KTH Electrical Engineering

On Optimal Maintenance Management for Wind Power Systems

FRANÇOIS BESNARD

Licentiate Thesis
KTH Royal Institute of Technology
School of Electrical Engineering
Division of Electromagnetic Engineering
Stockholm, Sweden 2009

Division of Electromagnetic Engineering
KTH School of Electrical Engineering
SE-100 44 Stockholm, Sweden

Akademisk avhandling som med tillstånd av Kungl Tekniska högskolan framlägges till offentlig granskning för avläggande av teknologie licentiatexamen i elektrotekniska system fredagen den 4 december 2009 kl 13.00 i sal D3, Lindstedtsv 5, Kungl Tekniska högskolan, Stockholm.

Tryck: Universitetsservice US AB

TRITA-EE 2009:051
ISSN 1653-5146
ISBN 978-91-7415-482-5

Abstract

Sound maintenance strategies and planning are of crucial importance for wind power systems, and especially for offshore locations. In the last decades, an increased awareness of the impact of human living on the environment has emerged in the world. The importance of developing renewable energy is today highly recognized and energy policies have been adopted towards this development. Wind energy has been the strongest growing renewable source of energy this last decade. Wind power is now developing offshore where sites are available and benefits from strong and steady wind. However, the initial investments are larger than onshore, and operation and maintenance costs may be substantially higher due to transportation costs for maintenance and accessibility constrained by the weather.

Operational costs can be significantly reduced by optimizing decisions for maintenance strategies and maintenance planning. This is especially important for offshore wind power systems to reduce the high economic risks related to the uncertainties on the accessibility and reliability of wind turbines.

This thesis proposes decision models for cost efficient maintenance planning and maintenance strategies for wind power systems. One model is proposed on the maintenance planning of service maintenance activities. Two models investigate the benefits of condition based maintenance strategies for the drive train and for the blades of wind turbines, respectively. Moreover, a model is proposed to optimize the inspection interval for the blade. Maintenance strategies for small components are also presented with simple models for component redundancy and age replacement.

The models are tested in case studies and sensitivity analyses are performed for parameters of interests. The results show that maintenance costs can be significantly reduced through optimizing the maintenance strategies and the maintenance planning.

Acknowledgments

This thesis was updated in December 2009 with revised results for paper II and paper III.

This thesis is part of the Ph.D. project “Optimal maintenance management for offshore wind power using condition based monitoring systems” at KTH School of Electrical Engineering, Division of Electromagnetic Engineering. The project is funded by Vindforsk Research Program. The financial support is gratefully acknowledged.

I am grateful to Prof. Lina Bertling my main supervisor for giving me the opportunity to carry out this work. I thank her for her support, her encouragement, and for the wonderful study visits at Smøla and Lillgrund.

I would like to thank Prof. Michael Patriksson my supervisor for many good comments, and together with Dr. Ann-Brith Strömberg and Adam Wojciechowski for interesting discussions on optimization.

I am thankful to Sven Erik Thor at Vattenfall Vindkraft for his support, Arild Soleim at Statkraft Energi and Tor Söderlund at Vattenfall Vindkraft for arranging the visit at Smøla and Lillgrund wind farms, respectively. I thank Karin Lindholm, previously at Vattenfall Vindkraft, for interesting discussions and for arranging the visit at Yttre Stengrund wind farm.

I am grateful to all my colleagues in the RCAM research group; Julia Nilsson, Patrik Hilber, Johan Setréus, Carl Johan Wallnerström, Johanna Rosenlind and former colleague Tommie Lindquist and Andrea Lang.

A special thanks to Julia, Dave, Kashif, Alexander, Henrik, Rathna, and especially Dmitry and Gaël for their friendship.

Last, but not least, I would like to thank my family for their support and love.

François
Stockholm, November 2009

List of papers

I F. Besnard, M. Patriksson, A. Strömberg, 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, 28th June–2nd July 2009.

II F. Besnard, J. Nilsson and L. Bertling. On the Economic Benefits of using Condition Monitoring Systems for Maintenance Management of Wind Power Systems. Submitted to the *11th International Conference on Probabilistic Methods Applied to Power System*, Singapore, 14th–17th June 2010.

III F. Besnard and L. Bertling. An Approach for Maintenance Inspection Optimization Applied to Wind Turbine Blades. Submitted to the *IEEE Transactions on Sustainable Energy*, November 2009.

Abbreviations

CBM	Condition Based Maintenance
CM	Corrective Maintenance
CMS	Condition Monitoring Systems
EWEA	European Wind Energy Association
f	failure
h	hour
HVAC	High-Voltage Alternative Current
HVDC	High-Voltage Direct Current
LCC	Life Cycle Cost
MILP	Mixed Integer Linear Programming
MTTF	Mean Time To Failure
NWP	Numerical Weather Prediction
PM	Preventive Maintenance
RCAM	Reliability Centered Asset Management
RCM	Reliability Centered Maintenance
rep	repair
SCADA	Supervisory Control And Data Acquisition
TBM	Time Based Maintenance
WT	Wind Turbine
yr	year

Contents

To Loïc

Chapter 1

Introduction

1.1 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 green 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% biofuel 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 36% of the new electricity generating capacity installed in 2008 [2].

At the end of 2008, 65 GW of wind power was installed in the European Union. The target of the European Wind Energy Association (EWEA) is to reach 180 GW in Europe by 2020 [3]. Wind energy at onshore coastal sites is already close to competitiveness compared to conventional power plants [4]. Wind energy may become more competitive in the future, due to the increase trend for fuel costs and implementation of real prices on carbon pollution in Europe. Each European country uses a mix of incentives (e.g. investment support, production support or demand creation) to make wind energy more attractive [5]. In order to reach the EWEA target, the share of offshore wind power in Europe is expected to increase, from 1.3% nowadays to 20% in 2020. Offshore wind power has the advantage of stronger and steadier wind, and lower visual and noise impact. However, investment costs are around 50% higher than onshore, and operation and maintenance costs may be substantially higher.

One of the sources of high maintenance costs is harsh weather conditions at good offshore locations. For safety reasons, the operation of transportation vessels is subject to wave and wind restrictions. Consequently, a small failure may result in a long downtime during bad weather conditions, resulting in a high cost from production loss. Another source of high maintenance costs is transportation and maintenance equipment expenses. A vessel is needed for daily maintenance, and in case of harsh weather conditions a helicopter may be necessary to access the WTs. Moreover, specific boats (e.g. a Jack-up boat) are required to perform major maintenance (i.e. the replacement of a component of the rotor or drive-train). The availability of these boats has an important influence on the maintenance planning and production loss after failure.

The costs of wind power have been reduced by increasing the size and complexity of wind turbines. These improvements have in general resulted in a higher failure rate [6, 7], probably due to the integration of more power electronic and control systems [8], and a short time for fatigue testing of the new WT designs.

The uncertainties on the reliability and accessibility result in risks regarding the operation and maintenance costs, especially concerning offshore wind power systems. In order to mitigate this risk, it is of interest to:

- optimize the design and reliability of WTs with respect to their application (onshore, offshore, cold climate), e.g. by investigating component redundancies and maintainability; and to
- optimize maintenance strategies and maintenance planning based on objective criteria.

Maintenance activities can be divided into Corrective Maintenance (CM) and Preventive Maintenance (PM). PM includes Time-Based Maintenance (TBM), i.e. maintenance performed at fixed intervals, and Condition Based Maintenance (CBM), maintenance performed based on the condition of the components assessed either by inspection or continuous monitoring. An approach called Reliability Centered Maintenance (RCM) was developed in the 1960th for the aircraft industry in order to identify cost-efficient maintenance strategies [9, 10]. RCM is implemented by some electrical power facilities, e.g. for hydropower in Norway [11]. RCM was further developed in [12] into a quantitative method called Reliability Centered Asset Management (RCAM). The objective of RCAM is to quantify the impact of maintenance strategies on the reliability and costs, in order to assist the decision making based on objective criteria. Two main steps in the RCAM approach are life time modeling and maintenance optimization.

Operational costs can generally be significantly reduced by optimizing the choice and implementation of maintenance strategies, by selecting suitable capital investments (e.g. transportation for the maintenance crew), and by optimizing maintenance planning. An overview of the existing literature resulted in the following conclusions. The choice for transportation vessels and benefits of an internal crane for offshore wind power systems were investigated in [13]. The benefits of using Condition Monitoring Systems (CMS) were investigated in [14,15]. The RCM methodology was used in [16] in order to identify suitable maintenance strategies. Only one model was found to optimize the implementation of maintenance strategies [17]. Reasons for this may be the rareness of using optimization models, and the lack of needed failure and maintenance data. However, computer maintenance management systems started to be implemented recently [18], and reliable failure and maintenance data are expected to be available in the coming years.

This PhD work aims at taking a step towards maintenance optimization for wind power systems.

1.2 Related research within the RCAM group

Following the development of the RCAM method, a research group named RCAM was created at KTH [19]. The RCAM group focuses on three main research areas; (i) Maintenance planning and optimization, (ii) Reliability assessment for complex systems, and (iii) Life-time modeling for electrical components. Dr. Patrik Hilber presented his PhD thesis on maintenance optimization applied to power distribution systems in [20]. Dr. Tommie Lindquist presented his PhD thesis on life-time and maintenance modeling in [21]. Johan Setréus presented his licentiate thesis on reliability methods quantifying risks to transfer capability in electric power transmission systems in [22]. Carl Johan Wallnerström presented his licentiate thesis on risk management of electrical distribution systems and the impact of regulations in [23]. Julia Nilsson presented her licentiate thesis on maintenance management for wind and nuclear power systems in [24]. Recent publications of other PhD work within the RCAM group are found in [25–30].

The originator of the RCAM research group, Prof. Lina Bertling, was appointed as Professor in Sustainable Electric Systems at Chalmers University of Technology in January 2009. This PhD project will be continued at Chalmers University of Technology at the Division of Electrical Power Engineering and the research group on wind power.

1.3 Project objective

The main objective of this PhD project is to develop maintenance optimization models for wind power systems, with respect to reliability and cost. An application of interest is offshore wind power systems, where high maintenance costs are expected.

1.4 Main results

The main scientific contributions in this thesis are summarized below.

- Development of a model for optimizing the maintenance planning of scheduled service maintenance for wind power systems, presented in Paper I.
- Development of a stochastic life cycle costs model for evaluating the benefits of vibration condition monitoring systems, presented in Paper II.
- Development of a method for estimating maintenance costs for components with classifiable deterioration, presented in Paper III. The method is used to optimize periodic inspection of the blades with condition monitoring techniques, and to evaluate the benefits of this maintenance strategy compared to visual inspection.

1.4.1 Author´s contributions

The author has written and contributed to the major parts of appended Papers I, II and III. Prof. Lina Bertling has contributed as the main supervisor for all papers with input of ideas and reviewing of draft versions. Prof. Michael Patriksson, Dr. Ann-Brith Strömberg and PhD student Adam Wojciechowski at Chalmers have contributed with input ideas and reviewing for Paper I. PhD student Julia Nilsson at KTH has contributed with the writing in Paper II.

1.5 Thesis outline

In Chapter 2 wind energy and wind power technology is introduced. Chapter 3 presents the underlying reliability theories in Paper II and Paper III. Chapter 4 provides an introduction to maintenance and to the underlying optimization theory in Paper III. Chapter 5 is the core of the thesis, and summarizes the main own contributions. The chapter presents the state-of-the-art in maintenance management for wind power systems, and highlights ideas for maintenance optimization. It includes the proposed models and results which are also presented in Paper I-III. Chapter 6 summarizes the results and presents ideas for future works.

Chapter 2

Introduction to wind power

This chapter provides an introduction to wind energy and technology.

2.1 Basics of wind energy

Energy in the wind. The power of an air mass flowing through an area A is [31]:

$$P_{air} = \frac{1}{2}\rho v^3 \cdot A \text{ [W]}, \tag{2.1}$$

where ρ is the air density $[kg/m^3]$ and v the wind speed $[m/s]$.

When flowing into the area of a WT rotor, a part of the wind power is converted into mechanical power. According to Betz´s law, a maximum of 59% of the wind power can be theoretically extracted in order to prevent the air mass to stop [31].

Wind power extraction. There are two main approaches for extracting wind power:

- **Drag devices** use the force perpendicular to the wind direction.
- **Lift devices** use the force resulting from the difference of air pressure on the two sides of a blade.

Lift devices are more efficient than drag devices [32]. Horizontal axis WTs, that are commonly used today, are lift devices.

The power coefficient. C_p is defined as the ratio between the extracted power and the power flowing in the blade area. C_p depends on the angle of attack (the angle between the blade and the wind direction) and tip speed ratio (the ratio between the blade tip speed and wind speed). The blade airfoil and possible control strategy (for the angle of attack and tip speed ratio) are designed in order to optimize the power coefficient efficiency at any wind speed. For a good wind turbine design, C_p is around 0.35.

Power curve. The theoretical output power curve of a WT as a function of the wind speed can be expressed as:

$$P(v) = C_p(v) \cdot \nu_t(v) \cdot \frac{1}{2}\rho v^3 \cdot A \text{ [W]}, \tag{2.2}$$

with ν_t the efficiency coefficient of the components in the wind turbine (up to 0.8).

Fig. 2.1 shows an example of a power curve. There are three important characteristics of a power curve:

- **The cut-in wind speed** (point A in Fig. 2.1), the wind speed at which a WT starts to generate power. (Below the cut-in wind, the inertia of the rotor prevents the WT to turn.)
- **The rated wind speed** (point B in Fig. 2.1), the wind speed at which a WT generates its nominal power.
- **The cut-out wind speed** (point C in Fig. 2.1), the wind speed at which a WT is shut down for safety reasons.

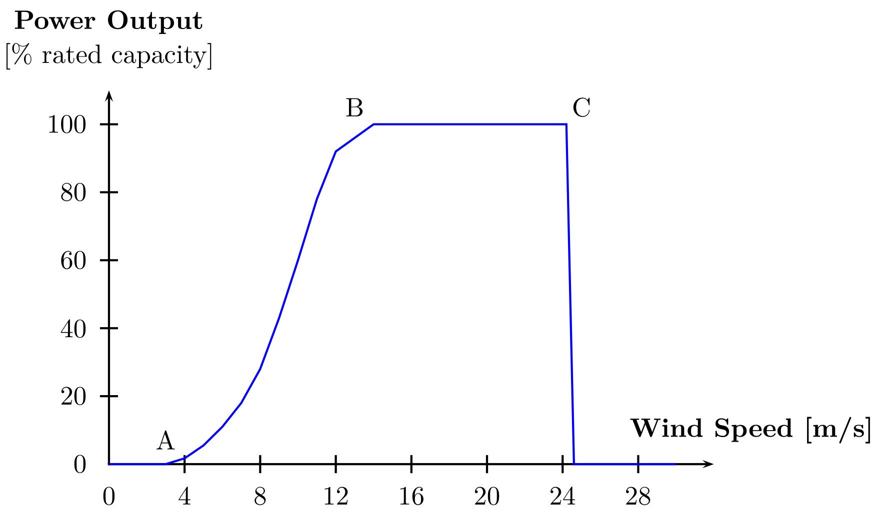


Figure 2.1: Example of power curve for a WT. Points A, B and C represent the cut-in, rated and cut-out wind speed, respectively.

