THESIS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY

Cost optimization of maintenance scheduling for wind turbines with aging components

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Abstract

A major part of the wind turbine operation cost is resulted from the maintenance of its components. This thesis deals with the theory, algorithms, and applications concerning minimization of the maintenance cost of wind power turbines, using mathematical modelling to find the optimal schedules of preventive maintenance activities for multi-component systems.

The main contributions of this thesis are covered by the four papers appended. The unifying goal of these papers is to produce new optimization models resulting in effective and fast algorithms for preventive maintenance time schedules. The features of the multi-component systems addressed in our project are: aging components, long-term, and short-term planning, planning for a wind power farm, end of the lifetime of the wind farm, maintenance contracts, and condition monitoring data.

For the long-term maintenance planning problem, this thesis contains an optimization framework that recognizes different phases of the wind turbine lifetime. For short-term planning problem, this thesis contains two modeling frameworks, which both focus on the planning of the next preventive maintenance activities. Our virtual experiments show that the developed optimization models adopt realistic assumptions and can be accurately solved in seconds. One of these two frameworks is further extended so that available condition monitoring data can be incorporated for regular updates of the components' hazard functions. In collaboration with the Swedish Wind Power Technology Center at Chalmers and its member companies, we test this method with real-world wind farm data. Our case studies demonstrate that this framework may result in remarkable savings due to the smart scheduling of preventive maintenance activities by monitoring the ages of the components as well as operation data of the wind turbines.

We believe that in the future, the proposed optimization model for short-term planning based on the component age and condition monitoring data can be used as a key module in a maintenance scheduling app.

Keywords: Age-based preventive maintenance scheduling, Wind turbine maintenance, Combinatorial optimization, Integer linear optimization, Linear programming, Weibull distribution, Renewal-reward theorem, Virtual replacement, Condition monitoring data, Cox proportional hazards method.

List of appended papers

This thesis is based on the work contained in the following papers:

Paper I: Quanjiang Yu, Michael Patriksson, Serik Sagitov. *Optimal scheduling of the next preventive maintenance activity for a wind farm*
Accepted by Wind Energy Science with minor revision.
DOI:10.5194/wes-2020-129

Paper II: Quanjiang Yu, Ann-Brith Strömberg. *Mathematical optimization models for long-term maintenance scheduling of wind power systems*
Preprint, arXiv:2105.06666.

Paper III: Quanjiang Yu, Ola Carlson, Serik Sagitov. *Optimal preventive maintenance schedule for a wind turbine with aging components*
Preprint, arXiv:2012.07307.

Paper IV: Quanjiang Yu, Pramod Bangalore, Sara Fogelström, Serik Sagitov. *Optimal preventive maintenance scheduling for wind turbines under condition monitoring*
Preprint, arXiv:2104.04460.

Thesis author contributions

Paper I-IV: I developed all the optimization models, wrote all the codes for the case studies, performed the analytic calculations and the numerical simulations all by myself. I contributed substantially to writing the papers. I am thankful for co-authors' help with writing, giving feedback on my ideas and all the fruitful discussions.

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I am deeply grateful to all the members of the Swedish Wind Power Technology Centre, especially Sara Fogelström. Thanks for helping me gathering all kinds of data regarding to wind turbines.

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List of abbreviations

ABM	Age-based Maintenance
CBM	Condition-based Maintenance
CM	Corrective Maintenance
CMS	Condition Monitoring System
IC	Interval Cost
MIC	Modified Interval Cost
OM	Opportunistic Maintenance
PHM	Proportional Hazards Model
PM	Preventive Maintenance
PMSPIC	Preventive Maintenance Scheduling Problem with Interval Costs
SWPTC	Swedish Wind Power Technology Center
VR	Virtual Replacement

Contents

1 Introduction

1.1 Background

During the last decades, there is an increased awareness of the impact of global warming in the world. In December 1997, the Kyoto protocol was adopted to combat global warming by the United Nations Convention on Climate Change. In the year 2021, 192 parties had signed and ratified the protocol. Since 2016, 195 countries have signed the Paris Agreement, agreeing to work towards limiting global temperature rise to well below 2 degrees centigrade.

Global warming has been attributed to increased greenhouse gas emission concentrations in the atmosphere through the burning of fossil fuels. Renewable energy, as an alternative, is capable of displacing energy from fossil fuels. According to [7], more than 50% of total electricity in the world might come from renewable energy sources by 2050.

In the year 2020, Europe had 220 GW of total wind energy capacity [6]. Wind accounted for 16.4% of the electricity consumed in 2020 (in EU27+UK), (13.4% from onshore and 3% from offshore wind turbines). According to a prediction in [3], close to 85% of electricity in the EU will be generated from renewable resources by 2050, with wind alone representing up to 26% in 2030 and up to 56% in 2050.

A large part of the operation cost is resulted from maintaining the wind turbine equipment, especially for offshore wind farms. This cost decreased by 44% in 10 years, reaching 45-79 EUR/MWh at the end of 2019 [40]. This thesis addresses the issue of further reducing the maintenance cost by means of mathematical optimization.

1.2 Purpose and aim

The *societal goal* of this thesis is to contribute to the increase of the availability of wind power, in tandem with the EU 2050 target of a reduction of CO_2 emissions by 85%, such that global warming would be limited to 2 degrees Centigrade. To this end, we focus on the reduction of the maintenance costs, which typically account for up to 25% of the total levelized cost of electricity (LCOE) of current wind power systems [21].

The *scientific goal* of this thesis is to mathematically represent the combination of the gathering of information from accumulated condition monitoring signals with maintenance optimization models, in order to faster and better estimate

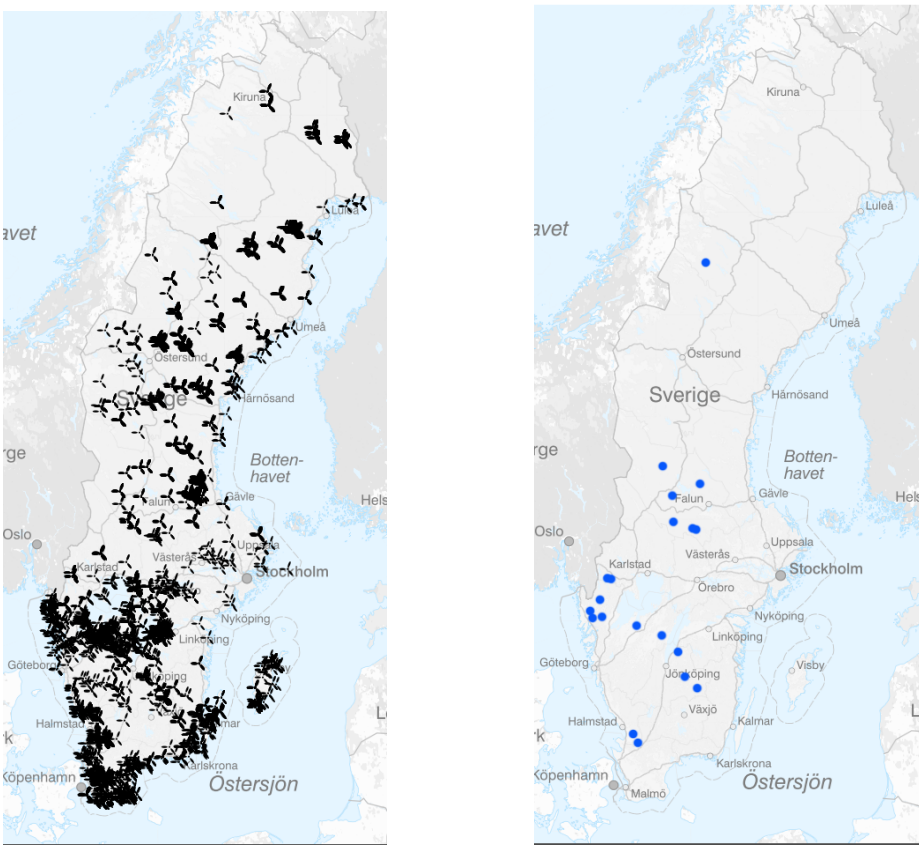

Figure 1.1: The left map marks all wind farms in Sweden(information gathered by Vindbrukskollen). The right map indicates the location of the wind farms included in the case study of Paper IV.

the optimal timing and selection of maintenance and replacement activities at an onshore or offshore wind farm.

The *practical goal* of this thesis is to combine the condition monitoring system with a set of maintenance optimization models and methods. In the future, such a development could result in a critical component of a practical maintenance app. Such an app for wind turbine maintenance scheduling would use as the input information: (a) the current ages of the key components of the turbine and (b) the recent data from a condition monitoring system for the components in question. As the output, the app would suggest the optimal time for the next preventive maintenance activity as well as which components should be attended to during this activity.

1.3 Limitations

In this thesis, by a maintenance action of a component (either corrective or preventive), we mean a replacement of the component, so that after the maintenance event the replaced component's condition is "as good as new".

For simplicity of presentation, in this thesis, we sometimes assume that at most one component of the wind farm may break down at any given time step.

Our optimization model for the PM scheduling under condition monitoring is illustrated in terms of the gearbox bearing temperature data. However, our methodology can be adapted to other kinds of monitoring data.

It is assumed that one component breaks do not influence another component's life length; i.e., the lifetimes of different components are independent random variables. For each component, we assume that its lifetime follows the Weibull distribution with a scale parameter $\theta > 0$ and shape parameter $\beta > 0$, so that the corresponding hazard function (failure rate at age t) takes the form

$$r(t) = \theta\beta t^{\beta-1}, \quad t > 0. \tag{1.1}$$

1.4 A first look at the appended papers

The preventive maintenance scheduling problem with interval costs (PMSPIC) model of paper [33] has been a major inspiration of our work. The key ingredient of the objective function of the PMSPIC model is the so-called interval cost. The interval cost for a time interval between two consecutive PM planned activities is defined as the maintenance cost (excluding mobilization costs) estimated for this interval, see Section 4.2.

The relationship between the four thesis papers and paper [33] is shown in Figure 1.2. The five paper are depicted as two clusters: two papers on the left are devoted to the long-term planning, while the three papers on the right focus on the short-term planning.

The connection, labeled as mIC, between PMSPIC paper and Paper 1 represents the fact that the idea of interval cost (IC) is drastically modified in Paper 1 resulting in a modified Interval Cost formula. The connection, labeled MIC, between Papers 1 and 2 indicates that in Paper 2 we further modified mIC formula to MIC formula, and it is the latter formula for the Modified Interval Cost that is presented in this thesis, see Section 4.3. Compared to PMSPIC, Paper 2 has two additional features mentioned in Figure 1.2: evaluation of the maintenance contract and more careful treatment of the end of the global planning period for a wind turbine.

Paper 3 introduces a new idea which we called virtual replacement (VR), which is used for defining the objective function as a more carefully estimated maintenance cost of a multi-component system. In Paper 4, the optimization model of Paper 3 is enhanced by a Cox proportional hazard model to incorporate condition monitoring data as input. The algorithm of Paper IV is tested on the data collected from a number of Swedish wind farms, see the right panel of Figure 1.1.

