THESIS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY

On maintenance optimization for offshore wind farms

FRANÇOIS BESNARD

Department of Energy and Environment
Division of Electric Power Engineering
Chalmers University of Technology
Gothenburg, Sweden 2013

On maintenance optimization for offshore wind farms
FRANÇOIS BESNARD
ISBN 978-91-7385-822-9

Doktorsavhandlingar vid Chalmers tekniska högskola
Ny serie nr 3503
ISSN 0346-718X

Division of Electric Power Engineering
Department of Energy and Environment
Chalmers University of Technology
SE-412 96 Göteborg, Sweden
Telephone + 46 (0)31-772 1000

Chalmers Bibliotek, Reproservice
Gothenburg, Sweden 2013

Abstract

The maintenance cost is known to be an important part of the levelized cost of energy generated by wind parks. Operational costs can be significantly reduced by optimizing decisions for maintenance strategies, maintenance support organization and maintenance planning. This is especially important for offshore wind power systems to reduce the high economic risks related to the uncertainties in the accessibility and reliability of wind turbines.

This thesis proposes decision models for cost efficient maintenance for offshore wind power systems. The economical benefits of condition based maintenance strategies are evaluated for drive train and for blades of wind turbines. A model is presented to optimize the inspection interval for the blade. Models are proposed to perform cost-benefit analysis of the maintenance support organization by evaluating the benefit of logistic and personnel planning on availability. The maintenance planning of service maintenance activities is optimized by taking advantage of opportunities arising at low wind or when corrective maintenance activities are necessary.

The models are tested in case studies with real environmental, reliability and cost data when available, and sensitivity analyses are performed for the parameters of interests. The results show that the proposed models can be used to reduce the maintenance costs through optimizing the maintenance strategies, the support organization and the maintenance planning.

Index Terms: Offshore wind energy, maintenance, reliability, optimization, life cycle cost, maintenance strategy, maintenance support organization, maintenance planning.

Acknowledgement

This report is part of the Ph.D. project "Reliability modeling and optimal maintenance management for wind power systems" funded by the Vindforsk III research program. The financial support is gratefully acknowledged.

I would like to thanks the following people for their contribution to this work:
Prof. Lina Bertling for giving me the opportunity to carry out this work and for all her support and encouragement.

Dr. Katharina Fischer for her friendship, and her thorough comments who helped to shape this work.

All my colleagues at Vattenfall, and especially Thomas Stalin for introducing me to the real world of offshore wind power and for his support on reliability and maintenance data, and Pär Attermo for interesting discussions and comments on reliability and maintenance modeling.

Prof. Michael Patriksson, Dr. Ann-brith Strömberg and Dr. Adam Wojciechowski for many good input and interesting discussions on opportunistic maintenance.

All the members of my reference group for their comments on my work; Anders Björck (Elforsk), Maria Danestig, Linus Palmblad and Angelica Pettersson (Energimyndigheten), Solgun Furnes (Energi Norge), Sven-Erik Thor, Thomas Stalin and Fredrik Carlsson (Vattenfall), Per Carlsson (Göteborg Energi), Gunnar Olsson Sörell (Fortum), Inge Aasheim (SKF) and Jørn Heggset (SINTEF).

I am grateful to all my colleagues at Chalmers and especially; Pramod, Chris, Peyuian, Miguel, Massimo and my previous colleagues at the RCAM research group at KTH; Patrik, Johan, Carl Johan, Johanna, Tommie and Andrea.

A special thanks to Sharon, Natalia, Julia, Laura, Bertrand, Helen and especially Gaël and Dmitry. Their friendship was a light in the difficult times.

Finally I would like to thank my family for their love and support, and Loïc who filled my heart with joy every day.

François,
Gothenburg, February 2013

List of publications

Appended papers

This thesis is mainly based on the following Papers:

Papers related to maintenance strategies:

I. F. Besnard, J. Nilsson and L. Bertling, "On the Economic Benefits of using Condition Monitoring Systems for Maintenance Management of Wind Power Systems", *In proc. of IEEE conference PMAPS 2010*, Singapore, 14-17 June 2010.

II. F. Besnard and L. Bertling, "An Approach for Condition-Based Maintenance Optimization Applied to Wind Turbine Blades", *IEEE Transaction on Sustainable Energy*, 1(2):77-83, 2010

III. Besnard F., Fischer, K and Bertling L., "Reliability-Centred Asset Maintenance – A step towards enhanced reliability, availability, and profitability of wind power plants", *In proc. of the conference IEEE PES Innovative Smart Grid Technologies*, Gothenburg, Sweden, 10-13 October 2010.

Papers related to maintenance support organization:

IV. F. Besnard, K. Fischer and L. Bertling, "A model for optimization of maintenance support organization for offshore wind farms", Accepted for publication, *IEEE Transactions on Sustainable Energy*, October 2012.

V. F. Besnard and L. Bertling, "A Simulation Model for Reliability Evaluation of Maintenance Support Organizations for Offshore Wind Farms", submitted to *IEEE Transactions on Sustainable Energy*, November 2012.

Papers related to optimization of maintenance planning:

VI. F. Besnard, M. Patriksson, A.-B. Stromberg, A. Wojciechowski and L. Bertling, "An Optimization Framework for Opportunistic Maintenance of Offshore Wind Power System", *In Proc. of IEEE PowerTech 2009 conference*, Bucharest, Romania, 28 June - 2 July 2009.

VII. F. Besnard, M. Patriksson, A.-B. Stromberg, A. Wojciechowski, K. Fischer and L. Bertling, "A Stochastic Model for Opportunistic Service Maintenance Planning of Offshore Wind Farms", *In Proc. of IEEE Powertech conference*, Trondheim, Norway, 19-23 June 2011.

Additional papers not appended

The following papers have been published but not appended to the Thesis.

VIII. F. Fischer, F. Besnard and L. Bertling, “Reliability-Centred Maintenance for Wind Turbines Based on Statistical Analysis and Practical Experience”, *IEEE Transaction on Energy Conversion*, 27(1): 184-195, 2012.

IX. K. Fischer, F. Besnard, L. Bertling, ”A Limited-Scope Reliability-Centred Maintenance Analysis of Wind Turbines“, *In Proc. of the European Wind Energy Conference EWEA 2011*, Brussels, Belgium, 14-17 March 2011.

Abbreviations

CBM	Condition Based Maintenance
CM	Corrective Maintenance
CMS	Condition Monitoring System
CTV	Crew Transfer Vessel
LCC	Life Cycle Cost
MILP	Mixed Integer Linear Programming
MTTF	Mean Time To Failure
O&M	Operation and Maintenance
PM	Preventive Maintenance
RCAM	Reliability Centered Asset Maintenance
RCM	Reliability Centered Maintenance
SCADA	Supervisory Control And Data Acquisition
SHM	Structural Health Monitoring
TBM	Time Based Maintenance
WT	Wind Turbine

Content

Chapter 1

Introduction

1.1 Problem background

In the last decades, an increased awareness of the impact of human living on the environment has emerged in the world. In December 1997, the Kyoto protocol to the United Nation Convention on Climate Change was adopted in use to combat global warming. As of January 2009, 183 states had signed and ratified the protocol. The protocol is legally binding each signatory country to a national commitment to limit or reduce their greenhouse gas emission levels. In January 2007, the European Commission presented an independent commitment in a report titled “Energy Policy for Europe" [1]. The proposal aims at reducing the gas emission by 20% relative to the 1990 levels (previously 8% in the Kyoto protocol), with an obligatory target for at least 10% bio-fuel and 20% of renewable energy. A resource is said to be renewable if it is replaced by natural processes at a rate comparable or faster than its rate of consumption by humans. Sources of renewable energy are e.g. biomass, hydroelectric, wind, photovoltaic, concentrated solar or geothermal energy. Wind energy has been the strongest growing renewable source of energy in the world this last decade, particularly in Europe where wind energy accounted for 6.3% of the electricity generated, and 21,4% of the generating capacity installed in 2011 [2].

Despite high capital cost and operation and maintenance costs, the installed capacity of offshore wind power has increased rapidly in Europe from 800 MW installed at the end of 2006 to 3.8 GW at the end of 2011 and many offshore wind farms are expected to be built in the near future, especially in the UK, Germany, Denmark and the Netherlands [2]. The reasons for this trend are high wind resources, the availability of space, low visual and noise impact, better understanding of the economic risks and high financial incentives [3]. The target of the European Wind Energy Association is to reach 230 GW of installed wind power in Europe by the end of 2020, of which 40 GW shall be generated by offshore wind power plants [4].

1.1.1 Maintenance costs, reliability and future challenges

The maintenance cost is known to be an important part of the levelized cost of energy generated by wind parks. In particular offshore, operation and maintenance contributes between 15-30% of the cost of energy [5].

At the 160MW Horns Rev offshore wind farm located 20 km off the coast of Esbjerg in Denmark, the maintenance was estimated to contribute to as much as

40% of the life cycle cost due to early serial failures, as well as low investment costs compared to the current market. The main drivers of the maintenance costs were identified as being the major component replacements, major retrofits and refurbishment of major components and the logistic as depicted in Figure 1-1. While the major retrofit can only be tackled by reliability improvements, the maintenance strategy of the major components has a major influence on the costs of replacement and refurbishment.

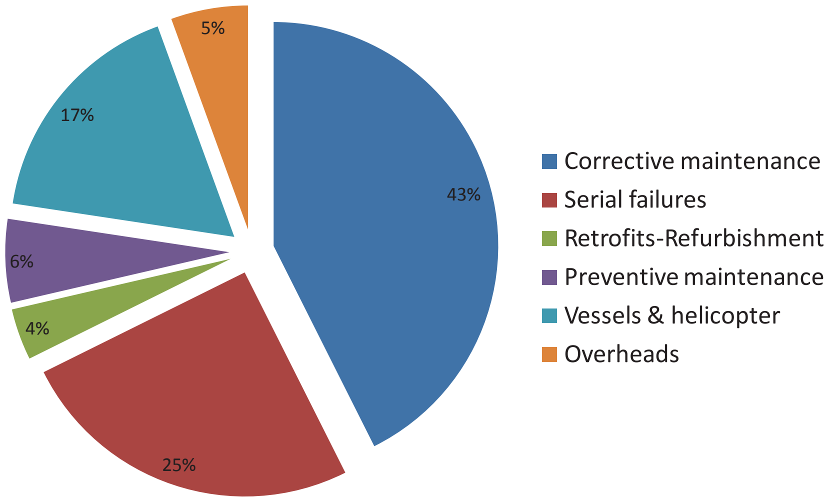

Figure 1-1: Estimation of O&M life cycle cost at Horns Rev wind farm. The costs have been estimated by the author with a modified version of the ECN O&M tool [6].

A challenging aspect of offshore wind farms is the logistic that needs to be planned according to the distance from shore and weather conditions at site. The transportation of maintenance technicians to the wind turbines must be performed by workboats, which are constrained by the wave height and may lead to poor accessibility resulting in long downtimes, or by a helicopter. Both alternatives are costly. The logistic and maintenance support organization for offshore wind farms will become even more crucial for the new projects being installed further from shore, in deeper water depth and harsher environment.

The reliability of onshore wind turbines has been reported in e.g. [7]-[10]. The availability of onshore wind turbines is typically in the range of 95-99% while for early offshore projects an availability as low as 60% has been observed at some wind farms due to serial failures and harsh weather conditions [11], [12]. This can also be observed in Figure 1-2. An interesting aspect of wind power compared to conventional electricity sources is the variability in the power production. In this respect, the energy-based availability is more representative of the actual production losses, and the planning of the scheduled maintenance activities should aim to maximize the energy-based availability.

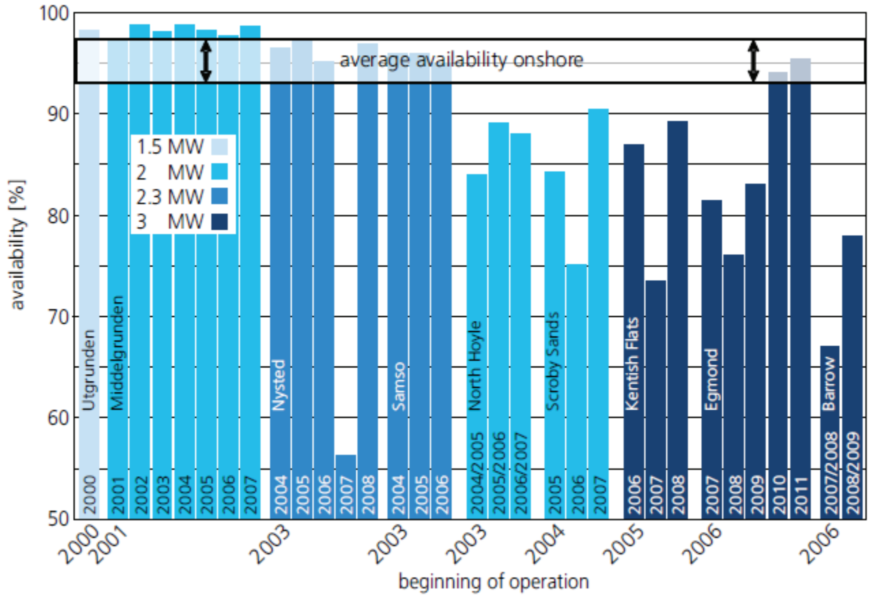

Figure 1-2: Availability per year for some offshore wind farms [12].

1.2 Related research projects

This PhD work was performed at the WindAM research group at Chalmers. A related project performed by Dr. Katharina Fischer within the WindAM group focused on the development of a quantitative model for failure prognosis based on information from Condition Monitoring Systems (CMS) for wind turbines [13]. In a similar area, Ph.D. student Pramod Bangalore focuses on failure prognosis and maintenance optimization based on information from Supervisory Control And Data Acquisition (SCADA).

This project was originally initiated by Prof. Lina Bertling at the RCAM research group at KTH. Several projects performed at the RCAM group have been focusing on developing quantitative approaches for maintenance optimization, reliability assessment and lifetime modeling. The RCAM methodology was first presented by Prof. Lina Bertling in [14]. Dr. Patrik Hilber presented his PhD thesis on maintenance optimization applied to power distribution systems in [15]. Dr. Tommie Lindquist presented his PhD thesis on life-time and maintenance modeling in [16]. Dr. Johan Setréus presented his licentiate thesis on reliability methods quantifying risks to transfer capability in electric power transmission systems in [17]. Dr. Carl Johan Wallnerström presented his PhD thesis on risk management of electrical distribution systems and the impact of regulations in [18]. Tech. Lic. Julia Nilsson presented her licentiate thesis on maintenance management for wind and nuclear power systems in [19]. Ph.D. student Johanna Rosenlind focuses on lifetime modeling for transformer [20].

1.3 Project objective

The objective of this PhD project has been to develop mathematical models for supporting decisions related to maintenance of wind farms, with a particular focus on offshore wind farms. In order to achieve the objective, the models have been developed based on industry needs and accessible reliability and cost data, and supported with case studies.

1.4 Main results and scientific contributions

The main scientific contribution of this thesis is the development of several maintenance optimization models case studies related to inter-connected areas:

- ***Optimal maintenance strategies*** with application to condition monitoring systems for the drive train and condition based maintenance for the blades (Papers I, II and III),
- ***Optimization of logistic and maintenance support organization*** applied to offshore wind farms (Papers IV and V),
- ***Optimization of the planning*** of scheduled maintenance activities for offshore wind farms based on weather forecasts and opportunistic maintenance (Papers VI and VII).

The optimization of maintenance strategies is based on stochastic Life Cycle Cost (LCC) models dependent on reliability and maintenance processes. The objective is firstly to optimize the implementation of the compared maintenance strategy, and secondly to compare the cost-benefit of the each maintenance strategies. The case studies demonstrate in which conditions the maintenance strategies are optimal, and what is the associated economic risk. Paper III consists of a summary of the state-of-the-art in Reliability Centered Maintenance (RCM) and cost-benefit analysis of maintenance strategies applied to wind power.

An analytical model for optimization of the maintenance support organization proposed in Paper IV considers several factors affecting the maintenance performance including the location of the maintenance accommodation and distance to the wind farm, the number and type of crew transfer vessels, the use of the helicopter and the work shift organization. The cost-benefit of the support organization is considering both the direct costs and indirect costs (production losses). The availability results are further analyzed in Paper V by a simulation model. The models were tested on a case study with real environmental data, reliability and cost data. The analytical and simulation models are compared and further improvements are suggested. A main conclusion is that the models are complementary, the analytical model enabling fast determination of the potential optimal support organization, and the simulation model enabling refinement of the modeling and risk analysis.

