elements of a complete system, the following schematic is proposed, see Figure 2.23 and [20].

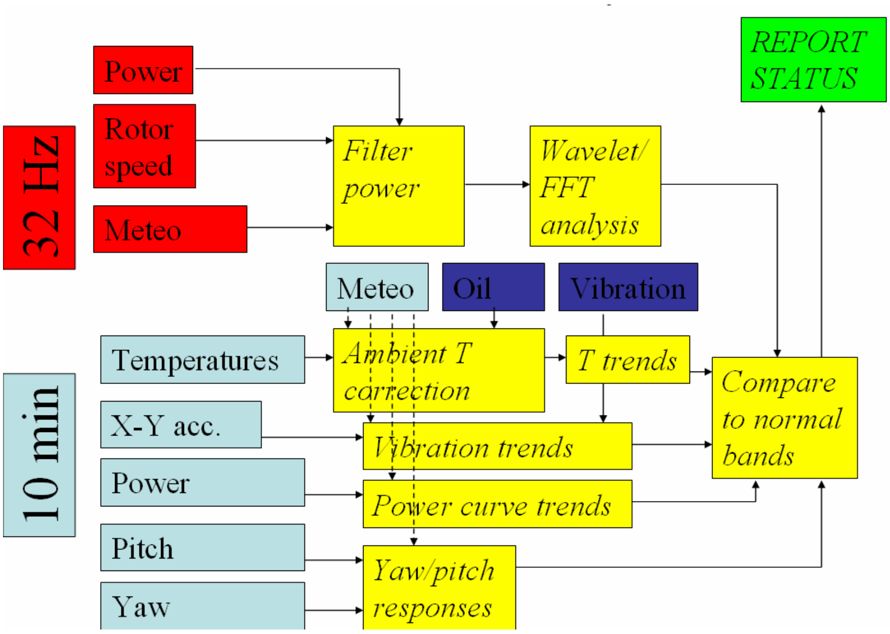


Figure 2.23: Proposed schematic for integration of signal processing algorithms.

The current algorithms need to be optimized, more extensively tested and further appropriate warning and alarm levels need to be set. Then from the practical side attention is needed to integrate the system into existing wind farm SCADA systems.

2.4 GH Bladed simulations of faulted conditions

Since it was not possible to introduce fault situations in the turbines, several simulations were made to determine the relationship between the failed situation and several "measurable parameters". Garrad Hassan has performed two studies in this area using GH Bladed software with a Nordex N80 model. A detailed report of can be found in [20] and [38].

2.4.1 Pitch bearing friction

An investigation into the feasibility of predicting pitch bearing friction from likely measurement signals. The aim of this investigation was to ascertain whether or not it is possible to infer levels of pitch bearing friction from existing measurement signals with reasonable accuracy. Such a derived value of pitch bearing friction would naturally be very useful for condition monitoring of the pitch bearings.

The measured input signals that are assumed to be available are: Pitch angle, Pitch rate and Pitch actuator torque. Measurements of wind speed from turbine mounted anemometry are ignored as these are thought to be potentially unreliable.

10-minute simulations were carried out using wind speeds above the rated wind speed as this is where blade pitching occurs: 16 to 24 m/s with 10 turbulence seeds. The standard linear model for pitch bearing friction was used. Balance of torque and moments at the blade pitch bearing:

$$M_{\mathrm{friction}} = Q_{\mathrm{a}} G + M_{\mathrm{Z}}$$

where:

Q_{a} is the pitch actuator torque

G is the pitch actuator gear ratio of gearbox and pinion

M_{Z} is the internal moment at the blade root

Therefore, if an accurate estimate of M_{Z} can be made (for example, as a function of pitch angle) then the true pitch bearing friction can be estimated at any time including periods outside normal operating conditions, when a pitch bearing fault has occurred. The focus then shifts to making an accurate estimate of M_{Z} for a given averaging period. Unfortunately it was found that even averaging over multiple whole rotor rotations, it was impossible to make a satisfactorily accurate estimate of M_{Z} as it is only a weak function of pitch angle. The investigation therefore shows it is not possible to make a reliable estimate of pitch bearing friction from the assumed input signals.

2.4.2 Rotor imbalance

Several turbine fault conditions were simulated including rotor mass imbalance and rotor aerodynamic imbalance (i.e. a set angle difference between blades). The aim was to study the resulting output to ascertain the most reliable signal for condition monitoring use. This was selected in terms of the periodic component of a signal having a clear correlation with the fault condition and a good signal to noise ratio.

10-minute long simulations were performed with turbulent wind conditions at a mean wind speed of 12m/s. Figure 2.24 and Figure 2.25 show the periodic component for two signals: nacelle side-to-side (y-dir.) acceleration and electrical power.

Rotor mass imbalance imparts a sinusoidal periodic force due to gravity once per rotor revolution (1P) at the hub and manifestations of this periodic variation are seen in both signals and also other signals, e.g. pitch angle. The nacelle side-to-side acceleration clearly shows the best signal to noise ratio at this wind speed of 12 m/s together with a plain difference between balanced and unbalanced cases.

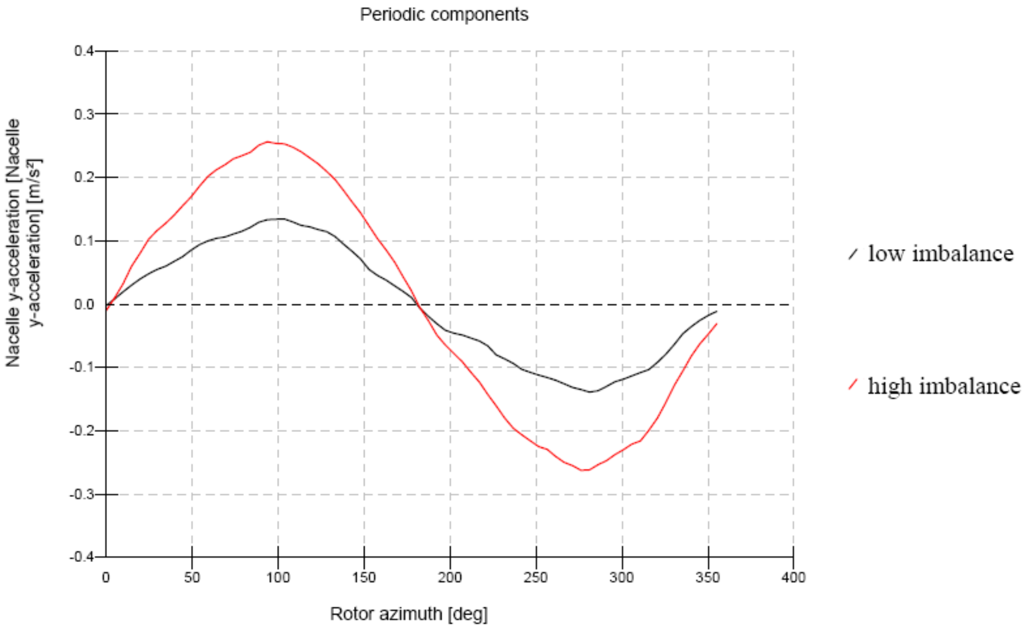


Figure 2.24: Fault modeling: rotor mass imbalance, 12m/s, nacelle side-to-side acceleration

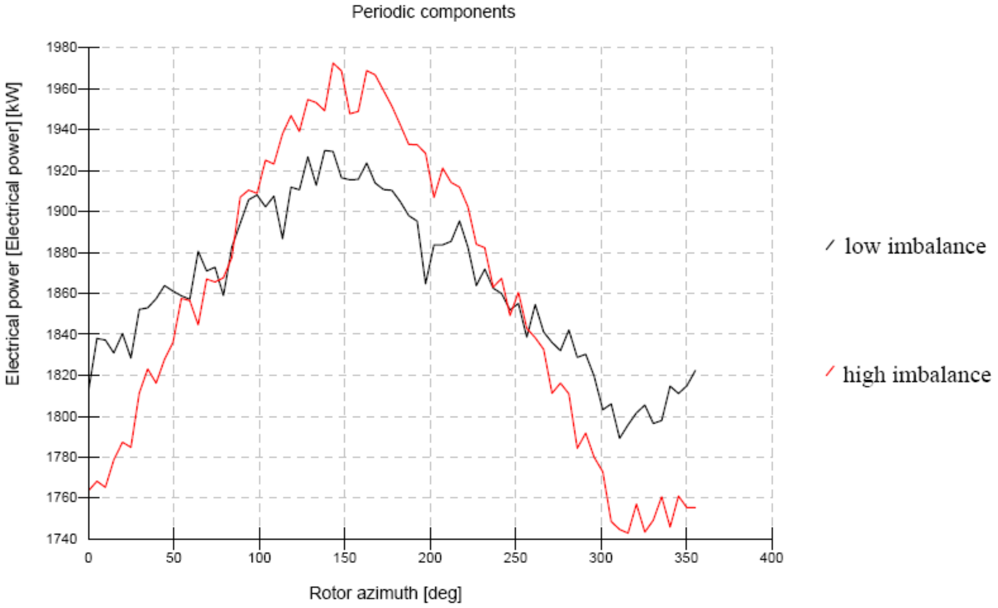


Figure 2.25: Fault modeling: rotor mass imbalance, 12 m/s, electrical power

From this result, nacelle side-to-side acceleration was investigated at other wind speeds: 4m/s and 24 m/s. These simulations show that the difference between the two cases is less apparent at lower wind speeds. The signal to noise ratio degrades slightly at higher wind speeds.