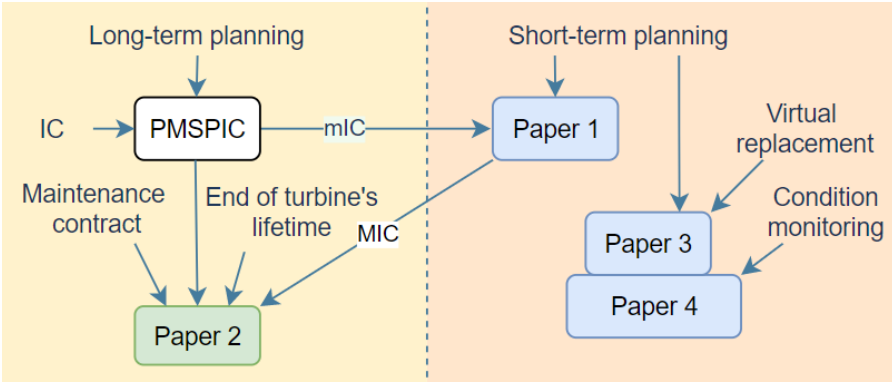

Figure 1.2: The relationship between the PMSPIC paper and the four appended papers. Paper 2, as PMSPIC paper, addresses the long-term maintenance scheduling. In contrast, Papers 1, 3, 4 deal with the short-term planning.

1.5 Outline

The thesis is organized as follows. In Chapter 2, we present the general information on wind turbines and their maintenance. Chapter 3 contains an overview of the literature on the optimal maintenance scheduling. Then long-term scheduling problem is discussed in Chapter 4 and the short-term scheduling problem is presented in Chapter 5. In Chapter 6, we demonstrate how a rescheduling algorithm based on the models developed in Chapter 5 works. Chapter 7 is devoted to a number of case studies illustrating our optimization models. In Chapter 8, we summarize the appended papers. The final Chapter 9 presents the main conclusions of the thesis and suggests some future research problems connected to our results.

2 Wind turbine maintenance

This chapter introduces the basic information regarding wind turbine and wind turbine maintenance.

Figure 2.1: The left figure shows an onshore wind farm. The right figure illustrates the practical challenges for performing a maintenance of a wind turbine.

2.1 A typical wind turbine

Depending on their shape, the wind turbines can be categorised into two types: vertical axis wind turbines and horizontal axis wind turbines. The majority of the wind turbines are horizontal axis. A typical wind turbine is schematically depicted in Figure 2.2 [51].

[i] *Blades*. When wind flows across the blade, the air pressure on one side of the blade decreases. The difference in air pressure across the two sides of the blade creates both lift and drag forces. The force of the lift is stronger than the drag and this causes the rotor to spin. For onshore wind turbines with power of 3–4 MW, the length of the blades can vary from 50 meters to 75 meters, see [70]. For offshore wind turbines, the blades are usually longer, for example, a Vestas 15-MW offshore wind turbine has 115.5-meter-long-blades, see [69].

[ii] *Rotor*. The function of the rotor is to convert kinetic energy of the wind to mechanical energy and to transmit this to the main shaft, see [28]. The rotor includes everything that rotates in front of the nacelle. There is a pitch system controlled by the computer of the wind turbine. The pitch angle of the blades is controlled by the pitch system, so that when the

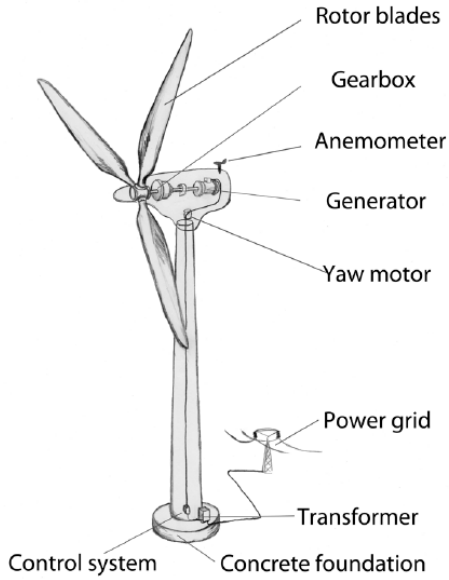

Figure 2.2: The main components of a wind turbine.

blades are pitched the power from wind is reduced. Usually, the rotors are three-bladed.

[iii] *Gearbox*. The gearbox increases the rotational speed by connecting the low-speed shaft to the high-speed shaft with different size gears. For example, if the rated power of the wind turbine is 1 MW, the rated rotational speed of the low-speed shaft is about 20 rotations per minute. The gearbox increases the rotational speed by a factor 90 to get the rotational speed of the high-speed shaft to reach about 1800 rotations per minute. For a larger turbine, e.g., 5 MW (REpower 5MW machine), the rotational speed of the low-speed shaft is about 12 rotations per minute at rated power. The gearbox increases the rotational speed by a factor 97 to get the rotational speed of the high-speed shaft to reach about 1173.7 rotations per minute [43]. (There are also direct-drive wind turbines without gearboxes. This kind of design, more common for the offshore turbines, helps to minimize the total maintenance cost.)

[iv] *Generator*. The generator transforms the rotational energy of blades into electrical energy. There are different types of generators used in wind turbines: induction generators, double fed induction generator, synchronous generators. The double fed induction generator is the most commonly used in the wind energy conversion systems, see [16].

[v] *Converter*. The converter converts the variable frequency output of a generator, driven by a variable speed wind turbine, to a fixed frequency appropriate for the grid, see [36]. The converter is located between the generator and the transformer. It enables wind turbine operation under

various speed, and control the torque in the drive train, protecting the gearbox from high torque.

[vi] *Control system*. The control system contains a computer that controls dynamic mechanical loads and maintains operating limits, based on a continuous measurement of rotation speed and wind direction. The control system controls the pitch angel, the current in the generator and the yaw direction. It is connected to several sensors in the wind turbine. For larger wind farms, the control systems from different turbines are monitored by a center of operations.

[vii] *Main bearing*. The principal role of the main bearing is to support the rotor while reacting non-torque loads either independently, preventing them from being transmitted further down the drive train, or in combination with the gearbox and mounts [35]. Depending on the type of wind turbine, triple-row roller bearings or double-row tapered roller bearings are used as main bearings. While the roller bearing leads to lower stresses in the adjacent construction, the tapered roller bearing is particularly attractive because it has zero play, therefore allowing for an optimal rolling behavior of the bearing.

[viii] *Supervisory control and data acquisition (SCADA)*. A SCADA system offers remote control and supervision of a wind farm and its components. There are also a lot of single wind turbines with SCADA systems. It can run on a computer in the wind turbine, the control room of the wind farm, or on any internet-connected computer accessing the wind farm using TCP/IP. SCADA systems can retrieve, store and export huge amounts of data, giving a full overview of all relevant parameters of wind turbines, like various temperatures, pitch angles, electrical parameters, rotor speeds, yaw systems, and so on. SCADA signals can be used for condition monitoring and early fault detection.

2.2 Typical maintenance policies

Over the past 100 years, the technology related to the maintenance of multi-component systems has been evolving as the systems become more and more complex. In this section, we present several typical maintenance policies and introduce abbreviations CM, PM, CBM, ABM, OM which are often used in this thesis.

[i] *Corrective maintenance (CM)*

> is a "maintenance carried out after fault recognition and intended to restore an item into a state in which it can perform a required function" [66].

A CM action is performed after the occurrence of a problem in order to restore the object to its operational condition or to replace it with another one in an operational condition [38, Chapter. 1]. Since the maintenance is performed after a failure has occurred, there will be a production loss and the failure may also affect the remaining lives of other components.

For major components in the wind turbines, the downtime is around one month for the onshore wind turbines. For the offshore wind turbines, the downtime can be several months. As a result, a CM activity may be quite costly. To avoid sudden breakdowns, sometimes it is beneficial to perform preventive maintenance actions.

[ii] *Preventive maintenance (PM)*

> is a "maintenance carried out intended to assess and/or to mitigate degradation and reduce the probability of failure of an item" [66].

A PM action is performed before a breakdown of the component [63]. There are two types of PM activities: a simple PM and a preventive replacement. A simple PM includes actions like inspecting the condition of the components, changing the oil of a certain equipment, and other minor adjustments just to make sure the object lasts longer. After a simple PM, the condition of the components is between "as good as new" and "as bad as old". A preventive replacement is the action of replacing an old but not broken component with a new one. In this thesis, by PM we mean solely a preventive replacement.

[iii] *Condition-based maintenance (CBM)*

> is a "preventive maintenance which include assessment of physical conditions, analysis and the possible ensuing maintenance actions" [66].

The condition monitoring techniques have been developing quite fast in the recent years. One common source of condition monitoring data for the wind turbines is the output of SCADA. Since the state of the major components can be monitored at a low cost and in an accurate way, CBM is becoming the most cost-effective form of PM. Using the information from the condition monitoring system, one can try to improve the PM scheduling by enhancing an existing optimization model to minimize the maintenance cost. For wind turbines, it is common to use temperature data, vibration data, current/voltage waveform analysis data, acoustic emission data, or oil analysis data to quantify the physical condition of the components [65].

[iv] *Age-based maintenance (ABM)* or predetermined maintenance

> is a "preventive maintenance carried out in accordance with established intervals of time or number of units of use but without previous condition investigation" [66].

Following this maintenance policy, only the age of the components is monitored. The solution of an optimization model taking into account the current age of the components, can be used to advise the maintenance personal when they should perform maintenance and which components they should attend. In the wind power industry, regular minor maintenance actions and annual services are widely used [23]. Changing the major components based only on the component ages is a quite uncommon maintenance policy.

[v] *Opportunistic maintenance (OM)*

> is a "preventive maintenance or deferred corrective maintenance undertaken without scheduling at the same time as other maintenance actions or particular events to reduce costs, unavailability, etc" [66].

OM is a kind of maintenance strategy that combines CM and PM. When one component breaks down, the maintenance personal alongside a CM on the broken component, may as well perform PM on other components whose condition is deemed to be critical. This is extremely beneficial for offshore wind farms, due to the large mobilization costs.

2.3 Wind farm maintenance contracts

The wind turbine maintenance involves four types of *stakeholders*: *manufacturers*, *wind farm owners*, *maintenance companies*, and *insurance companies*. The maintenance is performed by either the manufacturer, the farm owner, a contracted maintenance company, or a temporarily hired maintenance company; the interrelations of the companies involved are regulated by contracts. We consider the following four contract types, all of which are common within wind energy production and maintenance.

[C-I] *Full service maintenance contract* (between the wind farm owner and the manufacture). According to this contract, the manufacturer usually covers the costs to replace broken components. In addition, the contract includes either a *production-based* or a *time-based warranty*.
A *production-based warranty* guarantees a minimum level of 'measured average availability' for the wind farm, defined as

> "ratio of actual production to required production, or any other reference level, over a specified period of time" [66].

A *time-based warranty* guarantees a minimum level of 'technical availability' of the wind farm, defined as

> "during a given period of time, percentage of the time during which an item was able to perform when required" [66].

The manufacturer makes its own PM plan: if a component fails, the manufacturer performs CM of the broken component. Under this contract, the wind farm owner pays a fixed fee to the manufacture based on the contract period which covers all maintenance costs induced within the contract period. The manufacturer pays the actual cost of all maintenance work. The optimization of the maintenance scheduling is done on behalf of the manufacturer.

[C-II] *Basic insurance contract* (between the wind farm owner and the insurance company). Maintenance is performed either by a maintenance company or by the wind farm owner's maintenance team. Here we define a sudden failure as

> "a failure that could not be anticipated by prior examination or monitoring" [66].