The objective of the proposed model for the optimization of the maintenance planning is to determine the optimal time for performing the scheduled maintenance activities, taking into account the cost of transportation and the production losses. The model is based on a rolling horizon taking into account the knowledge on short term weather forecasts and long term weather statistics, together with opportunities at corrective maintenance. The scheduling is constrained by the weather conditions and maximum time to perform the scheduled maintenance activities. A deterministic model is first presented in Paper VI, which was further developed in a stochastic model in Paper VII considering weather scenarios. The models were tested with real environmental data. The case studies demonstrate the cost-benefit of the approaches as compared to a classic time based approach.

Table 1-1: Summary of modeling approaches applied in the present work

Area		Reliability		Optimization	
		Analytical	Simulation	Classic	Enumerative
Maintenance strategy	Paper I	X	X		
	Paper II		X		X
Support organization	Paper IV	X			X
	Paper V		X		
Maintenance planning	Paper VI		X	X	
	Paper VI		X	X	

The modeling approaches used in the different models presented in this thesis are summarized in Table 1-1. Paper III was excluded since it presents a review of the state of the art in optimization of maintenance strategies in the wind industry.

1.4.1 Authors contribution

The author has written and contributed to the major parts of the appended Papers I-VII. Prof. Lina Bertling has contributed as the main supervisor for all papers with discussion of ideas and reviewing of the writing. Dr. Katharina Fischer has contributed in Paper III, and Papers IV-V and Paper VII with discussion of the ideas and reviewing of the writing. Prof. Michael Patriksson, Dr. Ann-Brith Strömberg and PhD Adam Wojciechowski at Chalmers have contributed with input ideas and reviewing for Paper VI and VII. Tech. Lic. Julia Nilsson has contributed with the writing in Paper I.

1.5 Thesis outline

This thesis is organized as an introduction and summary of the attached Papers.

Chapter 2 and Chapter 3 provide an introduction to reliability and maintenance theory. The basics for the mathematical and economical modeling of the maintenance problems are presented. The chapters are partly based on Paper III.

Chapter 4 focuses on maintenance strategy optimization applied to condition monitoring of the drive train and condition based maintenance for blades. The chapter summarizes the Papers I and II.

Chapter 5 focuses on the maintenance support organization. It presents an analytical model for optimizing the support organization and a simulation model complementary to the analytical model for further analysis of the results from the analytical model. The chapter summarizes Papers IV and V.

Chapter 6 describes two models for the optimization of the planning of the scheduled maintenance activities based on weather forecasting and opportunistic maintenance. The chapter summarizes Papers VI and VII.

The results of the thesis and proposal for future work are presented in Chapter 7.

Chapter 2

Introduction to reliability theory

This chapter provides the theoretical background to the reliability models and simulation methods used in the thesis. The chapter begins with some basic definitions, and an introduction to the different types of reliability modeling approaches. The probability distributions and stochastic processes models used in the thesis are then presented. The last section provides an introduction to simulation models. This chapter is partly adopted from Paper III.

2.1 Terminology

The following definitions of terms commonly used in reliability analysis are adopted from [21], [22]:

- *Reliability*: The ability of a component or system to perform required functions under stated conditions for a stated period of time.
- *Failure*: The termination of the ability of a component or system to perform a required function.
- *Maintenance*: The combination of all technical and corresponding administrative actions intended to retain an item in, or restore it to, a state in which it can perform its required function.
- *System*: A group of components connected or associated in a fixed configuration to perform a specified function.
- *Component*: A piece of electrical or mechanical equipment viewed as an entity for the purpose of reliability evaluation.

2.2 Models for failures

Reliability models aim at predicting the future failure behavior of a system or component. There are generally three types of approaches for reliability modeling, referred in this thesis as to:

- Black box models: Failure occurrence is modeled with a probability distribution of the time to failure [23]-[26];
- Grey box models: The deterioration process underlying the failure is modeled. This implies that the deterioration can be observed (classified or measured) directly or indirectly by relevant deterioration indicators. The mathematical model is often a regression model or a stochastic process. [27]-[30];

- White box models: The physical process behind the deterioration is modeled, using stress factor input (such as load) to estimate the deterioration of the system in time [31].

While black and grey box approaches involve comprehensive statistical data to validate the models, the white box approach requires detailed knowledge of the physical processes that lead to failures.

In this thesis, black box models are used in Papers I, IV, V and a grey box model is assumed in Paper II.

2.2.1 Black box models

In a black box models, the condition of a component can only be in two states: functioning and non-functioning. A black box model is a probability distribution of the time to failure, or, if the component is repairable, a stochastic process, i.e. a sequence of probability distributions for successive times to failure. If X_t denotes the random variable associated with the state of a component,

$$X_t = \begin{cases} 1 \text{ if the component is functioning at time } t \\ 0 \text{ otherwise.} \end{cases} \tag{2.1}$$

An example of a sequence of failure realizations is illustrated in Figure 2-1. A black box model assumes that the times to failure T_f^i are independent and identically distributed, and can be represented by a probability distribution. Similarly, the times to repair T_m^i can be represented by a probability distribution.

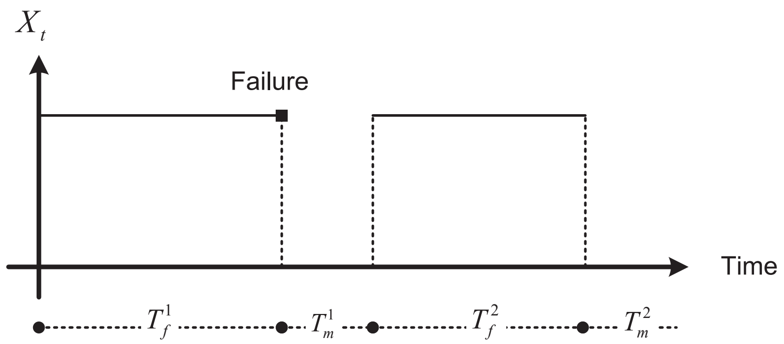

Figure 2-1: Relation between the condition variable X_t and the realization of times to failure T_f^i and time to repair T_m^i for the i^{th} failure.

2.2.2 Grey box models

Grey box models can be used if the underlying process and evolution of a failure, referred to as deterioration or degradation process, can be observed or simulated by a physical model. Figure 2-2 shows a general representation of a degradation process, known as P-F curve (where P is the abbreviation for Potential failure observable, and F for Failure). T_p represents the time until the failure is initiated and T_d the degradation time to failure, i.e. time between the initiation of a fault and the occurrence of a failure.

There are typically three main modeling approaches for grey box models:

- Three state models in which the time to potential failure T_p and time to failure T_d are represented as two probability distributions (also known as delay-time model) [32],
- Markov models with several degradation states which are suitable in case the deterioration is classifiable [30],
- Continuous stochastic processes, such as e.g. Wiener or Gamma processes [28], [29], which are useful when the deterioration is measurable.

The choice of the model depends on the physical process underlying behind the deterioration, as well as the level of information available on the condition of the system. A discrete state model is used in paper II.

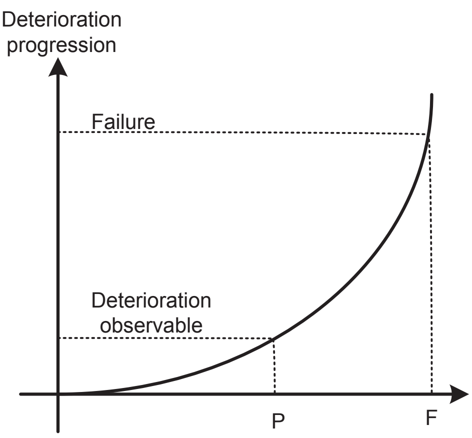

Figure 2-2: P-F curve concept. P represents the point in time when the indication of a potential failure can be first detected. F represents the point in time when the deterioration leads to a failure.

2.3 Probability distributions

This section presents the probability distributions that are used in this thesis. The reader is referred to the reliability books [23], [24], [26] and [29] for more information.

In this section, T is a stochastic variable representing a time to failure. The probability distribution function $F(t)$ is the probability that a component fails within the time interval $(0;t]$, i.e. $F(t) = P(T \le t)$. The derivative of $F(t)$ is the probability density function and is denoted $f(t)$:

$$f(t) = \frac{dF(t)}{dt} \tag{2.2}$$

The reliability function $R(t)$ is the probability that the component will not fail during the interval (0, t], i.e. $R(t) = 1 - F(t)$. The failure rate function $z(t)$ is the instantaneous probability of a failure at time t, provided that the item has survived until that time. It is defined as follows:

$$z(t) = \frac{f(t)}{R(t)} = \frac{f(t)}{1 - F(t)} \tag{2.3}$$

The Mean Time To Failure (MTTF) is a useful characteristic of failure probability distributions. It is defined as the expected value of the time to failure:

$$MTTF = E[T] = \int_{t=0}^{+\infty} t \cdot f(t)dt \tag{2.4}$$

Exponential distribution
The exponential distribution is a parametric probability distribution with a constant failure rate function denoted $\lambda > 0$ [23]:

$$\begin{aligned} & f(t) = \lambda \cdot e^{-\lambda t} \\ & R(t) = 1 - F(t) = e^{-\lambda t} \\ & z(t) = \lambda \\ & MTTF = \frac{1}{\lambda} \end{aligned} \tag{2.5}$$

The probability of failure does not depend on the age of the component. This property is often referred to as loss of memory.

Weibull distribution

The Weibull distribution is a parametric probability distribution with two parameters, the scale parameter $\alpha > 0$ and shape parameter $\beta > 0$ [23]:

$$\begin{aligned}
f(t) &= \frac{\beta}{\alpha} \cdot \left(\frac{t}{\alpha}\right)^{\beta-1} e^{-\left(\frac{t}{\alpha}\right)^{\beta}} \\
R(t) &= 1 - F(t) = e^{-\left(\frac{t}{\alpha}\right)^{\beta}} \\
z(t) &= \frac{f(t)}{1-F(t)} = \beta \cdot \frac{t^{\beta-1}}{\alpha^{\beta}} \\
MTTF &= \alpha \cdot \Gamma(\frac{1}{\beta} + 1)
\end{aligned} \tag{2.6}$$

where $\Gamma(x) = \int_{y=0}^{+\infty} e^{-y} y^{x-1} dt$ is the gamma function.

The exponential distribution is a special case of the Weibull distribution with $\beta = 1$. When $\beta > 1$, the failure rate increases with time which can represent the behavior of an ageing component.

2.4 Stochastic processes

Stochastic Processes are useful to model the deterioration process of a component or to model a sequence of failures (also referred to as counting processes). This section presents continuous time Markov chains used to model the deterioration process in Papers II, the queuing process in Paper IV, and the renewal counting process used in Papers I and V.

2.4.1 Continuous Markov Chains

A continuous time Markov chain is a stochastic process $X(t)$ defined by [23]:

- A finite or infinite discrete state space S;
- a sojourn time in state $i \in S$ that follows an exponential distribution with parameter λ_i;
- a transition probability p_{ij}, i.e. the probability that when leaving state i, $X(t)$ will enter state j, with $\sum_{j \in S} p_{ij} = 1$.

$\lambda_{ij} = p_{ij} \cdot \lambda_i$ is called the transition rate from state i to state j. Markov chains have the Markov property, i.e. the evolution of the process depends only on the present state and not on the states visited in the past:

$$\begin{aligned} \forall x(u),\ 0 \le u \le t,\ P\big(X(s+t) = j \big| X(s) = i, X(u) = x(u)\big) \\ = P\big(X(s+t) = j \big| X(s) = i\big) \end{aligned} \tag{2.7}$$

Let the Markov chain includes N states. Q denotes the transition matrix and $P(t)$ the vector probability for the states, with $\sum_{i \in S} p_i(t) = 1$,

$$Q = \begin{pmatrix} -\lambda_1 & -\lambda_{12} & \dots & -\lambda_{1N} \\ -\lambda_{21} & -\lambda_2 & \dots & -\lambda_{2N} \\ \dots & \dots & \dots & \dots \\ -\lambda_{N1} & -\lambda_{N2} & \dots & -\lambda_N \end{pmatrix},\ \mathrm{P(t)} = \begin{pmatrix} P_1(t) \\ P_2(t) \\ \dots \\ P_N(t) \end{pmatrix} \tag{2.8}$$

The Kolmogorov equation defines how to calculate $P(t)$ when $P(0)$ is known [23]:

$$P(t) \cdot Q = \frac{d}{dt} P(t),\ t \in [0, +\infty) \tag{2.9}$$

An asymptotic solution always exists to the Markov chain if it is irreducible, i.e. every state can be reached from another state. The asymptotic solution is denoted $P_\infty = (P_1, \dots, P_N)$. It is the solution of the system of equations:

$$\begin{cases} P_\infty \cdot Q = 0 \\ \sum_i P_i = 1 \end{cases} \tag{2.10}$$

In Paper II, the deterioration of the blade of a wind turbine is assumed to be classifiable and a Markov chain is used to represent the deterioration states. The evolution of the deterioration is evaluated on a finite time horizon by simulating state transitions using simulation. In Paper VI, the failure and maintenance process of a wind farm is modeled as a Markov chain solved in steady state. For more information on Markov models, the reader is referred to [23], [33] .

2.4.2 Counting processes

A counting process is noted $N(t),\ \mathrm{t} \ge 0$. It represents the number of event occurrences during the time interval $(0, t]$. The mean number of events in the same interval is denoted $W(t) = E[N(t)]$. The rate of the process (known as rate of occurrence of failures in reliability theory) is defined as the derivative of $W(t)$:

$$w(t) = W'(t) = \frac{dE[N(t)]}{dt} \tag{2.11}$$

Examples of counting processes are the Homogeneous Poisson Process (HPP), Non-Homogeneous Poisson Process, and Renewal Process [23].

Homogeneous Poisson Process

An HPP is a counting process whose inter-occurrence times are identically distributed and follow an exponential distribution with constant rate $\lambda > 0$. An interesting result for HPP is that the number of failures in an interval $(t, t+\Delta t]$ is Poisson distributed [23]:

$$P[N(t+\Delta t) - N(t) = n] = \frac{(\lambda \cdot \Delta t)}{n!} e^{-\lambda \cdot \Delta t} \tag{2.12}$$

An HPP is used in Paper V in order to simulate failure occurrences for a set of wind turbines during a given time period. It is assumed that the failure rate remains constant during this time period, although it is in reality dependent on the number of wind turbines in operation. The assumption can be justified by the fact that for large wind farms, the number of wind turbines and high availability should result in an almost constant occurrence rate for a short time period.

Renewal process

A renewal process is a counting process whose inter-occurrence times are identically distributed and are defined by a distribution function $F(t)$, reliability function $R(t)$ and probability density function $f(t)$.

In the context of maintenance modeling, it is of particular importance to consider if the component is repairable. If the component is non-repairable or the condition of the component after repair can be assumed as new, the maintenance can be modeled by means of a renewal process [23]. The modeling of repairs is an advanced subject that is discussed e.g. in [26], [34].

A renewal process is used in Paper I for estimating the number of failures of the components of the drive train of a wind turbine over its life time. The number of failures is estimated both by Monte Carlo simulation and directly with the following approximation.

Assume that the time is divided into steps indexed by $k \in \{1, 2, ..., N\}$ and at most one failure can occur during one time step. We would like to estimate the expected number of renewals during time step T. We assume that for all $k \in \{1,2,...,T-1\}$, $W(k)$ is known and we use the following approach to calculate $W(T)$.

It is assumed that the first renewal happened during the interval $[k;k+1]$. The probability of this event is $R(k)-R(k+1)$. If the renewal occurs, the average number of failures will be one plus the average number of failures during the remaining $T-(k+1)$ time steps, i.e. $W\left(T-(k+1)\right)$. By summing over all the possible time for the first failure events their probability multiplied by the expected number of failure occurrences, we obtain [25]:

$$W(T)=\sum_{k=0}^{T-1}\left[R(k)-R(k+1)\right]\cdot\left[1+W(T-k-1)\right] \tag{2.13}$$

Eq. (2.13) can be used recursively to approximate $W(t)$. The initial condition for the recursion is $W(1)=1-R(1)$ where Δt is the duration of a time step. The smaller the time step interval, the better the discrete approximation for $W(t)$. Once $W(k)$ is calculated, the discrete rate of the process is $w(k)=W(k)-W(k-1)$.

2.4.3 Simulation models

Simulations models are used for studying the reliability of complex systems when analytical tools cannot be used to calculate information of interest. The principle is to generate scenarios according to the stochastic variables of the model, and to calculate for each scenario the quantities of interest. A simulation method is used in Paper I to simulate sequences of failures, in Paper II to simulate the Markov chain deterioration model and in Paper V to simulate the failure occurrences and the usage of maintenance support organization accordingly.

The elementary task in the simulation is to generate random numbers for stochastic variables. A stochastic variable can e.g. be associated with events such as time to failures, time to perform maintenance, deterioration transition or number of failures during a given time period. The inverse sampling method, a procedure to generate realizations of random variables, is described below. For more information on simulation models, the reader is referred to [35] .