Rain flow cycle counting of the tower top side-to-side forces (F_Y) was performed to give damage equivalent loading (for an associated reference number of cycles) at a range of mass imbalances. The results in Figure 2.26 show that if such real time processing is possible, this seems very robustly correlated with rotor mass imbalance.

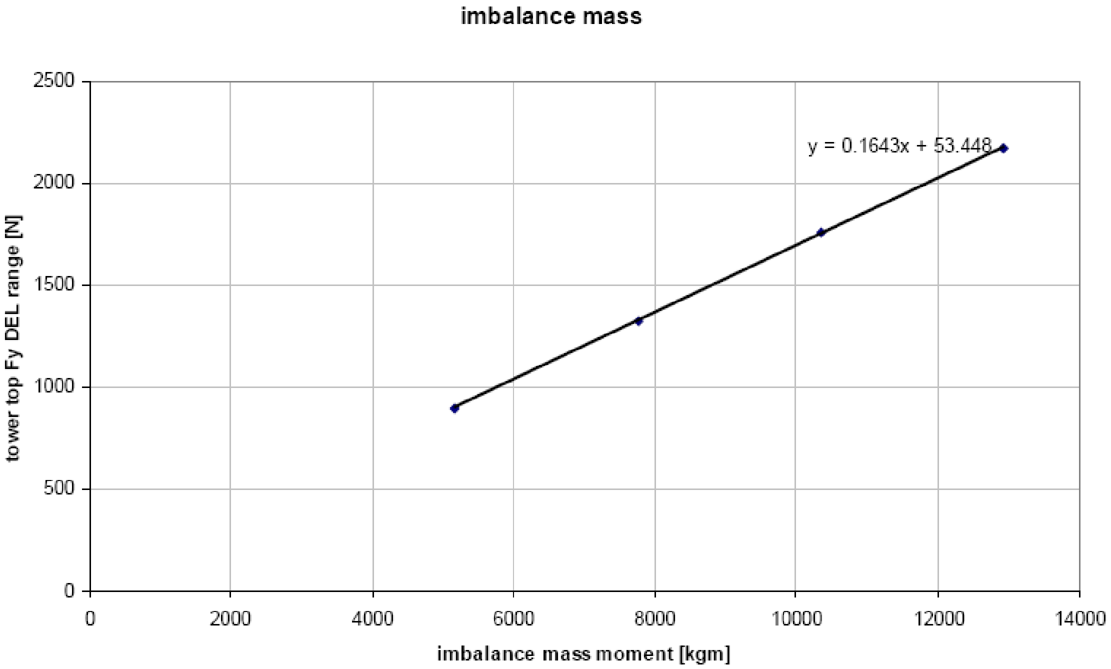


Figure 2.26: Fault modeling: F_Y DEL vs. rotor mass imbalance

2.4.3 Conclusions and recommendations

The model validation demonstrated reasonable agreement between measured and simulated power curves. This provided confidence to enable some useful modeling of fault conditions. It was shown that the choice of signal as condition monitoring input is very important for ensuring the most efficient fault detection. Aerodynamic codes were demonstrated to be invaluable tools in performing simulations fundamental to condition monitoring algorithm design. There may be considerable differences in the ease of diagnosis of different faults: the investigations here showed that a typical rotor mass imbalance is easy to detect, but a typical rotor aerodynamic imbalance is more challenging to identify and would need a more sophisticated algorithm.

The pitch friction investigation undertaken as reported here concluded that it is not possible to make a reliable estimate of pitch bearing friction from the available input signals.

2.5 Experiences with CM-techniques

This section describes the results from the installed drive train vibration monitoring systems of Gram&Juhl and Prűftechnik as well as some general experience with Pall oil monitoring equipment. Detailed reports from Gram&Juhl and Prűftechnik can be found in [20].

2.5.1 Gram&Juhl drive train vibration monitoring systems

2.5.1.1 Results

Data processed are from measurements on the Nordex turbine 7, which is equipped with the TCM® System. The kinematical data and measurement configuration have been reported in [20] and [40]. The processing of the data is made for two types of faults, namely damaged gear and damaged inner ring on a bearing. The following presents the result from the post processing, demonstrating the Signature Fault Strength for these faults and their evolution over time. For simplicity the presentation is limited to data recorded at relatively high power production of over 2200kW.

Theory of Signature Fault Strength

The Signature Fault Strength is based on three criteria:

- Location of Signature, i.e. degree of match in location on the frequency axis
- Shape of Signature, i.e. degree of (scaled) match in shape of the signature
- History of Signature, i.e. how its Location and Shape has evolved in time

The result of the Location Signature is expressed in a single scalar calculated in a Least Mean Square (LMS) sense, meaning that the value is zero when identical to the reference signature. For the Shape Signature the result is calculated as a correlation, meaning that the result is maximized at a perfect match. For the Historical Signature the result is expressed as the gradient at the evaluation time for a polynomial fit to the Location and Shape Signature values. The results are normalized based on experience deduced in the learning period. These four scalars is combined, as shown below, to express the strength of a signature, i.e. to detect if a fault signature is present and if so to judged the spare life time for this machine element. To relate this fault to other faults detected, the resulting strength is weighted based on experience.

The Total Signature Fault Strength is calculated as:

$$W \cdot \frac{HLS+HSS_N}{LS_N} \cdot SS_N$$

where,

W denotes the overall weight to relate this fault signature to other fault signatures,

LS_N denotes the LMS values for the Location Signature,

SS_N denotes the scalar value for the Shape Signature match

HLS_N and HSS_N denote the gradients for the polynomial fit to the historical values of these.

The subscript $_N$ denotes that all results are normalized based on experience. This means that a high Signature Strength indicates a fault, while a low Signature Strength indicates no fault - the exact levels is based on experience gained in the learning phase.

The implemented Fault Signature detection algorithm automatically scans all measurements for relevant signatures, as shown in blue in Figure 2.27, and calculates their Signature Fault Strengths.

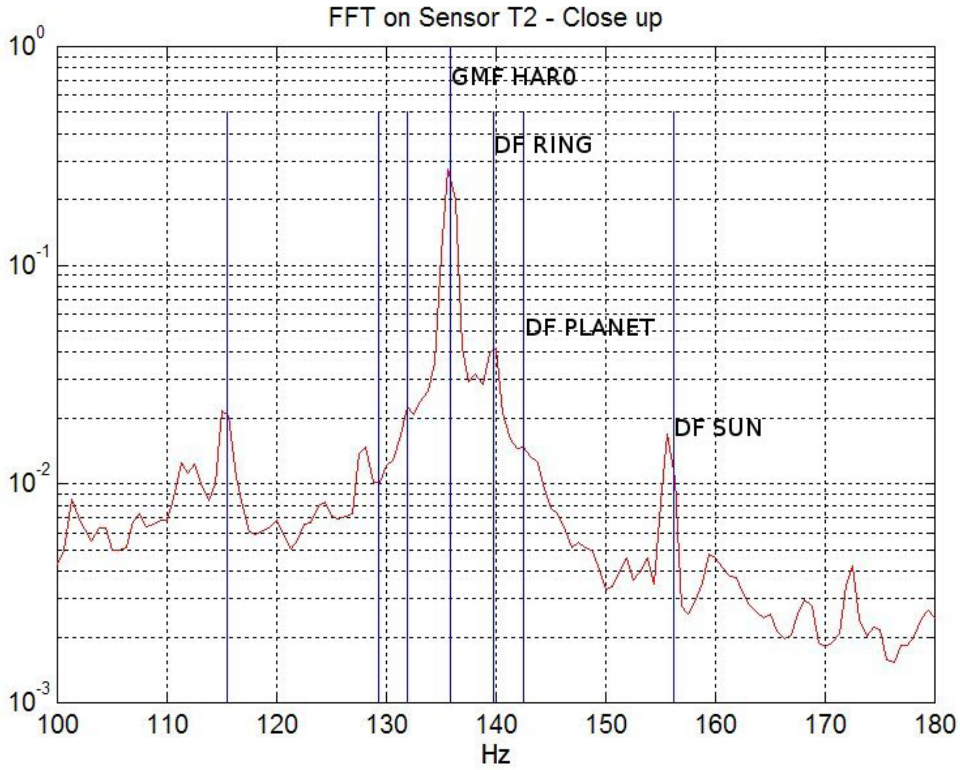
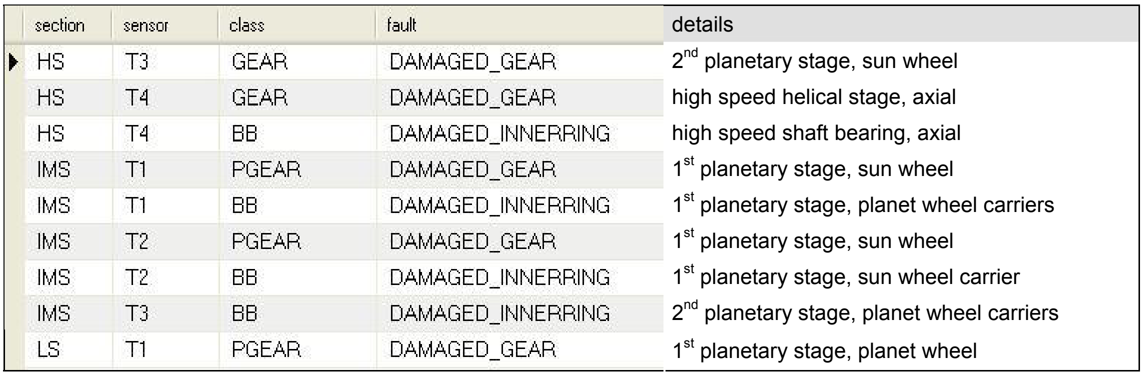


Figure 2.27: Fault Signatures applied to and FFT on data from sensor T2 on 1st planetary stage.