When a component fails due to a sudden failure, the insurance company will reimburse the owner for the cost of the component with a discount, while the work/labor costs are paid by the wind farm owner. In practice, the stakeholders negotiate to classify a failure as a sudden failure, in our modelling this feature is represented by a probability that 'the failure is classified as being sudden'. Since a sudden failure entails unwanted costs for both stakeholders, they both benefit from PM, to the extent depending on the value of the probability.
Under this contract, the wind farm owner and the insurance company share the maintenance cost. The insurance company covers a part of the maintenance cost during CM. The optimization of the PM scheduling is done on behalf of the wind farm owner.

[C-III] *No insurance contract.* Maintenance is performed either by a maintenance company or by the wind farm owner's maintenance team. The wind farm owner covers all maintenance costs. The owner plans for PM; if a component suddenly fails the owner asks a maintenance company or its own maintenance team to perform CM.
Under this contract, since the wind farm owner pays for everything, optimization of the maintenance scheduling is done on behalf of the wind farm owner.

[C-IV] *Maintenance contract with a maintenance company* (between the wind farm owner and the maintenance company). Four main types of agreements exist:

- *Call-off agreement.* The simplest variant: the wind farm owner contacts the service provider in the event of an error. The owner pays for the maintenance time and components costs.
- *Basic agreement.* Planned service is included in an annual fee; corrective maintenance is paid by the wind farm owner when it occurs. This agreement is available both with and without remote monitoring.
- *Full service "light".* Planned service, corrective maintenance, and spare parts, monitoring, as well as reporting, are included in an annual fee. The main components (blade/rotor, main bearing, gearbox, generator, nacelle, tower, and foundation) are excluded from the contract. Inverters and SCADA systems are either included or excluded. This agreement can be with or without an availability guarantee.
- *Full service.* Planned service, corrective maintenance (including spare parts and main components), monitoring, and reporting are included in the agreement. Blade wear–and–tear are included in certain agreements. Foundations are not included. This agreement is with an availability guarantee (time- or production-based).

According to discussions with a group of wind farm owners within the Swedish Wind Power Technology Centre (SWPTC) [1], there are two common setups for them. One is to have [C-I] contract with the manufacture from the beginning till the end of wind farm's lifetime. The other one only have [C-I] contract with the manufacture during the initial years of a wind farm's operating period. After

the initial operating period the wind farm owner either extends this contract (contract type [C-I]), or acquires a maintenance contract with a maintenance company (contract type [C-IV]), or acquires a basic insurance contract (contract type [C-II]), or does not have any insurance contract at all (contract type [C-III]). During the whole life of the wind farm, the owner may switch between the four types of contracts.

3 Literature overview on optimal scheduling

There is a broad body of literature devoted to various optimization strategies of maintenance scheduling. In this chapter, we present an overview of the literature related to the thesis topic. There is a multitude of papers devoted to solving the optimal PM scheduling problem for multi-component systems [75], [72], [56].

3.1 Age-based maintenance scheduling

In this section, we investigate literature regarding the age-based maintenance scheduling problem.

In Yeh and Chen [79], the authors develop a mathematical model to derive an optimal *periodical PM policy* for a leased facility. Within a lease period, any failures of the facility are rectified by minimal repairs and a penalty may occur to the lessor when the time required to perform a minimal repair exceeds a reasonable time limit. Further on, in Lee and Cha [47], periodic PM policies is considered for a deteriorating repairable system, and the effect of a PM action is classified into three categories 'failure rate reduction', 'decrease of deterioration speed', and 'age reduction'.

While the periodical PM policy considers equidistant PM occasions, [33] and [50] looks into the *PM schedule of a long time interval*. The model PMSPIC from Gustavsson et al. [33] is devised to schedule PM of the components over a finite and discretized time horizon, given a common mobilization cost and component costs dependent on the lengths of the maintenance intervals. This model can be used for PM scheduling, but can also be dynamically used in a setting allowing for rescheduling. It is the main inspiration of our work. In Moghaddam and Usher [50], optimization models are developed to determine optimal PM schedules in repairable and maintainable systems. It demonstrates that it is beneficial to conduct simultaneous PM activities, if the mobilization costs are high, then simultaneous PM activities is advantageous. This is also shown in this thesis. However, the suggested models in [50] are nonlinear, which means they are computationally hard to solve. On the other hand, in this thesis, we present two optimization models which only look at the next PM activity, they are linear integer optimization models, and very easy to solve.

While in [9] the authors assume that at a PM action, the components which

has been maintained are as good as new, papers [24], [25], [46], [83] instead look into *imperfect PM*, where after PM the components are not as good as new. In Ding and Tian [24][25], three OM optimization models are proposed dealing with both perfect PM and imperfect PM. Lam and Banjevic [46] introduce a sequential PM policy and analyze two imperfect PM models. Zhou et al. [83] propose an OM scheduling algorithm for the multi-unit series system based on dynamic programming with the integration of the imperfect effect into maintenance actions.

Papers [55], [59], [8] and [49] are devoted to optimization issues related to *different maintenance contracts*. Park and Pham [55] deal with the optimal maintenance policy under different warranty policies, considering both the warranty period and the post-warranty period. For the warranty period, the authors suggest a warranty cost model using a repair–replacement warranty policy with repair times and failure times. Qiu et al. [59] consider optimization of the maintenance costs under performance-based contracts. The paper investigates an optimal maintenance policy for inspected systems that are subject to both soft and hard failures. According to Almeida [8], the main parameters of maintenance contracts are downtime and maintenance costs. Lisnianski et al. [49] consider an aging system, in which the maintenance is performed by an external maintenance team. They consider different kinds of contracts between the two parties paying special attention to downtime costs. The authors suggest a model based on a piecewise constant approximation of the increasing failure rate function. In this thesis, we present a long-term model, which can be used for different contracts and different planning periods.

3.2 Condition-based maintenance scheduling

Condition-based maintenance recommends maintenance actions based on information collected through online monitoring of the crucial components, and it can significantly reduce maintenance costs by decreasing the number of unnecessary maintenance operations. A general assumption for CBM strategies, is that the system at hand is monitored continuously and one can intervene and maintain the system at any given moment, see [39], [38], and [58].

Christer [19] proposes a method of an inspection maintenance policy as opposed to an existing breakdown maintenance policy for a building complex. The method is based upon information likely to be available and specific subjective assessments which could be made available. Estimates of the expected number of defects identified at inspection and the consequential cost saving are presented as functions of the inspection frequency. In a follow-up paper, Christer and Waller [20] further develop the basic model of [19] and apply it in a practical study.

Cox's Proportional Hazards Model (PHM), proposed in [22], utilizes measurable entities as covariates to update the hazard function for a component, whenever data from condition monitoring systems are available. Several research teams have suggested various optimization models in an attempt to make use of condition monitoring data by applying some version of PHM, see

[76], [80], [48], [57]. Vlok et al. [71] develope a probabilistic model to estimate the machinery remaining lifetime using data from condition monitoring system. Their probabilistic approach involves a PHM with Weibull baseline hazard and a Markov process model. Vibration data is used as an input from the condition monitoring system to illustrate a practical application of this probabilistic model. Similarly in [13], the failure process along with the covariate process is represented by a discrete Markov process. A PHM algorithm is proposed for predicting the remaining lifetime of the machinery based on a condition monitoring process. In this thesis, we proposed a Cox's proportional hazard method for updating the Weibull parameters of the components based on condition monitoring data, then we use the updated Weibull parameters for the optimization model to get a better estimation of the lifetime of the components.

Jafari et al. [37] propose a joint optimization of the maintenance policy and the inspection interval for a multi-unit series system. They develop a model and algorithm that can be used to determine an optimal maintenance policy for a multi-component system to minimize the maintenance cost, where one unit is subject to condition monitoring, while just the age information is available for the other units, and the future survival time has a Weibull distribution. Tian et al. [68] develop a method of using the condition monitoring data to effectively predict the remaining life length of a component in a multi-component system.

Kalosi et al. [42] look at a model with both planned and unplanned maintenance opportunities, at which the system is restored to a perfect condition, showing some preliminary results that a control limit policy (depending on the remaining time until the next planned maintenance) is optimal.

Wang et al. [74] feed the online vibration and temperature signals of bearings from the condition monitoring system into a neural network and predict the features of bearing vibration signals at any time horizon. Furthermore, according to the features, by considering historical condition and failure of the components, degradation factor was defined. A PHM is used to estimate the survival function and forecast the remaining lifetime of the bearing.

Ghasemi et al. [31] develop an approach build upon a hidden Markov model, assuming that the equipment's unobservable degradation state evolves as a Markov chain. The Bayes rule is used to determine the probability of being in a certain degradation state at each observation moment. Cox's time-dependent PHM is applied to deal with the equipment's failure rate. Two main problems are addressed: the problem of imperfect observations, and the problem of taking into account the whole history of observations.

3.3 Opportunistic maintenance scheduling

Zhu et al. [84] and Zhu et al. [85] consider a single-unit system with periodically scheduled PM events together with unscheduled break downs whose arrival times form a homogeneous Poisson process. Both scheduled and unscheduled events are treated as opportunities for OM activities subject to the current condition of the functioning components. Similarly, Ba et al. [10] develop an OM model considering two critical properties of real-world opportunities: (i)

non-homogeneous opportunity arrivals and (ii) stochastic opportunity duration.

Jardine et al. [39] derive the optimal replacement policy for a 3-state component degrading over time with corrective replacements at failures and preventive replacements at both scheduled and unscheduled opportunities.

Zhou et al. [83] introduce opportunistic PM scheduling method for multi-unit series systems based on dynamic programming and on short-term optimization with imperfect maintenance integration.

Laggoune et al. [45] consider opportunistic replacement of components through grouping of components in such a way that replacement times for each component in a group is an integer multiple of the least replacement time.

3.4 Wind turbine maintenance scheduling

The majority of the papers on optimal maintenance scheduling for wind turbines focus on offshore wind turbines: due to the high mobilization costs of the offshore maintenance, PM scheduling can be extra beneficial. A recent review paper Ren et al. [62] presents the state-of-the-art research results on offshore wind turbine maintenance, with regard to strategy selection, schedule planning, onsite operations, and environmental threats. Carlos et al. [18], unlike many others, look into onshore wind farms and use a stochastic model to optimize the maintenance cost.

Rangel-Ramírez and Sørensen [61] propose a risk-based inspection planning optimization of offshore wind turbines, based on the methodologies developed for oil and gas installations, and taking into account the lower reliability level for wind turbines. This framework address fatigue prone in welded steel joints typically located in the wind turbine substructure. Karyotakis and Bucknall [44] examine 'planned intervention' as a possible operation and maintenance strategy for large offshore wind farms (planned intervention is a scheduled maintenance with deferred CM activities [66]).

Fischer [28] propose a new method for using PHM to integrate failure history of a fleet of turbines and vibration data from the condition monitoring system. Based on the age of the monitored component and its vibration levels, this method suggests a distribution of the residual life of the component, yielding a turbine-specific prediction, which is continuously updated when new condition monitoring system data become available.

Yang et al. [77] use data mining techniques to select the most informative variables from the SCADA systems of the turbine to improve the prediction accuracy. They employ an exponentially weighted moving average model-based control chart to implement the residual approach, in order to remove the auto-correlation in the data. An opportunistic model has been presented in [27]. The model is based on variable reliability thresholds—which varies with weather conditions—that provides flexibility to the decision-making process.

For wind turbines, Ech-Chhibat et al. [26] describe a PM methodology based on cost optimization to determine a systematic period of intervention and replacement of components. Hameed and Vatn [34] analyzed the role of grouping of components within an overall maintenance optimization framework for off-

shore wind turbines. The frequency of visits to the wind farm could be reduced significantly by grouping different activities together.