Vertical wind profile. The power curve can be used to estimate the energy production of a WT at given wind resources, i.e. expected wind speed distribution. The wind speed varies with the height above the ground. If the wind speed distribution is known at height z_r, it can be estimated at height z using the vertical profile of wind speed. A simple model is the logarithmic wind profile:

$$\frac{v(z)}{v(z_r)} = \ln(\frac{z}{z_0})/\ln(\frac{z_r}{z_0}), \tag{2.3}$$

where ln is the standard logarithmic function and z_0 is a surface roughness that depends on the type of landscape. The smoother the surface, the lower z_0 is and the higher $v(z)$ is. For example, z_0 can be 0.2 for a calm open sea, 8 for lawn grass or 500 for forests [31]. For offshore environments, z_0 is low, which results in high power at low height as well as low turbulences.

Capacity factor. The capacity factor C_f for one WT is defined as the ratio between the average power production of the WT over a selected period and the nominal power of the wind turbine. For onshore wind turbine, C_f is typically in the range 0.25-0.4, while for offshore it can be in the range 0.4-0.6, due to higher and steadier wind.

Wind forecasting. Wind forecasting has received a great interest in last years, both for the control of the wind turbine (very short-term forecasting, up to a few minutes) and energy trading (short-term planning, 48h - 72h). For maintenance applications, longer time horizons are of interest. It was shown in [33] that the limit of weather predictability is around two weeks. Beyond this limit, an alternative is to use seasonal forecasts, e.g. based on wind historical data. A short introduction to wind forecasting is provided below; for more information see [34].

There are two complementary approaches for forecasting wind: Statistical methods suitable for short horizons (hours) and physical models suitable for long horizons (days). Statistical methods are, for example, time series or neural networks. These methods use historical data to predict the future wind. Physical models refine meteorological forecasts provided by a Numerical Weather Prediction (NWP) to adapt to the required spatial and time resolution. The atmosphere is a fluid. Based on the current state of the atmosphere, a NWP predicts its future state using mathematical models of fluid and thermo-dynamic. The input data for NWP are measurements of e.g. temperature, humidity, velocity and pressure, made at grid points. In Europe, the European Centre for Medium-Range Weather Forecasts provides probabilistic weather forecasts for up to 10 days [35]. The spatial resolution of NWP needs to be interpolated to provide prediction at the level of the wind farm.

2.2 Wind turbine technology

This section provides an overview of systems in WTs and their functions; for more details the reader is referred to [31, 32].

The structure of a WT is constituted of the tower, the foundation, the nacelle and the rotor. Fig. 2.2 depicts the structure of a modern horizontal axis WT. Table 2.1 shows the development of the capacity through time and examples of rotor size and turbine height (the optimal size for the blade and tower height depends on the wind resource).

Table 2.1: Development of wind turbine capacity and size, partly adapted from [31, 36].

Year	1985	1989	1994	1998	2000	2003	2007
Capacity [kW]	50	300	600	1500	2000	3000	5000
Rotor diameter [m]	15	30	50	70	90	100	125
Tower height [m]	25	40	50	70	80	90	100

The nacelle supports and protects the drive train (i.e. the rotating components in the nacelle), control systems, auxiliary systems and brake systems. Fig. 2.3 shows an example of drive train inside the nacelle.

2.2.1 Tower

The tower carries the nacelle and the rotor. Most of large WTs have tubular steel towers made of 20–30 meters sections bolted together. For offshore applications, the lower part of the tower has to be protected from a sea corrosion and waves with a special paint. The tower and the nacelle are connected by a large bearing and their relative motion is controlled by the yaw system. The tower includes a ladder or an elevator for reaching the nacelle.

Yaw system. The rotation of the nacelle is controlled in order to align the blades with the wind. This function is performed by the yaw system using a large gear. The actuators for the yaw system can be hydraulic motors, hydraulic cylinders or electrical machines. Wind measurements (speed and direction) are provided by an anemometer with a wind vane located at the top of the nacelle.

2.2.2 Foundation

The foundation supports the tower and transmits loads on the tower to the soil. The foundation of an onshore WT is, in general, a pad foundation. For offshore environment, different types of foundation are possible, e.g.

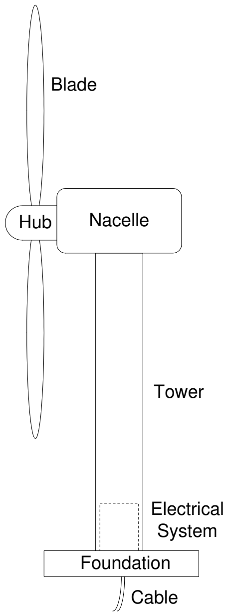


Figure 2.2: Structure of a wind turbine.

concrete gravity, concrete monopile, concrete tripod or steel monopile foundations [37]. Floating platform concepts have recently been proposed [38]. The suitable design depends on the sea soil and the water depth.

2.2.3 Rotor

The rotor is composed of the blades and the hub. It also includes the actuator for the pitch control of the blades.

Blades. The function of the blades is to capture the wind power. The number of blades depends on the application of the WT. The fewer the number of blades, the higher the aerodynamic efficiency is, and the lower the rotational speed can be. Modern WTs have two or three blades. Three blades WTs are the most common; they are dynamically smoother and have a higher visual acceptance from the public [32]. Blades are generally made from fiberglass reinforced with plastic, carbon fiber or laminated wood. Blades can include lightning sensors and heating systems if the WT operates in cold climates. Common failures for blades are discussed in [39].

Stall/Pitch system. There are two main approaches to control the angle of attack of the blades: stall control and pitch control. A stall control

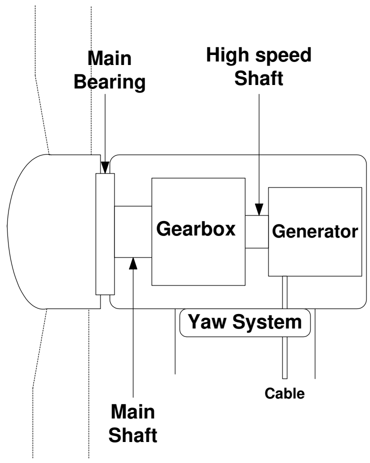


Figure 2.3: An example of a view inside the nacelle.

consists of blades designed with an aero dynamical profile that limits the output power. A pitch control system directly pitches the blades to the desired angle. Pitch control enables a better control of the output power, and it is commonly used for large WTs.

Hub. The hub transmits the rotational power from the blade to the main shaft of the drive train. There are three types of hubs: rigid, teetering and hubs for hinged blades. Rigid hubs are the most common for three blades WTs.

2.2.4 Drive train

The function of the drive train is to convert the rotational mechanical power, provided by the rotating hub, into electrical power. Different designs have been used for the drive train; for details see chapter 4 in [36]. The main differences between the different designs are the type of the control, i.e. fixed or variable speed, and the possible presence of a gearbox. The components included in the drive train depend on the approach and can consist of shafts, a main bearing, a gearbox and an electrical machine.

Shaft. A shaft transmits the rotational power between other converters (e.g. hub, gearbox and generator). Shafts are connected by a mechanical coupling and are supported by bearings. The main shaft of a WT (low speed shaft) is connected to the hub. It supports the rotor and transmits its weight to the bearing. The high speed shaft connects the gearbox to the electrical machine.

Main bearing. The main bearing supports the main shaft and transmits the weight of the rotor to the nacelle. It is designed to limit frictional losses during rotation by use of lubricants. Common failures for bearings are discussed in [40, 41].

Gearbox. A gearbox converts the high torque/low speed rotational mechanical power to a low torque/high speed rotational speed suitable for the electrical machine. The two basic designs of a gearbox for the drive train are parallel shaft and planetary gearboxes. Any gearbox consists of a case, shafts, gears, bearings and seals. Oil is used in the gearbox to reduce friction and mechanical losses on the gears and in the bearings. Common failures for gearboxes are discussed in [41].

Electrical machine. An electrical machine converts the rotational energy into electrical energy. The two basic types of electrical machines used for large WTs are induction machines and synchronous machines. Induction machines require reactive power that can be provided by capacitors or power electronic (doubly fed induction machines). Synchronous electrical machines can support low rotational speed and high torque, and are more suitable for gearless application. Common failures for electrical machines are discussed in [42].

2.2.5 Electrical systems

The electrical power provided by the electrical machine is transformed and transmitted to the grid by electrical systems, including cables, transformers and power electronics. Other electrical systems may be required for the control systems and electrical machines.

Cables. Cables transmit the electrical power between the electrical systems in the WT, the WTs, power transformers and power substations. There are generally two technologies for high voltage cables: High-Voltage Alternative Current (HVAC) and High-Voltage Direct Current (HVDC). HVDC technology may be used to reduce electrical losses if the wind power system is far from a grid connection point (see Chapter 22 in [36]).

Transformers. Transformers change the voltage level of the electrical power. They are used in WTs to increase the voltage in order to lower transmission losses. Transformers are generally located at the bottom of the tower. For large wind power systems, a transformer substation collects the electrical power from the WTs and transmit it to the grid. Common failures for transformers are discussed in [43].

Power electronics. Power electronics devices are used to convert and control the current, e.g. from AC current to DC current (or vice-versa) or to adapt to a specific voltage level or frequency. Power electronics converters provide the power supply to the control system units, possible electrical machine actuators and adapt the electrical power frequency of variable speed WTs to the frequency of the grid.

Capacitors. Capacitor banks are used to supply induction electrical machines with reactive power.

2.2.6 Control systems

The operation and control of a WT is performed automatically by a supervisory controller that can be controlled by the operator through a Supervisory Control And Data Acquisition (SCADA) system. Sensors provide input data to the control system.

SCADA system. A SCADA system helps to monitor and control wind power systems. It provides online access to operational and safety data (e.g. wind speed and direction, pitch angle, nacelle position, temperature in different part of a WT, current and voltage levels) for individual WTs, triggers automatic alarms if signals are beyond acceptable limits and enables remote control of each WT (e.g. switch on/off, limit the output level, operation of the turbine for tests and measurements). In case an alarm is triggered, an operator can check the alarm code and decide whether to restart the WT or if an inspection is necessary.

A description of a generic SCADA system for wind energy converter and communication requirements can be found in [44]; it mainly consists of a communication system infrastructure and a human-machine interface, e.g. a web-based interface. Common safety signals for WT are presented in Section 3.2 of [41].

Supervisory controller. The control of the WT is automatically performed by controllers integrated into the nacelle. Each WT includes a supervisory controller that communicates with the SCADA system of the wind power system. One function of the supervisory controller is to provide the control input for the dynamic controllers of various components in the WTs, e.g. in the pitching and yaw systems. Another function is to continuously check the operating conditions of the WT, and to trigger an alarm or to actuate emergency systems if signals are beyond acceptable limits. The input data are provided to the controllers by sensors. For maintenance activities, the supervisory controller can be controlled from inside the WT with a plug-in controller.

Sensors. WTs have many sensors to provide information, e.g. temperatures in different parts of the nacelle or components, position of the nacelle, current and voltage levels, wind speed and direction, cable twist or condition monitoring data, etc. The sensors are connected to the control systems.

2.2.7 Safety systems

Brakes and safety systems are used to stop or disconnect a WT, e.g. if the cut-out wind speed is reached or if an abnormal condition is detected.

Brakes. Aerodynamic brakes is the main braking mechanism for WTs. The principle is to turn the blades 90 degrees to the wind direction. The system is generally based on a spring to work in case of grid disconnection or hydraulic losses (see hydraulic system). Aerodynamic brakes can stop the WT after a few rotations.

Mechanical brakes are installed on the drive train as a complementary emergency system. Mechanical brakes can be of two kinds, disc brakes (requiring hydraulic pressure) and clutch brakes (using a spring released to brake).

Circuit breakers. A circuit breaker is installed between the generator and the grid connection. If the current increases too much (due to a fault or a short circuit), the WT is disconnected from the grid. The circuit breaker can be reset once the fault is cleared.

2.2.8 Other systems

Hydraulic systems. The pitch, yaw and breaking systems are commonly actuated by hydraulic cylinders. The hydraulic power is supplied to the cylinders by hydraulic accumulators and is controlled by an hydraulic control unit that may be located in the hub or nacelle. If located in the nacelle, the power to the pitch system is supplied through the main shaft of the WT. A pressure spring assures that the blades are stopped if no pressure is provided by the hydraulic system.

Cooling system. A cooling system (i.e. an electrical fan with a cooling distribution circuit) is used for cooling the electrical machine and the oil system of the gearbox.

Oil system. The lubrication of the gearbox is important to minimize the wear of the gear teeth and bearings. An injection system supplies the oil to the gearbox at high pressure. The oil is common to the bearing and gears of the gearbox. Filters are commonly used to avoid possible debris to damage the gearbox. Problems with oil can occur due to intermittent operations (if the oil is not running) or in cold or warm weather conditions. Sometimes, an oil heater or cooling system are necessary. Oil filters must be changed regularly. An oil analysis can be performed in order to check the quality of the lubricant and detect possible damages inside the gearbox.

Lubrication systems. Most of the electrical machines in the WT (from the yaw system to the main generator) are lubricated by automatic lubricant injectors that can be mechanical (spring) or electronically controlled. The lubrication systems have a finite autonomy, and must be changed regularly based on the lubricant consumption of the machines.

Chapter 3

Reliability theory

This chapter provides the theoretical background to the reliability models and simulation method used in Paper II and Paper III. It begins with some basic definitions, followed by an introduction to different types of reliability models. The types of models used in Paper II and Paper III are then described, and the last section provides an introduction to the simulation of stochastic variables used in the same papers.

3.1 Reliability definitions

Some definitions on reliability analysis used in this thesis, adopted from [45]:

- *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.
- *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.

3.2 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 black box, grey box and white box models. Grey and white approaches model the degradation process behind the failure.

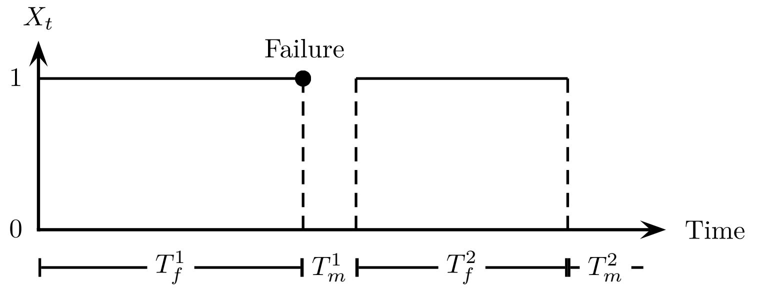


Figure 3.1: Connection between the condition variable X_t, times to failure T_f^i and times to repair T_m^i.

Black box models assume that 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.