Example of Signature Fault Strength

Data for all sensors on the gearbox i.e. sensor T1 to T4 are processed and the resulting Signature Strength for both _Location_ and _Shape_ is shown in the figures below. The result of the analysis in Table 2.8 shows the number of Fault signatures detected which need attention. Some sensors report the same result, which means that the both can "hear" the fault.

Table 2.8: Signature Fault Results gearbox



section	sensor	class	fault	details
HS	T3	GEAR	DAMAGED_GEAR	2nd planetary stage, sun wheel
HS	T4	GEAR	DAMAGED_GEAR	high speed helical stage, axial
HS	T4	BB	DAMAGED_INNERRING	high speed shaft bearing, axial
IMS	T1	PGEAR	DAMAGED_GEAR	1st planetary stage, sun wheel
IMS	T1	BB	DAMAGED_INNERRING	1st planetary stage, planet wheel carriers
IMS	T2	PGEAR	DAMAGED_GEAR	1st planetary stage, sun wheel
IMS	T2	BB	DAMAGED_INNERRING	1st planetary stage, sun wheel carrier
IMS	T3	BB	DAMAGED_INNERRING	2nd planetary stage, planet wheel carriers
LS	T1	PGEAR	DAMAGED_GEAR	1st planetary stage, planet wheel

The significant results plotted in Figure 2.27 and Figure 2.28 probably is a DAMAGED_GEAR in the 2nd planetary stage and a DAMAGED_INNERRING on the bearing the high speed section and the bearing in the intermediate speed section (IMS).

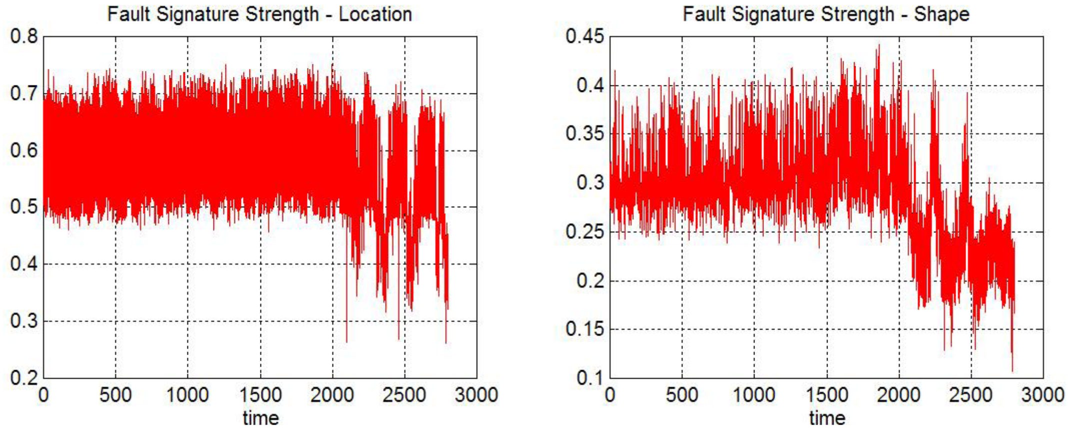


Figure 2.28: Fault Signature Strength for high speed shaft bearing on sensor T3

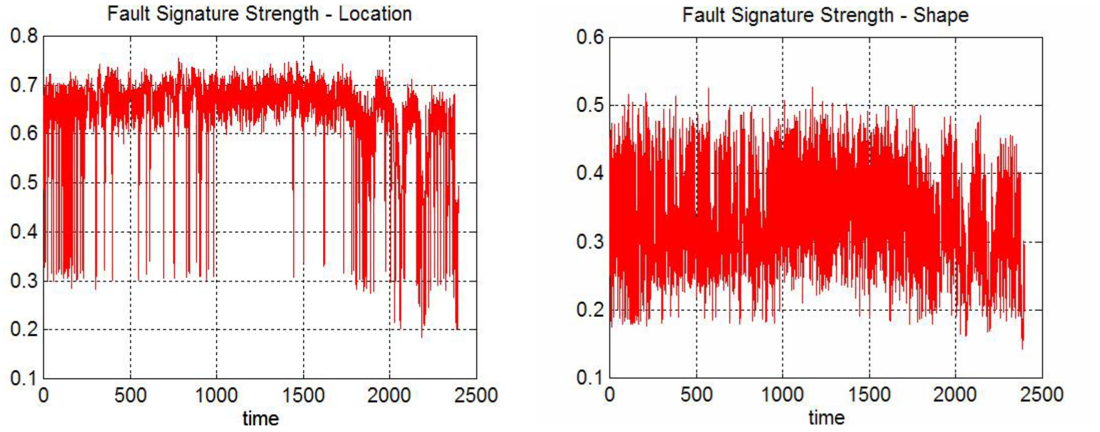


Figure 2.29: Fault Signature Strength for high speed shaft bearing on sensor T2

No significant change in the Fault Signal Strength is observed, although is seems that the signal on T3 has been changing within the last 3 months, but this is not significant since Location and Shape values should be inversely related, i.e. when the signature on the frequency axis fits better, the RMS value decreases but the shape correlation is then expected to increase.

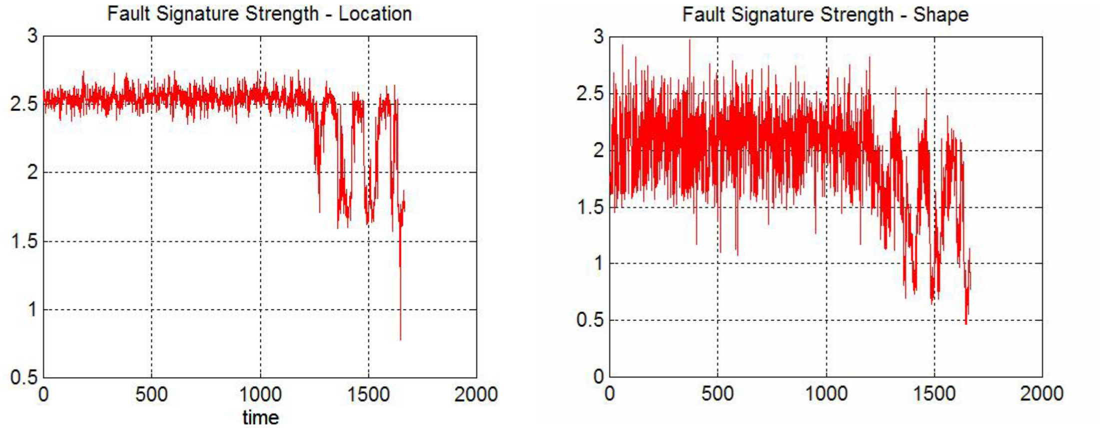


Figure 2.30: Fault Signature Strength for IMS planetary stage on sensor T2

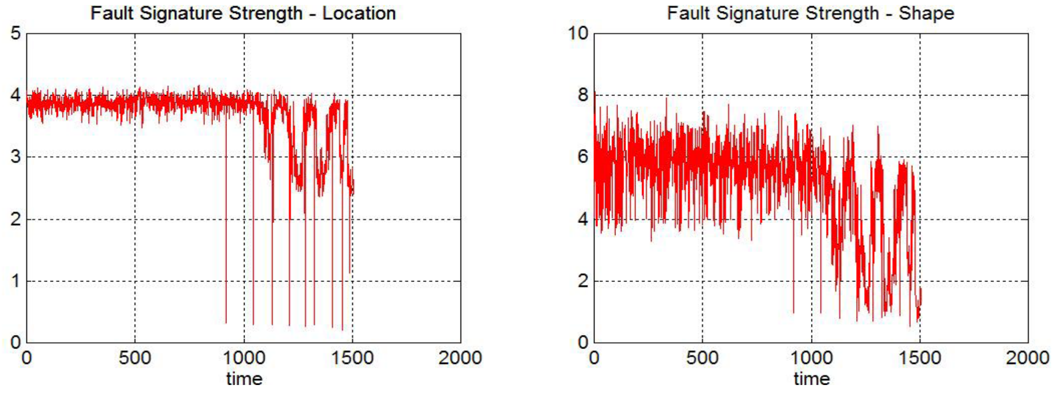


Figure 2.31: Fault Signature Strength for IMS planetary stage on sensor T1

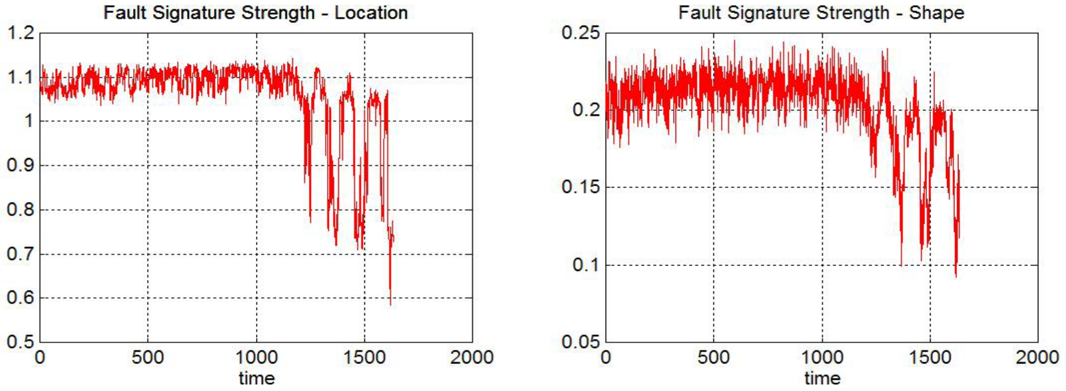


Figure 2.32: Fault Signature Strength for high speed shaft bearing on sensor T4

Since no significant Fault Signature Strength has been observed the Total Fault Signature Strength is not calculated. All measurements show the same instability within the last 3-4 months of the measurement period, which should be investigated further. Unfortunately, from this point of view, no significant Faults have been detected within the measurement period from March 2006 up until May 2007.