The inverse sampling method simply states that to simulate a realization of $F(t)$, one can first generate a sample x from a uniform distribution (using a pseudo-random number generator) and then calculate $t=F^{-1}(x)$. The value of t is then a realization of a stochastic variable with probability distribution $F(t)$.

Chapter 3

Introduction to maintenance and optimization theory

This Chapter provides a theoretical background to the maintenance optimization models proposed in this thesis. The first Section describes basic maintenance strategy concepts. This is followed by an introduction to qualitative and quantitative maintenance optimization. The last sections provide an introduction to the maintenance theory used in Papers IV and V and the economics used in the thesis. This chapter is partly adapted from Paper III.

3.1 Maintenance strategy concepts

Maintenance is defined as the combination of all technical and corresponding administrative actions intended to retain an item in, or restore it to, a state in which it can perform its required function [21]. Figure 3-1 shows a common classification of maintenance strategies which is based on the standard SS-EN 13306.

Corrective Maintenance (CM) is carried out after a failure has occurred and is intended to restore an item to a state in which it can perform its required function [21]. It is typically performed when there are no cost-effective means to detect or prevent a failure.

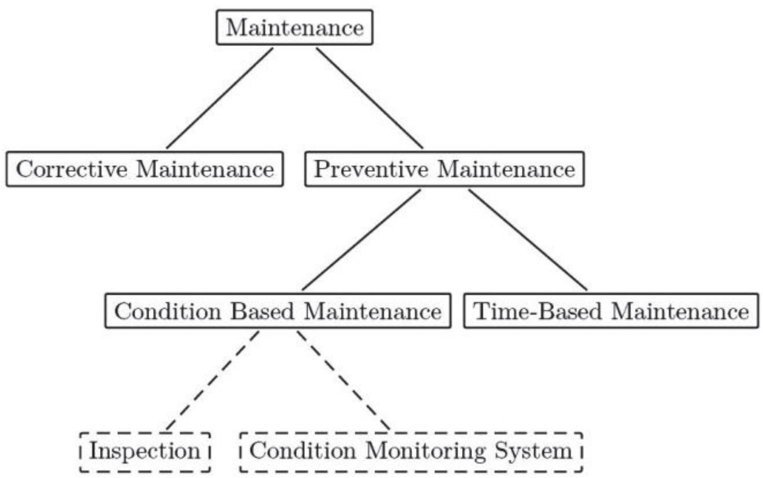

Figure 3-1: Types of maintenance strategies, partly adapted from [22].

Preventive Maintenance (PM) is carried out at predetermined intervals or corresponding to prescribed criteria, and intended to reduce the probability of failure or the performance degradation of an item [21]. There are two main approaches for preventive maintenance strategies:

- Time Based Maintenance (TBM) is preventive maintenance carried out in accordance with established intervals of time or number of units of use but without previous condition investigation [22]. TBM is suitable for failures that are age-related and for which the probability distribution of failure can be established.
- Condition Based Maintenance (CBM) is preventive maintenance based on performance and/or parameter monitoring [22]. CBM consists of all maintenance strategies involving inspections or permanently installed Condition Monitoring Systems (CMS) to decide on the maintenance actions. Inspection can involve the use of human senses (noise, visual, etc.), monitoring techniques, or function tests. CBM can e.g. be used for non-age related failures if the activity has the ability to detect/diagnose the degradation in time in a cost-effective manner.

The ability to detect the deterioration in time is linked to the concept of the P-F curve, which represents a typical deterioration of the condition of a component in time, as shown in Figure 2-2.

A CBM strategy is effective if it can observe the deterioration sufficiently in advance and ideally give a prognosis of the time to failure, in order to schedule a repair/replacement of the component before failure. This has the advantage to minimize downtime cost and often reduce further secondary damage.

If no cost-effective maintenance strategy exists for critical components or failures, design/manufacturing improvement should be considered in order to increase the inherent reliability of the component.

3.2 Reliability centered maintenance

RCM is a qualitative approach to determining suitable maintenance strategies being widely established and successfully applied in a variety of industries. This systematic risk-based method aims at optimizing maintenance achievements in order to preserve the functions of a system, also called physical asset. RCM is summarized in [23] as a systematic analysis of system functions and the way these functions can fail and a priority-based consideration of safety and economics that identifies applicable and effective preventive maintenance tasks.

A comprehensive introduction to the RCM method is given in [36], which summarizes the key attributes of RCM in seven basic questions:

1. What are the functions and associated desired standards of performance of the asset in its present operating context?
2. In what ways can it fail to fulfill its functions?
3. What causes each functional failure?
4. What happens when each failure occurs?
5. In what way does each failure matter?
6. What should be done to predict or prevent each failure?
7. What should be done if a suitable proactive task cannot be found?

Reliability Centered Asset Maintenance (RCAM) is an approach that brings together RCM with quantitative methods for reliability and maintenance modeling and maintenance optimization. RCAM was presented in [14] and it has been applied to distribution and transmission power systems in [15]-[16], [18].

A RCM analysis was presented in the additional Papers VIII and IX based on failure statistics and expert judgment for the most critical systems of wind turbines. The papers discuss the functional failures, their causes and underlying mechanisms, and identify remedial measures in order to prevent either the failure itself or critical secondary damage. RCAM is discussed in the context of wind power in [13] and in Paper III.

Other qualitative management methods for maintenance optimization, e.g. work and performance management and team based management, are described in [37].

3.3 Quantitative maintenance optimization

Quantitative maintenance optimization refers to the utilization of mathematical models with the aim to find the optimal balance between the costs and the benefits of maintenance while taking relevant constraints into account [38]. The main purpose of quantitative maintenance optimization is to assist the management in decision making, by utilizing available data and thus reducing reliance on subjective judgment of experts [25].

There are several inter-related maintenance decision areas:

- *Maintenance strategies* related to the identification of suitable maintenance concept for the components of the system according to their failure behavior, probabilities, and consequences, e.g. run-to-failure, fixed replacement strategies, inspection based or condition monitoring based maintenance, see Figure 3-1; Papers I-III focus on maintenance strategies.
- *Maintenance support organization* related to the optimization of the resources required to perform the maintenance, e.g. the size of the maintenance staff, the transportation strategy for the technicians and spare parts, the buy/lease of maintenance equipment or the spare part management; Papers IV and V focus on the maintenance support organization.

- *Maintenance planning* is related to the implementation of the maintenance strategy on a day-to-day basis, e.g. prioritization and planning of maintenance tasks with respect to the available maintenance crew, spare part and maintenance equipment; Paper VI and VII focus on maintenance planning.

The alternative decisions are evaluated according to an optimization criterion (e.g. availability, cost, safety, or environmental risks) with respect to possible constraints (e.g. costs, manpower, and time to perform an activity). In this thesis, the maintenance is optimized based on cost criteria with consideration for safety constraints if applicable. The costs consist of direct costs for the spare part, maintenance equipment and maintenance staff required for correcting the failures, as well as indirect costs due to production losses.

Maintenance optimization is a wide and active field of operation research. Introductions to the subject can be found in [23]-[26]. Models can generally be classified according to the type of issue investigated, the system (single/multi-components) and the horizon framework (finite/infinite, mixed/rolling). The reader is referred to [39]-[42] for general reviews and [43]-[47] for reviews on multi-components models.

An interesting concept is the one of opportunistic maintenance. It is defined as PM that can be performed at opportunities that arise randomly, independently or dependently of the components in the system [39]. The idea and models for two components are discussed in [26] and multi-component opportunistic models have been proposed, e.g. in [39] and [45]. In practice, opportunistic maintenance implies that the maintenance scheduling and planning is flexible, i.e. that the maintenance manager updates the planning when opportunities arise to perform the PM activity. Opportunistic maintenance for wind farms is the subject of Papers VI and VII.

3.4 Optimization theory

3.4.1 Optimization

The classic objective of mathematical optimization is to solve problems of the form

$$\min_{x \in X} f(x) \tag{3.1}$$

where x represents the vector of decision variables, $f(x)$ an objective function and X is the set of feasible solutions. The feasible set can often be defined with equality and inequality constraints of the form

$$\begin{aligned} g_i(x) &= 0, \ \mathrm{i} \in \mathrm{M} \\ g_i(x) &\leq 0, \ \mathrm{i} \in N \end{aligned} \tag{3.2}$$

where M and N are indexed sets. An optimal solution x^* is a feasible solution that satisfies:

$$f(x^*) \leq f(x), \ \forall x \in X. \tag{3.3}$$

It depends on the form of the objective function and the feasible set which optimization method is the most appropriate to determine the optimal solution. The next section provides an introduction to methods for solving linear and integer optimization problems, i.e. models in which the objective and constraint functions are linear and the decision variables can be continuous and/or integer valued.

3.4.2 Mixed Integer Linear Programming

Every linear optimization problem can be given in, or transformed into a standard form as follows:

$$\begin{aligned} \text{minimize} \ \ & c'x \\ \text{subject to} \ \ & Ax = b, \\ & x \geq 0. \end{aligned} \tag{3.4}$$

Herein, $x \in \mathbb{R}^n$ is the decision variable, $c \in \mathbb{R}^n$ is called cost vector and $\mathrm{A} \in \mathbb{R}^n \times \mathbb{R}^m$ and $b \in \mathbb{R}^m$ are data describing the linear constraints of the problem.

In this form, if the feasible set is nonempty and the optimal solution is finite, it can be shown that if there is an optimal solution, there is an optimal solution that is an extreme point of the feasible set [48]. Another possibility is that the optimal solution is $-\infty$. Figure 3-2 and Figure 3-3 illustrate the two possibilities on simple problems formulated in general form. Efficient methods have been developed to search for an optimal extreme point, e.g. the simplex method.

The simplex method exploits the geometry of the feasible set to move from one extreme point to another with a lower cost. Once a feasible extreme point has been identified, the algorithm searches for a feasible direction along a facet of the feasible set that reduces the cost function. The algorithm goes from one extreme point to a neighboring one, and continues until either there is no other feasible direction that can reduce the cost function (the current extreme point is then an optimal solution) or an unbounded feasible direction is found (in this case the optimal solution is $-\infty$). In the example in Figure 3-2, if the algorithm starts at corner a, it can follow the path a, b, c or a, d, c, depending on the search criteria for the direction. The reader is referred to [48] for details on the implementation of the simplex method and an introduction to the class of interior point methods, useful for very large problems.

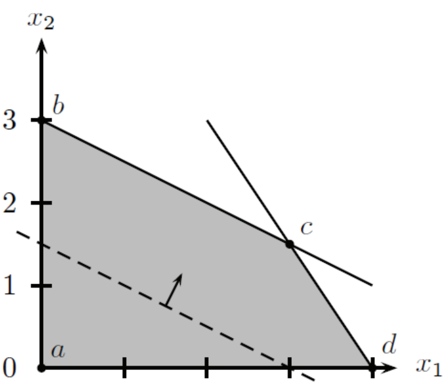

Figure 3-2: Graphical representation of the problem $\min -x_1 - x_2 \; s.t. \; x_1 + 2x_2 \le 6$. . $3x_1 + 2x_2 \le 12,\; x_1, x_2 \le 0$. The extreme point c is the optimal solution.

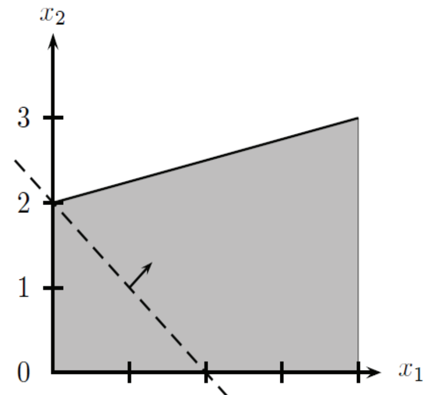

Figure 3-3: Graphical representation of the problem $\min -x_1 - x_2 \; s.t.$ $-x_1 + 4x_2 \le 12,\; x_1, x_2 \le 0$. There is no optimal solution in this case.

A Mixed Integer Linear Programming problem (MILP problem) is a problem with both integer and continuous variables. For example, $x_i \in \{0,...,k\}$ is a bounded, non-negative integer variable and $x_i \in \{0,1\}$ is a special type of integer variable known as a binary variable. The models presented in Papers VI and VII are of MILP type.

The standard form of a MILP optimization problem is:

$$\begin{aligned} \text{minimize} \quad & c'x + d'y \\ \text{subject to} \quad & Ax + Bx = b, \\ & x, y \ge 0, \\ & x \text{ integer}, \end{aligned} \tag{3.5}$$

where the vectors c and d define the cost function, and the matrices A and B, and vector b defines the linear constraints.

MILP problems are in general very difficult to solve. Except from dynamic programming, the most popular methods to solve MILP are based on linear optimization and require to solve a sequence of linear optimization problems. Exact methods can be cutting plane and branch and bound. The main idea of these methods is to relax the integrality contraints and to solve the relaxed problem with linear optimization. If the solution does not satisfy the integer constraints, new constraints are added and a new linear optimization problem is obtained or the problem is decomposed into sub-problems. These algorithms may involve an exponential number of iterations. Other methods can provide suboptimal solutions without information on the quality of the solution. Such methods are e.g. local search or evolutionary algorithms. Methods and algorithms for solving MILP are presented in [48]-[50].

3.5 Life cycle cost

When a cost or profit objective function is considered, a Life Cycle Cost (LCC) model is often used in order to take into account the value of money in time [27]. A LCC model is the sum of the discounted capital and operational expenditures over the life time of a system. In the context of maintenance, a general model is [51]:

$$LCC = C_{Inv} + \sum_{t=0}^{N} \left[C^t_{PM} + C^t_{CM} + C^t_{PL} + C^t_{Ser} \right] \cdot (1+\delta)^{-i} \tag{3.6}$$

where C_{Inv} is the initial investment for the maintenance strategy (equipment, monitoring system), C^t_{PM} , C^t_{CM} and C^t_{PL} are the costs for corrective maintenance, preventive maintenance costs and production losses respectively, and C^t_{Ser} the costs for service (monitoring, analysis, administration), during year t. N is the expected lifetime of the system (in years). The discount rate δ is a function of the real interest rate r_{int} adjusted for the inflation rate r_{inf} as follows:

$$\delta = \frac{1 + r_{\text{inf}}}{1 + r_{\text{int}}} \tag{3.7}$$

r_{int} depends on the interest rate for investment financed by a bank loan, or on the expectation on the return rate from other investments (opportunity cost) if the investment is financed by the company´s own fund.

Chapter 4

Optimization of maintenance strategy

This chapter presents first a summary of the state-of-the-art of maintenance strategies, and then summarizes the models proposed on Paper I and Paper II that investigate the cost-benefit of condition based maintenance for the drive train and for the blades.

4.1 Introduction

4.1.1 Reliability of wind turbines

The availability of onshore wind turbines is typically in the range of 95-99% while for early offshore projects an availability as low as 60% has been observed at some wind farms due to serial failures and harsh weather conditions [11], [12]. This can also be observed in Figure 1-2.

The downtime per sub-system at the Horns Rev offshore wind farm is depicted in Figure 4-1. Note that this excludes serial failures that occurred during the first years of operation. The yearly availability is currently 95-97%. The aggregate failure rate per wind turbines is approx. 5 failures per year.

It has been observed that the main contributors to the failure rates are the power electronics, gearbox oil system, hydraulic and control systems. Similar results have been found for wind turbines at onshore sites [7], [8], [9]. For these sub-systems, the availability can be improved by implementing redundancy, time based replacement (if the sub-system is ageing) or by improving the maintenance support organization (see Chapter 5).

The replacement of the major components, such as the gearbox, is responsible for the longest downtime per failure, as well as for 80% of the cost of corrective maintenance in Figure 1-1. The downtime results from the long lead time for the spare parts and crane ship. The availability and maintenance costs for the major components can be minimized by use of condition monitoring systems.

The reliability of the internal electrical grid and the transmission electrical system are also critical for the availability. Some analysis indicates that the availability of the transmission electrical system could be in the range 96-99% with HVDC technology depending on the topology [52], [53].