Let X_t denote the random variable associated with the state of a component:

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

$X_t = 0$ means that the component is in a maintenance state. Fig. 3.2 shows an example of a realization of X_t for a sequence of failures and repairs. T_f^i and T_m^i denote the transition time for the i^{th} failure and repair event, respectively.

In some cases, the underlying process and evolution of a failure, referred to as deterioration or degradation process, may be observable or simulated by a physical model. Fig. 3.2 shows a general representation of a degradation process, known as P-F curve (where P is the abbreviation for Potential failure, 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 failure to the fault.

When the degradation of the component can be observed, the observations can be used to construct a mathematical model of the deterioration process. This type of model is referred to as a grey box model, and often involves stochastic processes.

When a physical model for the deterioration exists, it can be used to estimate the evolution of the deterioration, e.g. as a function of the loads and environmental conditions. This type of model is referred to as a white box model.

In this thesis, black box models are used in Paper II and a grey box model is used in Paper III.

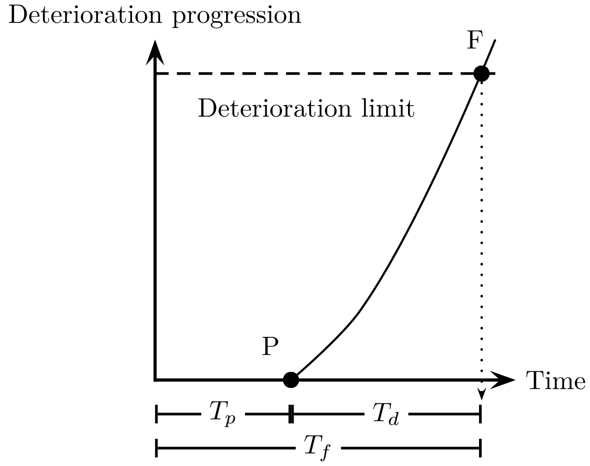


Figure 3.2: Deterioration P-F curve

3.3 Failure probability distribution

Failure probability distribution functions are black box models that represent the time to failure of a population of identical components. This section provides definitions of reliability measures for failure probability distribution functions, and presents two useful failure probability functions, the exponential and Weibull distribution functions.

3.3.1 Definition of reliability measures

In this section, T represents a stochastic variable for 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. $F(t) = P(T < t)$. The derivative of $F(t)$ is the probability density function and is denoted $f(t)$.

$$f(t) = \frac{dF(t)}{dt}. \tag{3.1}$$

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 defined as follows:

$$z(t) = \frac{f(t)}{R(t)}. \tag{3.2}$$

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:

$$MTTF = E[T] = \int_0^{+\infty} t \cdot f(t)dt. \tag{3.3}$$

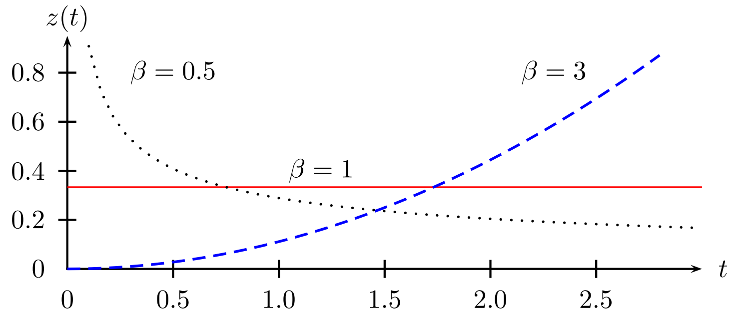


Figure 3.3: Failure rate of a Weibull distribution with $\alpha = 3$, $\beta = 0.5, 1, 3$.

3.3.2 Life time distributions

Exponential distribution

The exponential distribution is a parametric probability distribution with a constant failure rate denoted $\lambda > 0$ [46]:

$$f(t) = \lambda e^{-\lambda t}, \tag{3.4}$$

$$F(t) = 1 - e^{-\lambda t}, \tag{3.5}$$

$$R(t) = e^{-\lambda t}, \tag{3.6}$$

$$z(t) = \lambda, \tag{3.7}$$

$$MTTF = \frac{1}{\lambda}. \tag{3.8}$$

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 the shape parameter $\beta > 0$ [46]:

$$f(t) = \frac{\beta}{\alpha}\left(\frac{t}{\alpha}\right)^{\beta-1} e^{-(\frac{t}{\alpha})^{\beta}}, \tag{3.9}$$

$$F(t) = 1 - e^{-(\frac{t}{\alpha})^{\beta}}, \tag{3.10}$$

$$R(t) = e^{-(\frac{t}{\alpha})^{\beta}}, \tag{3.11}$$

$$z(t) = \frac{\beta}{\alpha}\left(\frac{t}{\alpha}\right)^{\beta-1}. \tag{3.12}$$

The Weibull distribution has an increasing failure rate if $\beta > 1$, a constant failure rate if $\beta = 1$ (i.e. exponential distribution), or decreasing failure rate if $\beta < 1$, as illustrated in Fig. 3.3. The parameter α scales the distribution in time; increasing α stretches out the probability distribution function. Note that $R(\alpha) = \frac{1}{e} \approx 0.3679$.

3.4 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 Paper III and is illustrated with an example on component redundancy, and the counting process used in Paper II.

3.4.1 Continuous time Markov chains

A continuous time Markov chain is a stochastic process $X(t)$ defined by [47]:

- 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. $\sum_{j \in S} p_{ij} = 1$. $\lambda_{ij} = p_{ij} \cdot \lambda_i$ is called the transition rate from state i to state j.

Markov chains have the Markov property (i.e. loss of memory), i.e. the evolution of the process depends only on the present state and not on the states visited in the past:

$$\begin{aligned} \forall x(u), 0 \le u < t, \quad & P(X(s+t) = j | X(s) = i, X(u) = x(u)) \\ & = P(X(s+t) = j | X(s) = i). \end{aligned}$$

Assume that the model has N states. $\boldsymbol{Q}$ denotes the transition matrix and $\boldsymbol{P}(t)$ the vector probability for the states, with $\sum_i P_i(t) = 1$,

$$\boldsymbol{Q} = \begin{pmatrix} -\lambda_1 & \lambda_{12} & \lambda_{13} & ... & \lambda_{1N} \\ \lambda_{21} & -\lambda_2 & \lambda_{23} & ... & \lambda_{2N} \\ \lambda_{31} & \lambda_{32} & -\lambda_3 & ... & \lambda_{3N} \\ ... & ... & ... & ... & ... \\ \lambda_{N1} & \lambda_{N2} & \lambda_{N3} & ... & -\lambda_N \end{pmatrix}, \quad \boldsymbol{P}(t) = \begin{pmatrix} P_1(t) \\ P_2(t) \\ P_3(t) \\ ... \\ P_N(t) \end{pmatrix}.$$

The Kolmogorov equation is useful to estimate $\boldsymbol{P}(t)$ when $\boldsymbol{P}(0)$ is known [46]:

$$\boldsymbol{P}(t) \cdot \boldsymbol{Q} = \frac{d}{dt}\boldsymbol{P}(t), \; t \in [0, +\infty). \tag{3.13}$$

A Markov chain is said to be irreducible if every state can be reached from any other state. In this condition, an asymptotic solution to Eq. (3.13) always exists and represents the behavior of the Markov chain over an infinite time horizon. The asymptotic solution is denoted $\pi = (\pi_1, ..., \pi_N)$. It is the solution of the system of equations:

$$\begin{cases} \pi \cdot \boldsymbol{Q} = 0 \\ \sum_i \pi_i = 1 \end{cases} \tag{3.14}$$

In Paper III, the evolution of the Markov chain is evaluated on a finite time horizon by simulating state transitions using Monte Carlo simulation.

Other interesting characteristics of the asymptotic solution are the visit frequencies ν_i. They can be calculated with the following formula [46]:

$$\nu_i = P_i \lambda_i,\ i \in \{1, ..., N\}. \tag{3.15}$$

In Paper III, the deterioration of the blade in WT is assumed to be classifiable. Discrete state stochastic processes, such as Markov chains, are useful in this situation [48]. When the deterioration is measurable, continuous state stochastic processes could be used, e.g. Wiener or Gamma processes [49]. Markov chains are also often used for reliability calculations of multi-component repairable systems. This is illustrated in the next section for a system with component redundancy.

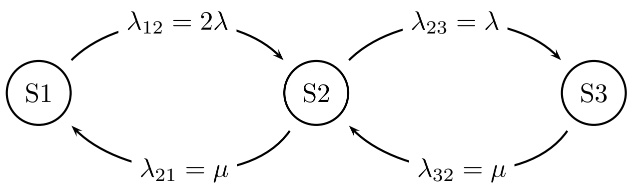


Figure 3.4: Three states Markov chain for component redundancy.

Markov model for component redundancy

Fig. 3.4 shows a Markov chain for one system with component redundancy, i.e. a system with two similar components functioning in parallel. The system is maintained by one maintenance team, i.e. one maintenance activity can be performed at the time. The model has three states: $S1$ for "Two components functioning", $S2$ for "One component failed" and $S3$ for "System failed". The failure rate for one component is λ and the maintenance repair rate is μ. Using Eq. (3.14) and Eq. (3.15), it can be shown that:

$$\begin{aligned}
\pi_1 &= \frac{\mu^2}{\mu^2 + 2\lambda\mu + 2\lambda^2}, \\
\pi_2 &= \frac{2\lambda\mu}{\mu^2 + 2\lambda\mu + 2\lambda^2}, \\
\pi_3 &= \frac{2\lambda^2}{\mu^2 + 2\lambda\mu + 2\lambda^2}, \\
\nu_3 &= \frac{2\lambda^2\mu}{\mu^2 + 2\lambda\mu + 2\lambda^2}, \\
&\approx \frac{2\lambda^2}{\mu},\ \mu >> \lambda.
\end{aligned}$$

Example: Redundancy of sensors

Redundancy could be used in WTs, e.g. for sensors. We consider here a sensor in the nacelle of a three megawatt WT with capacity factor $C_f = 0.4$. The average electricity price is 50 €/MWh. It is assumed that the sensor has a constant failure rate $\lambda = 0.0001$ [f/yr]. If the system fails, it results in a downtime of 5 days (harsh weather condition), i.e. $\mu = \frac{365}{5} = 73$[r/yr] and the production losses are $C_{CM} = 7200$ €. Note that the cost for a new sensor is not considered because it will be paid with and without redundancy.

Without redundancy, the expected maintenance cost for the 25 years lifetime of a WT is approximately $25 \cdot \lambda \cdot C_{CM} = 18$€. With redundancy, the expected maintenance cost is $25 \cdot \nu_3 \cdot C_{CM} \approx 0.00005$€. Redundancy could hence save 18 € of maintenance cost per sensor. If we assume that there are 600 sensors in a WT (the average failure rate of all sensors in a WT is 0.06, see Section 5.1.3), it would result in 10800 € of maintenance cost savings per WT.

3.4.2 Renewal process

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

$$w(t) = W'(t) = \frac{dE[N(t)]}{dt}. \tag{3.16}$$

Examples of counting processes are the homogeneous Poisson process, the non-homogeneous Poisson process and the Renewal Process [46]. A renewal process is a counting process whose interoccurrence times are identically distributed and are defined by a distribution function $F(t)$ and probability density function $f(t)$.

A renewal process is used in Paper II for estimating the number of failures of components over the life time of a WT. The number of failures is estimated both by Monte Carlo simulation and directly with the following approximation.

Discrete approximation of $W(t)$

Assume that the time is divided into steps indexed by $k = 1, 2, ...$ 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 $k = 1, ..., T-1$, $W(k)$ is known and we use the following approach to calculate $W(T)$.

Let´s assume 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 failure during the $T - (k+1)$ remaining weeks, i.e. $W(T - k - 1)$.

By summing over all the possible first failure events their probability multiplied by the expected number of failure occurrences, we obtain [50]:

$$W(T) = \sum_{k=0}^{T-1} [R(k) - R(k+1)] \cdot [1 + W(T - k - 1)]. \tag{3.17}$$

Eq. (3.17) can be used recursively to approximate $W(t)$. The initial condition for the recursion is $W(1) = 1 - R(1)$. The smaller the time step interval is, the better the discrete approximation for $W(t)$ is. Once $W(k)$ is calculated, the discrete rate of the process is $w(k) = W(k) - W(k-1)$.

3.5 Introduction to Monte Carlo simulation

Monte Carlo simulations are used for studying complex systems when analytical tools can not 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. The method is used in paper II to simulate sequences of failures and in paper III to simulate the Markov chain deterioration model.

The elementary task in the Monte Carlo simulation is to generate random numbers for stochastic variables (also called realizations of the stochastic variable). A stochastic variable can e.g. be associated with events such as time to failures, time to perform maintenance, or deterioration transition. The inverse sampling method, a procedure to generate realizations of random variables, is described below. For more information on Monte Carlo simulation, the reader is referred to [51].

Assume that $F(t)$ is the probability distribution of a stochastic variable T of interest and $X \approx U(0,1)$, where U is the uniform distribution. If x is a realization of X then $y = F^{-1}(x)$ is uniquely determined ($F(t)$ is strictly increasing and $\lim_{t\to+\infty} F(t) = 1$). If we denote Y the stochastic variable associated with y and $G(y)$ its probability distribution; then

$$G(y) = P(Y \leq y) = P(F^{-1}(x) \leq y) = P(x < F(y)) = F(y).$$

The last equality results from x being uniformly distributed. Y has the same probability distribution as F.

In conclusion, to simulate a realization of F, one can first generate x according to a uniform distribution (using a pseudo-random number generator) and calculate $t = F^{-1}(x)$. The value of t is then a realization of a stochastic variable with probability distribution $F(t)$.

Chapter 4

Maintenance and optimization theory

This chapter provides an introduction to the topics of maintenance and optimization. The chapter begins by presenting maintenance concepts, followed by an introduction to qualitative and quantitative maintenance optimization models. The last section provides an introduction to the mathematical optimization theory used in Paper I.

4.1 Maintenance 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 [45]. Fig. 4.1 shows a common representation of types of maintenance strategies.

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 [45]. It is typically performed when there are no effective means to detect or prevent a failure.

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 [45]. 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 [52]. TBM is suitable for failures that are age-related and for which the probability distribution of failure can be established.

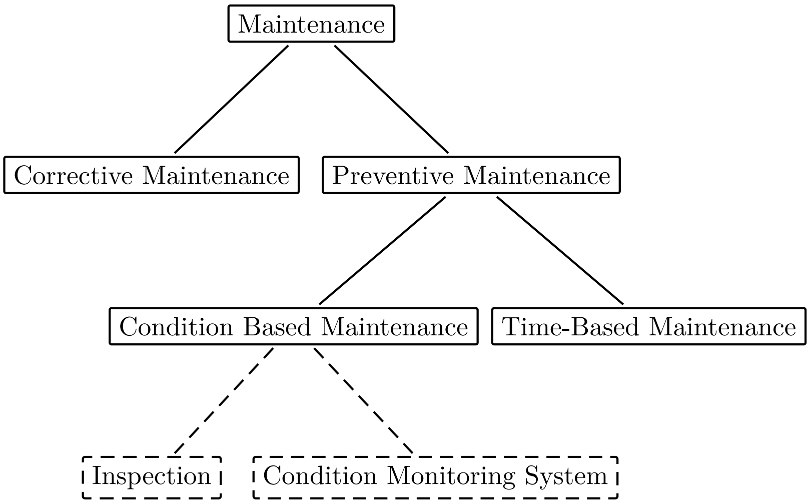


Figure 4.1: Types of maintenance strategies. Inspection and condition monitoring systems are two approaches for a condition based maintenance strategy.