2.5.1.2 Developments

Gram&Juhl has applied two CM-systems of which one was a TCM® (Turbine Condition Monitoring) System. Similar to the analysis of SCADA data it is concluded that no failures occurred during the measurements that could be detected by the TCM® System. In this project Gram&Juhl has also optimized their automatic fault frequency detection algorithms and measurement setup model, as described above, so that faults can be detected earlier.

Both the Gram&Juhl TCM®-system and the Prűftechnik VIBNODE® systems use displacement sensors at the low speed section of the drive-train, e.g. main bearing, which are superior to vibration sensors because of the slow rotational speeds.

2.5.1.3 Conclusion

No faults have been detected. Since no damage is found on the Nordex Turbine 7, which can demonstrate the real use of the Fault Signature detection method, an example from an anonymous wind turbine is shown below in figure 21. Three turbine spectra from the High Speed stage are plotted together, where the blue spectra are healthy turbines and the purple curve is for a turbine with a bearing fault in the high speed stage. The fault is a damaged inner ring as shown in pictures 22. The signature shown in figure 13 can be recognized in this plot, which in this relative developed damage stage, is mixed with other signatures. The damage where detected six month ahead before this pictures where taken. In this case downtime where avoided as well as breakdown.

2.5.2 Průftechnik drive train vibration monitoring systems

2.5.2.1 Results

Trending of generator bearing vibration velocities

The CM-system in turbine 8 detected vibration levels, which were about twice as high as in the other turbines and which increased during the second quarter of 2006. Inspections revealed that the cause was generator misalignment and action was taken to realign the high-speed shaft, however the high vibration levels remained present. Figure 2.33 shows the band filtered radial vibration velocity values of the generator bearing over 13 months as an example. A detailed analysis of the results in the frequency range from 10 to 30 Hz in the 3rd quarter of 2006 even shows a slight increase in vibration as opposed to the slightly decreased vibration at the beginning of this year.

Since according to Nordex no changes had been made to the turbine, the vibration decrease could only be interpreted as “settling” of the generator and/or “wearing” of the bearing. “Settling” of the generator can result from fatigue in the elastic elements at the base of the generator and at the gear support. “Wearing” increases bearing slackness and makes it possible for the rotor to move “evasively” and reduce vibrations. However, this puts more local strain on the roller bearings.

When zooming in on the development of the trend in Figure 2.33, the turbine 8 reveals that besides the static vibration strains superposed additional vibration strains take effect as well. The reason for this is the operating behavior of the controller. It should be mentioned here that CREST has found similar superposed vibrations in the load parameters.

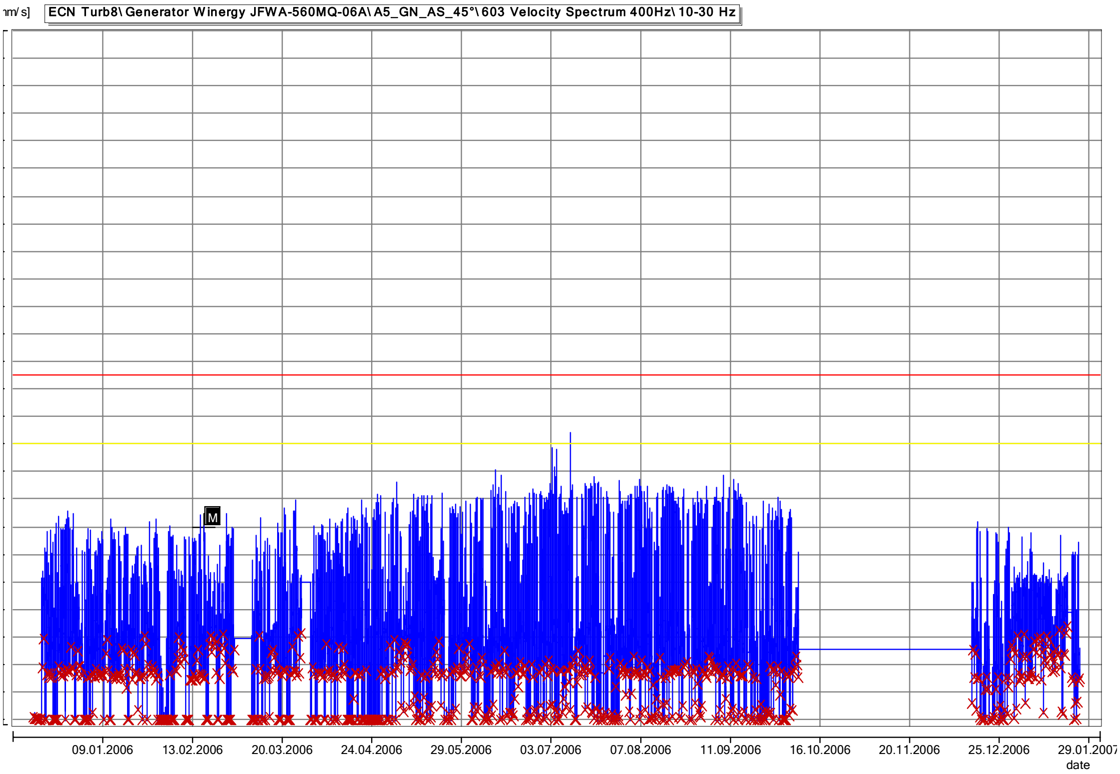


Figure 2.33: High vibration levels at generator bearing of turbine 8.

Frequency analysis of generator bearing vibration velocities

Besides the monitoring of trend parameters a comparison of frequency spectra of the generator, recorded under comparable circumstances, revealed the following. The spectra were dominated by the rotational frequency of the high-speed shaft and showed stable amplitudes on this in between January 2006 and October 2006. In the beginning of 2007 this frequency peak diminished, indicating a settling of the generator base. This also means that the generator is positioned too high and should be lowered.

Also increased vibration levels appeared in the high speed spur stage of the gearbox. These vibrations were not new and stayed at a high level for the complete period.

Trending of gearbox vibration velocities at high speed spur stage

Figure 2.34 illustrates the results of the "acceleration" parameter in the frequency range from 70 to 1700 Hz. Whereas the vibration strains remained similarly high throughout the year, first increases in the "acceleration" parameter (range from 70 to 1700 Hz) appeared at the beginning of 2007.

From an evaluation of the corresponding frequency spectra in Figure 2.35, it can be concluded that the 1st planetary stage is the dominating exciter and that the 2nd planetary stage has deteriorated in its vibration behavior. It is therefore recommended that the plant operator has the wind turbine gear inspected.

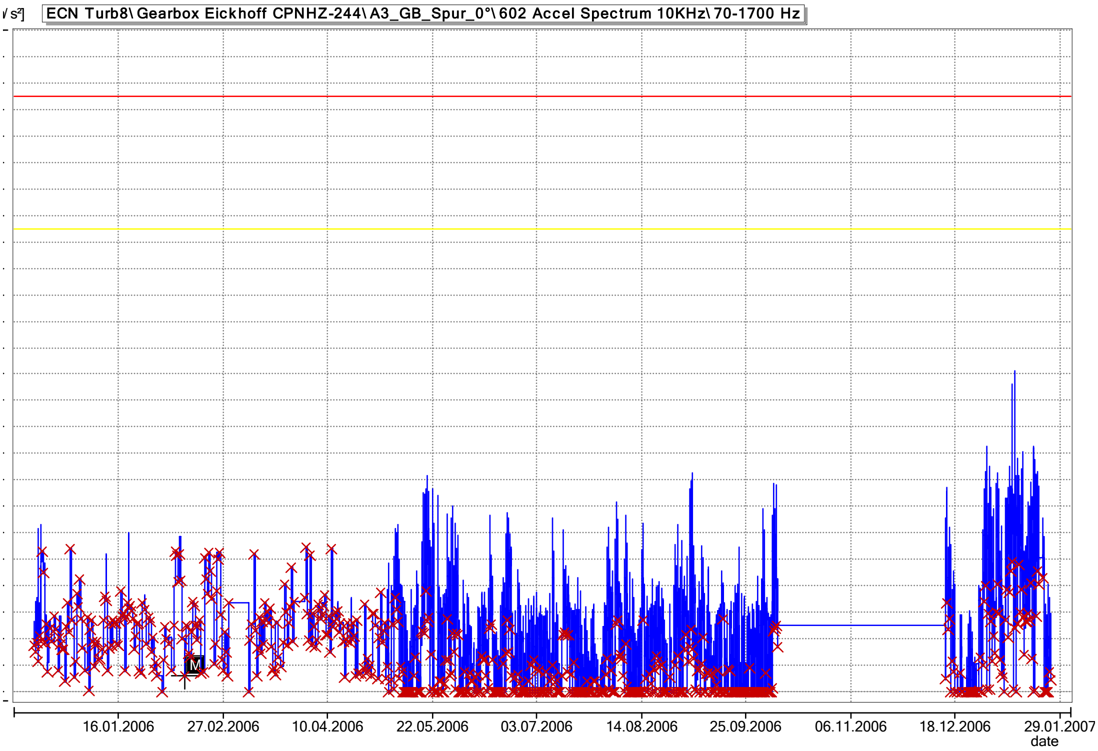


Figure 2.34: Bandpass filtered accelerations in the frequency range from 70 to 1700 Hz at the gear with a vibration increase at the beginning of 2007