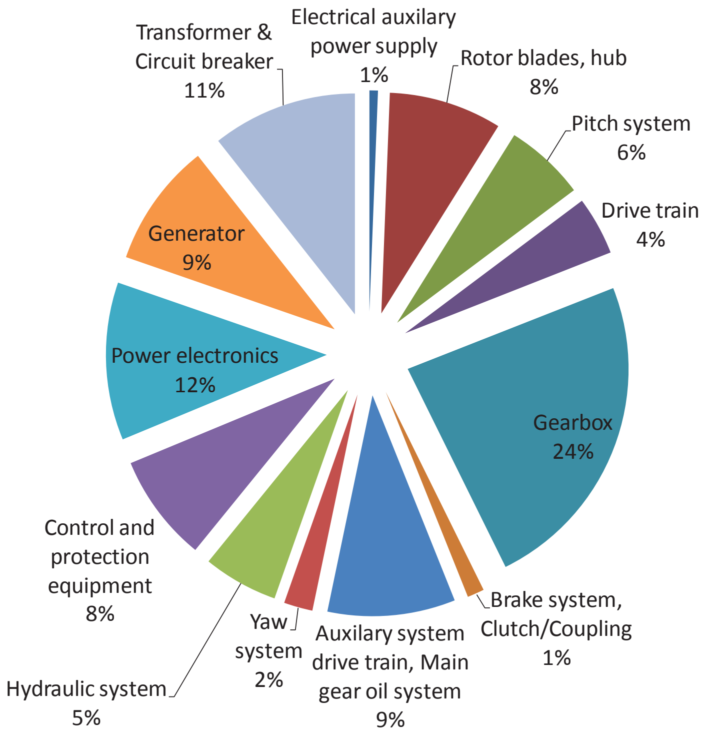

Figure 4-1: Estimated downtime per sub-system at Horns Rev based on work orders from years 2009-2010. The downtime has been estimated by the author based on failure rates and environmental constraints for the logistic at the site using a modified version of the ECN O&M tool [6].

4.1.2 Current maintenance strategies and related research

Maintenance activities at wind power systems consist typically of CM activities and PM including scheduled service maintenance activities. Onshore wind turbines are generally serviced and inspected twice a year. However, due to higher transportation costs and production losses, wind turbines located offshore are often serviced only once a year during spring or summer.

Yearly service maintenance takes generally 2-3 days per wind turbine and includes e.g. [54], [55]:

- Changes of lubrication systems and oil filters,
- Check of brushes and slip ring of DFIG,
- Inspection with respect to leakage,
- Test of safety systems and pad brake,
- Strength testing and retightening bolts,
- Oil sampling & analysis for the gearbox,
- Visual inspection of the blades.

Some recommendations for inspection based maintenance for wind turbines are proposed in [56], [57]. Other possible inspection performed as part of condition based maintenance are endoscopic inspection of the gearbox, ultrasonic or thermography inspection of blades, or infrared or thermography inspection of the electrical components (transformer, circuit breaker). For offshore wind farms, the inspection of the foundations, especially for corrosion, is generally performed every 2 years [58].

An overview of existing conditions monitoring system for wind turbines can be found in [13], [59], [60], [61]. Vibration and oil condition monitoring of the drive train of wind turbine is common practice for offshore wind turbines. It can provide useful information on the deterioration condition of the different components of the drive train which can help scheduling and clustering major replacements. In this respect, the efficiency of the condition monitoring system can have a major impact on the availability. Recently, online CMS for blades have also been proposed based on gauge strain or fiber optic strain or acoustic monitoring that can detect damages from delamination or cracks [62]. The analysis of the monitoring measurements for all type of condition monitoring system is generally performed by an expert, with support of software in order to detect changes in conditions.

Signal processing methods for detection and diagnosis based on condition monitoring systems have received much attention recently. A review of the methods and their applications to wind power can be found in [60], [62], [13]. Little work has been done in the area of prognosis models; a model for estimating the residual lifetime of generator bearing failure based on CMS data is proposed in [13]. Another approach to condition monitoring is to make use of existing measurements from the Supervisory Control And Data Acquisition (SCADA) system in order to detect and determine faults [63], [64], [65].

Several publications have focused on determining suitable maintenance strategies based on RCM methodology for wind power, see e.g. [66] - [69]. Some quantitative models for analysis of maintenance strategies for the major components of the wind turbine have also been proposed:

- Cost-benefit analysis of condition monitoring for the drive train [51], [68] , [70], [71],
- Time based replacement of major components [67],
- Inspection based optimization based on delay time model [72],
- Physic based maintenance optimization model [31],
- Condition based maintenance optimization based on fatigue models for offshore foundations [74].

Two models are proposed in this Chapter in order to optimize the maintenance strategies for the drive train (consisting of main bearing, gearbox, generator) and for the blades.

4.2 Cost-benefit of condition monitoring systems

Failures of the major components of the drive train are expensive due to the high costs for the spare parts, the logistic and maintenance equipment, and energy production losses. Vibration and oil CMS are available for the components of the drive train in WTs [59], [13]. The CMS may identify incipient failures far before major maintenance is required. If a fault is suspected, an inspection is performed, and either minor maintenance is performed to prevent the failure, or the replacement of the component is planned. In this condition, both the cost of the maintenance activity itself and the costs for production losses may be reduced.

The economic benefit of CMS depends on the probability of failure of the component in the drive train, the efficiency of the CMS, and damage and logistic time advantages provided by the use of CMS. An economic analysis is presented in Paper I. The novelty of the proposed approach, compared to publications [51], [70], [71] is to consider the cost and reliability of the drive train over the lifetime. The report in [68] presents a similar model as the one proposed in paper I, but it was developed later. This section summarizes the proposed model and results.

4.2.1 Model description

The proposed model is based on a stochastic LCC model with random variables for the occurrence of failure of the components of the drive train.

Economic model

The LCC model is divided according to equation (3.6) into the investment cost C_{Inv}, preventive and corrective maintenance costs C^t_{PM} and C^t_{CM}, costs for the production losses C^t_{PL} and service costs C^t_{Ser}, that are estimated for each year t as

$$\begin{aligned} C^t_{PM} &= \sum_{i=1}^{C} w_{it} \cdot \left(1 - \varepsilon_i / 100\right) \cdot K_i \\ C^t_{PM} &= \sum_{i=1}^{C} w_{it} \cdot \left(\varepsilon_i / 100\right) \cdot \left(\gamma_i / 100\right) \cdot K_i \\ C^t_{PL} &= \sum_{i=1}^{C} w_{it} \cdot \left[T_i + \left(1 - \varepsilon_i / 100\right) \cdot \tau_i\right] \cdot P \cdot C_{el} \end{aligned} \qquad (4.1)$$

where c is the number of components of the drive train, indexed by i. The efficiency of the CMS is the probability ε_i [%] to detect an incipient failure for component i. If a failure is not identified, a corrective maintenance cost K_i [€] must be paid. The logistic time is τ_i and the repair time T_i. If a failure is detected, PM is performed at a cost ${\gamma_i}/{100} \cdot K_i$, and there is no logistic time. After maintenance is performed, the component is assumed to be as good as new. The electricity price is C_{el} and the average power production is P.

Reliability model

w_{it} is the number of failures for component i in year t. The failures are assumed to follow a Weibull probability distribution with shape parameters β_i and scale parameters α_i (black box approach, see Section 2.2.1). Two approaches were used for generating w_{it}. A sensitivity analysis was performed analytically, by estimating the number of renewals per year using a recursive approach as described in Section 2.4.2. A simulation approach was used to perform a risk analysis.

4.2.2 Case study

The benefit of CMS is evaluated as the difference between the LCC with and without CMS. A case study based on 3MW wind turbines was performed and a sensitivity analysis was used to investigate the influence of some parameters. The CMS was assumed to have an efficiency of 90%, which means that 90% of the impending failures can be corrected with preventive repair, preventing from production losses and lowering consequential damages by 50% in cost. Moreover, the cost for the CMS was assumed to be 100,000 € according to [51], which is high compared to solutions proposed today and thus a conservative assumption regarding the cost-benefit.

Main results

In the base case, the LCC is 710,000€ without CMS and 520,000€ with a CMS. The cost-benefit of using CMS is therefore 190,000 € over the lifetime. The sensitivity of the results to the lifetime of the gearbox is shown in Figure 4-2. The gearbox is the most critical component of the drive train with respect to its impact on maintenance costs. It can be observed that the reliability of the gearbox has a large impact on the economic benefit of the CMS. Even under the conservative assumption made regarding the CMS investment cost, the CMS is expected to be beneficial if the MTTF of the gearbox is lower than 18 years, which is clearly the case in the majority of wind turbine gearboxes in operation today. Moreover, it could be shown that the use of CMS reduces the probability of high maintenance costs, as depicted in Figure 4-3.

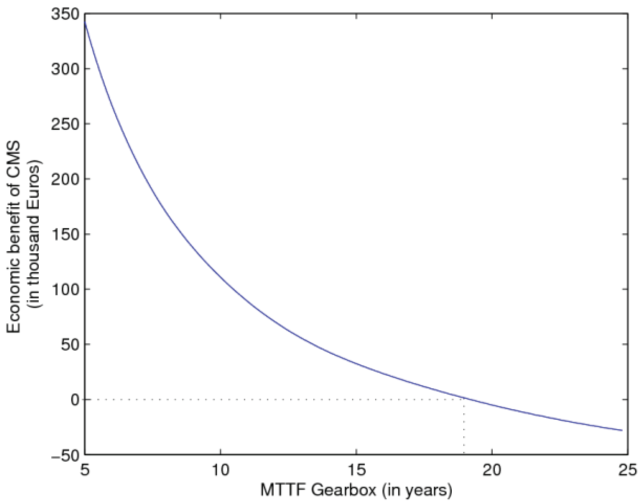

Figure 4-2: Expected economic benefit of vibration CMS for a wind turbine as a function of the Mean Time To Failure (MTTF) for the gearbox.

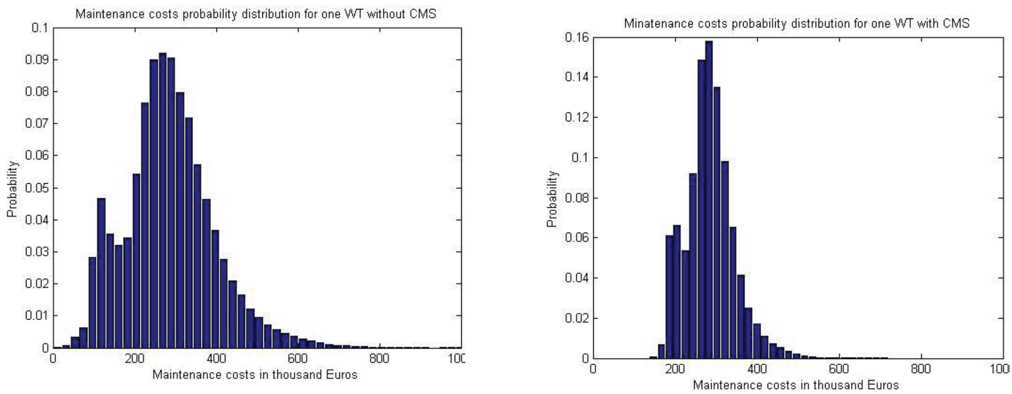

Figure 4-3: Probability distribution of the LCC costs without CMS (left) and with CMS (right).

4.3 Optimal condition based maintenance for blades

Another component being critical for the reliability, availability, and profitability of wind turbines is the rotor, today usually consisting of three rotor blades. The size of the blades for wind turbine has been increasing rapidly during these last decades and they are subject to high stress. Wind turbine blades are usually inspected once a year at service maintenance and at additional occasions e.g. after a lightning strike has been detected by lightning detectors.

Condition monitoring can be used in order to detect cracks and delamination, either at inspection or continuously. Inspection monitoring devices consist of infrared or ultrasound sensors installed on an inspection robot that will scan and examine the inner material of the blade [73]. On-line CMS (also known as Structural Health Monitoring, SHM in the context of tower, support structure and blades) can be achieved by inserting fiber optical sensors, whose emission frequency is modified by measured properties i.e. strain or temperature, mounted on an optical line in the material of the blades [73].

The objective of the model describe in Paper I are:

1. to compare the expected maintenance costs for the three maintenance strategies (a) only visual inspection, (b) inspection using condition monitoring technique, and (c) continuous monitoring with condition monitoring system (inspection are carried on only if a failure is detected);
2. to optimize the inspection interval for the inspection strategies.

4.3.1 Model

The model consists of a LCC model for the life time of the wind turbine as described in Section 3.5. A Markov chain is used for the deterioration model (grey box approach in Section 2.2.2) and for maintenance modeling. An introduction to Markov chain is given in Section 2.4.1. The model takes into account sudden failures that could be caused e.g. by a lightning impact.

Reliability and maintenance model

The Markov model for the deterioration and maintenance processes proposed for wind turbine blades is depicted in Figure 4-4. The blade can be in five states, $X_1 - X_4$ representing perfect condition, minor deterioration, advanced deterioration, major deterioration and the state F denoting failure. The different deterioration levels were introduced because they require different levels of maintenance intervention, ranging from a minor repair on site to a complete replacement of a rotor blade.

The main reliability parameters are the crack initiation rate λ_{init}, the deterioration rate $\lambda_{\det}$ (with average deterioration time denoted $T_{\det}$) and the lightning rate λ_l.

The maintenance strategies are modeled by the frequency of inspection and probability of success π_i of detecting the failures. It is assumed that if the condition monitoring system can detect a failure in a certain deterioration state, it will detect it directly at the state transition.

The analysis has been performed by simulating the maintenance over the finite life time horizon, calculating the yearly inspection, preventive and corrective maintenance costs and calculating the life cycle cost according to Equation (3.6).

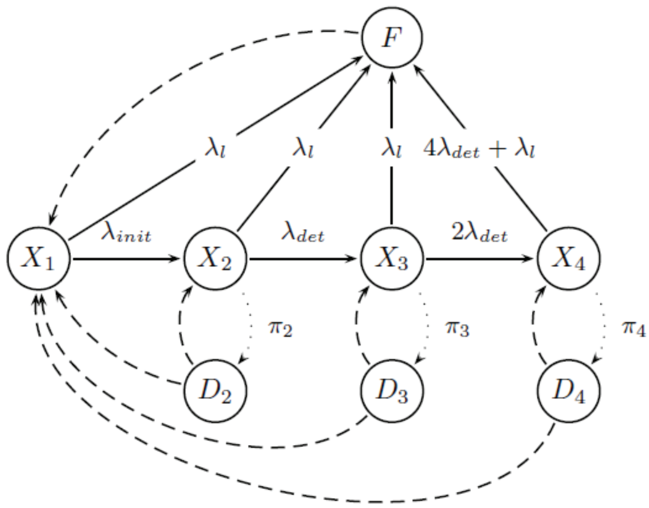

Figure 4-4: Markov model for the reliability and maintenance model for the wind turbine blades. X_i deterioration states, F failure state, D_i decision state. Full arrow: deterioration transition, dotted arrow: inspection transition, dashed arrows: maintenance transition.

4.3.2 Case study

The base case for the case study assumed a crack initiation rate of λ_{init} =0.01 per year, average deterioration time $T_{\det}$ of 1 year and the lightning rate λ_l of 0.01 per year. The cost parameters are provided in Paper II.

Main result

The central result of this analysis is shown in Figure 4-5, where the expected maintenance costs for the different maintenance strategies are plotted as a function of the inspection interval. Note that in case of the application of a condition monitoring system, the resulting cost is independent of any inspection interval. It can be observed that the optimal strategy among the alternatives (a-c) named above is to install a condition monitoring system (c), followed by inspection with condition monitoring techniques every 6 months (b) and, as least cost-effective solution, the visual inspection of blades every 3 months (a).

Sensitivity analysis

However, the benefit of the different maintenance strategies depends strongly on the dynamics of the failure process (see P-F curve in Figure 2-2), as it can be observed in Figure 4-6. The figure presents the expected maintenance costs for the three maintenance strategies a-c (with optimal inspection intervals in the cases (a) and (b)) as a function of the crack time to failure, i.e. the time between a crack is initiated until it leads to a failure. The shorter this time is, the less probably is the detection of a crack by offline inspection and the more beneficial are thus condition monitoring systems. This is due to the need for short inspection intervals for inspection strategies to be efficient, and the resulting high inspection costs.

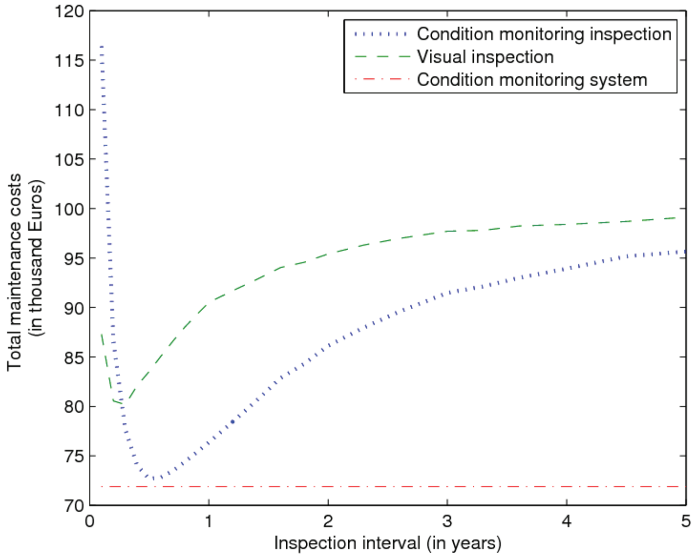

Figure 4-5: Expected maintenance costs of one blade over the lifetime of a wind turbine for different maintenance strategies as a function of the inspection interval.