- Condition Based Maintenance (CBM) is preventive maintenance based on performance and/or parameter monitoring and the subsequent actions [52]. CBM consists of all maintenance strategies involving inspections or Condition Monitoring Systems (CMS) to decide the maintenance actions. Inspection can involve the use of human senses (noise, visual, etc.), monitoring techniques, or tests. CMS are installed to continuously monitor a component. CBM can be used for non-age related failures.

4.2 Reliability centered maintenance

When deciding upon the choice of a maintenance strategy, one should consider the cost and effectiveness of the possible strategies, with respect to the failure behavior, probability and consequence. Reliability Centered Maintenance (RCM) is a systematic method used to investigate failures, and their causes and effect, in order to determine possible maintenance strategies to prevent failures. The method involves a tool known as Failure Mode and Effect Analysis. RCM can be summarized in 7 steps once the systems of interest have been identified [10]:

1. What are the functions and performances required of the system?
2. In what ways can each function fail?

3. What are the causes for each functional failure?
4. What are the effects of a failure?
5. What are the consequences of a failure effect?
6. How can each failure cause be prevented?
7. How does one proceed if no preventive activity is possible?

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 [12] and it has been recently applied to distribution power systems in [24], [21] and [20].

4.3 Quantitative maintenance optimization

Quantitative maintenance optimization refers to the utilization of mathematical models with the objective to determine the best decision from a set of alternatives for a maintenance problem.

There are several types of interrelated maintenance decision issues:

- Comparison of maintenance strategies with respect to reliability, cost and risk criteria.
- Analysis of the value of capital investment (e.g. transportation, maintenance equipment, condition monitoring systems).
- Optimization of a maintenance strategy (e.g. replacement age, inspection intervals and decisions, or on-line condition monitoring decisions).
- Maintenance planning, e.g. prioritization and planning of maintenance tasks with respect to available maintenance crew, spare part and maintenance equipment.
- Manpower optimization, i.e. to determine the optimal size of a maintenance or service crew.
- Spare part management optimization, i.e. the optimization of the size of spare part stocks.

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).

Maintenance optimization is a wide and active field of operation research. Introductions to the subject can be found in [46, 50, 53, 54]. Models can generally be classified according to the type of issue investigated, the system (single/multi-components) and the horizon framework (finite/infinite, fixed/rolling). The reader is referred to [55–57] for general reviews and to [58–61] for reviews on multi-components models.

An interesting concept is the one of opportunistic maintenance. It is defined as preventive maintenance that can be performed at opportunities that arise randomly, independent or dependent of the components in the system [55]. The idea and models for two components are discussed in [54] and multi-component opportunistic models have been proposed, e.g. in [55, 62]. In practice, opportunistic maintenance implies that the maintenance planning is flexible, i.e. the maintenance manager updates the planning when opportunities arise to perform the PM activity. Opportunistic maintenance for wind power system is investigated in paper I.

TBM replacement and CBM inspection for the drive train of the wind turbines were investigated in [16, 17] by use of an age and block replacement model and a delay time inspection model. The author of the present thesis believes that the TBM age replacement is suitable for ageing small components in wind turbines, i.e. components whose probability of failure is increasing with age. The age replacement model will be described below and illustrated for the hydraulic accumulator in a wind turbine. The TBM inspection strategy discussed in [17] is suitable for the drive train of small wind turbines (e.g. below 1 MW). For large wind turbines, condition monitoring systems are expected to be more beneficial, see Section 5.3. The delay time model is useful for optimizing inspections of components whose deterioration condition is not classifiable or measurable; for an introduction to the model and review of its application, see [63]. When the deterioration of the component is classifiable, models based on Markov chains are often used [48, 64–66]. When the deterioration of the component is measurable, models are often based on the Wiener or Gamma process; see [49] for a review of their application.

4.3.1 Age replacement problem

Notation

$C(t_r)$	Average cycle cost
C_{CM}	Cost for performing corrective replacement
C_{PM}	Cost for performing preventive replacement
t_r	Replacement age
t_r^*	Optimal replacement age

Model

The age replacement model was proposed in [67]. The model is simple and can be used to optimize the replacement of non-repairable components (or repairable components with perfect repair). The assumption of the model is that the failure rate increases with time and the cost for PM is lower than for CM. (Similar models for repairable components are discussed in [54].) Under an age replacement policy, a component is replaced at failure or when it reaches a certain age t_r.

In this application, the optimization criterion is to minimize the expected maintenance cost per time unit, and the decision variable is the replacement age, noted t_r. The main assumption is that the system will be used for an infinite horizon, which can be a good approximation for a long horizon. (An alternative optimization criterion is the cycle cost criteria proposed in [68].) It is also assumed that the probability distribution of failure $f(t)$ and reliability function $R(t)$ are known.

The expected maintenance cost per time unit is denoted by $C(t_r)$. It is the ratio between the expected cost per replacement cycle and the average replacement cycle length. It can be shown that (Section 2.5 in [50]):

$$C(t_r) = \frac{[1 - R(t_r)] \cdot C_{CM} + R(t_r) \cdot C_{PM}}{\int_{-\infty}^{t_r} t \cdot f(t)dt + t_r}. \tag{4.1}$$

The optimal replacement age t_r^* minimizes $C(t_r)$. It can be determined by use of numerical methods.

Example: Replacement of hydraulic accumulators

The age replacement strategy can be applied to hydraulic accumulators in wind turbines. A hydraulic accumulator is a component that provides the hydraulic pressure to hydraulic systems in the wind turbine, see Section 2.2. Failures of hydraulic components are often due to wear, so these components are ageing.

This numerical example assumes a 3MW wind turbine with average capacity factor $C_f = 0.4$ (see Section 2.1 for a definition of C_f). The failure probability functions are adapted from Section 5 in [69]. The failure rate follows a Weibull distribution with shape parameter $\beta = 3$ and scale parameter $\alpha = 5.6$.

It is assumed that a failure of the component results in a downtime of one day (including time to identify the failure, access the turbine, and replace the component). The cost for a corrective replacement corresponds to the average electricity losses (sold at 50 € /MWh) and component cost, 1000 Euros [69]; $C_{CM} = 24 \cdot 3 \cdot 0.4 \cdot 50 + 1000 = 2440$. The preventive maintenance cost is the cost for the component; $C_{PM} = 1000$.

Fig. 4.2 shows the maintenance cost per time unit as a function of t_r. The optimal age replacement is 4 years and 5 months and the expected maintenance cost is 415 € per year. If no preventive maintenance is done, it would result in a cost of 555 € per year. On the 25 years life time of a wind turbine, this policy reduces the maintenance costs by 3500 € per wind turbine. Note that if the duration of the downtime is longer (e.g. due to harsh weather conditions), the benefit of using an optimal age replacement policy is larger.

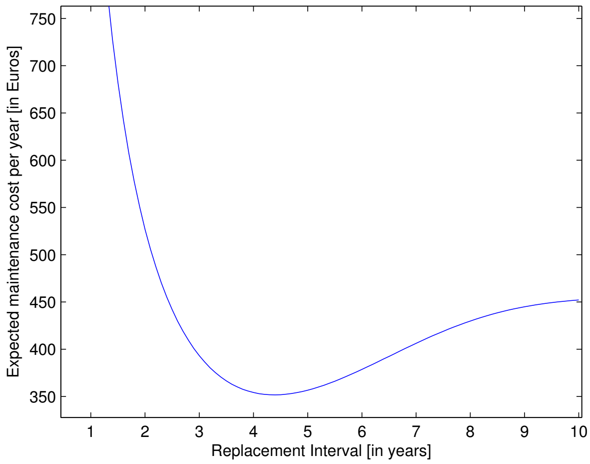


Figure 4.2: Expected yearly maintenance costs as a function of replacement age for an hydraulic accumulator.

4.4 Optimization theory

4.4.1 Optimization

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

$$min_{\boldsymbol{x} \in X} \, f(\boldsymbol{x}),$$

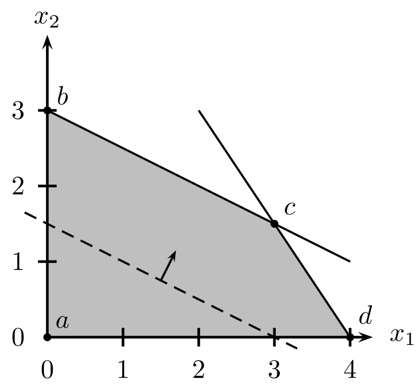
where $\boldsymbol{x} \in \Re^n$ represents the vector of decision variables, $f(x)$ an objective function and X is the set of feasible solutions. The feasible set can often be defined with equality and inequality constraints on the form:

$$\begin{aligned} g_i(\boldsymbol{x}) = 0, \quad i \in M, \\ g_i(\boldsymbol{x}) \leq 0, \quad i \in N, \end{aligned}$$

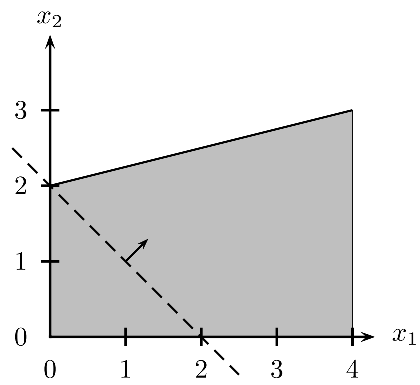
where M and N are indexed sets. An optimal solution $\boldsymbol{x^*}$ is a feasible solution that satisfies

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

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



(a) Graphical representation of the problem $\min -x_1 - 2x_2$ *s.t.* $x_1 + 2x_2 \leq 6$. $3x_1 + 2x_2 \leq 12,\ x_1, x_2 \leq 0$. The extreme point c is the optimal solution.



(b) Graphical representation of the problem $\min -x_1 - x_2$ *s.t.* $-x_1 + 4x_2 \leq 12,\ x_1, x_2 \leq 0$. There is no optimal solution in this case.

Figure 4.3: Examples of two optimization problems, with and without optimal solution. The feasible set is shown in grey. Dashed lines depicts equicosts and an arrow the gradient direction for the minimization.

4.4.2 Mixed integer linear optimization

Every linear optimization problem can be given in, or transformed into standard form;

$$\begin{array}{ll} \text{minimize} & \boldsymbol{c}'\boldsymbol{x}, \\ \text{subject to} & \boldsymbol{A}\boldsymbol{x} = \boldsymbol{b}, \\ & \boldsymbol{x} \geq 0, \end{array}$$

where $\boldsymbol{c} \in \Re^n$is called cost vector and $\boldsymbol{A} \in \Re^{m*n}$ and $\boldsymbol{b} \in \Re^m$ are data describing the linear constraints of the problem.

In this form, if the feasible set $\{\boldsymbol{x} \in \Re^n | \boldsymbol{A}\boldsymbol{x} = \boldsymbol{b}, \boldsymbol{x} \geq 0\}$ is nonempty, 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 [70]. Another possibility is that the optimal solution is $-\infty$. Fig. 4.3(a) and Fig. 4.3(b) 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 can be identified (in this case the optimal solution is $-\infty$). In the example in Fig. 4.3(a), 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 [70] for details on the implementation of the simplex method and an introduction to the class of interior point methods, useful for very large problems.

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 model presented in Paper I is a MILP.

The standard form of a MILP optimization problem is:

$$\begin{array}{ll} \text{minimize} & \boldsymbol{c}'\boldsymbol{x} + \boldsymbol{d}'\boldsymbol{y}, \\ \text{subject to} & \boldsymbol{A}\boldsymbol{x} + \boldsymbol{B}\boldsymbol{x} = \boldsymbol{b}, \\ & \boldsymbol{x}, \boldsymbol{y} \geq \boldsymbol{0} \\ & \boldsymbol{x} \text{ integer}, \end{array}$$

where the vectors $\boldsymbol{c}$ and $\boldsymbol{d}$ define the cost function, and the matrices $\boldsymbol{A}$ and $\boldsymbol{B}$, and vector $\boldsymbol{b}$ define 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 constraints and 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 subproblems. 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 algorithm for solving MILP are presented in [70, 71].

Chapter 5

Optimal maintenance management

This chapter presents the status of maintenance in the wind industry, and ideas to optimize maintenance decisions. The first section provides a state-of-the-art and framework for maintenance management optimization. The following three sections summarize the proposed models and results, which are presented in Papers I–III.

5.1 State-of-the-art and opportunities

The section summarizes general maintenance management at wind power systems. It is based on a literature study and visits at Smøla wind power system in Norway, and two offshore wind power systems: Utgrunden/Yttre Stengrund located on the east coast of Sweden, and Lillgrund in the south of Sweden.

5.1.1 Status of maintenance in the wind industry

Maintenance management

A maintenance team is in general composed of one maintenance manager, and two maintenance technicians for ten WTs. For safety reasons, the nacelle of a WT should not be accessed individually and maintenance technicians therefore often work in pairs. At a service maintenance, the maintenance team may be augmented in order to perform the activities in the given time period. Maintenance activities on large components (e.g. on the drive train or blades) require a large crane and specific vessel for offshore WTs (e.g. jack up boats). Consequently, maintenance experts are neces-

Table 5.1: Example of wind constraints for maintenance activities [72].

Wind speed [m/s]	Restrictions
≥30	No access site
≥20	No climbing turbines
≥18	No opening of the roof doors
≥15	No working on the roof of the nacelle
≥12	No work in the hub
≥10	No lifting roof of nacelle
≥7	No blade removal
≥5	No climbing on the met masts

sary, and, in general, the activity is observed by a third party in order to validate the procedure. The crane capacity and cost depend mainly on the height of the wind turbine [69].

At the acquisition of a WT, the manufacturer provides a warranty period, in general between two and five years. During this period, the manufacturer is responsible for the maintenance of the WT. Depending on the warranty contract, this period may be used by the operator maintenance team to learn from the maintenance technicians of the manufacturer. At the end of the warranty contract, a third party evaluates the condition of the systems in the WTs in order to confirm that the clauses in the warranty contract have been respected. Maintenance activities are subject to wind constraints fixed by the operator of the wind power system. Table 5.1 gives an example of such constraints for an onshore WT. Major maintenance activities, such as the replacement of a component of the drive train, require a "good" weather window. For offshore wind power systems, the maintenance team is transported by boats, or helicopters in case of harsh weather condition. The suitable type of boat varies with wind and wave conditions. The height and length of waves depends on the wind direction and undersea landscape. Depending on the type of vessel and access platform, the vessel may operate with waves up to 1.3m–2.5m [73]. The choices for transportation vessel and benefits of an internal crane for offshore wind power systems were investigated in [13]. Transportation is in general an outsourced activity. With the recent development of offshore wind power systems, the vessels used for the maintenance of large components are expected to be highly solicited.