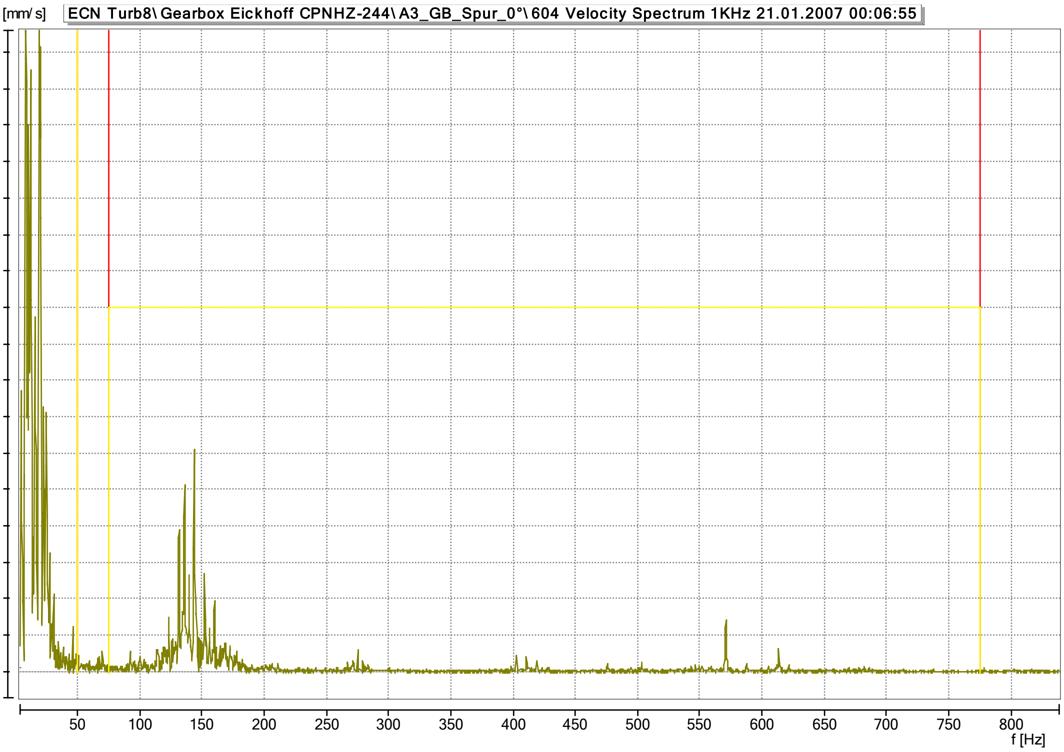


Figure 2.35: Corresponding frequency spectrum of the gear (excitations of the 1st planetary stage dominate!)

2.5.2.2 Developments

VIBNODE® systems of Prűftechnik installed in two of the N80 turbines. The VIBNODE® CMS, which has been newly developed for smaller wind turbines, is cheaper and does not feature additional functions as rotational (re-)sampling and measuring in two operational states (according to GL-Regulations). Instead it continuously measures the vibration behavior and performs real-time diagnosis and preliminary evaluations over the whole operating range, thereby reducing the amount of data for later offline analysis in the diagnostic centre, see also [41]. The system has shown to detect phenomena, e.g. high vibration levels, as described in section 2.5.3.1, outside of the two operating states as applied in certified systems.

The applied axial displacement sensors to monitor the axial movements and vibrations of the gearbox planet carrier provided new information on gearbox axial loading, cf. Figure 2.36.

Further Prűftechnik gained experience with increased ADC resolution of the VIBNODE® in WT9, which enables accurate filtering (suppression) of low-frequency vibrations, e.g. from rotor imbalance, while studying drive train vibrations in the range of 0.1 – 1 Hz.

Another feature is that automated data transfer was implemented, which made it possible to transmit continuously measured rotational speed values as well as load, vibration severity, and wind speed to the control centre. It also permitted the analysis of conditions at very high wind speeds. For example Figure 2.36 illustrates how axial movements and axial forces on this “stormy day” during trundling and normal operation impacted the gear drive stage. During nominal operation, the drive shaft was “pushed” into the gear up to 1 mm, and was permanently displaced during operation by 0.5 mm despite helical gearing. At moderate wind speeds the overall planetary stage moved about 1 mm.

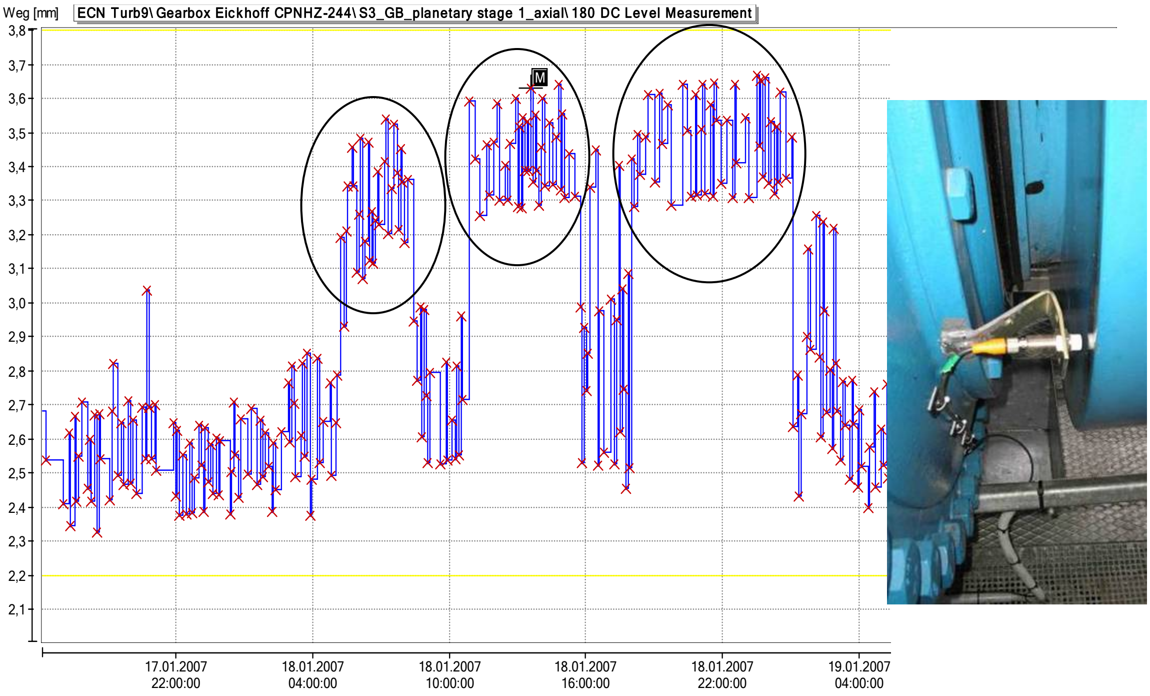


Figure 2.36: Sample plot of the axial displacement of the planetary stage (including a hurricane on January 18 from 11 a.m. to 12 midnight, with the WEA trundling at peak wind speeds, which is marked with the three circles)

2.5.3 Evaluation of vibration monitoring systems

In the measurement campaign experience was gained with several different types of online vibration monitoring systems, of which two were certified systems according to the current GL regulations, cf. [39].

2.5.3.1 Experience from measurement campaign

The presently available systems for drive train monitoring, supplied by Gram&Juhl and Prűftechnik performed well and reliable. It was demonstrated that the systems are able to detect (1) component errors at an early stage, and (2) off-design conditions such as shaft misalignment.

As during this short measurement campaign on relatively new turbines no other failures were detected, operating experience from other projects was gathered, see Section 2.5.3.2.

For the applied vibration monitoring systems, as well as for all other types of measurements (SCADA data, time series) it is concluded that large amounts of data are being produced which are difficult to interpret by wind farm operators. A dedicated expert team is required to derive meaningful recommendations for O&M optimization.

In this project both Prűftechnik and Gram&Juhl have further developed their reporting tools. These tools facilitate the generation of reports and access to these reports via the company websites. For a non-specialist however it is still difficult to make a selection out of the many available reporting types and to interpret the reported results.

2.5.3.2 Generic experience

From experience in other projects it is shown that a properly configured online vibration monitoring systems can detect a number of developing faults in bearings and gears as well as off-design conditions, e.g. shaft misalignment, for example a detected damaged inner ring, cf. Figure 2.37. The damage where detected six month ahead before this pictures where taken. In this case downtime where avoided as well as breakdown.