Kahrobaee and Asgarpoor [41] show, through a case study of wind turbines, how a hybrid analytical-simulation approach works for maintenance optimization of deteriorating equipment. Shafiee [64] report a critical study on the current progress and perspectives of maintenance logistics organization for offshore wind energy. Ye et al. [78] develop a non-optimality detection technique for continuous processes. Nielsen and Sørensen [52] compare two different maintenance strategies, e.g., condition-based and corrective maintenance for a generic offshore wind turbine with single component. The model is formulated as a benefit maximization problem with constraints of design, inspection and decision rules. Influencing parameters of the model are minimum damage level to initiate repair, interval of inspection, mean time between failures of the component. A case study is presented to compare two strategies of maintenance and investigate the effects of various parameters.

Nilsson and Bertling [53] study the effect of condition monitoring as the maintenance strategy on life cycle cost for two cases, a single onshore turbine and an offshore wind farm. According to their study, condition monitoring benefits maintenance management of offshore power systems by increasing in turbine availability for power generation (by 0.43%).

Besnard et al. [15] propose an optimization framework for OM of offshore wind turbines. Their model demonstrates that it is possible to save major maintenance costs by taking advantage of low power forecasts and corrective maintenance opportunities to perform the PM tasks. Later on, Besnard et al. [14] propose a model for offshore wind turbine maintenance support organization. Their model considered location of the maintenance accommodation, the number of technicians, the choice of transfer vessels, and the use of a helicopter as decision variables. Backlogging of maintenance activities are presented through a queuing model. A case study shows that (under specific assumptions) the most cost effective arrangement for the maintenance teams is the offshore accommodation with 24 h a day, 7 days a week availability for service.

Fischer et al. [29], [30] present a limited-scope reliability-centred maintenance analysis of the wind turbines. The analysis focuses on the major components: gearbox, generator, hydraulic system, and electrical system. They compare visual inspection and condition monitoring to either prevent the failure itself or to avoid critical secondary damage. The study forms the basis for the development of quantitative models for maintenance strategy selection and optimization.

Tian et al. [67] consider the failure probability of the whole turbine system and suggested an optimal CBM policy depending on certain failure probability threshold values. Odgaard et al. [54] develop a fault-tolerant control of wind turbines that served as a benchmark model for similar studies.

For offshore wind turbines, the logistic and downtime costs are major issues. Raknes et al. [60] propose a mathematical model that considers how maintenance tasks should be scheduled and performed by technicians transported by a fleet of dedicated vessels. The model considers such aspects as different work shifts, the handling large maintenance tasks, and a calculation of the downtime

costs. Zheng et al. [82] look into the effects of the varying wind speed on the wind turbine maintenance planning. Wang et al. [73] and Zhang et al. [81] deal with imperfect PM. By utilizing the information about the state of various critical components, the maintenance routines can be further improved.

Bangalore and Patriksson [11] and Bangalore et al. [12] develop a machine learning approach to maintenance scheduling for a wind turbine whose condition is monitored by a time series $\{\xi(1), \xi(2), \ldots, \xi(t)\}$ summarising some key characteristics of the turbine which can be used for predicting the failure times after time t. A deep learning algorithm is trained to predict the next value $\hat{\xi}(t+1)$ for a time series observed up to the current time t. Then at time $t+1$, depending on a certain measure of discrepancy between the observed $\xi(t+1)$ and predicted $\hat{\xi}(t+1)$ values, a decision is made whether a PM should be performed in the near future or not. A key assumption (to simplify the model) is that the turbine's component in question has an exponential life length distribution.

4 Long-term scheduling

In this chapter, we address the long-term planning of PM activities for an n-component system. An n-component system in the current context refers to a wind turbine consisting of n major components. Section 4.1 introduces notation some of which will be used even in later chapters. In Section 4.2, we propose an interpretation of the interval cost function first defined in Section 5.1 of [33]. Then in Section 4.3, we propose a new approach to the interval cost idea. Section 4.4 contains the main results of this chapter.

4.1 Key notation

We consider the maintenance planning for a system comprised of components indexed by $j \in \{1, \ldots, n\}$ during the planning period $(s, r]$. Our models involve the following parameters describing different maintenance costs:

b_t^j is the CM cost of component j consisting of the price of a new component, the mobilization costs, and the expected downtime cost at time $t \in (s, r]$,

h_j is the component specific PM cost of component j consisting of (a) the difference between the price of a new component and the expected market value of the component to be replaced, and (b) the cost of the physical replacement of the component j in the PM regime,

d_t is the downtime cost and the mobilization cost of the PM activities planned at time $t \in (s, r]$.

It is assumed that the life lengths of the components are independent from each other and follow a Weibull distribution with different parameters for different j. The notation below can deal with various entities, enabling a track of the current ages of the components:

θ_j and β_j are the scale and shape parameters of the Weibull distribution describing the life length of component j,

$U_{u1}^j, U_{u2}^j, \ldots$ are the consecutive random failure times since time u for component j, we define $U_{u0}^j = u$,

T stands for the lifetime of the wind turbine.

4.2 The interval cost function

The idea of the interval cost (IC) is initially proposed in [33]: different forms the IC-function were suggested, but here we focus on a particular formulation, see

Section 5.1 in [33]. Notice that the definition of the IC-function c^j_{ut} given in this section is valid only for the case of constant costs $d_t \equiv d$.

Consider component j during the time interval $(u, t]$. Assume that at time u the component is in the state of being "as good as new" and that at time t a PM replacement is scheduled for this component. Then the associated IC-function

$$C^j_{ut} = \mathbb{E}\left[\sum_{k=1}^{\infty} 1_{\{U^j_{uk} \le t\}} b^j_{U^j_{uk}}\right] + h_j - (h_j + d)P^j_{t-u}, \tag{4.1}$$

involves the expected value of the CM cost

$$B^j_{ut} = \mathbb{E}\left[\sum_{k=1}^{\infty} 1_{\{U^j_{uk} \le t\}} b^j_{U_{uk}}\right] \tag{4.2}$$

caused by the component failures during the time interval $(u, t]$. The IC-function can be decomposed into three terms

$$C^j_{ut} = B^j_{ut} + (1 - P^j_{t-u})h_j - P^j_{t-u}d, \tag{4.3}$$

where the second and the third terms represent estimated cost savings due to rescheduling. Here, P^j_{t-u} is defined by

$$P^j_t = \mathbb{E}\left[\sum_{k=1}^{\infty} 1_{\{U^j_{0k} \le t\}} \left(\tfrac{1}{t} U^j_{0k}\right)^{\lambda}\right], \tag{4.4}$$

and will be called the cost reduction factor for the planning time interval of length t.

The definition (4.4) of the cost reduction factor involves a new positive parameter λ which is assumed to be independent of the indices j and whose role is explained next under the simple scenario of a single failure at time $U^j_{01} = \sigma$, where $\sigma \in [0, t]$. In the simple case of a single failure at time σ, the intuitive explanation of the expression $(\frac{\sigma}{t})^{\lambda}$ is a compromise between two extreme cases: a failure at the start of the planning period, $\sigma = 0$, and a failure just before the planned PM replacement, $\sigma = t$.

If $\sigma = 0$, then such a component failure will not change the PM plan, implying that almost no cost can be saved due to rescheduling. According to (4.4), the corresponding cost reduction factor takes value 0. On the other hand, if $\sigma = t$, then the new scheduling is just simply plan a CM activity on component j instead of a PM activity. This results in the cost reduction factor 1 by formula (4.4), and a big cost reduction term in (4.1). For $\sigma \in (0, t)$, the expression $(\frac{\sigma}{t})^{\lambda}$ gives a factor which lies between the extreme values 0 and 1. The role of the parameter λ is to control to what extent the proximity of the failure time to the planned PM time influences the extra costs. For example, if $\lambda = 1$ the intermediate cost is found by a linear extrapolation.

To illustrate the definition (4.1), consider an example of a maintenance plan described by Figure 4.1, where the marked times are planned PM times for

a two-component system. For this particular example, the total maintenance

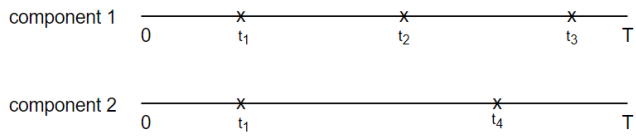

Figure 4.1: An example of a long term maintenance plan for a two-component system.

cost is computed as the sum of the interval costs across different intervals and components:

$$C^1_{0,t_1} + C^1_{t_1,t_2} + C^1_{t_2,t_3} + C^1_{t_3,T} + C^2_{0,t_1} + C^2_{t_1,t_4} + C^2_{t_4,T}. \tag{4.5}$$

For the above definition of the IC-function, we identify an issue which makes the definition problematic in the case when two or more failures occur within a short time interval. The issue is clarified in the form of two examples below: Example 1 deals with the case of two failures for component 1 before the planned PM activity, and Example 2 deals with both components experience failures before the planned PM activity. Both examples illustrate a possibility of the total cost reduction factor for a certain interval getting a value larger than 1, which results in an overcompensating possibility associated with formula (4.1).

Example 1. Consider the particular interval cost C^1_{0,t_1}. Suppose $t_1 = 100$ months, and there are two failures of the component 1 before time t_1 at times $U^1_{01} = 50$ months and $U^1_{02} = 80$ months. Let $\lambda = 1$, then the cost reduction factor takes a value larger than 1:

$$\tfrac{1}{t_1} \sum_{k=1}^{\infty} 1_{\{U^1_{0k} \le t_1\}} U^1_{0k} = 1.3.$$

Example 2. Consider the sum of two interval costs C^1_{0,t_1} and C^2_{0,t_1}. Once again, suppose $t_1 = 100$ months and put $\lambda = 1$. Assume that both components experience a single failure before time t_1 at times $U^1_{01} = 80$ months and $U^2_{01} = 90$ months. Then the corresponding cost reduction factor for d at time t_1 is also larger than 1:

$$\tfrac{1}{t_1} \sum_{k=1}^{\infty} 1_{\{U^1_{0k} \le t_1\}} U^1_{0k} + \tfrac{1}{t_1} \sum_{k=1}^{\infty} 1_{\{U^2_{0k} \le t_1\}} U^2_{0k} = 1.7.$$

We address the above mentioned problematic issue illuminated by Examples 1 and 2 by suggesting a modified definition of the IC-function introduced in the next section.

4.3 Modified interval cost function

Here we propose a modification of the formula (4.1) in a way that separates the maintenance costs associated with the interval $(u, t]$ on the component level

$$c_{ut}^j = \mathbb{E}\left[\sum_{k=1}^{\infty} 1_{\{U_{uk}^j \le t\}} b_{U_{uk}}^j\right] + (1 - p_{t-u}^j)h_j, \tag{4.6}$$

on the whole system level

$$(1 - p_{t-u})d_t,$$

where

$$p_t^j = \mathbb{E}(V_t^j), \quad V_t^j = \max_{k \ge 0}\left\{\frac{U_{0k}^j}{t} \,\middle|\, U_{0k}^j \le t\right\}, \tag{4.7}$$
$$p_t = \mathbb{E}(V_t), \quad V_t = \max_{i \in \mathcal{I}}(V_t^j).$$

Here, p_t^j is the expected proportion of the failure-free right-most part of the time interval $[0, t]$ computed on the component level. A similar proportion p_t is computed on the whole system level.