Maintenance strategies

Today, maintenance activities at wind power systems consist typically of CM activities and PM including scheduled service maintenance activities such as: bolt re-tightening; changes of oil filters, lubrication systems and bearing lubricant collectors; oil analysis for the gearbox; visual inspection of the blades, brushes of the main electrical machine, and gears of the gearbox; endoscopy of planetary stages of the gearbox with a borescope; design modifications.

Condition Monitoring Systems (CMS) with on-line vibration monitoring systems are commonly used for the drive train of large WTs (vibration analysis is discussed in the next section). In general, the condition monitoring diagnosis is performed by the manufacturer. Scheduled service maintenance is based on manufacturer recommendations. It is generally performed every three months during the first year of the WT, and later on every six months or year depending on the type of service maintenance tasks and WT model.

A handbook for condition based maintenance is presented in [74]. The handbook provides a classification of the deterioration of components and advises for maintenance activities to be performed for each deterioration level, e.g. further inspection or repair/replacement of the component. RCM is a systematic method to identify maintenance strategies. It was applied to WTs in [16]. RCM is a qualitative method and its results depends much on subjective judgement. The author of this thesis believes that the maintenance strategy decisions and their implementation should be driven by objective criteria, based on expected failure rates, failure consequences, as well as the efficiency of the PM strategy.

5.1.2 Condition monitoring techniques

Condition Monitoring is defined as observation, measurement, or trending of condition or functional indicators with respect to some independent parameter (usually time or cycles) to indicate the current and future ability to function within acceptance criteria [45].

There are two main approaches for condition monitoring: condition monitoring inspection and on-line condition monitoring, also known as CMS. Condition monitoring inspections for WT can be, e.g. visual inspections, advanced inspections (e.g. endoscopy of the gearbox), or measurements such as oil sampling and analysis. Common CMSs in WTs are measurements on temperature, pressure, current and voltage. These are a part of the SCADA system and are used for safety warning. In general, limits are defined for these measurements, and an alarm is triggered if one value is beyond the limit.

Other condition monitoring techniques can be used to detect incipient failures far before it results in a failure. Common condition monitoring techniques applied to WTs are vibration and oil monitoring that are described below; for more details see [41]. The section also provides a short description of other condition monitoring techniques applicable to WTs.

For advanced condition monitoring techniques, signal processing techniques are used to extract features of interest. The analysis of condition monitoring signals is referred to as diagnosis. It consists in detecting and identifying incipient failures and their possible causes. If time to failure can be estimated, it is referred to as a lifetime prognosis. Some diagnosis tools can provide automatic diagnosis, e.g. for vibration analysis in WTs. The results of automatic diagnosis must often be confirmed by vibration experts and component inspection. Automatic diagnosis and prognosis are recent technologies; a general review is found in [75] and applications to WTs in [76–78].

Vibration analysis. Vibration analysis is typically used to monitor the condition of rotating components, i.e. the drive train in WTs. It can be done at inspection with a portable vibration monitoring device, or with a CMS. The principle is based on two basic facts:

1. Each component of the drive train has a natural vibration frequency and its amplitude will remain constant under normal conditions.

2. The vibration spectrum will change if a component is deteriorating and the changes will depend on the failure mode.

Principles for vibration analysis are presented in [41] with a survey of some device manufacturers for WTs. Fig. 5.1 depicts the location of vibration sensors in a WT.

Sensor 1 is an inductive sensor that measures the absolute position of the rotor. The oscillations of the nacelle are captured by the static accelerometers 2, 3 and 4. Sensors 5 and 6 are accelerometers measuring the vibrations of the bearings of the gearbox and generator. Additional sensors can be installed, for example on the low shaft of the gearbox and bearing of the main shaft. Each type of sensors is sensitive to a specific frequency spectrum.

Frequency analysis with Fourier transform is the most popular processing technique for vibration analysis. It provides the frequency content of the vibrations during a selected time period. Filters are used to analyze frequency bands of interest. Demodulation may be used to remove modulation induced by other signal sources [80].

The “normal” spectrum signature of machinery varies with factors such as its environment, mounting and installation. Moreover, a WT may operate at variable speed, and the frequency distribution (even relative to the rotational speed) depends on the rotational speed. Consequently, a initial period is required to define the “normal” condition. Threshold limits can then be defined on the whole spectrum or on specific sidebands, and should depend on the rotational speed. An alarm is triggered if the signals are beyond the defined limits.

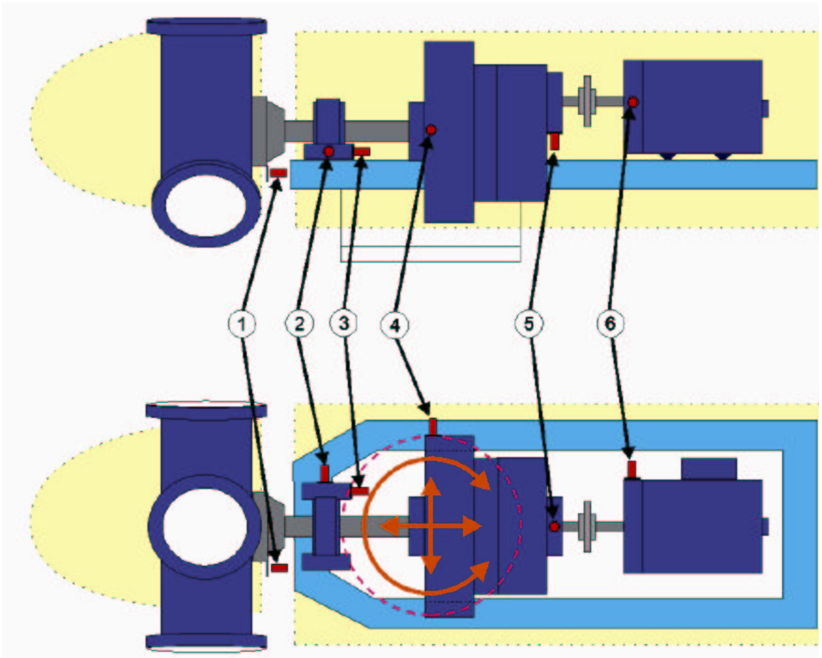


Figure 5.1: Example of sensors locations (1–6) for a condition monitoring system in a wind turbine, from [79].

Advanced signal processing approaches may also be used to extract more information, e.g. the bi- or tri-spectrum, or time-frequency analysis, such as wavelet transform, that enable to detect defects whose vibration signature is not cyclic [81]. However, the interpretation of the results can be more complicated for direct analysis. These techniques can be used for automatic diagnosis. Prognosis was recently discussed in [77, 82].

Oil analysis. Oil analysis is used to determine the chemical properties and content of oil lubricant. Monitoring the gearbox and bearings lubricant can provide relevant information about the deterioration of oil-wetted components and the quality of lubricant [41, 76]. Gear wheels and bearings deterioration depends mainly on the lubricant quality, i.e. particle contamination and properties of the oil and additives used to improve the performance of the oil. Oil analysis is discussed in [41] with a survey of device manufacturers for WTs.

The most basic particle contamination analysis is particle counting (typically with laser or eddy current sensors). If an abnormal level of particle contamination is detected, wear debris can be analyzed with ferrous density tests or spectroscopy.

The condition of the oil is determined by analyzing its viscosity, moisture contamination and additives content. The viscosity is measured with a calibrated tube called a viscometer. Spectrometric techniques, such as classical spectroscopy and infrared spectroscopy, can be used to determine the lubricant chemical content (e.g. moisture, oil additives).

Oil analysis can be performed by taking oil samples, periodically or at request if an abnormal situation has been detected. CMSs are also available for on-line particle counting and moisture analysis [41].

Ultrasonic inspection. Ultrasonic testing is typically used to characterize material properties. Short ultrasonic pulse waves are launched on the material and their reflections and attenuations are analyzed to determine the properties of the material. The technique can be very useful for detecting incipient cracks in blades, far before being visible [83,84]. Today, it is often used if a defect is suspected.

Strain measurements for blades. Different types of optical fibre sensors can be embedded in the structure of the blades in order to measure load, vibration, temperature and strain [85, 86]. The transmission properties (e.g. intensity, phase, wavelength or transmission time of light) of a fibre are modified by the measured quantity, either due to the intrinsic properties of the fibre or due to sensors connected to the fibre. The technology is still in development. Cost effective optic fibre sensors are expected in the future [76].

Thermography monitoring. Infrared thermography is a technique used to capture thermal images of components. Every object emits infrared radiation according to its temperature and its emissivity. The radiation is captured by a thermographic camera. Hot spots can be identified (bad contacts or deteriorated parts) and other failures may be detected by analyzing the thermal trend. Infrared thermography is applicable to electrical machines and electronic components (e.g., power electronics, circuit breakers, transformers) [76]. Infrared thermography is also used to investigate the structure of the blades [83].

Performance monitoring. The trend of the response (or some response parameter) to an input (power, signal) may provide information on the condition of a component [76] . This technique can, for example, be used to detect blade imbalances and surface roughness, or to detect failure of the yaw system and gearbox [87].

5.1.3 Reliability of wind turbines

It has been observed that the main contributors to the failure rates are electrical, hydraulic and control systems, and the sensors [30,88,89]. Moreover, that large mechanical components are responsible for the longest downtime per failure. This may result from the acquisition time for the spare part (i.e. supply chain) and the acquisition time for the required maintenance equipment. The downtime from control system failures may also be important, probably due to the complexity of the system and the difficulty to identify failure modes. Fig. 5.2 summarizes failure frequencies and downtimes per system in Sweden in the period 2000–2004.

Large WTs experience higher failure frequencies than small WTs, probably due to the use of more advanced and complex technologies [89]. The reliability of different WT concepts was compared in [6, 7, 18]. The studies highlight an upward trend of the failure rate for electrical systems with new design concepts. Direct-drive concepts have a higher availability for large WT than geared concepts, but in general experience higher failure frequencies [6, 7]. It should be borne in mind that new concepts may have large possibilities for reliability improvement [88]. Moreover, new standards have been recently introduced for the design of the gearbox in WT [90], and the reliability of geared-wind turbine is expected to improve in the future.

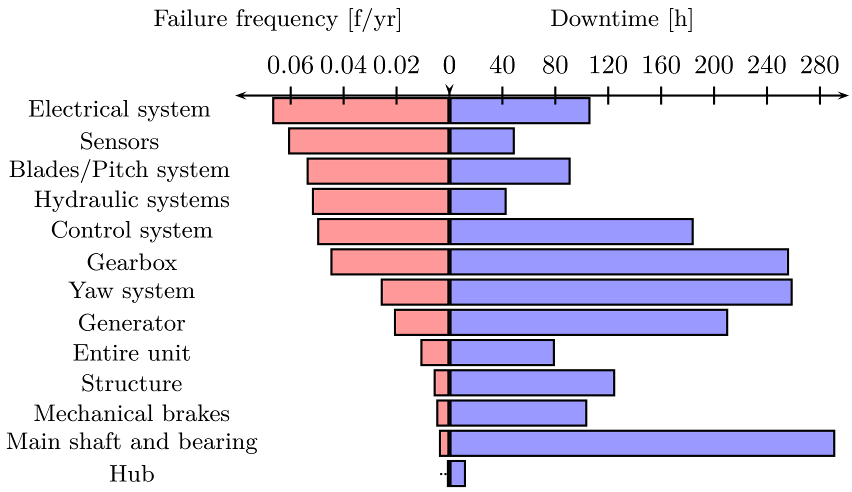


Figure 5.2: Average failure frequency and downtime per system in Sweden in the period 2000–2004, as adapted from [30].

5.1.4 Framework for maintenance optimization of wind power systems

There are generally three main areas where optimization is applied in the maintenance of wind power systems: choice and implementation of maintenance strategies, maintenance planning, and capital investments for maintenance equipment. Capital investments will not be discussed here, except CMS which is also related to the maintenance strategy. Components in WTs can be separated into two main categories, referred to here as large and small components. Maintenance strategies and maintenance planning for these two categories are analyzed separately.

Large components are the components of the drive train and rotor. These components are expensive, large and heavy, and possible long acquisition time for spare part and maintenance equipment may result in high costs for production losses. Small components include, for example, the electrical system, hydraulic systems, pitch system, control system, lubrication systems and sensors. Due to their relatively high failure frequencies, the maintenance of small parts is an important issue, especially for offshore wind power systems where a minor failure may result in a long downtime.

Maintenance strategies

For large WTs with a gearbox, high failure rates for the drive train have been experienced in the past. CMS can be used to prevent expensive failures and plan maintenance activities. The value of CMS was investigated in [14, 15], and it is further discussed in Paper III. With the emergence of lifetime prognosis for components in WT (see [77, 82]), condition based maintenance decisions may be optimized as proposed for the aircraft industry in [55] or for bearings with vibration monitoring in [91].

Blades are large and expensive components of WTs. Blades are inspected visually at scheduled maintenance occasions or on-condition if lightning sensors are installed. Condition monitoring techniques, such as ultrasonic or thermography, are used if a defect is suspected. Paper II investigates the benefits of periodic inspection using condition monitoring techniques. Fibre optic strain measurement is a promising technique for blades, but the technology is expensive and needs improvements [76].

Studies have shown that the electrical, hydraulic and control systems, ane the sensors have high failure rates in WT [30, 88]. For ageing components, such as hydraulic systems, it could be beneficial to use preventive repair or replacement, as discussed in Section 4.3. For electrical systems, thermography could be used periodically in order to access the condition of the components. If no cost-efficient PM strategy is available, an alternative may be to increase the reliability of these components by improving the design and manufacturing of the component or by using redundancy, e.g. for the sensors as discussed in Section 3.4.1.

Maintenance planning

The planning of maintenance activities is an important part of maintenance management. It includes the decision on the time to perform the maintenance activities, as well as organization of the staff, logistics and spare part requirements to perform the activities. Today, scheduled service maintenance is often performed at fixed time periods. Paper I investigates an alternative planning approach, based on opportunistic maintenance. Other possibilities to optimize maintenance planning, including spare parts management and maintenance planning for large components, are discussed in the future work in Section 6.2 of this thesis.

5.2 Optimal maintenance planning

Generally, scheduled service maintenance is performed during a fixed time period without consideration of the power production. When maintenance is performed, the WT is stopped, which results in costs for production losses. If these maintenance activities were performed at low wind production, it would result in cost savings. Moreover, WTs are subject to failure, and each failure is 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.

Paper I proposes a model to optimize the maintenance planning of scheduled maintenance activities by taking advantage of opportunistic occasions that are low wind forecasts and corrective maintenance at failures. Opportunistic maintenance implies that the planning of maintenance is flexible. The model is inspired by an opportunistic maintenance optimization model that was developed for the aircraft industry in [55]. This section summarizes the model and results which are presented in Paper I.