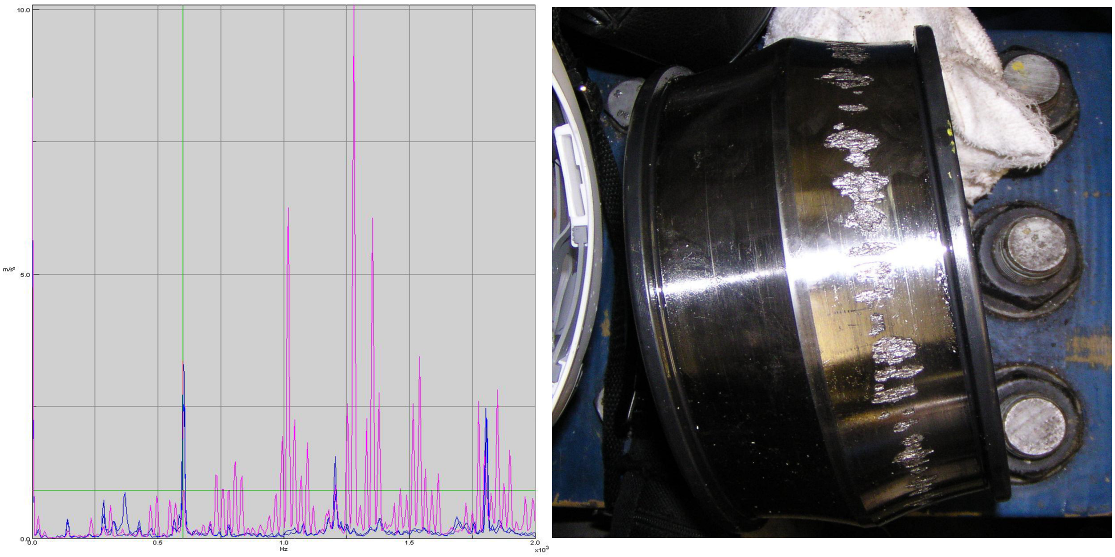


Figure 2.37: Fault Signature Inner Ring (left), inspection (right) - Anonymous wind turbine

In general it should be noted that this requires experienced personnel to analyze the results. Further, what is still difficult is to make accurate prognosis of the developing fault in order to improve O&M planning. Therefore a visual inspection is still superior in assessing the stage of the degradation. For severe faults CM-systems have proven to be useful to stop the turbine on time as to prevent consequence damage.

2.5.3.3 Application

Partly based on the results of the CONMOW project, but mainly on the experiences of Prűftechnik and Gram&Juhl elsewhere we can state that at least 5 requirements must be met, to implement a well functioning condition monitoring system for wind turbines:

1. Drive-train vibration monitoring must be permanent and online, as failures may develop within a period of time that is shorter than the regular maintenance interval. Further, vibrations often show up under specific operating conditions
2. Signals must be correlated and sorted with the wind turbine status parameters, active power, wind speed, yaw error etc. Gram & Juhl implements this as binning and conditional recording
3. Data should be centralized stored so cross analysis and comparisons between turbines and sites can be made. Also post processing is necessary.
4. A large number of turbines must be monitored to gain sufficient experience with a specific wind turbine type
5. The systems produce large amounts of data which are difficult and time consuming to interpret by wind turbine owners. A dedicated expert team should work with monitoring results, i.e. interpretation of measurement signals, handling of alarms, planning maintenance, design feedback etc.

Up to now, the response on abnormalities in the data is either more frequent inspections or an immediate shut down to avoid consequence damage. Within the CONMOW project it was concluded (and also confirmed by experiences outside the project) that at present insufficient knowledge is available to make prognoses how the failures will develop in order to change from calendar based maintenance to condition based maintenance. Such knowledge can only be obtained from a larger population of identical wind turbines and longer measurement periods during which faults occur.

2.5.4 Oil quality monitoring systems

2.5.4.1 Equipment

The understanding of the effects of contamination (solid particles, water and air) on fluid systems has promoted fluid cleanliness monitoring to a front line maintenance technique. Studies have shown that between 55 and 70% of failures to fluid systems are caused by the presence of contaminants in the hydraulic fluid or lubricant, so this is still one significant area to remedy by the application of contamination control techniques.

It was foreseen that the following Pall Diagnostic Monitoring products were going to be built in into at least one of the N80 turbines:

A) The PCM200 series portable online fluid cleanliness monitor to measure contamination;

B) Water sensor probe WS05S to determine the percentage of saturation of the fluid and a temperature in °C;

C) The DeltaSense differential pressure transmitter to monitor the filter element service life.

With the online monitoring equipment timely preventive actions to restore the target oil cleanliness level can be taken, such as flushing the gear box using a filter element with a finer micron rate. These actions are relatively cheap and may well prevent consequence damage resulting in lower O&M costs. As the systems were not installed in the turbines, the benefits of online oil monitoring compared to periodic analysis oil samples offline could not be assessed.

2.5.4.2 Experience from other projects

As part of continued component cleanliness ′pass off‶ checks or predictive maintenance programs the PCM 200 and the Remaining Life Indicator monitors quickly reports test data so that ongoing assessments can be made.

Early detection of abnormal fluid cleanliness and consequently the increment of the differential pressure across the filter element allows for timely investigation and corrective actions to be implemented. Maintenance can be planned, days or weeks in advance, when the filter is close to blocking and when it is convenient.

In 2 wind turbines of 1.3 MW located in Northern Spain, the Oil Condition Monitoring has been installed, using Pall's equipment & service integration program. In one wind turbine the fluid cleanliness monitor PCM series has been installed and in the second wind turbine the Remaining Life Indicator monitor. The described equipment installed in both wind turbines since 4 years demonstrate a full reliability and availability compared with other wind turbines belonging to the same wind farm by significantly reducing operational and maintenance costs. This reduction is related to scheduled outages (production losses, component costs, labor cost, etc.) and unscheduled outages where it was necessary to change out the gear box.

The lube oil system cleanliness is one of the top causes of forced and unscheduled outages of the wind turbines. It represents a tremendous opportunity to apply an adequate state-of-the-art filtration and condition monitoring in order to improve reliability and availability of the wind turbines.

2.6 Assessed added value for O&M and cost benefits from CM

2.6.1 Baseline study ECN: Quantification of O&M aspects

To investigate the economic benefits of condition monitoring techniques on the expected O&M effort, cost estimates have been made for a fictitious but realistic offshore wind farm. As a starting point a fictive but realistic wind farm has been defined consisting of 100 turbines of 2.5MW with some adjustments for offshore, such as a small platform crane above the splash zone. The wind farm is located at the North Sea at 15km from a harbor from which the maintenance can be arranged. The wind- and wave conditions for the location “IJmuiden Munitiestortplaats” have been used. For the baseline configuration the failure rate is set to 4.5 failures per year per turbine, divided over 5 different maintenance categories of varying seriousness of this wind farm has been defined. For this baseline configuration the ECN cost modeling tools [42] have been applied to determine the long-term average effort and costs for maintaining the wind farm and to calculate the downtime and revenue losses.

2.6.2 Scenario studies ECN: contribution of CM-techniques on O&M

Next two different scenarios for condition monitoring have been considered. In the 1st scenario the effect of early fault detection is addressed, and it is assumed that for a number of failures the consequence damage can be limited by applying condition monitoring techniques (less severe Failure Repair Class). In this scenario it is assumed that in case of an alarm the turbine still has to be shut down. The effectiveness of the condition monitoring system has been considered by varying:

- the capability of early detection (non detected failures are set to 20%, 40% and 60%);
- the quality of the system (false alarms are set to 10%, 30%, and 50%);
- the fraction of failures that can be repaired in a less severe maintenance category, f.i. for the repair a simple supply boat is sufficient instead of a large crane ship and with less material costs.

In a second scenario it is assumed that after an alarm the turbines are inspected and based on the results of the inspection it is decided whether it is allowed to keep the turbine in operation for some time, so that the maintenance can be carried out at a suitable moment. This scenario is a further completion of scenario 1 with the following aspects is considered:

- the fraction of failures for which the repair can be postponed while the turbine is kept in operation (fraction is set to 20%, 40% and 60%);
- the period during which the turbine can be kept in operation after a degradation has been detected (delays of 1, 3, 6 and 12 months).

For the baseline the availability has been calculated as 90.0%, which corresponds with a revenue loss of about € 70,000.- per year per turbine. The costs of repair amount to 0.29 €ct/kWh. All variants for both scenarios have been analyzed by the ECN costs modeling tools also, where the results have been split up for the main systems (gearbox, generator, etc.). As the results of these analyses strongly depend on the assumptions made for the baseline, the effect for the different variants is calculated as the relative improvement as compared to the baseline. As an example of scenario 1 the reduction in revenue losses and the reduction in repair costs for the gearbox are depicted in Figure 2.38.

The reduction is given as function of the fraction of non-detected failures, and the number of false alarms, while the fraction of failures that can be shifted to a less severe maintenance category equals 60%. Based on these type of analyses decisions can be made about the technical requirements to be demanded for a condition monitoring system in relation to investments to be made to install and operate such a system. In [20] and [43] this study has been reported in detail.