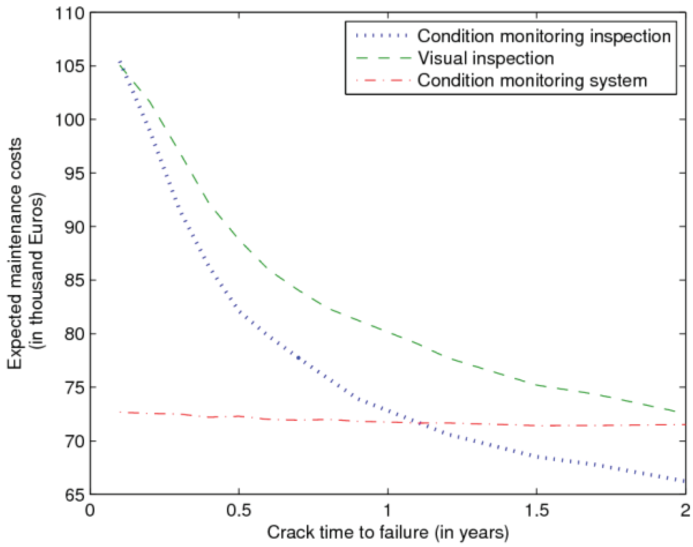

Figure 4-6: Expected maintenance costs of one blade over the lifetime of a wind turbine for different maintenance strategies as a function of the crack time to failure.

Chapter 5
Optimization of maintenance support organization

This chapter presents firstly the state of the art in maintenance support organization for offshore wind farms, and secondly summarizes the analytical model and the simulation model proposed in Paper IV and Paper V for the cost-benefit evaluation of maintenance support organizations.

5.1 Introduction

The maintenance support organization can be defined as all the resources required in order to perform maintenance activities. The following aspects of support organizations have been identified as critical for offshore wind farms:

(1) Location of maintenance accommodation,
(2) Number and type of crew transfer vessels,
(3) Use of helicopter,
(4) Work shift organization,
(5) Number of maintenance teams per work shift,
(6) Spare part stock management,
(7) Technical support,
(8) Buy or contract of crane ship.

For safety reasons, the nacelle of a WT should not be accessed individually and the maintenance is generally performed teams of at least two technicians supervised by a site and maintenance manager. The work is organized in work-shifts which for offshore wind farms without offshore accommodation vessel would generally consist of day shifts (12/7). For wind farms located far from shore, an offshore based maintenance organization (with an accommodation platform or accommodation vessel) enables to have night work-shift (24/7) to respond to failure any time during the day. The maintenance teams may be complemented by supplementary technicians in order to perform specific maintenance activities such as service maintenance activities or major component replacements (for which maintenance expert are generally required). The main factors that determine the optimal number of technicians and work-shift arrangement is the reliability of the wind turbine, the efficiency of the transportation, the accessibility (in terms of working hours spent in the wind turbines), and weather conditions. Several factors depend therefore on the logistic strategy.

The access to the wind turbines is performed either by climbing a ladder located on the foundation from a Crew Transfer Vessel (CTV), accessing directly the foundation platform via a gangway on an accommodation vessel, or by hoisting on the nacelle platform by helicopter. Example of transportation and access systems are depicted in Figure 5-1. Recently, much effort has been put on developing access systems, and launch and recovery systems for daughter craft on accommodation vessel; see e.g. [75]. The safety and efficiency of such systems have a major impact on the overall logistic strategy. A major driver for the transportation strategy is the distance of the wind farm from shore, or more precisely from a suitable harbor for maintenance. For distances beyond 50-60 km, the traveling distance and expected sea sickness after a long time on a vessel requires an offshore maintenance accommodation either in the form of a living platform or an accommodation vessel (generally with a length above 65m).

Figure 5-1: Example of transportation solutions for offshore wind farms. Left: Crew transfer vessel [76], middle: Helicopter hoisting [77], right: access system for Crew Transfer Vessel [78].

The spare part strategy consists in the choice of the location of the main storage base, maintenance workshop (for repair of components) and supplier lead time contracts for each component, in order to optimize the availability of the spare parts needed for maintenance at site. Several general models applicable to offshore wind have been developed for the optimization of spare parts, see e.g. [79], [80].

Several commercial models have been developed for the analysis of the maintenance support organization for offshore wind farms. An analytical model has been proposed in [6] in order to estimate the average operation and maintenance costs. The model includes a regression model of the waiting time due to weather constraints by which the downtime due to harsh weather can be estimated. A main limitations of the model is to assume deterministic values for the preparation time and availability of the technicians and vessels, and the results therefore consist of average values for the operational costs and availability. Moreover, no alternative logistic solutions, i.e. mix of vessels such as CTV and helicopter, is directly possible.

Three simulation models have been proposed in [81]-[83]. The models have different levels of details in the modeling of the reliability of the wind turbines. Recently a general maintenance simulation model that was developed for the military industry has also been applied to offshore wind farms [84]. The model can be very detailed and enables to analyze the effect of fault tolerance, redundancy, efficiency of condition monitoring systems and advanced spare part management strategies.

Two models are proposed in this chapter which focuses mainly on the location of maintenance accommodation, number and type of crew transfer vessels, use of helicopter, and work shift organization. The first model is based on an analytical approach, and it considers the effect of queuing of maintenance activities that can occur due to a lack of maintenance team available for work. The second model is based on simulation of the maintenance process. The two models are complementary, the analytical model being much faster, which is suitable if many strategy scenarios are investigated. The simulation models is more accurate, and can be used to evaluate the interaction between the different maintenance resources in more detail, and to calculate the energy-based availability, and the risk associated with achieved availability. The simulation model was also used to validate the analytical model.

5.2 Analytical model

The proposed model presented in Paper IV focuses on the aspects (1) through (5) identified in Section 5.1. The model distinguishes between major and minor failures with respect to repair time and required means of transportation. The wind turbine can be accessed by both CTV or helicopter for minor failures, while a major failure always requires a CTV. It does not consider the replacement of major components e.g. blades, main bearing, gearbox or generator. These components are continuously monitored, which enables pro-active planning of resources, and their replacement is afflicted with different logistic needs than those taken into account in the present study, e.g. a crane ship. It also assumes that the spare parts are always available at site.

The model enables the evaluation of possible alternative transportation means (e.g. the use of a helicopter in cases when the transportation by workboat is impeded by harsh weather), and it considers the effect of the work shift and the queuing of maintenance work in case of a lack of technicians. To the knowledge of the author, no analytical model had been published that considered all these factors.

The objective of the model is to compare different scenarios for a maintenance support organization. For each scenario, the optimal number of technicians permanently working on site, and supplementary technicians for performing the service maintenance, is determined, as well as the resulting expected availability and cost of the support organization. The following section summarizes the reliability model proposed in Paper IV.

5.2.1 Model description

The flowchart in Figure 5-2 summarizes the steps in the model for the evaluation of a maintenance support organization including a helicopter. Steps A-C focus on determining the total downtime per failure as a function of the number of maintenance teams n. The number of supplementary technicians $n_{PM}^{s}(n)$ required for performing the PM and the number of CTVs $b^{s}(n)$ are calculated in Step D. The wind farm availability, the cost of production losses, and the cost of the support organization are assessed in step E. The final step is to determine the optimal number of maintenance teams n^* for the given scenario of support organization.

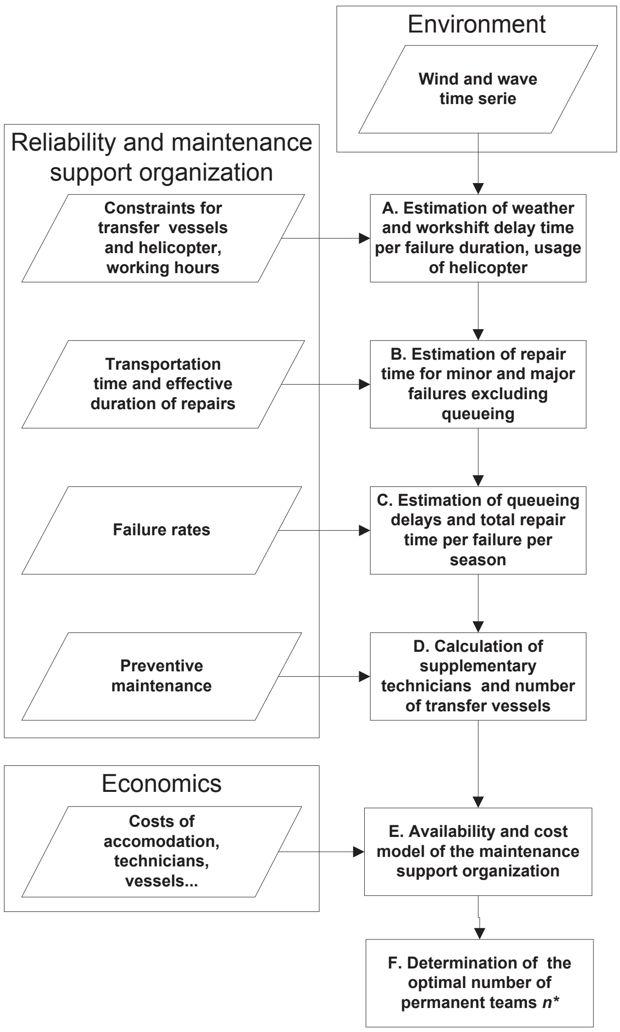

Figure 5-2: Workflow of the different steps of the model.

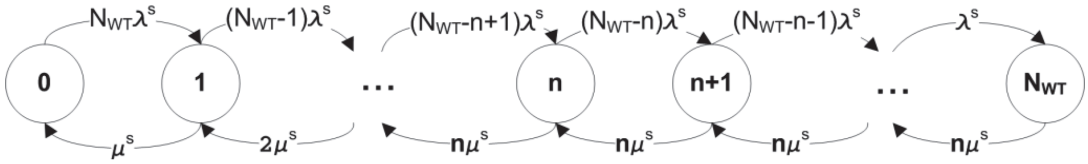

Figure 5-3: Markov diagram for the queuing model of maintenance activities for a wind farm of N_{WT} wind turbines. The state numbers represent the number of wind turbines in the wind farm that are in a failed state.

Weather delay and repair time

The total downtime per failure is the sum of the downtime due to the waiting for suitable weather conditions, the downtime due to the queuing resulting from a lack of maintenance technicians, and the downtime due to the repair in the wind turbine. The expected maintenance delay due to the weather and work shift constraints is statistically determined for the given duration of maintenance activities r_m and r_M based on environmental time series for the site and wind and wave constraints for the vessels considered. The reader is referred to Paper IV for a full description of the algorithm.

The repair downtime including waiting of weather (excluding the effect of queuing) is denoted d_m^s and d_M^s for minor and major repair respectively. The average failure rate and repair time per failure and per season can be calculated as:

$$\lambda^s = \lambda_m^s + \lambda_M^s \tag{5.1}$$

$$d_{CM}^s = \frac{\lambda_m^s \cdot d_m^s + \lambda_M^s \cdot d_M^s}{\lambda^s} = \frac{1}{\mu^S} \tag{5.2}$$

Where μ^S is the resulting repair rate.

Queuing model

A queuing of maintenance activities may occur when there are not enough maintenance teams to simultaneously perform maintenance on all failed wind turbines. This is especially prevalent after harsh weather conditions, during which failures may accumulate and the existing maintenance workforce may not be sufficiently large to perform work on each failure when wind turbines are accessible.

The back-log of maintenance activities can be represented by a Markov chain as depicted in Figure 5-3 (see Section 2.4.1 for an introduction to Markov Chains). It consists of the states i, in which i represents the number of failed turbines. The failure transitions shown in the upper part of the diagram occur at a rate which is proportional to the number of wind turbines in operation. The repair transitions given in the lower part of the diagram occur at a rate which is proportional to the minimum number of wind turbines in repair and the number of permanent maintenance teams.

The Markov model can easily be solved in steady state. The average queuing time per failure $Q^s(n)$ can then be calculated by using Little´s law. It is the ratio of the average length of queuing (average number of failed wind turbines waiting for a maintenance team to perform the repair work) and the average number of failures per time unit [33]:

$$Q^s(n) = \frac{1}{\lambda^s} \cdot \frac{\sum_{i>n} P(\mathrm{i}) \cdot (\mathrm{i} - n)}{\sum_{i} P(\mathrm{i}) \cdot (N_{WT} - i)} \tag{5.3}$$

Based on the failure rate and the total repair duration per failure, including the waiting of weather and queuing downtime, as well as the duration for the preventive maintenance activities, the expected availability per season and per year can be estimated.

Economic model

The final step is to calculate the cost of the maintenance support organization and the production losses. The reader is referred to Paper IV for the equations of the economic model. The optimal number of permanent teams for the support organization is finally determined by minimizing the sum of the cost for the support organization and the production losses:

$$n^* = \arg\min_{n \in \mathrm{Z}^+} \left\{ C_{losses}^{tot}(n) + C_{org}^{tot}(n) \right\} \tag{5.4}$$

For each support organization scenario investigated, the optimal number of permanent technicians is determined numerically by calculating the cost of the support organization and the cost of the production losses for a range of possible numbers of maintenance teams, and by selecting the solution based on the lowest total cost, as illustrated in Figure 5-4.

5.2.2 Results

Case study

The proposed model has been demonstrated by means of a case study of a fictitious offshore wind farm consisting of N_{WT} =100 wind turbines located 60 km from a harbor. Each turbine has a rated capacity of 5MW. Wind and wave data are based on real data from the 160MW Horns Rev offshore wind farm located 15 km off the coast of Esbjerg in Denmark. The reader is referred to Paper IV for a description of the assumptions.

The present study compares several maintenance support organizations with respect to different locations of the maintenance accommodation (onshore or offshore accommodation platform), work shift arrangements (12/7 or 24/7) and transportation means, for the purpose of identifying the most cost-effective solution. Two different types of CTVs are investigated, CTV1 and CTV2, as well as the use of a helicopter. The main difference between the vessels is that the CTV2 is equipped with an access system in the form of a gangway or stabilizing platform to enable access to the wind turbine at higher significant wave height.

Main results

The main results obtained from the analysis of the maintenance support organizations investigated are presented in Table 5-1. It can be observed that the organization scenario 10, which consists of an offshore accommodation with 24/7 work shifts and the use of CTV2, offers the most cost-efficient solution closely followed by the options 12, 2 and 4. All these scenarios include the use of CTV2, clearly more cost-beneficial than using CTV1. The economic benefit of scenario 10 is in the range 0.6 M€-5.2 M€ compared to the other scenarios.

The benefit of using the helicopter differs with the type of CTV as well as the work shift arrangement. The yearly availability increase is in the range of 0.2%-0.7% for an organization with 24/7 work shifts and type CTV2 vessels as well as for an organization with 12/7 work shifts and CTV1, respectively. The use of the helicopter is cost-beneficial in all cases except for the case of an offshore accommodations with 24/7 work shifts and CTV2.

It can also be observed that an offshore accommodation is cost beneficial only in the case of the 24/7 work shift. This can be attributable to the relatively low increase in the availability and work efficiency due to the location of the accommodation alone. The benefit would increase with a longer distance from the shore and harsher weather conditions. It can be noted that the availability increases by almost 1% for each logistic solution by using 24/7 work shifts instead of 12/7 work shifts.

Table 5-1: Summary of the results for the maintenance support organization scenarios in Paper IV. $n_{PM}^{spr}(n^*)$ denotes the number of supplementary technicians during the summer, b^{win} / b^{spr} the number of CTV per season, U_h^{yr} [%] the usage rate of the helicopter, $A(n^*)$ the availability [%] and $C_{org}^{tot}(n^*)$ and $C_{losses}^{tot}(n^*)$ [M€] the cost of the maintenance support organization and production losses.