5.2.1 Model

The proposed model considers a rolling time horizon, i.e. the maintenance planning is optimized every working day. The time horizon is separated into a short horizon interval followed by a long horizon interval. The short horizon is discretized in days for which electricity production forecasting is available. The long horizon interval is discretized in weeks for which a discretized power production distribution is available, based on statistics.

The set of time steps for the short horizon is T_{short} and the set of time steps for the long horizon is T_{long}. The time steps are indexed by $t \in T_{short} \cup T_{long}$. The expected hourly power production during the short horizon is $P_t, t \in T_{short}$. The power production distribution for the long horizon is defined by a number of hours $h_{kt}^{max}, t \in T_{long}$ at production level $P_k^{LH}, k \in \{1, ..., L\}$, where k is the index for the production levels and L is the number of possible production levels. Fig. 5.3 depicts an example of a power production distribution for the long horizon.

The system consists of a set WT of wind turbines indexed by $i \in WT$. A set PM indexed by $j \in CM$ defines the preventive maintenance tasks that have to be performed within the total time horizon. Parameters τ_j^{PM} represents the duration in hours of the preventive maintenance task $j \in PM$, and w_{ij0} defines the remaining number of time steps for the PM task $j \in PM$ to be performed in the wind turbine $i \in WT$.

A subset $CM \subset WT$ defines the wind turbines requiring corrective maintenance, and τ_i^{CM} [h], $i \in CM$ is the expected time to perform the activity. Corrective maintenance activities are forced to be performed during the short horizon interval. The energy production losses, if corrective maintenance is done at time step t, is P_t^{CM} [kWh].

The electricity cost is C_{el} [€ /kWh]. Transportation costs consist of a fixed cost C_{tr} [€] for each day when transportation is required.

Normally, the maintenance team works h hours per day during the short horizon. A penalty cost C_{pen} [€] is to be paid for each supplementary working hour. The time for accessing the nacelle of one WT is τ_w [h]. During the long horizon, the available number of working hours is defined for every time step t and production level k by h_{kt}^{max} [h] and no supplementary hours are considered.

Mathematical formulation

The problem is formulated as a MILP as follows. (Section 4.4.2 provides an introduction to MILP and methods to solve the problems.)

Decision variables

$$x_{ijt} = \begin{cases} 1, & \text{if preventive maintenance task } j \text{ in wind} \\ & \text{turbine } i \text{ is performed at step } t \\ 0, & \text{otherwise,} \end{cases} \tag{5.1}$$

$$t \in T_{short},\ j \in PM,\ i \in CM,$$

$$y_{it} = \begin{cases} 1, & \text{if corrective maintenance task in wind} \\ & \text{turbine } i \text{ is performed at step } t \\ 0, & \text{otherwise,} \end{cases} \tag{5.2}$$

$$t \in T_{short},\ i \in CM.$$

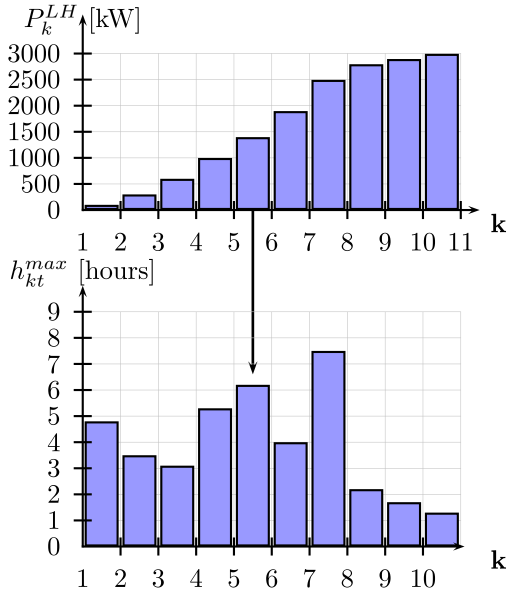


Figure 5.3: For a given production level $k \in \{1, ..., L\}$ and a time step for the long horizon $t \in T_{long}$ corresponds a number of available maintenance hours h_{kt}^{max} at production level P_k^{LH} [kW]. In this example, 8 maintenance hours are available at production level 1400 kW.

Auxiliary binary variables

$$z_t = \begin{cases} 1, & \text{if the wind park is visited at step } t, \\ 0, & \text{otherwise,} \end{cases} \tag{5.3}$$

$t \in T_{short}$,

$$v_{it} = \begin{cases} 1, & \text{if the WT } i \text{ is visited at step } t \\ 0, & \text{otherwise,} \end{cases} \tag{5.4}$$

$t \in T_{short}, i \in WT$.

Auxiliary non-negative variables

h_{tk} : Maintenance hours used at power loss level k at step t, (5.5)

$t \in T_{long}, k \in \{1, ..., L\}$,

e_t : Supplementary maintenance hours, $t \in T_{short}$, (5.6)

$t \in T_{short}$.

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):

Objective function

$$\min \sum_{t \in T_{short}} \Bigg[\Big[\sum_{i \in CM} \overbrace{y_{it} \cdot P_t^{CM}}^{\text{CM costs}} + \sum_i \overbrace{\sum_j x_{ijt} \cdot \tau_j^{PM} \cdot P_t}^{\text{PM loss costs}} \Big] \cdot C_{el} + \overbrace{z_t \cdot C_{tr}}^{\text{Transport cost}} + \overbrace{e_t \cdot C_{pen}}^{\text{Penalty working hours}} \Bigg] + \overbrace{\sum_{t \in T_{long}} \Big[\sum_k h_{tk} \cdot [P_{kt} \cdot C_{el} + \frac{C_{tr}}{h - 2 \cdot \tau_w}] \Big]}^{\text{Long horizon PM loss and transport costs}} . \tag{5.7}$$

Constraints are defined to force z_t and v_{it} to have values in accordance with their definitions, and to force the CM and PM tasks to be performed in the defined time periods; see Paper I for detail.

5.2.2 Results

The proposed model was tested in an example with five 3MW wind turbines, with two PM tasks to be performed (3 and 4 hours long). The optimization scenario had 60 days. Task 1 should be performed within the first 20 days of the horizon and Task 2 during the first 50 days. Failures were generated randomly. The wind scenario was inspired by wind data during the summer time in the south of Sweden. Wind forecasts were assumed to be available for the first 10 days (with uncertainty, see paper I for details) and expected production distribution for the following 6 months. These assumptions were based on wind forecasting capability, see Section 2.1. The costs and other parameters are described in Paper I.

Fig. 5.4 depicts the failure and power production scenario, as well as a solution for the maintenance optimization.

It can be observed that preventive maintenance is only performed at low power production and if corrective maintenance is required. For example, at time step 16 the wind power production is low and it is advised to perform preventive maintenance task 1 in wind turbine 1 and task 2 in wind turbine 3. At time step 7, a failure occurs in wind turbine 2 and the solution indicates to perform preventive maintenance task 1 in both wind turbines 2 and 3.

It was shown in this example that 43% of the cost for performing PM tasks could be saved with opportunistic maintenance, compared to performing the tasks during the first days of the scenario.

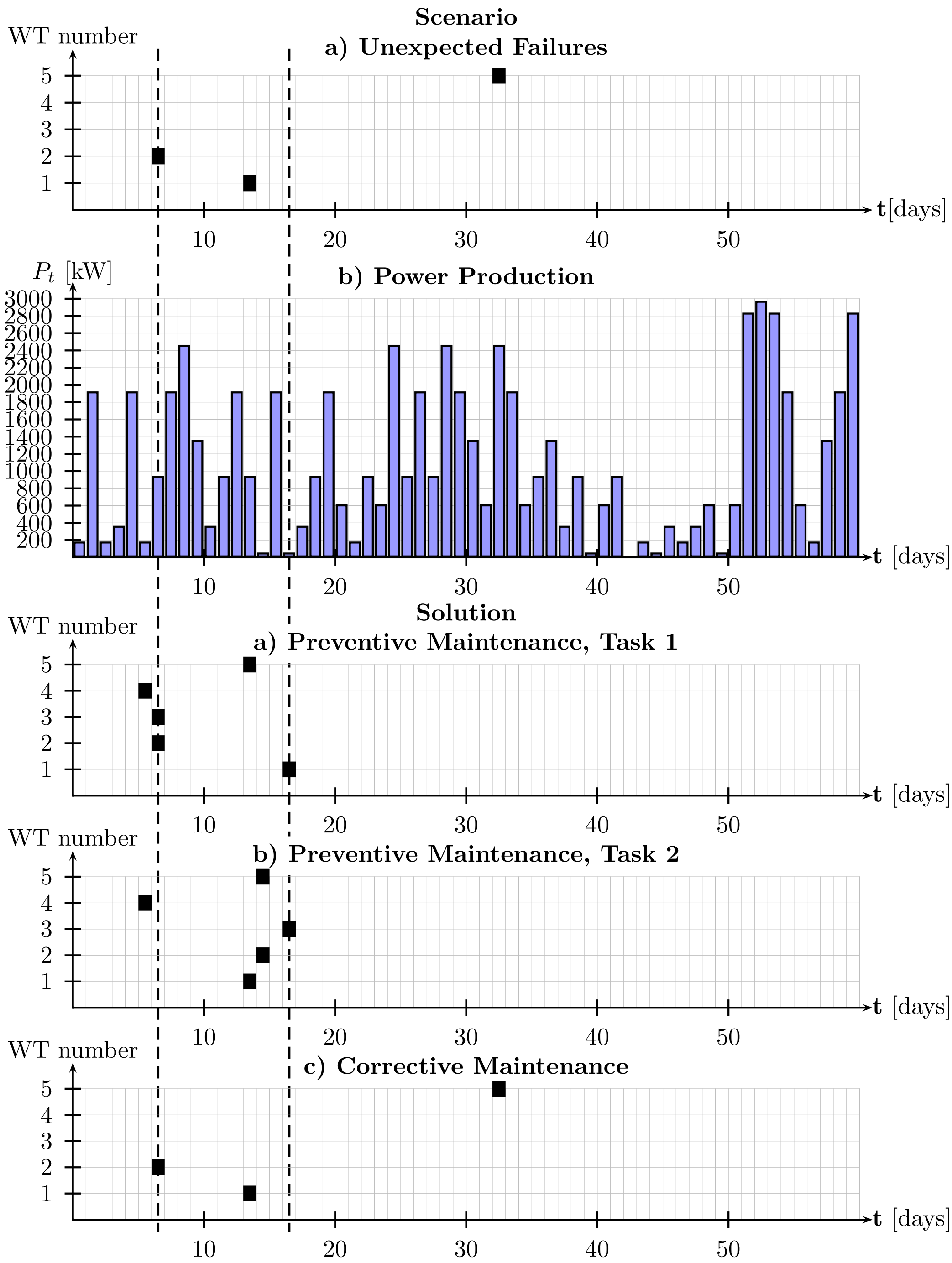


Figure 5.4: Failure and power production scenarios and one optimization result for one simulation of the example. The dashed lines show the advised maintenance schedules for the days 7 and 16.

5.2.3 Conclusions

An optimization model was presented to take advantage of low wind power production and unexpected failures in order to perform preventive maintenance tasks at low costs. The properties of the model was validated with an example, and the cost of the preventive maintenance tasks could be reduced by 43%.

The case study demonstrates that it is possible to save maintenance costs by taking advantage of the production forecasts and corrective maintenance opportunities. However, the implementation of opportunistic maintenance implies that the maintenance schedule is flexible.

5.3 Benefits of condition monitoring systems

Major failures of components of the drive train are expensive. This is due to the cost of the component, the cost of the maintenance equipment required to perform the maintenance, and the costs of energy production losses resulting from the spare part and maintenance equipment acquisition time as well as weather constraints.

Vibration CMS are available for the components of the drive train in WTs (see Section 5.1.2). The CMS may identify incipient failures far before major maintenance is required. If a failure 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 CMS, and damage and logistic time advantages provided by the use of CMS. An economic analysis of CMS is presented in Paper II. This section summarizes the model and results.

5.3.1 Model

The proposed cost model is a stochastic Life Cycle Cost (LCC) with random variables for the occurrence of failure of the components of the drive train. The LCC is divided into the investment cost C_{inv}, preventive and corrective maintenance costs C_{PM} and C_{CM}, costs for the production losses C_{PL} and service costs C_{ser}, that are estimated each year t. The total LCC is the discounted sum of the yearly costs over the life time of the system (N years):

$$LCC = \sum_{t=1}^{N} \delta^{-t} \cdot [C_{inv}(t) + C_{PM}(t) + C_{CM}(t) + C_{PL}(t) + C_{ser}(t)], \quad (5.8)$$

where $\delta = \frac{1}{1+r}$ and r is the interest rate. The discount rate is used to calculate the present value of the future costs.

The investment cost C_{inv} is in this application the cost of the CMS and it has to be paid only the first year. The service C_{ser} is the yearly cost of the CMS service; it is assumed constant during the life time of the WT.

$C_{PM}(t)$, $C_{CM}(t)$ and $C_{PL}(t)$ are functions of the number of failures in year t, the efficiency of the CMS, and benefits from identifying an incipient failure (both for maintenance cost reduction and logistic time):

$$C_{CM}(t) = \sum_{i \in C} \omega_{it} \cdot (1 - \epsilon_i), \qquad t \in \{1, ..., N\}, \tag{5.9}$$

$$C_{PM}(t) = \sum_{i \in C} \omega_{it} \cdot \epsilon_i \cdot \gamma_i \cdot K_i, \qquad t \in \{1, ..., N\}, \tag{5.10}$$

$$C_{PL}(t) = \sum_{i \in C} \omega_{it} \cdot (T_i + (1 - \epsilon_i)\tau_i) \cdot P \cdot C_{el}, \qquad t \in \{1, ..., N\}. \tag{5.11}$$

C is the set 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 $\gamma_i \cdot K_i$, 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.

ω_{it} is the number of failures for component i is for year t. Failures of the components follow a Weibull probability distribution with scale parameter α_i and shape parameter β_i (see Section 3.3.2 for the definition of the Weibull distribution). Two approaches were used for generating ω_{it}: scenarios generated with Monte Carlo simulation, and the average rate of component renewals (estimated with a renewal process) for the successive failure, estimated as in Section 3.4.2. An introduction to Monte Carlo simulation and renewal processes is provided in Section 3.5.

Table 5.2: Components data for the case study (3MW wind turbine).

Component	Gearbox	Generator	Main Bearing
α	8 [3–25]	17	17
β	3.5	3.5	3.5
ϵ	90%	90%	90%
γ	54.3%	53.6%	52.1%
C (€)	390000	105000	57000
τ (days)	21	21	21
T (days)	2	1	3

* range for the sensitivity analysis.

The benefit of CMS is the difference between LCC with and without CMS. A similar cost model was used for the LCC without CMS. The model was implemented with cost data based on [4, 14]. Wind turbines of the size above 2 MW constitute new technologies and have experienced early failures with components of the drive train, i.e. the gearbox. Moreover, new standards have been proposed to improve the reliability, e.g. for the gearbox [90]. Consequently it is difficult to estimate the failure rates of component in wind turbines. The sensitivity analysis provides an inside on the influence of the failure probability parameter for the gearbox, the most expensive component of the drive train whose reliability is subject to uncertainty. Table 5.2 summarizes the components data.