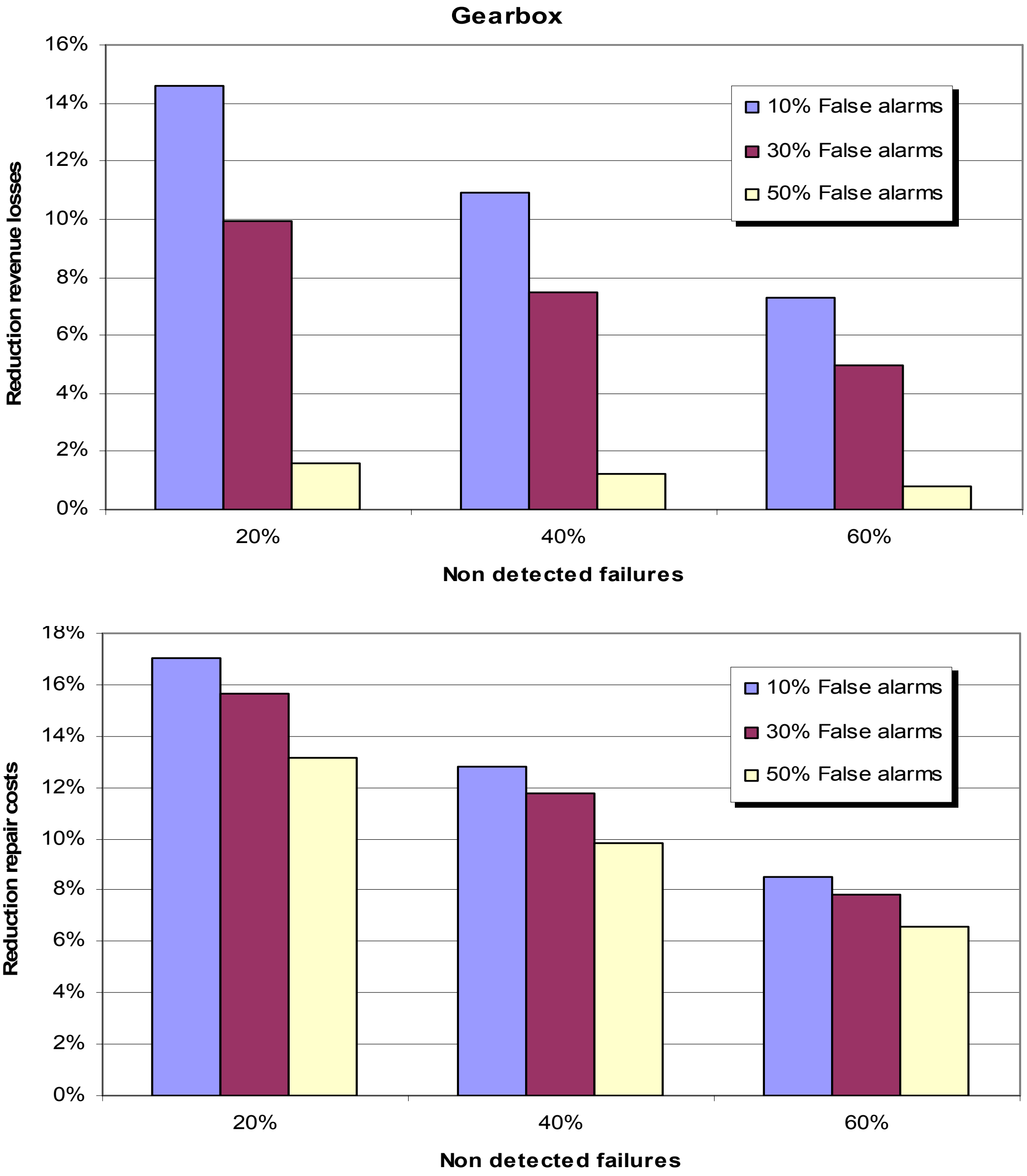


Figure 2.38: Relative reduction in revenue losses and repair costs as function of the fractions of non-detected failures and false alarms. The fraction of failures that can be shifted to a less severe maintenance category is set to 60%.

From this economic assessment no general conclusions can be drawn on the benefits of condition monitoring system, but the method is able to quantify the added value taking into account aspects like false alarms, the capability of early detection, the fraction of failures that can be repaired in a less severe maintenance category, and the fraction of failures for which the repair can be postponed. Based on these type of analyses decisions can be made about the technical requirements to be demanded for a condition monitoring system in relation to investments to be made to install and operate such a system.

2.6.3 Availability modeling for wind farms with condition monitoring Risø

In [43] simulations of Risø are reported that give some indication of the improvements in availability of a wind farm, when some of the turbine components are condition monitored. Two examples of simulations are described, i.e. the Rødsand wind farm with different measures of condition monitoring under the influence of the climatic model from [44] and the same wind farm placed under the climatic conditions of Horns Rev.

For the Horns Rev case using a large ship as the maintenance platform, the result is as follows:

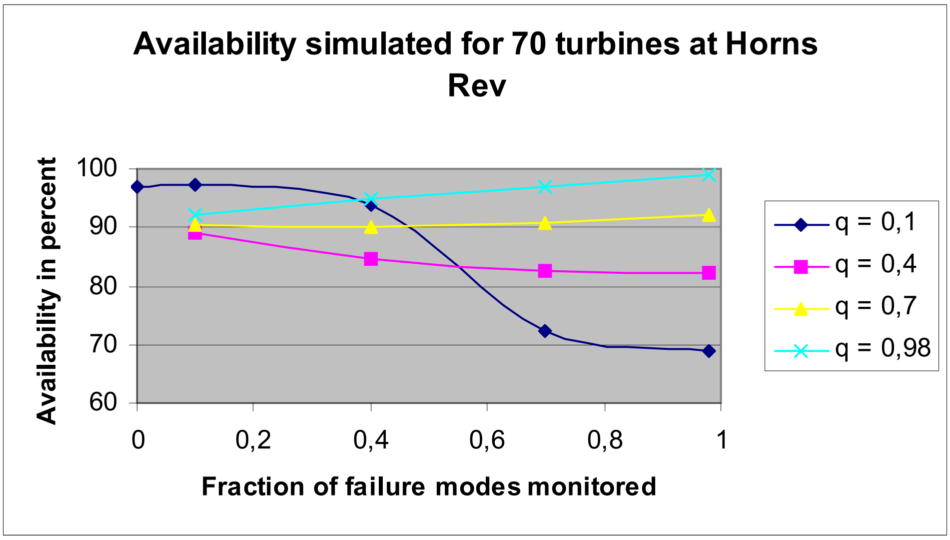


Figure 2.39: Simulated availability for Horns Rev. q is the CMS hit rate.

For a realistic CM-system having a detection rate of 70% or better, availability increases with the number of monitored modes. For bad CM-systems leading to a high frequency of standstill of the turbines, monitoring more failure modes actually increases the standstill time so much that not having that system is better. A very encouraging result is the large increase in availability for the near-perfect CM-system (q=0.98) when most failure modes are monitored. In this case, the availability can be nearly 99%, which is a strong increase from the about 90% without a CM-system.

3 Assessment of results and conclusions

3.1 Inventory of CM-techniques

The State-of-the-art report resulted in a selection of promising CM-techniques for wind energy. The FMEA proved to be an effective method to assess which condition monitoring system can be used for which kind of component failure.

3.2 Contribution of signal processing to improvement of CM-techniques

The developed algorithms for analysis of high frequency measurements based on wavelets, focused on the electrical power signal. Using these algorithms a drive train misalignment in the Nordex N80 turbine 8 has been detected. Although this is a promising result, extensive validation of these algorithms is required before implementation. Future developments should also be focused on diagnosis of the failure cause and prognosis of the failure development.

Analysis of SCADA data is regarded as very useful, as these data are readily available and implementation is likely to be straightforward. Several standard analysis techniques (partly automated) are available and showed to facilitate data interpretation; however this remains difficult for several reasons. First the data is meant for turbine control and operation, rather than for failure diagnosis and prognosis. Secondly detailed information on the measurements, e.g. location, sensor type, quality control and actual settings are mostly not available.

From analyzed generator bearing temperatures as well as several other signals shaft misalignment problems have been detected in the GE 1.5 S turbine as well as in the Nordex N80 turbine 8.

A generic implementation scheme for several signal processing techniques has been presented.

Simulation of faulted conditions showed that rotor imbalances can be detected from several periodic signals, e.g. electrical power and nacelle vibrations. The simulations were hampered by insufficient turbine information, e.g. actual controller settings and limited quality of some measurement signals and the unavailability of individual blade load measurements.

3.3 Experiences with vibration monitoring systems

At the ECN Wind turbine Test site Wieringermeer five CM-systems have been applied in combination with other measurement systems during a period of around 1.5 years.

With the application of vibration monitoring systems a misalignment of the high speed shaft was diagnosed in turbine 8, providing details on the cause of the problem including indications of damage to components. The CM-systems also showed that no drive-train problems were present in the other four Nordex N80 turbines, as all signals stayed below the warning levels and did not show significant increase during the monitoring period.

The novel Signal Fault Detection algorithm of Gram&Juhl has been applied successfully in their TCM system. Although no faults have occurred in the turbine it was not possible to demonstrate real use of the Fault Signature detection method, the benefits of this technique have been demonstrated in other wind turbine applications.

Prűftechnik has demonstrated that their VIBNODE® system, which is cheaper than their certified VIBROWEB XP® system, is capable of detecting premature faults. As data is acquired in all operating states and data is processed locally, the VIBNODE® system provides extra information of the turbine outside the 2 operating states which are defined for certified systems.

Both Gram&Juhl and Prűftechnik have applied displacement sensors as well as acceleration sensors suitable for low frequencies combined with increased resolution data acquisition techniques, which has improved the failure detection at the low-speed stage.

3.4 Benefits of CM-techniques

Up till now, the response on abnormalities in data from CM-systems is either more frequent inspections or an immediate shut down to avoid consequence damage. Within the CONMOW project it was concluded (and also confirmed by experiences outside the project) that at present insufficient knowledge is available to make prognoses how the failures will develop in order to change from calendar based maintenance to condition based maintenance. Such knowledge can only be obtained from a larger population of identical wind turbines and longer measurement periods during which faults occur.

For all types of measurements (SCADA data, time series, vibration monitoring) it is concluded that large amounts of data are being produced which are difficult to interpret by wind farm operators. One is dependent on a dedicated expert team to derive meaningful recommendations for O&M optimization.

An economic assessment has been carried out to determine the benefits of condition monitoring systems. In fact, general conclusions cannot be drawn from this, but the method is able to quantify the added value taking into account aspects like false alarms, the capability of early detection, the fraction of failures that can be repaired in a less severe maintenance category, and the fraction of failures for which the repair can be postponed. Based on these types of analyses decisions can be made about the technical requirements to be demanded for a condition monitoring system in relation to investments to be made to install and operate such a system.

Configuration of CM-systems still requires significant effort. Standards for communications can contribute to easier installation and improved compatibility of CM-provisions.

3.5 Dissemination

The following dissemination activities can be reported as a result of the CONMOW project.