Compared to (4.3), we now have

$$c_{ut}^j = B_{ut}^j + (1 - p_{t-u}^j)h_j,$$

which is the sum of the CM costs (4.2) and a reduced component specific PM cost. To justify the latter term, assume that component i is as good as new at time 0, and that the first PM replacement of this component is planned at time t. Suppose that component i is going to fail at times $\sigma_1 < \sigma_2 < \ldots < \sigma_k$ during the time interval $(0, t]$. Observe that in this case, we have $V_t^j = \frac{\sigma_k}{t}$. We now argue the reduced PM cost should be computed as

$$(1 - \tfrac{\sigma_k}{t})h_j. \tag{4.8}$$

Notice, that the last expression equals 0 in the case $\sigma_k = t$, which is a natural property, since in this case the planned PM at time t should be cancelled because of a CM occurring at the time of failure.

We derive the proportion $\frac{\sigma_k}{t}$ in (4.8) starting from

$$(\tfrac{\sigma_1}{t})^\lambda + (\tfrac{\sigma_2 - \sigma_1}{t})^\lambda + \ldots + (\tfrac{\sigma_k - \sigma_{k-1}}{t})^\lambda, \tag{4.9}$$

which should be compared to its counterpart stemming from (4.4):

$$(\tfrac{\sigma_1}{t})^\lambda + (\tfrac{\sigma_2}{t})^\lambda + \ldots + (\tfrac{\sigma_k}{t})^\lambda.$$

We now argue that expression (4.9) for the proportion of the saved PM cost due to rescheduling is more relevant than the latter one. Notice that the first term $(\frac{\sigma_1}{t})^\lambda$ is the same for both expressions, and its justification is given in the

previous section. The new approach is now explained by referring to the second term in (4.9),

$$(\tfrac{\sigma_2-\sigma_1}{t})^\lambda.$$

Clearly, this term is a natural counterpart of the first term, assuming that at the failure time σ_1 after a CM replacement had been performed, a rescheduling is done such that the interval $[0,t]$ is replaced by $[\sigma_1, \sigma_1+t]$.

With (4.9) in hand, it remains to observe that the only way to satisfy the boundary relation discussed above

$$(\tfrac{\sigma_1}{t})^\lambda + (\tfrac{\sigma_2-\sigma_1}{t})^\lambda + \ldots + (\tfrac{\sigma_k-\sigma_{k-1}}{t})^\lambda = 1, \text{ for } \sigma_k = t,$$

is when $\lambda = 1$. Now, with $\lambda = 1$, we get the desired ratio

$$(\tfrac{\sigma_1}{t})^\lambda + (\tfrac{\sigma_2-\sigma_1}{t})^\lambda + \ldots + (\tfrac{\sigma_k-\sigma_{k-1}}{t})^\lambda = \tfrac{\sigma_1}{t} + \ldots + \tfrac{\sigma_k-\sigma_{k-1}}{t} = \tfrac{\sigma_k}{t}.$$

4.4 MICPM model

For a given planning period $[s+1, r] \subset [0, T]$, we define a long-term PM plan as a pair $(\boldsymbol{x}, \boldsymbol{z})$, of arrays

$$\boldsymbol{x} = \{x^j_{ut}, j \in \{1,\ldots,n\}, u \in \{s,\ldots,r-1\}, t \in \{u+1,\ldots,r+1\}\}$$
$$\boldsymbol{z} = \{z_{ut}, u \in \{s,\ldots,r-1\}, t \in \{u+1,\ldots,r\}\}$$

with binary components

$$x^j_{ut} \in \{0,1\}, \quad z_{ut} \in \{0,1\}, \qquad \text{for all } (j,u,t), \tag{4.10}$$

which satisfy the following linear constraints

$$\sum_{t=s+1}^{r+1} x^j_{st} = 1, \quad j = 1,\ldots,n, \tag{4.11}$$

$$\sum_{u=s}^{t-1} x^j_{ut} = \sum_{v=t+1}^{r+1} x^j_{tv}, \quad j = 1,\ldots,n,\ t = s+1,\ldots,r, \tag{4.12}$$

$$z_{ut} \geq x^j_{ut}, \quad j = 1,\ldots,n,\ u = s,\ldots,r-1,\ t = s+1,\ldots r. \tag{4.13}$$

The meaning of the binary variables x^j_{ut} and z_{ut} is explained below by specifying when each of them takes value 1 in terms of planned PM activities for a single component i, or the whole system.

For $s < u < t \leq r$, equality $x^j_{ut} = 1$ means that component replacements are planned at time steps u and t, but no PM activities for component j are planned between times u and t. If $t \leq r$, then $x^j_{s,t} = 1$ means that the first PM is planned at time step t. If $u > s$, then $x^j_{u,r+1} = 1$ means that the last PM is planned at time step u. Finally, $x^j_{s,r+1} = 1$ means that no PM activities during $[s+1, r]$ are planned for component j.

Whenever $x^j_{ut} = 1$, we say that a PM interval for component j starts at time step u and ends at time step t. Due to the constraints (4.11), for each component j either the first PM is scheduled in one of the time steps $\{s+1, \ldots, r\}$, or no PM is scheduled (i.e., $x^j_{s,r+1} = 1$). The constraints (4.12) ensure that, for each component j, the end of any PM interval is the start of the next PM interval.

For the whole system, equality $z_{ut} = 1$, $s < u$ means that for at least one of the components, a PM is planned at time steps u and t, but no PM is planned in-between these times. Equality $z_{st} = 1$ means that the first PM for the whole system is planned at time t, see (4.13).

For a given long term PM plan $(\boldsymbol{x}, \boldsymbol{z})$, the total maintenance cost is obtained as the sum of the interval costs on the component level plus the PM cost estimated on the system level

$$f_{\mathbf{1}}(\boldsymbol{x}, \boldsymbol{z}) := \sum_{j \in \mathcal{J}} \sum_{u=s}^{r} \sum_{t=u+1}^{r+1} c^j_{ut} x^j_{ut} + \sum_{u=s}^{r-1} \sum_{t=u+1}^{r} (1 - p_{t-u}) d_t z_{ut}.$$

In terms of the objective function $f_{\mathbf{1}}(\boldsymbol{x}, \boldsymbol{z})$ the MICPM optimization model for the long-term maintenance scheduling problem is stated as

MICPM optimization model

MINIMISE:	$f_{\mathbf{1}}(\boldsymbol{x}, \boldsymbol{z})$
SUBJECT TO THE CONSTRAINTS:	(4.10), (4.11), (4.12), and (4.13)

5 Short-term scheduling

This chapter deals with the short-term PM scheduling for a n-component system. Here, the focus is to find the optimal time for the next PM activity and specify which of the n components should be replaced at that time. Section 5.1 presents an approach based on the MICPM-function which is introduced in Section 4.3. A different approach based on a new idea of virtual replacement is suggested in Section 5.2.

In this chapter, we use the notation introduced in Section 4.1.

5.1 NextPM^{MIC} model

For a given planning time interval $(s, r] \subset [0, T]$, we define a short-term PM plan as a pair $(\boldsymbol{x}, \boldsymbol{z})$ of arrays

$$\boldsymbol{x} = \{x_{st}^j, j = 1, \ldots, n, t = s+1, \ldots, r+1\}, \quad \boldsymbol{z} = (z_{s+1}, \ldots, z_{r+1})$$

with binary components

$$x_{st}^j \in \{0, 1\}, \quad z_t \in \{0, 1\}, \quad t = s+1, \ldots, r+1, \; j = 1, \ldots, n, \tag{5.1}$$

which satisfy the following linear constrains

$$\sum_{t=s+1}^{r+1} x_{st}^j = 1, \quad j = 1, \ldots, n, \tag{5.2}$$

$$x_{st}^j \leq z_t, \quad t = s+1, \ldots, r+1, \; j = 1, \ldots, n. \tag{5.3}$$

For $t = s+1, \ldots r$, the equality $x_{st}^j = 1$ means that

$(\boldsymbol{x}, \boldsymbol{z})$-plan *tentatively* schedules a PM of the component j at the time step t, however, whenever a failure of the component occurs during the period $[s+1, t]$, the plan requires rescheduling of the next PM, (5.4)

and on the system level, $z_t = 1$ means that

$(\boldsymbol{x}, \boldsymbol{z})$-plan tentatively schedules at least one PM activity on one or several components at the time step t. (5.5)

Furthermore, $x^j_{s,r+1} = 1$ means that the $(\boldsymbol{x}, \boldsymbol{z})$-plan tentatively schedules no PM activity for the component j during the time period $[s+1, r]$. The equality $z_{r+1} = 1$ means that no PM activity is planned during the time period $[s+1, r]$.

The objective function for the NextPM^{MIC} model is defined as the time average maintenance cost

$$f_{\mathbf{2}}(\boldsymbol{x}, \boldsymbol{z}) := \frac{1}{t-s}\Big(\sum_{j=1}^{n}\sum_{t=s+1}^{r+1} c^j_{st} x^j_{st} + \sum_{t=s+1}^{r+1}(1-p_{t-s})d_t z_t\Big),$$

where the ratios p_t and the modified interval costs c^i_{st} are defined in Section 4.3. The corresponding optimization model

NextPM^{MIC} optimization model	
MINIMISE:	$f_{\mathbf{2}}(\boldsymbol{x}, \boldsymbol{z})$
SUBJECT TO THE CONSTRAINTS:	(5.1), (5.2), (5.3), and (5.6)

requires an additional constraint

$$D^j_{st} x^j_{st} \geq 0, \quad t = s+1, \ldots, r, \; j = 1, \ldots, n. \tag{5.6}$$

It ensures that a suggested PM at time t brings some benefits, as compared to a simple strategy when no PM is performed. With the PM-free strategy, the total maintenance cost (including mobilization costs) for the component j during the period $[s, T]$ would be

$$\mathrm{E}\left[\sum_{i=1}^{\infty} 1_{\{U^j_{s,i} \leq T\}}\Big(b_j + d_{U^j_{s,i}}\Big)\right].$$

Alternatively, if the plan is to perform a PM for the component j at time t, and then to perform replacements of the component j whenever it breaks down, then the total cost would be

$$c^j_{s,t} + \mathrm{E}\left[\sum_{i=1}^{\infty} 1_{\{t+U^j_{0,i} \leq T\}}\Big(b_j + d_{t+U^j_{0,i}}\Big)\right].$$

Taking into account the difference between these two total costs

$$D^j_{s,t} = \mathrm{E}\left[\sum_{i=1}^{\infty} 1_{\{U^j_{s,i} \leq T\}}\Big(b_j + d_{U^j_{s,i}}\Big)\right] - c^j_{s,t} - \mathrm{E}\left[\sum_{i=1}^{\infty} 1_{\{t+U^j_{0,i} \leq T\}}\Big(b_j + d_{t+U^j_{0,i}}\Big)\right],$$

we conclude that the planned PM of the component j at time t is justified only if $D^j_{s,t} \geq 0$.