5.3.2 Results

In the basic case, the average LCC is 710,000 € without CMS and 520,000 € with a CMS, and the cost benefit of using CMS is 190,000 €. Fig. 5.5 shows the result of the sensitivity analysis for the scale parameter α for the failure distribution of the gearbox.

The scale parameter affects the LCC in two ways. Firstly, it influences the expected number of failures during the lifetime of the WT. Secondly, it shifts the occurrence of the failures. The higher the value of the scale parameter, the lower number of failure events occur and the later they are expected to occur. This results in a lower value of the CMS, due to the effect of the discount rate on late maintenance activities. It can be observed that the CMS is beneficial if the scale parameter is lower than 21.

In order to observe the influence of CMS on the economic risk, it is assumed that the average economic benefit is zero, i.e. the scale parame-

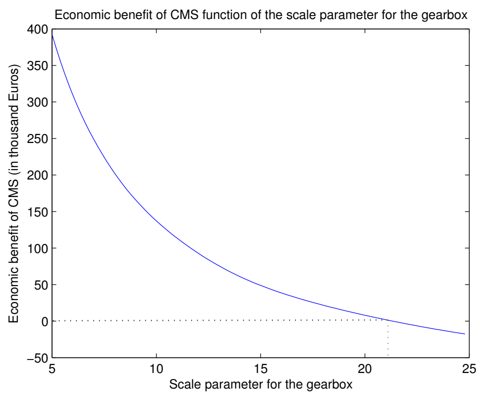
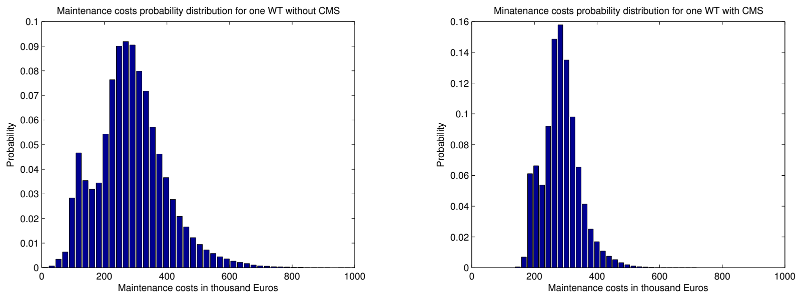


Figure 5.5: Sensitivity analysis of the economic benefit of a CMS for Scale parameter α for the gearbox.



(a) Without CMS. (b) With CMS.

Figure 5.6: LCC probability distributions.

ter for the gearbox is 21. Fig. 5.6 shows the LCC probability distribution with and without CMS. It can be observed that the risk of high maintenance costs is limited with the use of CMS. However, the lower bound for maintenance costs is also higher due to the CMS installation and service costs.

5.3.3 Conclusions

It was shown in the basic case that the economic benefit of using CMS was 190,000 €. Sensitivity analysis was performed to observe the influence of the scale parameter of the gearbox on the economic benefit of the CMS. The CMS is beneficial if the scale parameter for the gearbox is lower than 21. Moreover, even if there is no economic benefit, the stochastic analysis of the LCC showed that the risk of high cost was lowered by the use of a CMS.

The costs of component failure increase with the capacity of the WT, due to the higher cost of the components and higher costs for production losses. Moreover, for large WT, there is much uncertainty concerning the reliability of the components of the drive train. Under these conditions, a CMS has an important benefit on the economic risk. For WTs under one megawatt, CMSs may not be cost efficient due to a low probability of failure. The drive train could instead be periodically inspected, e.g. with portable vibration monitoring devices.

5.4 Optimal condition monitoring inspection for blades

The size of blades increases with the capacity of the WTs. Blades are subject to high stresses and unexpected events such as storms, bird collisions or lightning that can initiate cracks.

In general, visual inspection of the blades is part of the scheduled service maintenance and may be performed at lightning events if lightning sensors are installed in the blades. If a defect is identified, condition monitoring techniques, e.g., ultrasonic techniques or infrared thermography, may be used to evaluate the internal damage. Most of the damages are hidden in the composite structure and it may be beneficial to use the condition monitoring regularly in order to identify the damages as soon as possible. The sooner the crack is identified, the lower the cost for repair will be [92].

Paper III investigates the benefit of using condition monitoring techniques at regular time interval. The inspection interval is first optimized with respect to a cost criteria. The optimal condition monitoring inspection is then compared to periodic visual inspection. The proposed model was inspired by a model proposed in [64] for maintenance inspection in hydropower plants. This section summarizes the model and results which are presented in Paper III.

5.4.1 Model

The deterioration of the blade has been modeled with a continuous time Markov chain. Section 3.4.1 provides an introduction to Markov chain. Fig. 5.7 shows the deterioration model. $S1$ represents the state "Good", $S2$ "Minor degradation", $S3$ "Advanced degradation", $S4$ "Major degradation" and $S5$ "Failure".

$$X_1 \xrightarrow{\lambda_{init}} X_2 \xrightarrow{\lambda_{det}} X_3 \xrightarrow{2\lambda_{det}} X_4 \xrightarrow{4\lambda_{det}} X_5$$

Figure 5.7: Markov chain for the deterioration model of the blades

Maintenance inspections occur at fixed time interval in the model. The deterioration follows the Markov chain between two inspections or until failure. At inspection, the state and next time for inspection are updated based on the maintenance decision for the current state. Preventive repair is performed immediately if a defect is identify using condition monitoring technique (i.e. the condition of the component is $S2$, $S3$ or $S4$ at inspection), and the system is in an "as good as new" condition after maintenance. At failure, the component is replaced. Inspection with condition monitoring technique is compared with visual inspection. If visual inspection is used instead of condition monitoring inspection, defects are detected only in deterioration states $S3$ and $S4$. Visual inspections are assumed to be perfect and performed once a year, as part of the yearly service maintenance.

Monte Carlo simulation is used to generate scenarios and costs for a fixed set of maintenance decisions, i.e. inspection interval. The simulation method is described in detail in Paper III, and Section 3.5 in this thesis provides an introduction to Monte Carlo simulation. The length of the simulation horizon is 25 years (the assumed lifetime for a WT). A large number of scenarios is used to estimate the expected maintenance costs and the costs probability distribution.

The costs for inspection and CM are C_I and C_{CM}, respectively. The PM cost depends on the degradation level $i \in \{2, ..., N-1\}$. It is noted $C_{PM,i}$. The maintenance cost for one scenario and average maintenance cost with inspection interval t_{ins} are defined as follows:

$$C^s(t_{ins}) = N^s_{ins} C_I + \sum_{i=2}^{4} N^s_{PM,i} C_{PM,i} + N^s_{CM} C_{CM}, \tag{5.12}$$

$$C(t_{ins}) = \frac{1}{N_{sim}} \sum_{s \in S} C^s(t_{ins}), \tag{5.13}$$

where N^s_{ins}, $N^s_{PM,i}$ and N^s_{CM} are the number of inspection, PM activities at deterioration state i and CM activities during scenario s.

The crack initiation rate is $\lambda_1 = \lambda_{init}$. Once a crack is initiated, the mean crack time to failure is assumed to be T_{crack}. The expected length

Table 5.3: Summary of the model parameters.

Parameter	Value
t_{ins}[yr]	[0.1-5]
λ_{init}[/yr]	0.03 [0.01–0.05][a]
T_{crack}[yr]	1 [0.2–2][a]
λ_{det} [/yr]	$4/(7 \cdot T_{crack})$
C_I[€]	4000[b]/1000[c]
C_{CM}[€]	440000
$C_{PM,2}$[€]	3500
$C_{PM,3}$[€]	35000
$C_{PM,4}$[€]	390000

[a] range for the sensitivity analysis.
[b] condition monitoring inspection.
[c] visual inspection.

of the crack as a function of time is in general concave. To obtain this property, it is assumed that the transition rate for $S3$ is twice the one for $S2$ and a similar relation is assumed between $S4$ and $S3$, as shown in Fig. 5.7. Consequently, if λ_{det} is the crack deterioration rate in state $S2$, it is required that $\lambda_{det} = \frac{4}{7 \cdot T_{crack}}$ for the mean crack time to failure to beT_{crack}.

The parameters used in the case study are described in Table 5.3, with the range of sensitivity analysis for the λ_{init} and T_{crack}. See Paper III for details on the input data.

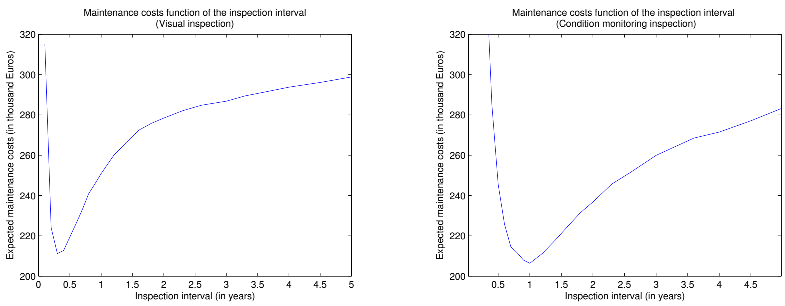
5.4.2 Results

Fig. 5.8 shows the expected maintenance costs as a function of the inspection interval for visual inspection and inspection with condition monitoring technique. The optimal inspection interval is 4 months for visual inspection with an expected maintenance cost of 212,000 € per blade during the life time of the wind turbine. The optimal inspection interval is a year for inspection with condition monitoring technique, with an expected maintenance cost of 206,000 € per blade. The benefit of using condition monitoring inspection is 6,000 € per blade and 18,000 € for one wind turbine.

Nowadays visual inspection is often carried out once a year, which corresponds to an expected maintenance cost of 250,000 € per blade. If the yearly inspection was performed with condition monitoring technique, the cost benefit would be 44,000 € per blade and 132,000 € per wind turbine.

Fig. 5.9 presents the results of the sensitivity analysis. If the crack initiation rate is lower than 0.026, the probability of failure is too low to advise the use of periodic condition monitoring inspection.

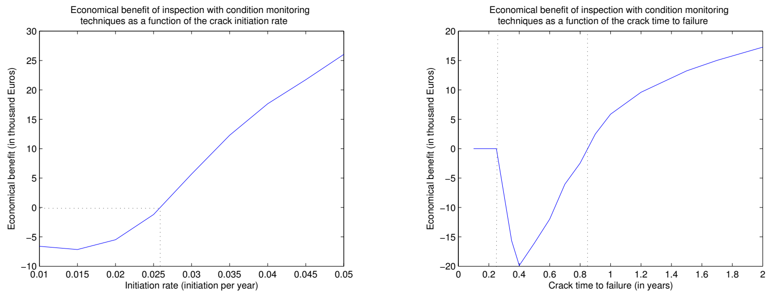
If T_{crack} is lower than 3 months (0.25 years), a short inspection interval



(a) Visual inspection.

(b) Inspection with condition monitoring technique.

Figure 5.8: Maintenance costs as a function of the inspection interval t_1 for the case study, for visual inspection and inspection with condition monitoring technique.



(a) Influence of λ_{init}.

(b) Crack of T_{crack}.

Figure 5.9: Sensitivity analysis for the cost benefits of condition monitoring inspection (one blade).

has to be used to identify initiated cracks before failure, and inspection costs are high. Consequently, neither visual inspection nor inspection with condition monitoring is advised. If T_{crack} is higher than 3 months but lower than 10 months (0.85 years), visual inspection is advised. If T_{crack} is higher than 10 months, inspection with condition monitoring is more beneficial than visual inspection.

5.4.3 Conclusions

In the basic case study, the optimal inspection interval was 1 year for inspection with condition monitoring technique and 4 months for visual inspection. The cost benefit of using condition monitoring inspection was 18,000 € per wind turbine when compared to visual inspection.

Sensitivity analysis was used to determine the minimum crack initiation rate and the minimum expected crack time to failure, for visual and condition monitoring inspection to be beneficial. Condition monitoring inspection was economically justified if the crack initiation rate is higher than 0.026. Visual inspection is beneficial if the crack time to failure is higher than 3 months and inspection with condition monitoring technique is advised if the crack time to failure is higher than 10 months.

Chapter 6

Closure

This chapter concludes the thesis. It summarizes the results and presents ideas for future work.

6.1 Conclusions

This thesis presents models to optimize the maintenance management of wind power systems. The main results are recommendations for maintenance strategies, including an optimal implementation for some of the strategies, and a demonstration of the benefits of opportunistic maintenance for maintenance planning.

This thesis proposes a model to optimize the planning of service maintenance for wind power systems. The main idea of the model is to reduce transportation and production losses by taking advantage of opportunities that arises at failure or low production forecasts. The results show that opportunistic maintenance can significantly reduce maintenance costs.

A stochastic Life Cycle Cost approach has been proposed to investigate the economic benefit of vibration condition monitoring systems for the drive train of wind turbines. The benefit is mainly influenced by the size of the wind turbine and its reliability. Moreover, the risk of high maintenance costs is lowered by the use of condition monitoring systems.

This thesis investigates the benefits of using periodic condition monitoring techniques for blades, with e.g. infrared or ultrasound techniques. The inspection interval is first optimized with respect to a cost criterion. The optimal condition monitoring inspection is then compared to periodic visual inspection. The proposed maintenance strategy is justified if the crack initiation rate and crack time to failure are sufficiently high.

Maintenance strategies for small components are also investigated. The benefits of component redundancy for sensors and age replacement for hydraulic systems were demonstrated with simple models.

6.2 Future work

The following sections summarize ideas for future works for the continuation of this PhD project.

6.2.1 Stochastic maintenance planning optimization

The maintenance planning model proposed in Paper I could be improved by taking advantage of probabilistic production forecasts. The proposed approach could be demonstrated with a real case study, e.g. at Lillgrund wind farm that benefits from good weather conditions. The model could also be extended by including accessibility and electricity price forecasts.

6.2.2 Maintenance planning optimization for large components and large offshore wind power systems

The replacement of large components in wind turbines requires specific boats (e.g. Jack-up boats) that are expected to be highly solicited in the future. It will be advantageous to prioritize and group the large maintenance activities in order to reduce transportation costs (e.g. mobilization costs). This is an opportunistic maintenance problem that could benefit from weather forecasts and available life time prognosis.

6.2.3 Life time prognosis with condition monitoring systems

Vibration and oil monitoring systems provide continuous information on the condition of the components in the wind turbine drive train. By extracting relevant features from the monitoring signals, it is possible to identify incipient failures and maybe their cause, long before the failure leads to a fault. Moreover, it is of interest for maintenance planning to determine the remaining life of the monitored components. This evaluation should be possible by modeling the degradation of the components.

6.2.4 Spare part optimization

In the past years, spare part management was often a service subject to charges provided by wind turbine manufacturers. Nowadays, large power companies that are investing in large wind power systems may decide to manage spare parts on their own. Optimizing spare parts stocks and locations will be important to minimize downtime costs.