Scenario description					Results							
Org.	Location	Workshift	CTV	Heli.	n^*	$n_{PM}^{spr}(n^*)$	b^{win} / b^{spr}	U_h^{yr}	$A(n^*)$	$C_{org}^{tot}(n^*)$	$C_{losses}^{tot}(n^*)$	**Total cost**
1	onshore	12/7	CTV1	No	7	0	2 - 2	n.a.	95.7%	6.6	12.9	19.5
2	onshore	12/7	CTV2	No	6	0	2 - 2	n.a.	96.8%	6.9	9.6	16.5
3	onshore	12/7	CTV1	Yes	6	0	2 - 2	25%	96.3%	7.3	11.2	18.5
4	onshore	12/7	CTV2	Yes	4	5	1 - 2	14%	96.6%	6.6	10.0	16.7
5	offshore	12/7	CTV1	No	6	0	2 - 2	n.a.	96.0%	9.0	11.9	21.0
6	offshore	12/7	CTV2	No	4	4	1 - 2	n.a.	96.8%	8.5	9.7	18.2
7	offshore	12/7	CTV1	Yes	6	0	2 - 2	25%	96.7%	10.3	9.7	19.9
8	offshore	12/7	CTV2	Yes	4	4	1 - 2	14%	97.2%	9.8	8.2	18.0
9	offshore	24/7	CTV1	No	4	0	1 - 2	n.a.	97.0%	10.9	9.2	20.0
10	offshore	24/7	CTV2	No	3	0	1 - 1	n.a.	97.9%	9.6	6.2	15.8
11	offshore	24/7	CTV1	Yes	3	0	1 - 1	12%	97.5%	10.2	7.5	17.7
12	offshore	24/7	CTV2	Yes	3	0	1 - 1	7%	98.1%	10.8	5.6	16.4

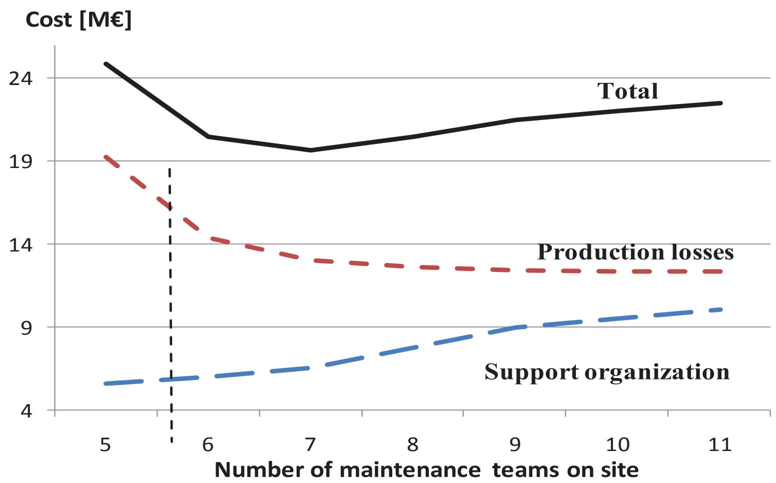

Figure 5-4: Cost based on the organization Scenario 1 in Table 5-1 as a function of the number of maintenance teams. The optimal number of teams is $n* = 7$.

5.3 Simulation model

The proposed model in Paper V considers the aspects (1) through (5), and partly the aspect (8), identified in Section 5.1. The model is a further development of the analytical model proposed in Paper IV but focuses only on estimating availability. The economic model presented in Paper IV can be used similarly with the simulation model.

The simulation model has several benefits compared to an analytical model, for example, it enables to evaluate the interaction between the different maintenance resources, to calculate the energy-based availability, and to evaluate the risk of the availability results over a given period. This section summarizes the simulation model and results from Paper V.

Queuing model

The failures enter the maintenance queue to be performed. The total number of ongoing and awaiting CM maintenance activities are denoted N_t^m, N_t^M, $N_t^{R,c}$ and $N_t^{R,nc}$. If the resources for the logistic and personnel necessary to perform the maintenance activities are available, the activity is performed. At each time step the percentage of achievement of the maintenance activity is updated, and the activities that have been completed are removed from the queue. In the case of the minor repair, this is calculated as follow:

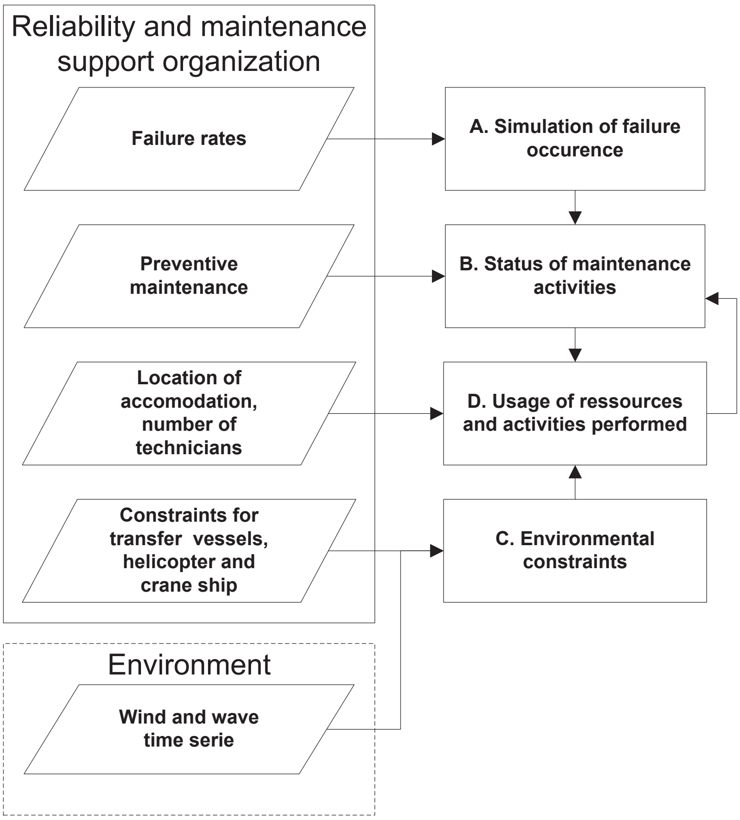

Figure 5-5: Flowchart of the main steps of the proposed simulation model, with the associated sections for the description.

$$N_t^m = N_{t-1}^m + n_t^{m+} - n_{t-1}^{m-} \tag{5.5}$$

where n_{t-1}^{m-} denotes the number of minor repairs that have been completed in the time step $t-1$. The total number of wind turbines in operation N_t^{WT} at each time can then be calculated by the total number of wind turbines on site, minus the wind turbines requiring maintenance, or at which maintenance is being performed, except for the incipient failures in non critical condition detected by the CMS.

Logistic and personnel constraints

The logistic resources are available for performing work only if these are not constrained by the weather conditions. The effective resource availabilities are denoted L_t^{CTV}, L_t^{hel} and $L_t^{cra} \in \{0;1\}$. In the case of the CTV, the resource is available if $L_t^{CTV} = 1$ according to:

$$L_t^{CTV} = \begin{cases} A_t^{CTV}, \text{ if } w_t \le W_{CTV} \text{ and } \mathrm{h}_t \le H_{CTV} \\ 0, \text{ else.} \end{cases} \tag{5.6}$$

where A_t^{CTV} represents the availability of the vessel on site during the time step t.

At time step t, it is assumed that N_t^{tech} technicians are available for performing maintenance. The usage of the personnel is modeled by removing the number of technicians working from the available personnel resources. The maintenance activities need to be prioritized. It is assumed that if technician resources are available, they would be used in priority to fix minor repairs since this type of failure can be corrected in a shorter time than major repairs. The number of technicians available for performing major repairs is e.g. calculated as:

$$N_t^{tech,M} = N_t^{tech} - m_t^m \cdot N_m^{tech} \tag{5.7}$$

where m_t^m represents the number of maintenance team working on minor failures and N_m^{tech} the number of technicians per team.

Time-based and energy-based availability

The final step is to calculate the time-based availability during the time instance t which is the ratio of the number of wind turbines in operation N_t^{WT} and the total number of wind turbines N^{WT}. Therefore the annual availability is:

$$A_y^{WF} = \frac{1}{N^{WT}} \cdot \sum_{t \in T^y} N_t^{WT} \tag{5.8}$$

The annual energy based availability E_y^{WF} is calculated as the ratio of the electricity production and the theoretical total electricity production, which had been obtained if the wind farm had been fully available:

$$E_y^{WF} = \frac{\sum_{t \in T^y} N_t^{WT} \cdot p_t}{N^{WT} \cdot \sum_{t \in T^y} p_t} \tag{5.9}$$

where p_t represents the energy production for one wind turbine in time step t.

5.3.1 Results

The same case study as in Paper IV has been performed in Paper V and the base scenarios were selected according to the optimized solution.

Main results

Table 5-2 summarizes the main results. A general conclusion is that, as expected, the availability increases when the support organization is enhanced by higher accessibility and lower transportation time. However, the availability depends also on the effective working hours and the number of technicians as it can be observed by comparing the results for the Scenario 1 and 5.

It can also be observed that the energy-based availability is generally slightly lower than the time-based availability except if the accessibility is low, i.e. if only the CTV1 and no helicopter is used as in the case for the scenarios 1, 5 and 9 for which the difference between the energy-based and time-based availability is in the range of 0.4-0.9%.

The helicopter increases the energy-based availability by 1.3%-1.9% if the CTV1 is used, while the benefit is much lower if the CTV2 is used. It should be noted that the benefit of the increased working hours due to transportation with the helicopter has not been modeled. This would slightly increase the availability and improve the working efficiency of the technicians.

Similarly to the conclusion for the helicopter, the CTV2 leads to an improvement of the energy-based availability by 1.3%-1.9% in all the scenarios for which the helicopter is not used. Since the improvements in availability are high, it can be expected that each choice would be cost beneficial, but that the cost-benefit of using both at the same time might be limited. For a larger wind farm, the CTV2 and the helicopter may complement each other and improve the robustness of the logistic solution.

The benefit of placing the maintenance accommodation offshore seems limited from an availability point of view, which can be due to the lower number of technicians resulting from the economic optimization in Paper IV. However there is an indication that the energy-based availability can be increased by 0.7%-1.1% if the maintenance work can be performed during the night.

There is an intrinsic uncertainty associated with the randomness in failure occurrence, as well as in the variability in the annual weather. This uncertainty can be evaluated by the standard deviation of the annual availability which is noted $\sigma_{P_y^{WF}}$ in Table 5-2. It can be observed that the uncertainty decreases when the accessibility is enhanced.

Comparison with the analytical model

The availability results from the proposed simulation model are compared with the results from the analytical model in Paper IV in the last three columns in Table 5-2. Since the analytical model excludes the major component failures, the unavailability due to the failure of the major component is excluded in the adjusted time-based availability A_y^{WF*}.

It can be observed that the availability calculated by the simulation model is higher in all scenarios considered, and that the difference is in the range 0.3-0.5% except for the scenarios with CT1 and helicopter for which the difference is 0.7-0.9%. A possible explanation is that the Markov queuing model used in the analytical model considers only an average repair time per failure without differentiation between minor and major repair. The consequence is that the waiting time per failure due to a lack of technicians is over-estimated in the analytical model due to the averaging. This suggests that the analytical model may be improved by differentiating the type of failures in the state model.

It was expected that the results are different since some approximations are necessary in the analytical model, for example that the durations of the repairs are exponentially distributed. If the differences in the results for the scenarios can be reduced to a narrow range, the analytical model could be used as a first step for a fast determination of the promising scenarios. Then the selected scenario may be further analyzed with a simulation model to evaluate the energy availability, availability risks, and other parameters such as major component replacements.

Table 5-2: Results of the analysis for different maintenance support organization scenarios.
A_y^{WF*} is the availability excluding major component replacements (as calculated with the analytical model in Paper V).

Scenarios							**Results**			**Comparison with analytical model in Paper IV**		
Org.	Location	N_t^{tech} day	N_t^{tech} night	Effective working hours	CTVs	Heli.	A_y^{WF}	E_y^{WF}	$\sigma_{P_y^{WF}}$	A_y^{WF*}	Analytical model	Difference
1	onshore	21	0	8	2 CTV1	No	95.4%	94.5%	1%	96.1%	95.7%	-0.4%
2	onshore	18	0	8	2 CTV2	No	96.5%	96.4%	0.6%	97.2%	96.8%	-0.4%
3	onshore	18	0	8	2 CTV1	Yes	96.5%	96.4%	0.6%	97.2%	96.3%	-0.9%
4	onshore	12	0	8	1 CTV2	Yes	96.4%	96.3%	0.6%	97,1%	96.6%	-0.5%
5	offshore	18	0	11	2 CTV1	No	95.8%	95.1%	0.8%	96.5%	96.0%	-0.5%
6	offshore	12	0	10	1 CTV2	No	96.6%	96.4%	0.5%	97.3%	96.8%	-0.5%
7	offshore	18	0	11	2 CTV1	Yes	96.8%	96.7%	0.5%	97.5%	96.7%	-0.8%
8	offshore	12	0	10	1 CTV2	Yes	97.0%	97.0%	0.4%	97.7%	97.2%	-0.5%
9	offshore	12	12	10	1 CTV1	No	96.8%	96.2%	0.7%	97.5%	97.0%	-0.5%
10	offshore	9	9	10	1 CTV2	No	97.5%	97.5%	0.5%	98.4%	97.9%	-0.5%
11	offshore	9	9	10	1 CTV1	Yes	97.5%	97.5%	0.5%	98.2%	97.5%	-0.7%
12	offshore	9	9	10	1 CTV2	Yes	97.7%	97.7%	0.4%	98.4%	98.1%	-0.3%

Chapter 6

Optimization of maintenance planning

This chapter summarizes the models and results presented in Papers VI and VII on the optimization of maintenance planning for scheduled maintenance activities.

6.1 Introduction

Maintenance planning is the prioritization and planning of maintenance tasks with respect to the available maintenance crew, spare parts and maintenance equipment. Maintenance planning applies to all maintenance activities, and much saving can be achieved by its optimization. The main cost savings are related to the production losses and logistic costs including fuel and mobilization costs.

A model has been proposed in order to minimize the cost of major component replacement by grouping maintenance activities [40]. The idea is to take advantage of reliability prognosis, i.e. based on condition monitoring, in order to group the replacement of the component and thus minimize the costs for crane ship mobilization.

Generally, scheduled service maintenance is performed during a fixed period of time and with little consideration for the power production. When maintenance is performed, the WT is stopped, which results in costs for production losses. If these maintenance activities were instead performed at low wind production, it would result in cost savings. Moreover, WTs are subject to failure, and each failure provides an occasion to perform part of the scheduled service maintenance. By doing so, it would avoid the need to access the WT later on, and may reduce transportation and work costs as well.

Wind power forecasting tools are important for the maintenance planning. Forecasting models have been developed to predict wind power production up till 7 days using ensemble input from numerical weather prediction as available from the European Centre for Medium Range Weather Forecasts in Europe, see more details in [85]. Chaos theory was used in [86] to show that the limit of weather predictability is around two weeks. Longer horizons are of interest for the purpose of maintenance planning. An option is to use seasonal forecasts based on wind power historical data for the horizon above the 7 days.

The objective of the models presented in paper VI and VII is to develop an approach for optimizing the planning of service maintenance activities by taking advantage of opportunities at failure and low production forecasts to reduce costs for transportation and production losses. The models are even more relevant with the increased level of redundancy and increased efficiency of the condition monitoring systems for offshore wind turbines. These changes will result in more scheduled maintenance activities that could be planned similarly as the service maintenance activities.

This work was inspired by an opportunistic maintenance optimization model proposed for the aircraft industry [39]. The model in Paper VI assumes a deterministic production forecast (also known as point forecasting) and neglected the wind and wave constraints. The model is further improved in Paper VII by considering ensemble wind production forecasting instead of point forecasting. Moreover, constraints on the accessibility to the wind turbines were added, as well as transportation decision on using the helicopter in case of bad weather.

The following section summarizes the model presented in Paper VII. The reader is referred to paper VI for a description of the deterministic model.

6.2 Optimization model

The model proposed in Paper VII is a rolling horizon stochastic optimization model which considers the production forecast and corrective maintenance activities in order to determine a set of preventive and corrective maintenance tasks that are advised to be performed during the present day and maintenance planning forecasts for the following days.

6.2.1 Model description

Time framework

In the proposed model, the time framework is separated into short and long horizon intervals according to the forecasting information available for each horizon. It is assumed that N_S scenarios are available for wind speed and production forecasts for the short horizon interval as well as seasonal forecasts for the long horizon interval. Moreover, it is assumed that the uncertainty in the first time step is negligible, i.e. the expected wind, wave and production are the same for each scenario. This assumption enables to build to a stochastic optimization model with one recourse stage; see [50] for an introduction to stochastic programming. The planning decisions at the first time step in the short horizon are common to each scenario.

- The short horizon interval is discretized into N_{Tshort} time steps, each consisting of one day. The time steps is indexed by $T_{Short} = \{1, .., N_{Tshort}\}$.

- The expected average hourly power production during one time step t and scenario s is P_{ts} , $t \in T_{short}$, $s \in S$. An example is shown in Figure 6-1(a).
- The long horizon interval is discretized into N_{Tlong} time steps, consisting of one week steps except for the last step which is one month. The set of time steps in this interval is defined as $T_{long} = \{1,\ldots,N_{Tlong}\}$
- The expected power production during maintenance hours is estimated by a discretized distribution with L levels of production. For each level $k \in \{1,\ldots,L\}$,, a power production is associated, denoted P_{ks}^{lev}, as well as a number of maximum available working hours for each time step $t \in T_{long}$ and scenario $s \in S$, denoted $h_{kts}^{\max}$. An example is shown in Figure 6-1(b).