5.2 NextPM^{VR} model

Suppose the ages of n components at time s are given by the vector

$$\boldsymbol{a} = (a^1, \ldots, a^n),$$

where the value of $\boldsymbol{a}$ is non-negative. For the first component failure after time step s, the label of the failed component is denoted by $\gamma \in \{1, \ldots, n\}$, and the corresponding failure time is $s + L_{\boldsymbol{a}}$. Observe that both γ and $L_{\boldsymbol{a}}$ are random variables. Suppose the next PM is planned at time t. Then using formulas

$$C_{\boldsymbol{a}} = (T - s - L_{\boldsymbol{a}})c^* + b^{\gamma}_{s+L_{\boldsymbol{a}}} + \sum_{j \neq \gamma} M^j_{a^j + L_{\boldsymbol{a}}},$$

$$P_{\boldsymbol{a}t} = d_t + (T - t)c^* + \sum_{j=1}^{n} M^j_{a^j + t - s},$$

we can estimate by $C_{\boldsymbol{a}}$ the expected total maintenance cost if a failure happens before the planned PM activity, by $P_{\boldsymbol{a}t}$ the total maintenance cost if there is no failure before the planned PM activity at time t. Here c^* denotes the expected average monthly maintenance cost of the whole system, and

$$M^j_a = \min\{h^j_a, m^j_a\}$$

is *effective replacement cost* of a PM activity targeting component j having age a. The latter is defined as the minimum between *virtual replacement cost* m^j_a associated with component j with age a, and

$$h^j_a = h_j + g_j a, \tag{5.7}$$

is the actual PM replacement cost which is now assumed to depend on the component's age a. For simplicity, we assume that h^j_a linearly increases with age a, so that $g_j \geq 0$ is a new parameter specifying the slope of this linear function.

How c^* and m^j_a are computed is explained in the next section.

For a given time $s \subset [0, T]$, treated as the planning time, we define a short-term PM plan as a pair $(\boldsymbol{x}, \boldsymbol{z})$ of arrays

$$\boldsymbol{x} = \{x^j_t, j = 1, \ldots, n, t = s + 1, \ldots, T\}, \quad \boldsymbol{z} = (z_{s+1}, \ldots, z_{T+1})$$

with binary components

$$x^j_t \in \{0, 1\}, \quad z_t \in \{0, 1\}, \quad \text{for all } (j, t), \tag{5.8}$$

which satisfy the following linear constrains

$$\sum_{t=s+1}^{T+1} z_t = 1, \tag{5.9}$$

$$z_t \leq \sum_{j=1}^{n} x_t^j, \quad t = s+1, \ldots, T, \tag{5.10}$$

$$h^j_{a^j+t-s} x_t^j + m^j_{a^j+t-s}(x_t^j - z_t) = M^j_{a^j+t-s} z_t, \quad t = s+1, \ldots, T,\ j = 1, \ldots, n. \tag{5.11}$$

As in the previous section, $x_t^j = 1$ defines in (5.4), and $z_t = 1$ defines in (5.5). Constraint (5.9) means that we only look at the next PM of the whole system, and equality $z_{T+1} = 1$ means that no PM activity is planned during the planning period $(s, T]$.

Now we are ready to introduce another optimization model

NextPM^{VR} optimization model	
MINIMISE:	$f_{\boldsymbol{3}}(\boldsymbol{z})$
SUBJECT TO THE CONSTRAINTS:	(5.8), (5.9), (5.10), and (5.11)

with the objective function

$$f_{\boldsymbol{3}}(\boldsymbol{z}) = \sum_{t=s+1}^{T} \mathrm{E}\Big(C_{\boldsymbol{a}} 1_{\{s+L_{\boldsymbol{a}} \leq t\}} + P_{\boldsymbol{a}t} 1_{\{s+L_{\boldsymbol{a}} > t\}}\Big) z_t + \mathrm{E}\Big(C_{\boldsymbol{a}} 1_{\{s+L_{\boldsymbol{a}} \leq T\}}\Big) z_{T+1},$$

defined as the expected total cost during the whole lifetime of the system.

Notice that the total cost function $f_{\boldsymbol{3}}(\boldsymbol{z})$ does not explicitly depend on the set of variables $\boldsymbol{x}$. The role of $\boldsymbol{x}$ becomes explicit through the constraints (5.10) and (5.11). The latter says that if $z_t = 1$, that is if a PM for at least one component is scheduled at time t, then for each component j, there is a choice between two actions at time t:

- either perform a PM, so that $x_t^j = 1$ and $z_t - x_t^j = 0$,
- or do not perform a PM and compensate for the current age of the component by increasing the cost function using the virtual replacement cost value (corresponds to $x_t^j = 0$ and $z_t - x_t^j = 1$).

5.3 The renewal-reward argument

The estimated lifetime maintenance costs $C_{\boldsymbol{a}}$ and $P_{\boldsymbol{a}t}$ that introduced in the previous section are obtained using a renewal argument in the multiple component setting. To overcome the problem of the absence of true renewal events in the multi-component setting, we rely on the idea of virtual replacements: at the moment of an actual replacement, either a CM or PM replacement, we treat

all the components of the system to become as good as new at this moment. In this way, we get access to renewal events, and to adjust for introducing the virtual replacements, we compute what we call virtual replacement costs m_a^j, in a manner explained below.

Observe that the renewal argument is much more straightforward in a single component setting, since each replacement of the component, either a CM or PM replacement, is a renewal event resetting the component to the state as good as new. To define the virtual replacement cost m_a^j, consider a system consisting of a single component j and assume that at time 0 the component is as good as new. Assuming that the first PM activity is planned at time t, the component is going to experience the first replacement at times $U_t = \min\{t, L_j\}$, where L_j is the failure time of the initial component j. Treating U_t as the first renewal time and applying the classical renewal-reward theorem, see [32], we derive $c_j^*(t)$, the long-term monthly maintenance cost of the component j. Minimizing over planning time t,

$$c_j^* = \min\{c_j^*(t), t > 0\},$$

we obtain the optimal monthly maintenance cost of the component j.

Using c_j^* and applying the renewal-reward theorem in the single component setting once again, we are able to determine the optimal next PM plan for the single component j assuming that at time 0 it has age a. Let $f_j^*(a)$ be the total PM cost associated with the optimal PM plan for the single component j with starting age $a > 0$. Its counterpart in the case $a = 0$ is Tc_j^*. Taking the difference

$$m_a^j = f_j^*(a) - Tc_j^*$$

we define the long term virtual replacement cost of the component j of age a. This difference evaluates the extra maintenance cost over the time period $[t, T]$ due to the component's age a at the starting time t of the observation period. The larger a is, the higher the expected maintenance cost is.

Clearly, a multi-component system is not fully renewed at the failure events unless all n components break down at the same time. Using the idea of virtual replacements, we can apply the renewal-reward argument in the multi-component setting to obtain c^*, the expected average monthly maintenance cost of the whole system, in a way similar to that of for obtaining c_j^*. For more details, see **Paper III**.

6 NextPM rescheduling algorithms

Using the NextPM models described in the previous chapter one can build a practical algorithm for optimal rescheduling of the next PM plan after each CM and PM activity. Figure 6.1 depicts a flowchart that illustrates the basic idea of such an algorithm.

The left bottom box depicts the key step of the algorithm, the NextPM step, which can be based on the optimization model described in Section 5.1 or in Section 5.2.

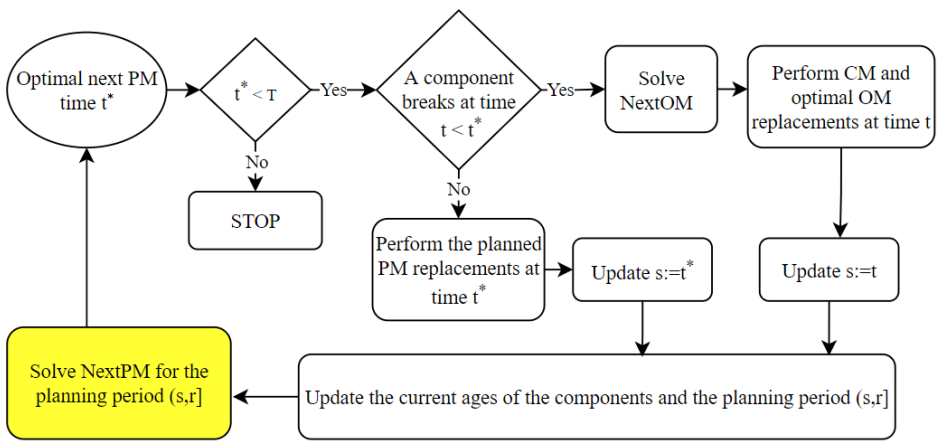

Figure 6.1: Flow diagram of optimal rescheduling algorithm based on a NextPM module.

Later in this chapter this idea will be further developed to include condition monitoring data, see Figure 6.2 below.

6.1 Optimal rescheduling algorithm for the next PM

In this section, we show the algorithm in a more formal way (Algorithm 1), compare to the one shown by the flowchart Figure 6.1. This algorithm produces a new optimal next PM schedule according to the NextPM model, but the components may break before the scheduled PM event. To save some mobilization

cost, it may be beneficial to maintain other components as well. Thus in this section, we briefly mention the NextOM model for the OM planning step.

Algorithm 1 Optimal rescheduling algorithm

Input $\boldsymbol{a}, s, r$
Start Solve NextPM$\{\boldsymbol{a}, s, r\}$
Output: $(t^*,\ \mathcal{P})$, where $\mathcal{P} \subset \{1, \ldots, n\}$ is the set of components subject to PM activities at time t^*
If $t^* < T$
  If a failure during the period $(s, t^*]$ damages component i at time t
    Set $u := t$
    Solve NextOM$\{i, \boldsymbol{a}, u\}$
    Output: $\mathcal{O} \subset \{1, \ldots, n\}$ is the set of components subject to OM activities at time u
    Perform CM of component i at time u
    Perform PM of each component $j \in \mathcal{O}$ at time u
    Update $r := \min(u + r - s, T)$, $s := u$
    Update $t_j := u,\ j \in \mathcal{O} \cup \{i\}$
  Else Perform PM of each component $j \in \mathcal{P}$ at time t^*
    Update $r := \min(t^* + r - s, T)$, $s := t^*$, $a_j := s,\ j \in \mathcal{P}$
  End
  Go to **Start**
Else
  Stop
End

The NextOM model is tightly connected with the corresponding NextPM model, so that there are two versions of NextOM models as well. Here we briefly explain the idea of NextOM connected to the NextPM^{MIC} model. The NextOM model deals with only two time steps: the time step a CM replacement for the failed component i is performed and the next time step. Essentially, we use a version of the NextPM^{MIC} model with $r = s + 2$, and an additional constraint $x^i_{s+1} = 1$.

6.2 Rescheduling under condition monitoring

An up-to-date algorithm for optimal scheduling must incorporate available condition monitoring data beyond the current age information of the key components of the system. As a development towards this goal we present an enhancement of the rescheduling Algorithm 1 represented by the flowchart Figure 6.2. Compared to Figure 6.1, the enhanced algorithm has extra steps represented by colored boxes of Figure 6.2.

The five new steps deal with a regular update of the condition monitoring data which is assumed to occur every 3 months (this explains expression $s + 3$ appearing in the top three additional boxes in Figure 6.2). In the remainder of this section, we explain the step following the data collection step. This crucial

step uses the latest condition monitoring data for updating the Weibull parameters of the components of the systems, so that the next round of the NextPM optimization will be adjusted to either worsened or improved conditions of the components (as compared to the baseline, i.e., normal conditions).