References

[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] C. Rose. EWEA - annual report 2008. Technical report, European Wind Energy Association, Brussels, Belgium, 2009.

[3] A. Zervos, C. Kjaer, and S. Clifford. Pure power - wind energy scenarios up to 2030. Technical report, European Wind Energy Association, Brussels, Belgium, 2008.

[4] S. Krohn, P. Morthorst, and S. Awerbuch. The economics of wind energy. Technical report, European Wind Energy Association, Brussels, Belgium, 2009.

[5] IEA wind energy - annual report 2008. Technical report, International Energy Agency, Paris, France, 2009.

[6] P.J. Tavner, F. Spinato, G.J.W. van Bussel, and E. Koutoulakos. Reliability of different wind turbine concepts with relevance to offshore application. In *Proc. of European Wind Energy Conference 2008, Brussels Expo, Belgium, 31th March–3rd April*, 2008.

[7] S. Faulstich and B. Hahn. Upwind project - comparison of different wind turbine concepts due to their effects on reliability. Technical report, Institut für SolareEnergieversorgungstechnik, Kassel, Germany, 2009.

[8] 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.

[9] F.S. Nowlan and H.P. Heap. Reliability-centered maintenance. Technical report, U.S. Department of Commerce, Springfield, Virginia, 1978.

[10] J. Moubray. *Reliability Centered Maintenance - 2nd Edition*. Industrial Press, New York, United States, 1997. ISBN 9780831131463.

[11] O. Wilhelmsson. Evaluation of the introduction of RCM for hydro power generators at vattenfall vattenkraft. Master's thesis, Royal Institute of Technology, 2005.

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

[13] L.W.M.M. Rademarkers, H. Braam, M.B. Zaaijer, and G.J.W. van Bussel. Assessment and optimisation of operation and maintenance of offshore wind turbines. In *Proc. of the European Wind Energy Conference 2003, Madrid, Spain, 16th–19th June*, 2003.

[14] J. Nilsson and L. Bertling. Maintenance management of wind power systems using condition monitoring systems - life cycle cost analysis for two case studies. *IEEE Transaction on Energy Conversion*, 22(1):223–229, 2007.

[15] D. McMillan and G.W. Ault. Condition monitoring benefit for onshore wind turbines: sensitivity to operational parameters. *IET Renewable Power Generation*, 2(1):60–72, 2008.

[16] J.A. Andrawus. *Maintenance optimization for wind turbines*. PhD thesis, Robert Gordon University, Aberdeen, United Kingdom, 2008.

[17] J.A. Andrawus, J. Watson, and M. Kishk. Wind turbine maintenance optimisation: principles of quantitative maintenance optimisation. *Wind Engineering*, 31(2):101–110, 2007.

[18] S. Faulstich, B. Hahn, H. Jung, K. Rafik, and A. Ringhandt. Appropriate failure statistics and reliability characteristics. In *Proc. of the European Wind Energy Conference 2007, Milano, Italy, 7th–10th May*, 2007.

[19] L. Bertling. The RCAM research group-history and status. Technical report, Royal Institute of Technology, Stockholm, Sweden, 2008. TRITA-EE 2008:011.

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

[21] 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.

[22] J. Setréus. On reliability methods quantifying risks to transfer capability in electric transmission systems. Licentiate thesis, Royal Institute of Technology, Stockholm, Sweden, May 2009. TRITA-EE 2009:015.

[23] C.J. Wallnerström. On risk management of electrical distribution systems and the impact of regulations. Licentiate thesis, Royal Institute of Technology, Stockholm, Sweden, April 2008. TRITA-EE 2008:023.

[24] 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.

[25] P. Hilber, V. Miranda, M.A. Matos, and L. Bertling. Multiobjective optimization applied to maintenance policy for electrical networks. *IEEE Transactions on Power Systems*, 22(4):1675–1682, 2007.

[26] J. Nilsson, M. Patriksson, A. Wojciechowski, A-B. Strömberg, and L. Bertling. An opportunistic maintenance optimization model for shaft seals in feed-water pump systems in nuclear power plants. In *Proc. of the IEEE PowerTech 2009 Conference, Bucharest, Romania, 28th June–2nd July*, 2009.

[27] J. Setréus, S. Arnborg, R. Eriksson, and L. Bertling. Components impact on critical transfer section for risk based transmission system planning. In *Proc. of the IEEE PowerTech 2009 Conference, Bucharest, Romania, 28th June–2nd July*, 2009.

[28] C. J. Wallnerström and L. Bertling. Risk management applied to electrical distribution systems. In *Proc. of the 20th International Conference on Electricity Distribution, Prague, Czech Republic, 8th–11th June*, 2009.

[29] M.H.J. Bollen, L. Wallin, T. Ohnstad, and L. Bertling. On operational risk assessments in transmission systems - weather impact and illustrative example. In *Proc. of the 10th International Conference on Probabilistic Methods Applied to Power System, Rincón, Puerto Rico, 25th–29th May*, 2008.

[30] 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.

[31] J.F. Manwell, J.G. McGowan, and A.L. Rogers. *Wind Energy Explained - Theory, Design and Application.* Wiley, Chichester, England, 2002. ISBN 0-471-49972-2.

[32] R. Gasch and J. Twele. *Wind Power Plants - Fundamentals, Design, Construction and Operation*. Solarpraxis, Berlin, Germany, 2002. ISBN 1-902916-38-7.

[33] E.N. Lorentz. A study of the predictability of a 28-variable atmospheric model. *Tellus*, 17:321–333, 1965.

[34] P. Pinson. *Estimation of the uncertainty in wind power forecasting*. Doctoral thesis, Ecole des Mines de Paris, Paris, France, 2006.

[35] A. Persson and F. Grazzini. User guide to ecmwf forecast products. Technical report, European Centre for Medium-Range Weather Forecasts, Shinfield Park, England, 2007.

[36] T. Ackermann et al. *Wind Power in Power Systems*. Wiley, Chichester, England, 2005.

[37] G. Loman. Conceptual foundation study for kriegers flak offshore wind farm. In *Proc. of the European Offshore Wind 2009 Conference, Stockholm, Sweden, 14th–16th September*, 2009.

[38] J. Jonkman. A quantitative comparison of the responses of three floating platforms. In *Proc. of the European Offshore Wind Conference 2009, Stockholm, Sweden, 14th–16th September*, 2009.

[39] B. Hayman, J. Wedel-Heinen, and P. Brønsted. Materials challenges in present and future wind energy. *Material Research Society Bulletin*, 33(4):343–354, 2008.

[40] Bearing failures and their causes. Technical report, SKF, Göteborg, Sweden, 1994.

[41] C. McGowin, C. Walford, and D. Roberts. Condition monitoring of wind turbines - technology overview, seeded-fault testing and cost-benefit analysis. Technical report, EPRI, Palo Alto, USA, 2006.

[42] S. Nandi, H.A. Toliyat, and Xiaodong L. Condition monitoring and fault diagnosis of electrical motors - a review. *IEEE Transactions on Energy Conversion*, 20(4):719–729, 2005.

[43] A. Franzén and S. Karlsson. Failure modes and effects analysis of transformers. Technical report, Royal Institute of Technology, Stockholm, Sweden, 2007. TRITA-EE 2007:040.

[44] O. Anaya-Lara, N. Jenkins, and J.R. McDonald. Communications requirements and technology for wind farm operation and maintenance. In *Proc. of the IEEE First International Conference on Industrial and Information Systems, Peradeniya, Sri Lanka, 8th–11th August*, 2006.

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

[46] A. Hoyland and M. Rausand. *System Reliability Theory: Models and Statistical Methods - Second Edition*. Wiley, New Jersey, USA, 2004. ISBN 0-471-47133-X.

[47] S.M. Ross. *Stochastic Processes - 2nd Edition*. Wiley Series in Probability and Mathematical Statistics, New York, United States, 1996. ISBN 0-471-12062-6.

[48] T. Welte. Using state diagrams for modeling maintenance of deteriorating systems. *IEEE Transaction on Power Systems*, 24(1):58–66, 2009.

[49] J.M. van Noortwijk. A survey of application of gamma processes in maintenance. *Reliability Engineering and System Safety*, 94(1):2–21, 2009.

[50] 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.

[51] A. Law and W. Kelton. *Simulation Modeling and Analysis, 3rd ed.* Mcgraw-Hill, New York, USA, 2000. ISBN 0-07-059292-6.

[52] *Maintenance terminology - Svensk Standard SS-EN 13306*. SIS Förlag AB, Stockholm, Sweden, 2001. ISBN 9789171626509.

[53] R.E. Barlow and F. Proschan. *Mathematical Theory of Reliability*. Wiley, New York, USA, 1965.

[54] J.A. Nachlas. *Reliability Engineering - Probabilistic Models and Maintenance Methods*. Taylor and Francis, Boka Raton, United States, 2005. ISBN 0-8493-3598-1.

[55] 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. Licentiate Thesis.

[56] R. Dekker. Applications of maintenance optimisation models: A review and analysis. *Reliability Engineering*, 51(3):229–240, 1996.

[57] 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.

[58] R. Dekker, R.E. Wildeman, and F.V. der Schouten. A review of multi-component maintenance models with economic dependence. *Mathematical Methods of Operations Research*, 45(3):411–435, 1997.

[59] D.I. Cho and M. Parlar. A survey of maintenance models for multi-unit systems. *European Journal of Operational Research*, 51(1):1–23, 1991.

[60] 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.

[61] H. Wang. A Survey of maintenance policies of deteriorating systems. *European Journal of Operational Research*, 139(3):469–489, 2002.

[62] R. Wildeman, R. Dekker, and A. Smit. A dynamic policy for grouping maintenance activities. *European Journal of Operational Research*, 99(3):530–551, 1997.

[63] R.D. Baker and A.H. Christer. Review of delay-time or modelling of engineering aspects of maintenance. *European Journal of Operational Research*, 73(3):407–422, 1994.

[64] T. Welte, J. Vatn, and J. Heggest. Markov state model for optimization of maintenance and renewal of hydro power components. In *9th International Conference on Probalistic Methods Applied to Power Systems, Stockholm, Sweden, 11th–12th June*, 2006.

[65] M.J. Kallen. *Markov processes for maintenance optimization of civil infrastructure in Netherlands*. PhD thesis, Delft University of Technology, Delft, Netherlands, 2007.

[66] S.H. Sim and J. Endrenyi. Optimal preventive maintenance with repair. *IEEE Transactions on Reliability*, 37(1):92–96, 1988.

[67] R.E. Barlow and L. Hunter. Optimum preventive maintenance policies. *Operation Research*, 8(1):90–100, 1960.

[68] J. Ansell, A. Bendell, and S. Humble. Age replacemet under alternative cost criteria. *Management Science*, 30(3):358–367, 1984.

[69] R. Poore and C. Walford. Development of an operations and maintenance cost model to identify cost of energy savings for low wind speed turbines. Technical report, National Renewable Energy Laboratory, Golden, United States, 2008.

[70] D. Bertsimas and J.N. Tsitsiklis. *Introduction to Linear Optimization*. Athena Scientific, Belmont, USA, 1997.

[71] L. A. Wolsey. *Integer Programming.* Wiley Interscience Series in Discrete Mathematics and Optimization, New York, United States, 1998. ISBN 0-471-28366-5.

[72] D. McMillan and G. Ault. Towards quantification of condition monitoring benefit for wind turbine generators. In *Proc. of the European Wind Energy Conference 2007, Milano, Italy, 7th–10th May*, 2007.

[73] G. Marsh. What price O & M? *Refocus*, 8(3):22–27, 2007.

[74] A.O. Eggen. Handbook on condition monitoring of wind turbines. In *Proc. of the European Wind Energy Conference 2009, Marseille, France, 16th–19th March*, 2009.

[75] A.K.S. Jardine, D. Lin, and D. Banjevic. A review on machinery diagnostics and prognostics implementing condition-based maintenance. *Mechanical Systems and Signal Processing*, 20(7):1483–1510, 2006.

[76] 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.

[77] 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. *Institute of Materials, Minerals and Mining*, 1(3):187–203, 2006.

[78] M.R. Wilkinson, F. Spinato, and P.J. Tavner. Condition monitoring of generators and other subassemblies in wind turbine drive trains. In *Proc. of the IEEE International Symposium on Diagnostics for Electric Machines, Power Electronics and Drives, Cracow, Poland, 6th–8th September*, 2007.

[79] P. Caselitz and J. Giebhardt. Advanced maintenance and repair for offshore wind farms using fault prediction and condition monitoring techniques. Technical report, Institut für SolareEnergieversorgungsTechnik, Kassel, Germany, 2006.

[80] Vibration diagnostic guide. Technical report, SKF Reliability Systems, Luleå, Sweden, 2005.

[81] Y. Amirat, M.E.H. Benbouzid, E. Al-Ahmar, B. Bensaker, and S. Turri. A brief status on condition monitoring and fault diagnosis in wind energy conversion systems. *Renewable and Sustainable Energy Reviews*, 13:2629–2636, 2009.

[82] J. Wheals. Novel early warning prognostics for bearings in wind turbine generator gearboxes. In *Proc. of the European Offshore Wind conference 2009, Stockholm, Sweden, 14th–16th September*, 2009.

[83] M.A. Drewru and G.A. Georgiou. A review of NDT techniques for wind turbines. *Insight*, 49(3):137–141, 2007.

[84] A. Juengert and C.U. Grosse. Inspection techniques for wind turbine blades using ultrasound and sound waves. In *Non-Destructive Testing in Civil Engineering, Nantes, France, 30th June–3rd July*, 2009.

[85] Improved performance of wind turbines using fibre optic structural monitoring. Technical report, Technical University of Denmark, Kongens Lyngby, Denmark, 2007.

[86] G. Marsh. In-service monitoring of turbine blades. *Reinforced Plastics*, 52(5):24–27, 2008.

[87] E.J. Wiggelinkhuizen, Rademakers L.W.M.M., T.W. Verbruggen, S.J. Watson, J. Xiang, G. Giebel, E.J. Norton, M.C. Tipluica, A.J. Christensen, and E Becker. Conmow - final report. Technical report, Energy Research Centre of the Netherlands, Petten, Netherlands, 2007.

[88] P.J. Tavner, J. Xiang, and F. Spinato. Reliability analysis for wind turbines. *Wind Energy*, 10(1):1–18, 2007.

[89] S. Faulstich, M. Durstewitz, B. Hahn, K. Knorr, and K. Rohrig. Windenergy report germany 2008. Technical report, Institut für Solare EnergieversorgungsTechnik, Kassel, Germany, 2009.

[90] ISO 81400-4:2005 - design and specification of gearboxes for wind turbines. Technical report, International Organization for Standardization, Geneva, Switzerland.

[91] A.K.S. Jardine, T. Joseph, and D. Banjevic. Optimizing condition-based maintenance decisions for equipment subject to vibration monitoring. *Journal of Quality in Maintenance*, 5(3):192–202, 1999.

[92] J. Wallace Jr and M. Dawson. O & M strategies: Wind turbine blades. *Renewable Energy Focus*, 10(3):36–41, 2009.