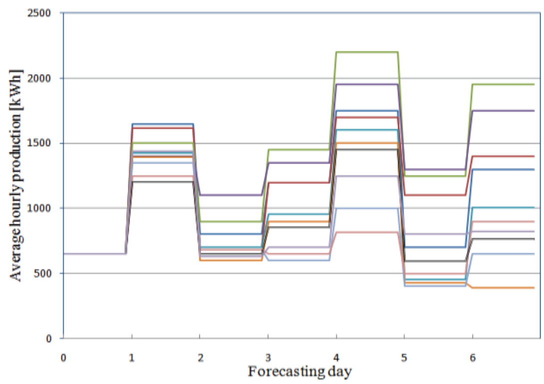

Figure 6-1(a): Example of 7 days production forecast scenarios. The increasing range in the daily forecast is due to the increasing uncertainty in the wind speed.

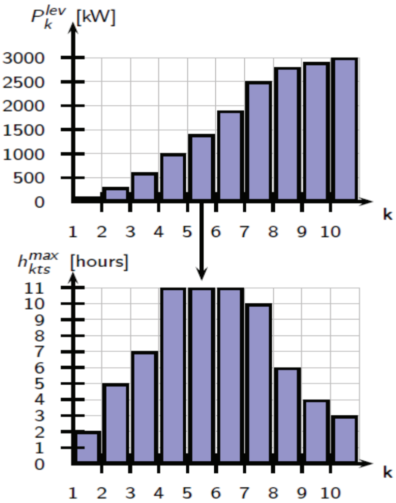

Figure 6-1(b): Example of hourly production probability distribution defining number $h_{kts}^{\max}$ of available maintenance hours at power loss $P_k^{\max}$ for one scenario.

System description

The system consists of a set of N_{WT} wind turbines. All the scheduled preventive maintenance tasks within the time horizon as well as corrective maintenance tasks required have to be defined. A set PM of preventive maintenance tasks that have to be performed within the horizon is defined. It includes subtasks of at least one hour. For each task $j \in PM$ the time to perform the activity is τ_j^{PM} hours. A subset $CM \subset WT$ is defined for the wind turbines requiring corrective maintenance. The expected time to perform the corrective maintenance activity $i \in CM$ is τ_i^{CM}. It is assumed that there is at most one corrective maintenance activity per wind turbine at a time and it can be performed in at most a day. The production losses if corrective maintenance is done at time step $t \in T_{short}$ in scenario $s \in S$ is E_{ts}^{CM}.

Costs and working hours

The electricity market price is C_{el} [€/MWh]. The transportation costs consist of a fixed cost C_{tr} each day when transportation is required. This cost may include fuel, sailing crew and boat/helicopter location costs depending on the type of service contracted with the transport company.

The maintenance team works normally h hours per day during the short horizon. The working time includes the time to perform the maintenance tasks as well as the time for accessing the nacelle of one wind turbine, denoted τ_w. A penalty cost C_{pen} is to be paid for each supplementary working hour. During the long horizon, the available number of working hours is defined by $h_{kts}^{\max}$ and no supplementary hours are considered. An example is depicted in Figure 6-1 (b).

Decision variables

$$x_{ijts} = \begin{cases} 1 & \text{if preventive maintenance task } j \text{ in wind turbine } i \\ & \text{is performed in time step } t \text{ in scenario } s, \\ 0 & \text{otherwise,} \end{cases} \tag{6.1}$$

$j \in PM, i \in WT, t \in T_{short} \cup T_{long}, s \in S$

$$y_{its} = \begin{cases} 1 & \text{if corrective maintenance task in wind turbine } i \\ & \text{is performed in time step t in scenario } s, \\ 0 & \text{otherwise,} \end{cases} \tag{6.2}$$

$i \in WT, t \in T_{short}, s \in S$

$$d_{ts} = \begin{cases} 1 & \text{if the helicopter is used in time step t} \\ & \text{in scenario s} \\ 0 & \text{otherwise.} \end{cases} \tag{6.3}$$

$t \in T_{short}, s \in S$

The notations for the related variables in the first time step are denoted nx_{ijs}, ny_{is} and nd_s respectively. Supplementary number of working hours are denoted ne and e_{ts} for the first step and short horizon.

Objective function

The objective function is composed of the costs of the production losses, as well as transportation costs for the short horizon and expected transportation costs for the long horizon (assuming an average of $h-2\cdot\tau_w$ work hours each time the wind park is visited) over the production scenarios:

$$
\begin{aligned}
\min \quad & \overbrace{\overbrace{nz\cdot C_{boat}}^{\text{Cost Boat}} + \overbrace{nd\cdot(C_{hel}-C_{boat})}^{\text{Cost Helicopter}} + \overbrace{ne\cdot C_{pen}}^{\text{Penalty Cost}} + \left[\overbrace{\sum_{i\in CM} ny_i\cdot E_1^{CM}}^{\substack{\text{Production losses}\\ \text{Corrective Maintenance}}} + \overbrace{\sum_{i,j} nx_{ij}\cdot\tau_i^{PM}\cdot P_1}^{\substack{\text{Production losses}\\ \text{Preventive Maintenance}}}\right]\cdot C_{el}}^{\text{Cost for the initial time step}} + \\
& \frac{1}{N_S}\sum_{s\in S}\left[\overbrace{\sum_{t\in T_{short}\backslash T_1} z_{ts}\cdot C_{tr} + d_{ts}\cdot(C_{hel}-C_{boat}) + e_{ts}\cdot C_{pen} + \left[\sum_{i\in CM} y_{its}\cdot E_{ts}^{CM} + \sum_{i,j} x_{ijts}\cdot\tau_i^{PM}\cdot P_{ts}\right]\cdot C_{el}}^{\text{Costs for the short horizon}} + \right. \\
& \left. \overbrace{\sum_{t\in T_{long}}\left[\sum_k h_{tks}\cdot\left(P_k^{lev}\cdot C_{el} + \frac{C_{boat}}{h-2\cdot\tau_w}\right)\right]}^{\text{Cost for the long horizon}}\right]
\end{aligned}
\tag{6.4}
$$

Constraints are defined to force the CM and PM tasks to be performed in the defined time periods; See Paper VII for more details.

6.2.2 Results

Case study

The example consists of five 3MW wind turbines with four PM tasks to be performed on each turbine. In total this corresponds to two days of work, e.g. the major service maintenance during the summer in an offshore wind farm. The tasks 1 and 3 take 4 hours per turbine and the tasks 2 and 4 take 3 hours. A scenario of 60 days is used, which means that 60 maintenance planning optimizations are performed using the model. It is assumed that the PM tasks 1 and 2 have to be performed within the first 20 days and the PM tasks 3 and 4 should be performed during the first 50 days:

$$N_{Tshort} = 7, N_{Tlong} = 4$$

$$\tau_{10} = \tau_{30} = 4 \text{ h}, \tau_{20} = \tau_{40} = 3 \text{ h}$$

The failure scenario was generated randomly assuming a failure rate of 5 failures per turbine per year. The failure scenario is depicted in Figure 6-2. The repair time was assumed to be 4 hours for each failure.

The wind data were based on a summer period at Lillgrund offshore wind farm. 7-days forecasting scenarios were considered for the example case. The wind forecast for each scenario was generated randomly assuming a normal distribution of the forecasting error with increasing variance. The production forecasts were based on the wind scenarios using a power curve. An example of the power production scenarios is shown in Figure 6-2. The power losses for the CM activities, denoted P_{ts}^{CM}, were calculated using the production scenarios and repair times τ_i^{CM}.

Main results

A selected scenario and solution is presented in Figure 6-2 and Figure 6-3. The maintenance manager performs an optimization of the maintenance planning every day based on the present CM tasks to be performed and available power forecasts. The result is a set of PM and CM tasks that are advised to be performed during the present day and maintenance planning forecasts for the following days. Figure 6-3 shows the daily advised schedule. The advised tasks are assumed to be performed during the day.

One can notice that PM is only performed at low power production and if CM is required. For example, in day 7 (highlighted by the left dashed line) a failure occurs in wind turbine 1 and the solution indicates to perform the preventive maintenance task 2 in the wind turbine 2 at the same time. This is due to the fact that the tasks 1 and 2 had already been performed in the wind turbine 1, and the maintenance tasks 3 and 4 are not urgent. In day 14 (highlighted by the right dashed line), no failure occurs but the wind power production is quite low. The solution advises to perform the maintenance activities 2 and 4 in wind turbine 3.

The average total maintenance cost for performing the PM tasks was 15,172 €. It is assumed that the transportation costs should not be paid if corrective maintenance is performed at the same time. This cost can be compared with the case where all preventive maintenance tasks are performed without taking into consideration wind forecasts, e.g. during the first days of the scenario, two days per turbine. The maintenance cost without optimization is 22,342 €. It means that 7,170 € or 32% of the costs of the transportation and production losses could have been saved using the proposed approach.

This example demonstrates that it is possible to save costs by taking advantage of low power forecasts and CM opportunities to perform the PM tasks. The implementation of the methodology requires that the maintenance schedule is flexible. The maintenance technicians need to be prepared to perform some service maintenance activities after a failure has been corrected (i.e. material and consumables for the service should be located in the wind turbine or on the boat), if the time allows it.

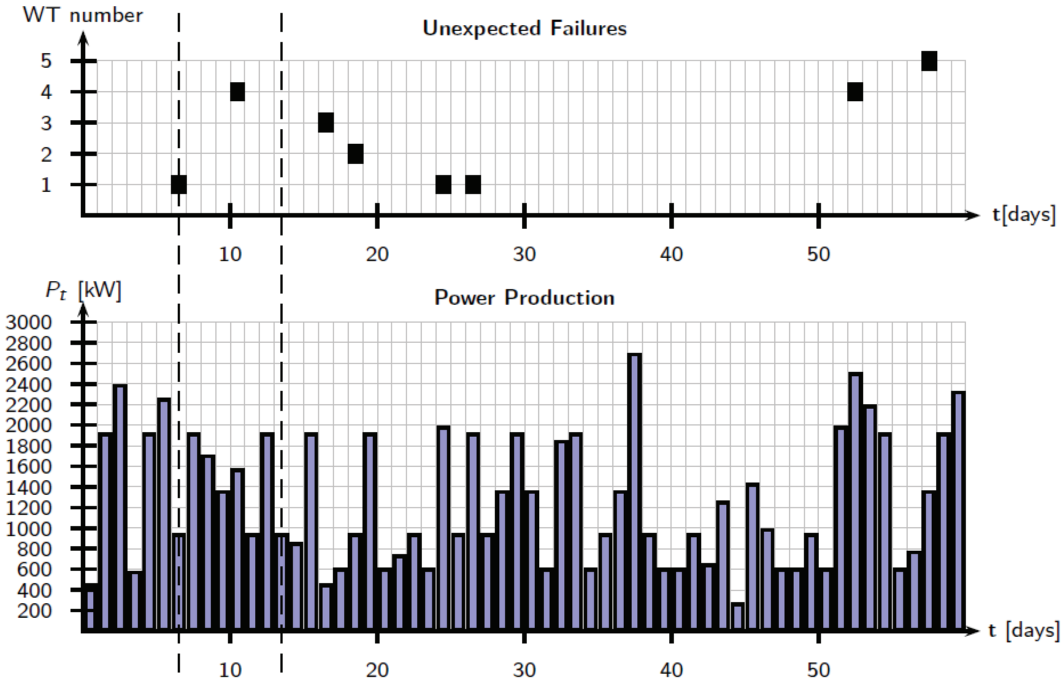

Figure 6-2: Production and failure scenario

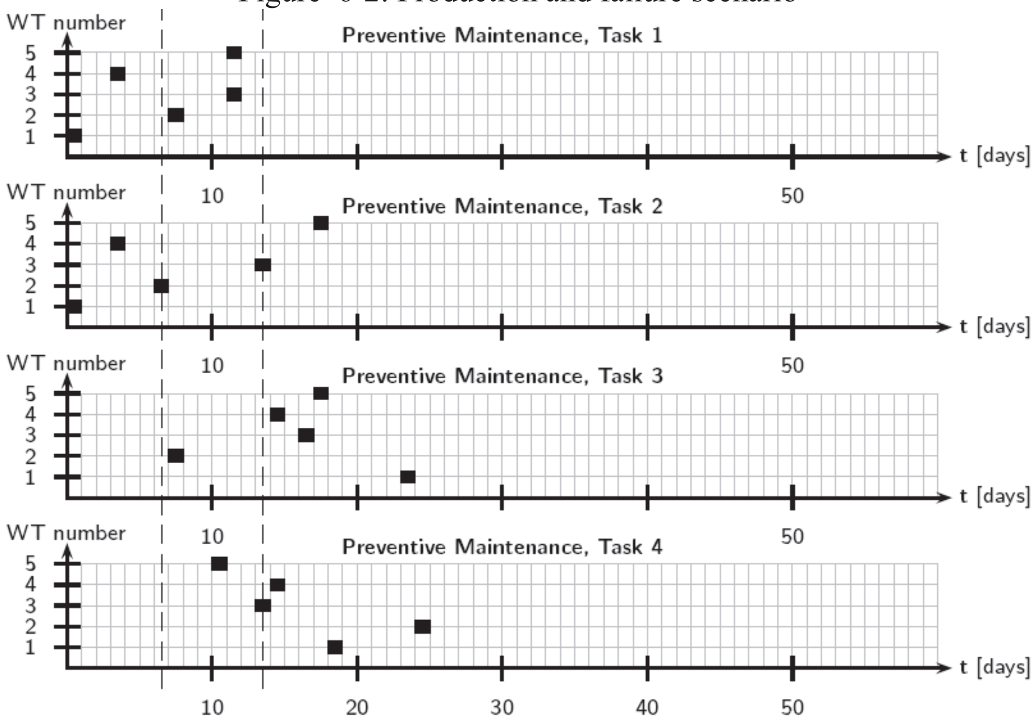

Figure 6-3: Results from the planning optimization

Chapter 7

Closure

This chapter summarizes the main results from the thesis and presents ideas for future work.

7.1 Conclusions

This thesis presents models to optimize the maintenance of offshore wind farms in different inter-connected areas. The main results are recommendations for maintenance strategies, maintenance support organization and a demonstration of the benefit of opportunistic maintenance for maintenance planning.

Maintenance strategies

Two models are introduced to optimize the maintenance strategies for the drive train and for blades. The main idea of both models was to evaluate the benefit of condition based maintenance strategies based on inspection or continuous condition monitoring. The models are stochastic life cycle cost models dependent on reliability and maintenance processes. The results indicate that condition monitoring of the drive train results in an economic benefit of 190,000 € over the lifetime and that it reduces the risk of high maintenance costs. The cost-benefit of inspection based on condition based maintenance techniques, or continuous monitoring of blades is much dependent on the reliability assumptions. The results indicate under which conditions the maintenance strategies are optimal, and how these strategies can reduce the economic risk.

Maintenance support organization

Two complementary models have been proposed to optimize the maintenance support organization for offshore wind farm, considering several factors affecting the maintenance performance: the location of the maintenance accommodation and distance to the wind farm, the number and type of crew transfer vessels, the use of a helicopter and the work shift organization. The models enable to determine the optimal support organization for a given wind farm according to the reliability of the wind turbine, weather conditions, distance from shore and logistic costs. An analytical model enables fast computation of the optimization, which can be further investigated by a simulation model in order to calculate energy-based availability and the risk associated with the solution. The results from a case study for a wind farm of 100 wind turbine with 5MW rated capacity indicate that an economic benefit in the range of 0.6 M€-5.2 M€ per year can be achieved by selecting the optimal maintenance support solution, as compared to other possible solutions.

Maintenance planning
A model for the optimization of maintenance planning is proposed to determine the optimal time for performing the scheduled maintenance activities, with consideration for the cost for transportation and production losses. The model is based on a rolling moving horizon taking into account the knowledge on short term weather forecasts and long term weather statistics, together with opportunities at corrective maintenance. The case studies indicate that an economic benefit of up to that 7,170 € per wind turbine per year could be achieved compared to a classic time based approach.

The results show that maintenance costs can be significantly reduced through optimizing the maintenance strategies and the maintenance planning.

7.2 Future work

Maintenance support organization
It was identified that the analytical model presented in this thesis could be further improved by differentiating between the minor and major repairs in the queuing model. This improvement could be implemented and the results compared with the simulation model.

Several simulation models have been proposed in order to optimize the maintenance support organization for offshore wind farms. Each model has different level of detail and limitations. It would be beneficial to compare the different models that have been proposed and to validate them by comparison with reliability and maintenance time-series data from an existing wind farm.

Maintenance planning optimization for major components
The replacement of large components at offshore wind farms requires crane ships that have limited availability and high costs. It could be advantageous to prioritize, group and optimize the planning of these activities based on reliability and weather statistics in order to reduce the production losses due to unavailable crane ship, long weather downtime or mobilization costs. A related topic is the optimization of the supply strategy for the crane ship, where alternative such as supply via the spot market, periodic contracting or purchase could be compared.