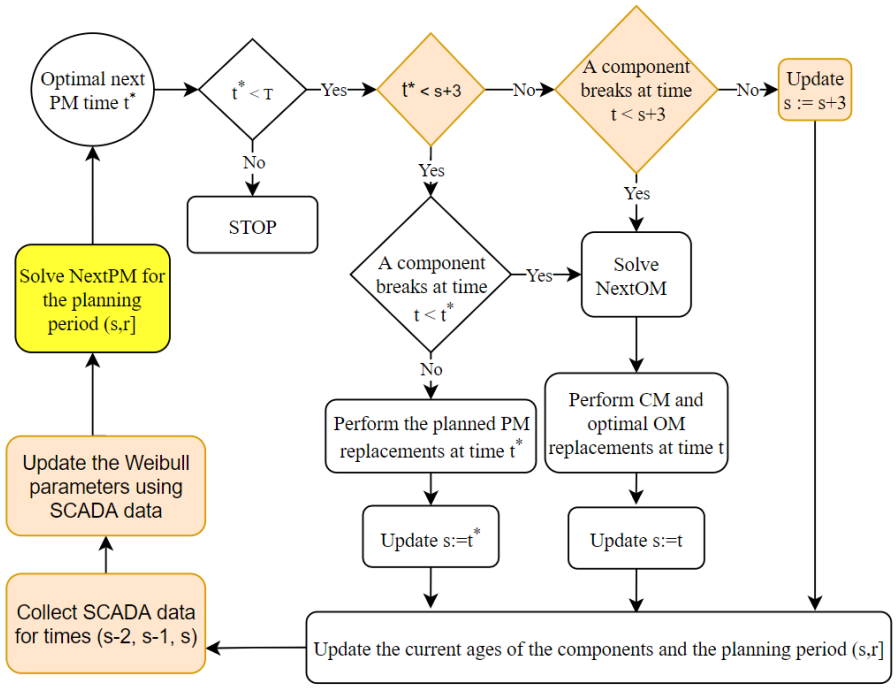

Figure 6.2: Flow diagram of optimal rescheduling algorithm under condition monitoring

Let us focus on a single component, say gearbox, whose life length under "normal" conditions is described by a Weibull distribution with the baseline parameter values θ and β, corresponding to a hazard function in the form (1.1). Suppose we have access to two sets of data from the SCADA system:

- containing the observed ages of the components which is still operational; $u_1, \ldots, u_K$
- and yet another historical data set for components that have failed

$$(v_1, \boldsymbol{\xi}^{(1)}), \ldots, (v_N, \boldsymbol{\xi}^{(N)}), \tag{6.1}$$

  where, v_k is the failure age of a gearbox k, and $\boldsymbol{\xi}^{(k)} = (\xi_1^{(k)}, \ldots, \xi_{v_k}^{(k)})$ is the corresponding recorded history of the monitoring data.

The baseline Weibull parameter values θ and β are estimated from the two sets of observed lifetimes

$$U = \{u_1, \ldots, u_K\}, \quad V = \{v_1, \ldots, v_N\},$$

by maximising the likelihood function

$$\mathcal{L}(\theta,\beta) = \prod_{t\in V} \mathrm{P}(L=t) \prod_{t\in U} \mathrm{P}(L>t) = \prod_{t\in V} (e^{-\theta(t-1)^{\beta}} - e^{-\theta t^{\beta}}) \prod_{t\in U} e^{-\theta t^{\beta}}.$$

A flexible model for describing the variable condition of the gearbox is based on the Cox proportional hazards method, see [22]. In the framework of the Weibull parametric distribution, we will assume that the Weibull shape parameter β stays unchanged, while the scale parameter $\hat{\theta}$ changes over time

$$\hat{\theta} = \theta\phi(t), \tag{6.2}$$

where the Cox factor $\phi(t)$ takes positive values and is a function

$$\phi(t) = e^{\kappa(\bar{\xi}(t)-\bar{\xi})}, \tag{6.3}$$

of the times series describing the pertinent condition monitoring data

$$\boldsymbol{\xi} = (\xi(1), \xi(2), \ldots).$$

In (6.3),

$$\bar{\xi} = \frac{\xi(1) + \ldots + \xi(12)}{12}$$

is the first year average of the covariate ξ, and

$$\bar{\xi}(t) = \frac{\xi(t-2) + \xi(t-1) + \xi(t)}{3}$$

is the latest three-month moving average. Obviously, this approach requires that the farm has been in operation for at least 15 months.

The Cox regression parameter κ mentioned in (6.3) is estimated from the data set assuming that the data is labeled in such a way that the failure times are sorted in the ascending order

$$v_1 < v_2 < \ldots < v_N.$$

Replacing in (1.1) the baseline parameter θ with $\hat{\theta}$ defined by (6.2) and (6.3), we arrive at the following hazard function

$$r(t,\boldsymbol{\xi}) = \theta\beta t^{\beta-1}\phi(t). \tag{6.4}$$

The key argument of the Cox method is that (6.4) implies the following expression for the partial likelihood function of the regression parameter κ

$$\mathcal{L}^*(\kappa) = \prod_{j=1}^{N} \frac{r(v_j,\boldsymbol{\xi}^{(j)})}{\sum_{i=j}^{N} r(v_j,\boldsymbol{\xi}^{(i)})} = \prod_{j=1}^{N} \frac{\exp\{\kappa\bar{\xi}^{(j)}(v_j)\}}{\sum_{i=j}^{N} \exp\{\kappa\bar{\xi}^{(i)}(v_j)\}}.$$

Maximization of this partial likelihood leads to the desired maximum likelihood

estimate κ.

The Cox factor (6.3) has the following effect on the failure rate of the gearbox, provided κ is positive (in other words, assuming that the chosen covariate is such that higher values of $\xi(t)$ indicate higher stress on the gearbox at time t). At the time of observation t, the first year average $\bar{\xi}$ is compared with the last three months average $\bar{\xi}(t)$. If the difference $\bar{\xi}(t) - \bar{\xi}$ is close to zero, then the current condition of the gearbox is deemed to be normal and formulas (6.2) and (6.3) suggest using the baseline parameter $\hat{\theta} = \theta$ for describing the failure rate of the gearbox. However, if it turns out that $\bar{\xi}(t) > \bar{\xi}$, then $\hat{\theta} > \theta$, so that the corresponding hazard rate (6.4) becomes larger that the base line value $r(t)$ given by (1.1). Alternatively, if $\bar{\xi}(t) < \bar{\xi}$, then of course, the failure rate of the gearbox at time t is below the normal.

7 Case studies for the long-term maintenance scheduling

The case studies of this section are based on the following information. The life length of a wind turbine is assumed to be 240 months (i.e., 20 years), namely

$$T = 240$$

in month, which is a typical life length for onshore wind farms; see [86]. It is assumed that four major components of a typical wind turbine have the Weibull distribution parameters and replacement costs as listed in Table 7.1. These data

j	Component type	Failure replacement cost [$1000]	Preventive replacement cost [$1000]	Weibull shape parameter	Mean life length [months]
1	Rotor	162	36.75	3	89.9
2	Main bearing	110	23.75	2	110.8
3	Gearbox	202	46.75	3	71.4
4	Generator	150	33.75	2	97.5

Table 7.1: Key parameters for four major components of a wind turbine.

are derived from [67, Table 4] which is based on the data gathered from 6630 wind turbines during different periods of time from year 1994 to 2004.

All computations are performed on an Intel 2.40 GHz dual core Windows PC with 16 GB RAM. The mathematical optimization models are implemented in AMPL IDE [2], the parameters of the model are calculated by Matlab [5], and the optimization models are solved using CPLEX [4].

7.1 Long-term rescheduling after sudden component failures

In this section, an enhanced MICPM model is implemented for a wind farm consisting of 10 wind turbines.

In Chapter 6 we addressed the important issue of rescheduling of the next PM plan at times when one or several components of a wind turbine is replaced. This section illustrates the performance of the long-term planning model MICPM as it is repeatedly applied after several consecutive component

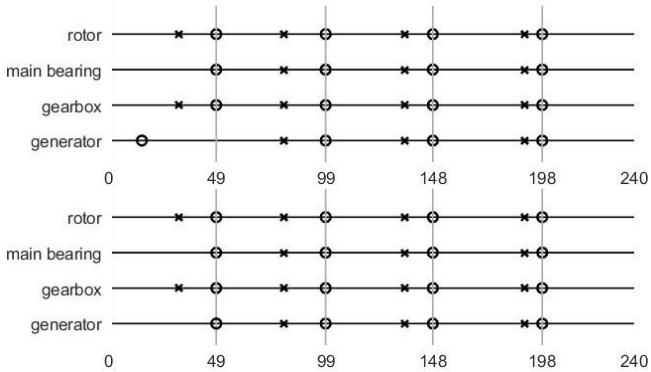

Figure 7.1: Rescheduling of PM plans for wind turbine 7 (top panel) and wind turbine 2 (bottom panel). The vertical lines delineate PM_0^*, the original PM plan, the circles show the PM times for the PM_1^* plan obtained after the first failure, and crosses correspond to PM_2^*, the third plan obtained after the second failure.

failures. When a component fails, it has to undergo CM while the PM plan needs to be rescheduled from the time point of the failure. The new schedule is then used until another component fails, at which time the PM plan is rescheduled.

Here we apply MICPM for PM scheduling of a wind farm containing of 10 wind turbines during the period $[0, T]$ with $T = 240$ months. To estimate the total maintenance cost of the whole wind farm, we introduce a new model parameter by assuming that the mobilization cost of \$50,000 is independent of the number of wind turbines to be attended during a given maintenance activity, see Tian et al. [67, Table 2]. We also assume that the downtime cost, both CM and PM, for a single turbine is \$10,000.

At time $t = 0$, all 40 components are considered to be new, and after applying MICPM we have obtained the same long-term PM schedule for each of the ten wind turbines, namely all four components should be replaced at times

$$u_1 = 49, \quad u_2 = 99, \quad u_3 = 148, \quad u_4 = 198.$$

These PM times are delineated by four vertical lines in Figure 7.1. Graphically, these four vertical lines represent the initial PM plan, PM_0^*, with the total cost of

$$\text{cost of } \mathrm{PM}_0^* = 10155,$$

in the unit of $\$1000$.

Next, we introduce PM plans PM_1^* and PM_2^* produced by MICPM at the first two times of component failures. These times we simulate based on the corresponding Weibull distributions, resulting in following two earliest failure events:

1. the generator of turbine 7 breaks at month $s_1 = 15$,
2. the rotor in turbine 2 breaks at month $s_2 = 32$.

At the first failure time, the generator of turbine 7 must be replaced and MICPM is applied to the new planning period $(s_1, T]$ with all the components. The starting age of all components (except for the replaced one) is 15. The resulting new optimal plan PM_1^* is identical to PM_0^* for all turbines except turbine 7, see circles in Figure 7.1 indicating the updated PM times. The total maintenance cost, including the CM cost associated with the first failure, becomes

$$\text{cost of PM}_1^* = 10175,$$

in the unit of \$1000.

At the second failure time, the rotor of turbine 2 must be replaced and MICPM is applied to the new planning period $(s_2, T]$ with all the components, except for the generator of turbine 7 and the rotor of turbine 2, with the starting age 32. The resulting new optimal plan PM_2^* is identical to PM_0^* for all turbines except for turbines 7 and 2. The times of another optimal plan PM_2^* are shown as crosses in Figure 7.1. Observe that the algorithm decides that at time $s_2 = 32$ not only the failed rotor of turbine 2 should be replaced, but also other three components. The total maintenance cost, including the cost associated with two CM and three OM replacements, is

$$\text{cost of PM}_2^* = 10122,$$

in the unit of \$1000.