CREST has submitted a journal paper in “IEEE Transactions on Energy Conversion”, a conference poster and paper and produced a paper for an industry magazine [19].

ECN has presented a poster presentation at EWEC 2006 and in 2007 a paper was presented at the EWEC2007, [21] and has been submitted to the Journal of Solar Energy Engineering (JSEE).

In 2006 ECN has made a presentation on the Dutch Wind Workshops with about 30 international participants including manufacturers, operators, utilities and researchers [22].

Risø participates in the IEC standardization effort IEC 61400-25-6, Communications for monitoring and control of wind power plants – Logical node classes and data classes for condition monitoring. In September 2006, the group published the first Community Draft, with a probably publication date in 2008.The standard, together with the related standards 61400-25-1 to 5 "Communications for monitoring and control of wind power plants" will allow CM-system manufacturers to have one well-defined interface to the SCADA system of any turbine or wind farm, and will be able to plug their data seamlessly into the same information architecture.

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5 References

[1] Durstewitz, M. et.al.: “Wind Energy Report Germany 2001; *“Annual Evaluation of WMEP”*; ISET, Germany 2002

[2] Energie- og Miljødata (EMD), *“Database with energy production figures, incidents and accidents.”*

[3] BTM Consult: “*World Market Update 2001”,* (Ch. 6). Denmark, March 2002.

[4] *"Concerted Action on Offshore Wind Energy in Europe"*, Report no. DUWIND 2001.006, Delft University of Technology, December 2001

[5] Bundesverband Windenergie: “*Market Survey 2001*”

[6] Refeld, K. et. al.: “*Untersuchungen der Aktuellen Kostensituationen der Windenergienutzung in Deutschland*”; DEWEK 2000, Wilhelmshaven, Germany, 07-08 June 2000.

[7] Braam, H., Rademakers, L., Zaaijer, M., and van Bussel, G.: *"Assessment and Optimization of Operation and Maintenance of Offshore Wind Turbines"*, Proceedings EWEC 2003, Madrid 16 - 19 June 2003

[8] Hendriks, H.B. and Zaaijer, M.: *"DOWEC: Executive Summary of the Public Research Activities ECN and TUD"*, January 2004

[9] Kooijman, H.J.T. et al; "*Cost and Potential of Offshore Wind Energy on the Dutch part of the North Sea*." Paper presented at the 'EWEA Special Topic Conference' in Brussels, 10-12 December 2001. ECN-RX--01-063, Petten, December 2001

[10] Barthelmie, R. et al: *"State of the Art and Trends Regarding Offshore Wind Farm Economics and Financing";* Paper presented at the 'EWEA Special Topic Conference' in Brussels, Risø, 10-12 December 2001

[11] C-Power: *"Belgian Offshore Wind Energy Park Wenduinebank (North Sea)"*; Paper presented at the 'EWEA Special Topic Conference' in Brussels, 10-12 December 2001

[12] http://www.offshore-sea.org.uk/site/scripts/documents_info.php?documentID=6&pageNumber=2

[13] BTM Consult: *"International Wind Energy Development; World Market Update 2005";* Denmark, March 2006.

[14] Rademakers, L.W.M.M., Braam, H. and Verbruggen, T.W.; "*R&D needs for O&M of Wind Turbines*", Paper presented at the O&M Workshop of EWEC 2003, Madrid.

[15] Kühn, M. et al: *"Opti-OWECS Final Report; volume 0 through 5*"; Report no. IW-98139R Delft University of Technology, 28 August 1998

[16] Bengtsson, M. (Mälardalen University, Sweden): *"Condition Based Maintenance System Technology - Where is Development Heading?",* Euromaintenance 2004, Proceedings of the 17th European Maintenance Congress, 11-13 May 2004, Barcelona, Spain

[17] Davies, A., editor: "*Handbook of Condition Monitoring; Techniques and Methodology*"; Chapman & Hall, 1998, ISBN 0 412 61320 4

[18] Cozens, N. J. and Watson, S. J: *"State of the art condition monitoring techniques suitable for wind turbines and wind farm applications"*, CONMOW project report, public, 2003.

[19] Watson, S. J. Infield, D. G. and Xiang, J: *"Condition Monitoring of Wind Turbines – Measurements and Methods"*, submitted to IEEE Transactions on Energy Conversion, 2006.

[20] Wiggelinkhuizen,E.J., Watson,S.J., Giebel,G., Norton,E., Tipluica,M.C., Becker,E., Christensen,A.J., *"Conmow Technical Annexes and Management Final Report"*, ECN-X--07-078, June 2007

[21] Wiggelinkhuizen,E.J., Verbruggen,T.W, Rademakers,L.W.M.M., Braam,H., Watson,S.J., Xiang, J., Giebel,G., Norton,E., Tipluica,M.C., Becker,E., Christensen,A.J., Scheffler,D. *"CONMOW: Condition Monitoring for Offshore Wind Farms"*, ECN-M--07-037, May 2007

[22] Wiggelinkhuizen,E.J.,*" CONMOW: Condition Monitoring for Offshore Wind Farms"*, Proceedings Dutch Wind Workshops, Oct. 2006

[23] G. C. Larsen, A. M. Hansen and O. J. D. Kristensen, *"Identification of Damage to Wind Turbine Blades by Modal Parameter Estimation"*, Risø National Laboratory, Roskilde, Denmark, Technical Report Risø-R-1334(EN), 2002.

[24] B. F. Sørensen et al., *"Fundamentals for remote structural health monitoring of wind turbine blades – a preproject"*, Risø National Laboratory, Roskilde, Denmark, Technical Report Risø-R-1336(EN), 2002.

[25] R. Errichello and J. Muller, *"Application requirements for wind turbine gearboxes"*, National Renewable Energy Laboratory, Golden, CO, USA, Technical Report NREL/TP-442-7076, 1994.

[26] Jeffries W Q, Chambers J A, Infield D G, Coonick A H, Freris L L (1996), *"Condition monitoring of wind turbine blades via electrical power output"*, Proceedings of the European Union Wind Energy Conference, Gotenburg, Sweden, May 1996

[27] Caselitz, P., Giebhardt, J.: *"Rotor Condition Monitoring for Improved Operational Safety of Offshore Wind Energy Converters"*, Journal of Solar Energy Engineering, Volume 127, Issue 2, pp. 253-261, May 2005

[28] Hans-Peter Waldl, Ubbo de Witt: *„Online-Fernüberwachung von Windturbinen mittels Internet und Video"*,http://www.cleverfarm.com/docs/video-paper-dewek2000-ig-lv-with-head.pdf

[29] Leaney, V.C., Sharpe,D.J. & Infield, D.G.: *"Condition Monitoring Techniques for Optimization of Wind Farm Performance"*, International Journal of COMADEM, 1999, pp 5-13, ISSN 1363-7681

[30] T.W. Verbruggen, H. Braam: "*Generic failure modes relevant for condition monitoring"*, Conmow report TEC-04-01, public, Rev. 1, April 2004

[31] Yang, S. J., *"Low-noise electrical motors"*, Oxford: Clarendon Press, 1981

[32] Vas, Peter, *"Parameter estimation, condition monitoring, and diagnosis of electrical machines."*, Oxford : Clarendon Press, 1993

[33] T. Thiringer, *"Periodic Pulsations from a Three-Bladed Wind Turbine"*, IEEE Transactions on Energy Conversion, vol. 16, No. 2, June 2001.

[34] Chin-shun Tsai, Cheng-Tao Hsieh, Shyh-Jier Huang, *"Enhancement of damage-detection of wind turbine blades via CWT-based approaches"*, IEEE Transactions on Energy Conversion, vol. 21, Issue: 3, pp. 776- 781, Sep 2006.

[35] Shyh-Jier Huang, Cheng-Tao Hsieh, *"High-impedance fault detection utilizing a Morlet wavelet transform approach"*, IEEE Transactions on Power Delivery, Vol, 14, Issue: 4, pp. 1401- 1407, Oct 1999.

[36] P.J. Eecen: *"Wind Farm Monitoring, Reduction and presentation of SCADA data for decision support systems."*, ECN report ECN-X--07-025, May 2007

[37] Jette Lundtang Paulsen, Steen Weber, *"ConMow -Data Analysis Multivariate Regression Analysis"*, Risø-I-2569(EN)

[38] Ed Norton, *"Condition Monitoring for Offshore Wind Farms (CONMOW), Final Report, Annex D: Results from Garrad Hassan"*, 3418/BR/01, March 2007.

[39] P. Dalhoff, T. Muuss: "*Richtlinie für die Zertifiziering von Conditon Monitoring Systemen für Windenergieanlagen*", Germanischer Lloyd, 2003.

[40] Axel Juhl, *"Fault Signature Detection"*, Gram & Juhl A/S, paper, May, 9, 2007

[41] Dr. Edwin Becker, Roland Schűhle, *"Condition monitoring on 'small' systems up to 1500kW"*, *Erneuerebare Energien*, Ed. 6/2006.

[42] H. Braam, L.W.M.M. Rademakers: *"Scenario study on the effects of condition monitoring on the O&M costs of an offshore wind farm"*, ECN report ECN-X--07-036, April 2007.

[43] Palle Christensen and Gregor Giebel: *"Availability modeling for wind farms with condition monitoring"*, Risø-I-2573(EN)

[44] Christensen, P.; Paulsen, J.L.; Thøgersen, M.L.; Krogh, T.; Raben, N.; Donovan, M.H.; Jørgensen, L.; Winther-Jensen, M., *"Pålidelighedsmodel for havvindmølleparker."* Risø-R-1346 (Danish) (2002)