Reliability analysis

The prerequisite for maintenance strategy optimization models is to have component lifetime models. Lifetime models were unfortunately not available during this thesis work mainly due to a lack of structured and systematic reliability data collection and therefore reliability assumptions had to be made. Reliability and maintenance data collection has now received much focus, and standardized data collection systems will enable to develop lifetime models. It is important that not only failures but also inspection results are recorded in order to be able to develop deterioration models.

Since the technology is evolving rapidly and the lifetime is dependent on many environmental factors, physic based reliability model would be most beneficial to estimate the reliability of new technology or concepts, and to develop prognosis models. Some components of interest for such models could be the blades, gearbox, power electronics and foundations.

High voltage power system

The focus of this thesis has been on wind turbines at offshore sites. The high voltage export system connecting the wind farm to the electrical grid onshore is, however, critical for the transmission of the power. Due to the higher distance from shore, complex HVDC grid solutions and long underwater cables are likely to be introduced. The reliability, maintenance and risks related to the high voltage export system will be critical. Synergies with the maintenance support organization for the wind farm could also be identified in order to reduce the total maintenance costs.

Reference list

[1] "Communication from the commission to the european council and the european parliament - an energy policy for Europe", Technical report, Commission of the European Communities, Brussels, Belgium, 2007.

[2] "Wind in Power – 2011 European Statistics", Technical report, European Wind Energy Association, February 2012.

[3] "Offshore Wind in Europe – 2010 Market Report", Technical Report, KPMG/ German Offshore Wind Energy Foundation, 2010.

[4] "Annual Report 2010 – Powering the energy debate", Technical Report, European Wind Energy Association, 2011.

[5] W. Engels, T. Obdam and F. Savenije, "Current developments in wind – 2009", Technical report, ECN-E–09-96, ECN, 2009.

[6] L.W.M.M. Rademakers, H. Braam, T.S. Obdam, P. Frohböse and N. Kruse, "Tools for Estimating Operation and Maintenance Costs of Offshore Wind Farms: State of the Art", In Proc. of European Wind Energy Conference 2008, Brussels, Belgium, 31 March-3 April, 2008.

[7] J. Ribrant and L.M. Bertling, "Survey of failures in wind power systems with focus on Swedish wind power plants during 1997-2005", IEEE Transaction on Energy Conversion, 22(1): 167-173, 2007.

[8] F. Spinato, P.J. Tavner, G.J.W. van Bussel and E. Koutoulakos,, "Reliability of wind turbine subassemblies", IET Renewable Power Generation, 3(4): 387 – 401, 2010.

[9] E. Echavarria, B. Hahn, G.J.W. van Bussel and T. Tomiyama , "Reliability of wind turbine technology through time", Journal of Solar Energy Engineering, 130(3): 1-7, 2008.

[10] K. Harman, R. Walker and M. Wilkisnon, "Availability trend observed at operational wind farms", In Proc. of the European Wind Energy Association conference, Brussels, Belgium, 31 March-3 April, 2008.

[11] Y. Feng, P.J. Tavner and H. Long, 'Early experiences with UK Round 1 offshore wind farms.', Proceedings of the Institution of Civil Engineers - Energy, 163 (4): 167-181, 2011.

[12] S. Faulstich, P. Lyding, B. Hahn, D. Callies and R. Rothkegel, "Wind energy report Germany Offshore", Technical Report, Fraunhofer IWES, 2010.

[13] K.Fischer, "Maintenance Management of Wind Power Systems by means of Reliability-Centred Maintenance and Condition Monitoring Systems", Technical Report, Chalmers University, February, 2012.

[14] L. Bertling, R. Allan, and R. Eriksson. "A reliability centred asset maintenance method for assessing the impact of maintenance in power distribution systems", IEEE Transactions on Power Systems, 20(1):75–82, 2005.

[15] P. Hilber, "Maintenance optimization for power distribution systems", PhD thesis, Royal Institute of Technology, Stockholm, Sweden, April 2008. TRITA-EE 2008:012.

[16] T. Lindquist. On reliability and maintenance modelling of ageing equipment in electric power systems. PhD thesis, Royal Institute of Technology, Stockholm, Sweden, 2008. TRITA-EE 2008:016.

[17] J. Setreus, "Identifying critical components for system reliability in power transmission systems", PhD thesis, Royal Institute of Technology, Stockholm, Sweden, October 2011. TRITA-EE 2011:053.

[18] C.J Wallnerström, "On Incentives affecting Risk and Asset Management of Power Distribution", PhD thesis, Royal Institute of Technology, Stockholm, Sweden, August 2011. TRITA-EE 2011:022.

[19] J. Nilsson. On maintenance management of wind and nuclear power plants. Licentiate thesis, Royal Institute of Technology, Stockholm, Sweden, November 2009. TRITA-EE 2009:042.

[20] F. Edstrom, J. Rosenlind, P. Hilber and L. Söder,." Modeling Impact of Cold Load Pickup on Transformer Aging Using Ornstein-Uhlenbeck Process", IEEE Transactions on Power Delivery, 27(2) 590–595, 2012.

[21] "Std 100 - The Authoritative Dictionary of IEEE Standards Terms",Standards Information Network, IEEE Press, 2000", New York, USA. ISBN 0-7381-2601-2.

[22] "Maintenance terminology - Svensk Standard SS-EN 13306", SIS Förlag AB, Stockholm, Sweden, 2001". ISBN 9789171626509.
[23] A. Hoyland and M. Rausand, "System Reliability Theory: Models and Statistical Methods - Second Edition", Wiley, New Jersey, USA, 2004. ISBN 0-471-47133-X.
[24] R.E. Barlow and F. Proschan,, "Mathematical Theory of Reliability", Wiley, New York, USA, 1965. ISBN 978-0-898713-69-5.
[25] A.K.S. Jardine and A.H.C. Tsang, "Maintenance, Replacement, and Reliability - Theory and Applications", Taylor and Francis, Boka Raton, USA, 2006, ISBN 0-8493-3966-9.
[26] J.A. Nachlas, "Reliability Engineering - Probabilistic Models and Maintenance Methods", Taylor and Francis, Boka Raton, USA, 2005. ISBN 0-8493-3598-1.
[27] D. M. Frangopol, M.-J. Kallen and J. M. van Noortwijk, "Probabilistic models for life-cycle performance of deteriorating structures: review and future directions", Journal of Progress in Structural Engineering and Materials, 2004, 6(4):197 – 212.
[28] J.M. van Noortwijk. "A survey of application of gamma processes in maintenance", Reliability Engineering and System Safety, 94(1):2-21, 2009.
[29] W. Q. Meeker and L. A. Escobar, "Statistical Methods for Reliability Data", Wiley, New York, USA, 1998. ISBN 978-0-471-14328-4.
[30] T. Welte, J. Vatn, and J. Heggset, "Markov state model for optimization of maintenance and renewal of hydro power components". In proc. of the 9th International Conference on Probalistic Methods Applied to Power Systems, Stockholm, Sweden, 11-12th June, 2006.
[31] C. S. Gray and S. J. Watson, "Physics of Failure approach to wind turbine condition based maintenance", Wind Energy, Published online, 2009.
[32] R.D. Baker and A.H. Christer, "Review of delay-time or modeling of engineering aspects of maintenance", *European Journal of Operational Research*, 73(3):407-422, 1994.
[33] D. Gross, J.F. Shortle, J.M. Thompson and C. Harris, "*Fundamentals of queuing theory - Fourth Edition* ", 2008, Wiley, New Jersey, ISBN 978-0-471-79127-0.
[34] T. Welte, "Using state diagrams for modeling maintenance of deteriorating systems", IEEE Transaction on Power Systems, 24(1):58-66, 2009.
[35] J. Banks, J. Carson, B. Nelson and D. Nicol, "*Discrete-event system simulation - Fourth edition"*, 2009, Prentice Hall, New Jersey, ISBN-10: 978-0-136-06212-7.
[36] J. Moubray, "Reliability-Centered Maintenance", Industrial Press Inc., New York, USA, 1997. ISBN 0-8311-3078-4.
[37] J. D. Campbell and J. V. Reyes-Picknell, "Uptime, 2nd Edition: Strategies for Excellence in Maintenance Management", Productivity Press, 2006. ISBN 1-5632-7335-7.
[38] R. Dekker, "Application of maintenance optimization models: a review and analysis", Journal of Reliability Engineering and System Safety, 1996, 51(3):229-240.
[39] N. Andréasson, "Optimisation of opportunistic replacement activities in deterministic and stochastic multi-component systems", Technical report, Chalmers, Göteborg University and Chalmers University of Technology, Göteborg, Sweden, 2004.
[40] A. Wojciechowski, "Polyhedral and complexity studies in integer optimization, with applications to maintenance planning and location–routing problems", PhD thesis, Chalmers, Göteborg University and Chalmers University of Technology, Göteborg, Sweden, 2012.
[41] R. Dekker. "Applications of maintenance optimisation models: A review and analysis", *Reliability Engineering*, 51(3):229-240, 1996.
[42] J. Endrenyi et al. "The present status of maintenance strategies and the impact of maintenance on reliability", IEEE Transactions on Power Systems, 16(4):638-646, 2001.
[43] R. Dekker, R.E. Wildeman, and F.V. der Schouten, "A review of multicomponent maintenance models with economic dependence", *Mathematical Methods of Operations Research*, 45(3):411-435, 1997.
[44] D.I. Cho and M. Parlar, "A survey of maintenance models for multiunit systems", *European Journal of Operational Research"*, 51(1):1-23, 1991.
[45] R. Wildeman, R. Dekker, and A. Smit. "A dynamic policy for grouping maintenance activities", *European Journal of Operational Research*, 99(3):530-551, 1997.
[46] R.P. Nicolai and R. Dekker, "Optimal maintenance of multi-component systems: A review", Technical report, Erasmus University Rotterdam, Econometric Institute, Rotterdam, Netherlands, 2006. EI 2006-29.
[47] H. Wang, "A Survey of maintenance policies of deteriorating systems", *European Journal of Operational Research*, 139(3):469-489, 2002.

[48] D. Bertsimas and J.N. Tsitsiklis. Introduction to Linear Optimization. Athena Scientific, Belmont, United States, 1997. ISBN-10: 1-886529-19-1.
[49] L. A. Wolsey. Integer Programming. Wiley Interscience Series in Discrete Mathematics and Optimization, New York, United States, 1998. ISBN 0-471-28366-5.
[50] P. Kall and Stein, “Stochastic Programming”, John Wiley & Sons, Chichester, 1994.
[51] J. Nilsson and L. Bertling, “Maintenance Management of Wind Power Systems Using Condition Monitoring Systems - Life Cycle Cost Analysis for Two Case Studies”, IEEE Transactions on Energy Conversion, 22(1), pp.223-229, March 2007.
[52] B.Frankén, “Reliability Study - Analysis of Electrical Systems within Offshore Wind Parks”, Technical report 07:65, Elforsk, Sweden, 2007.
[53] A. Beddard, M. Barnes,“VSC-HVDC Availability Analysis”, Technical Report, The University of Manchester, 2011.
[54] J. Nilsson, “Maintenance management of wind power systems - Cost effect analysis of condition monitoring systems” Master Thesis, Royal Institute of Technology, Stockholm, Sweden, 2010.
[55] J. Broehl, “Servicing a turbine”, Wind Power Special Report – Supplement to Wind Power Monthly March, 2010.
[56] “Principles for condition-based maintenance of wind turbines”, Technical Report, German Wind Energy Association, September, 2007.
[57] A.O. Eggen. “Handbook on condition monitoring of wind turbines”. In Proc. of the European Wind Energy Conference 2009, Marseille, France, 16-19 March, 2009.
[58] M.P. de Jong,“Results corrosion inspections Offshore wind farm Egmond aan Zee”, Technical Report, KEMA, 2010.
[59] S. Sheng and P. Veers, “Wind Turbine Drivetrain Condition Monitoring – An Overview”, In Proc. of Mechanical Failures Prevention Group: Applied Systems Health Management Conference 2011, Virginia Beach, Virginia, 10 – 12 May, 2011.
[60] Z. Hameed, Y.S. Hong, Y.M. Cho, S.H. Ahn, and C.K. Song. “Condition monitoring and fault detection of wind turbines and related algorithms: a review”. Renewable and Sustainable Energy Reviews, 13(1):1-39, 2009.
[61] C.J. Crabtee, ”Survey of Commercially Available Condition Monitoring Systems for Wind Turbines”,Durham University, November, 2010.
[62] R.W. Hyers, , J.G. McGowan, K.L. Sullivan, J.F. Manwell and B.C. Syrett, “Condition monitoring and prognosis of utility scale wind turbines”, Energy Materials, Vol. 1(3), 2006, p. 187-203.
[63] A. Zaher, S.D.J. McArthur, D.G. Infield, Y. Patel, “Online wind turbine fault detection through automated SCADA data analysis”, Wind Energy, Vol. 12(6), 2009, p. 574–593.
[64] K. Kim, G. Parthasarathy, O. Uluyol, W. Foslien, S. Shuangwen and P. Fleming “Use of SCADA Data for Failure Detection in Wind Turbines”, in Proc. of the 2011 Energy Sustainability Conference and Fuel Cell Conference, Washington D.C.,United State of America, 7-10 August, 2011.
[65] S. Lindhal, K.Harman,“Analytical techniques for performance monitoring of modern wind turbines”, In proc. of the European Wind Energy Assiciation Conference 2012, Copenhagen, 16-19 April, 2012.
[66] P. J. Quinlan, "Reliability centered maintenance applied to wind park operations," in proc. of *Sixth ASME Wind Energy Symposium*, Dallas, USA, 1987.
[67] J.A. Andrawus, “Maintenance optimization for wind turbines”, PhD thesis, Robert Gordon University, Aberdeen, United Kingdom, 2008.
[68] R. Bellens and P. Chemweno, "Business case for condition based maintenance of wind turbine gearboxes," Master's thesis, Katholieke Universiteit Leuven, Leuven, 2010.
[69] K. Fischer, F. Besnard and L. Bertling, “Reliability-Centred Maintenance for Wind Turbines Based on Statistical Analysis and Practical Experience”, IEEE Transaction on Energy Conversion, 27(1): 184-195, 2012.
[70] D. McMillan, G. Ault, “Towards Quantification of Condition Monitoring Benefit for Wind Turbine Generators”, 2007 EWEC conference, Milan, Italy.
[71] D. McMillan, A. Graham, “Condition monitoring benefit for onshore wind turbines: sensitivity to operational parameters”, IET Renewable Power Generation, 2(1), pp. 60–72, 2008.
[72] J.A. Andrawus, J. Watson, and M. Kishk, “Wind turbine maintenance optimisation: principles of quantitative maintenance optimisation”, *Wind Engineering*, 31(2):101-110, 2007.
[73] M.A. Drewru and G.A. Georgiou, “A review of NDT techniques for wind turbines”, Insight, 49(3):137-141, 2007.

[74] J. G. R. Ramírez, "Reliability Assessment and Reliability-Based Inspection and Maintenance of Offshore Wind Turbines", PhD Thesis, Aalborg University, October, 2010.
[75] D.J. Cerda Salzmann, "Ampelmann, Development of the Access System for Offshore Wind Turbines", PhD thesis, TU Delft, 2004.
[76] http://www.windcatworkboats.com.
[77] http://www.uni-fly.dk.
[78] http://www.osbitpower.com.
[79] C. Sherbrooke "*Optimal inventory modeling of systems: multi-echelon techniques- Second Edition"*, 2004, Springer, Boston, ISBN 978-1-4020-7849-1.
[80] M. Lindqvist and J. Lundin, "Spare part logistics and optimization of wind turbines - Methods for cost-effective supply and storage", Master Thesis, Uppsala University, 2010.
[81] L.W.M.M. Rademakers, H. Braam, .T.S. Obdam and R.P. van de Pieterman, "Operation and maintenance cost estimator (OMCE) to estimate the future O&M costs of offshore wind farms", In Proc. of European Offshore Wind 2009 Conference, Stockholm, Sweden, 14-16 September, 2009.
[82] J.L. Phillips, C.A. Morgan and J. Jacquemin, "Multi-dimensional optimisation of OM provisions for offshore wind", In Proc. of European Offshore Wind Conference, Berlin, Germany, 4-6 December, 2007.
[83] A. Karyotakis, "On the Optimisation of Operation and Maintenance Strategies for Offshore Wind Farms", PhD thesis, University College London, 2011.
[84] C. Hersenius, U. Möller, "Operation and Maintenance of Offshore Wind Farms-A study for Systecon AB", Master Thesis, Lund University, 2011.
[85] G. Giebel et al., "Wind Power Prediction using Ensembles", Risø DTU, Roskilde, Denmark, Tech. Rep. Risø-R-1527(EN), 2005.
[86] E.N. Lorentz, "A study of the predictability of a 28-variable atmospheric model, TELLUS, 17:321-333, 1965.