7.2 Modified interval costs for the four components

In this section, we get a closer look at the modified interval cost functions c_{0t}^j which are calculated using (4.6) for the four components of the wind turbine. The main findings of this study are summarized by Figure 7.2 in terms of the

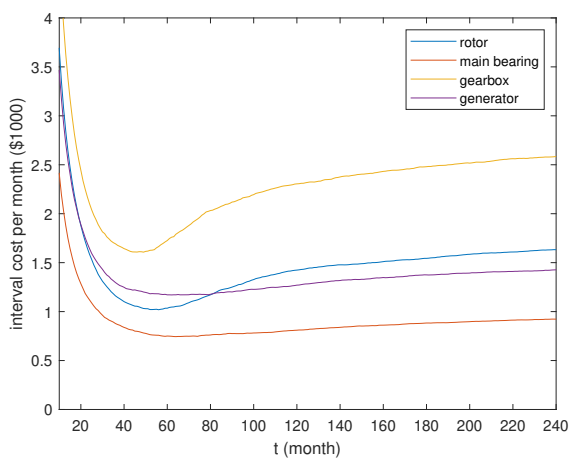

Figure 7.2: Average interval costs $\frac{1}{t}c_{0t}^j$ computes over the interval $[0, t]$.

average interval costs $\frac{1}{t}c_{0t}^{j}$ computed for different interval lengths. Observe that each of the curves has its minimal value:

1. the lowest value for rotor is achieved at month 54,
2. the lowest value for main bearing is achieved at month 62,
3. the lowest value for gearbox is achieved at month 47,
4. the lowest value for generator is achieved at month 60.

These component-specific optimal times illuminate the optimal PM times obtained for one or several wind turbines viewed as four-components systems in the case studies of Sections 7.1 and 7.3. For example, recall that the typical interval between consecutive PM times of Section 7.1 is around 50 months.

7.3 Comparison of different maintenance scheduling methods

In this section we compare the performance of three models introduced in the previous sections with that of the PMSPIC model by applying them to the same situation of a wind farm with ten wind turbines. Each wind turbine is treated as a four-component system under the assumptions given in table 7.1. The computed maintenance costs are also compared to the cost of the pure CM strategy.

Tables 7.2-7.3 summarize the results of the two different constant cost

$$d_t = d, \quad t \geq 0.$$

These tables not only show the optimal schedules for the next PM occasion and

Maintenance scheduling method	Next PM time [month] for components				Monthly maintenance cost [$1000]	CPU time [sec]	
	1	2	3	4		Matlab	AMPL
NextPM^{MIC}	x	x	43	x	4.733	56	0.01
NextPM^{VR}	x	x	43	x	4.703	2	–
MICPM	x	x	42	x	4.018	161	2.36
PMSPIC	x	x	41	x	4.749	100	2.25
Pure CM	x	x	x	x	6.205	–	–

Table 7.2: Outputs and running times of different maintenance methods for $d = 1$ [$1000].

the associated monthly maintenance cost, but also specify the computational times required by different algorithms. For NextPM^{MIC}, PMSPIC and MICPM, the "Matlab" column presents the time it takes to generate the main parameters of the model. The "AMPL" column presents the time it takes to solve the optimization model. Here we run 5000 simulations and take the average to estimate the parameters. For NextPM^{VR}, we use Matlab to solve the optimization

problem. The main advantage of the optimization models NextPM^{MIC} and NextPM^{VR} compared to PMSPIC and MICPM lies in the computational speed. For example, if $d = 10$ [\$1000], NextPM^{MIC} runs 10,000 times faster than the PMSPIC optimization, and NextPM^{VR} is even faster than NextPM^{MIC}.

Maintenance scheduling method	Next PM time [month] for components				Monthly maintenance cost [\$1000]	CPU time [sec]	
	1	2	3	4		Matlab	AMPL
NextPM^{MIC}	52	52	52	52	5.082	58	0.01
NextPM^{VR}	52	52	52	52	5.040	2	–
MICPM	49	49	49	49	4.211	143	45.82
PMSPIC	47	47	47	47	5.025	101	13.47
Pure CM	x	x	x	x	6.536	–	–

Table 7.3: Outputs of different maintenance methods for $d = 10$ [\$1000].

Tables 7.2-7.3 reveal that the next PM schedules produced by the four optimization models are quite similar. When d is large, to save on high downtime costs, the optimal plan always requires maintenance of all components. When d is small, then the optimal solution is to plan a preventive replacement for the most vulnerable component given the knowledge of the current ages of the components.

According to the third column of Tables 7.2-7.3, all four methods report significant savings if compared to the pure CM strategy. The MICPM model gives the lowest monthly maintenance cost. This is because MICPM is the only model considering the effect of the end of wind turbine lifetime. Towards the end of lifetime, not only PM activities should not be planned, but even CM replacements should not be performed if a component failure happens too close to the end of the turbine's life. Taking into account this factor, reduces the monthly maintenance cost in the long run. Simulations show that without considering the end of lifetime, MICPM produces a monthly maintenance cost similar to other models.

Notice that the monthly cost of PMSPIC compared to monthly cost produced by the NextPM models is slightly higher with $d = 1$, and slightly lower with $d = 10$. This is due to the specific way of parameter d entering into the formula for the interval cost employed by PMSPIC, see Section 4.2.

The CPU time to solve the models MICPM and PMSPIC is just a few seconds. However, this case study deals with only one turbine with four components, and the time step length is one month. As we show by the next case study, this time increases exponentially with increased number of components and decreased time step length.

Table 7.4 presents a comparison analysis with much shorter time steps comprising three days instead of one month. After a ten-fold increase of the number of time steps compared to the setting of Table 7.3, the algorithms of PMSPIC and MICPM have failed to complete calculations after ten hours of running and are terminated. We can conclude that the solution time for PMSPIC and MICPM increased exponentially, this is due to the complexity of their optimization models which are both NP-hard problems (see [33]). On the

Maintenance scheduling method	Next PM time [month] for components				Monthly maintenance cost [$1000]	CPU time [sec]	
	1	2	3	4		Matlab	AMPL
NextPM^{MIC}	51.7	51.7	51.7	51.7	5.073	26 [min]	0.08 [sec]
NextPM^{VR}	51.9	51.9	51.9	51.9	5.030	10 [sec]	–
MICPM	49.4	49.4	49.4	49.4	4.207	65 [min]	terminated
PMSPIC	47.3	47.3	47.3	47.3	5.023	38 [min]	terminated
Pure CM	x	x	x	x	6.536	–	–

Table 7.4: Outputs of different maintenance methods for $d = 10$ [$1000] with a finer time step length of three days. Notice that the results for the long-term planning models MICPM and PMSPIC are obtained by the corresponding programs being terminated after ten hours of running, so that the solutions presented in the table might be sub-optimal.

other hand, we see that NextPM^{VR} can be solved fast even in this case, thanks to the special structure of the optimization model: all the parameters of NextPM^{VR} are computed theoretically, avoiding the time-consuming simulations required by the other models.

7.4 A case study based on the data from a Swedish wind farm

To demonstrate the algorithm of Section 6.2 we use historical data of a Swedish wind farm consisting of 16 turbines (labeled by numbers 1 to 16), with each turbine being represented by a single component, its gearbox. The main challenge of this case study is to see if our approach is able to avoid a failure event by placing PM events at right times and for the right gearboxes.

The wind farm is observed for 137 months and during this period 8 failures of gearboxes were recorded, as given in Table 7.5.

Gearbox ID	9	12	11	15	16	5	6	13
Failure time (months)	25	43	73	73	97	109	121	121

Table 7.5: Historical data on failure times.

In this case study, we use the linear formula (5.7) for the function h_a^3. A detailed description of the parameters of the model (including g_3 and h_3) used in this case study is given in Section 5 in **Paper IV**.

Observe that two pairs of equal failure times indicate violations of the model assumption of independence between the gearbox lifetimes. Our guess is that for each of the paired events, one of the gearboxes might have broken down earlier and the turbine stayed idle until the second gearbox went down, so that both gearboxes were replaced simultaneously.

The results of our study based on the historical data of the wind farm are summarized in Figure 7.3. They show the recurrent 3-month updates of the PM planning, so that if the next PM activity is planned after the next 3-

month time period, it will not be performed. After 3 months, we update the data from SCADA and resolve the optimal problem again to obtain a new maintenance plan. The green line represents the observation time and the black line represents the planning horizon 3 months ahead. Each planning round giving the next time for PM as a point lying above the black diagonal, will be followed by a new planning round with an updated time for the next PM. The next PM plan will be implemented only if the next PM point lies between the two diagonals on the graph.

As shown on the x-coordinate of Figure 7.3, the first PM event is scheduled at time step 15. The resulting optimal planning time at month 54 is shown on the y-coordinate. The corresponding point $(15, 54)$ is marked on the graph by label 2 meaning that two gearboxes out of 16 should be replaced at month 54. Since point $(15, 54)$ lies above the black diagonal, we apply our algorithm once again at time step $15 + 3 = 18$ and find the new PM time to be at month 45 when two gearboxes should be replaced. At time step 21, an updated PM plan says that three gearboxes should be replaced at month 43, and so on.

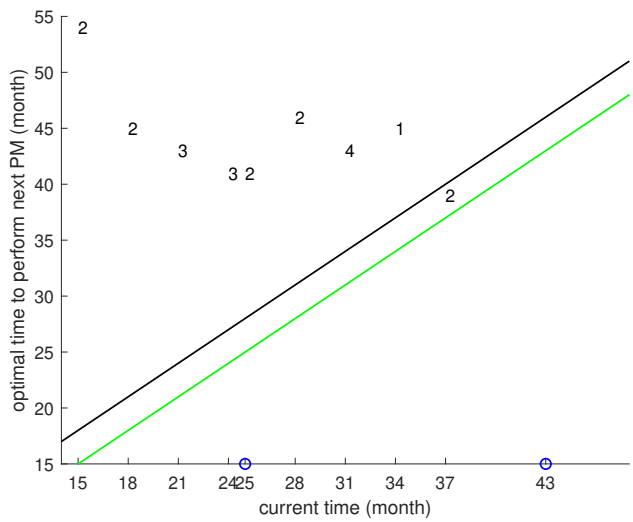

Figure 7.3: The recurrent next PM planning for the wind farm

The most interesting points on the graph are first, the time step 25, coming from Table 7.5, marked by a circle on the x-axis, and secondly, the point $(37, 39)$. At time step 24, the optimal PM plan is to replace gearbox 9 at month 41 together with two other gearboxes. However, according to the historical data, a sudden failure of gearbox 9 takes place at time step 25, which cancels the next PM plan and requires a CM replacement. The OM step of our rescheduling algorithm suggest to perform at time step 25 only the replacement of the failed gearbox 9. After the CM event, the next round of the NextPM step produce an optimal plan suggesting to replace two gearboxes at month 41.

First, at time step 37, the next PM time falls within the 3-month window.

The plan suggests that two gearboxes, number 12 and number 13, should be replaced at month 39. We stop implementing our algorithm after time step 39, because the historical data does not include these replacements.

To summarize, we note that even though our algorithm missed the first, unusually early failure at time step 25, it successfully prevented the sudden failure of gearbox 12 at time step 43, see Table 7.5, by suggesting a PM replacement of gearbox 12 at time step 39.

8 A summary of the appended papers

8.1 Paper I: Optimal scheduling of the next preventive maintenance activity for a wind farm

This article presents a binary linear optimization model, which solution may suggest to wind turbine owners which components, and when, should undergo the next PM. In the thesis, we further develop this model into NextPM^{MIC}. The scheduling strategy takes into account eventual failure events of the multi-component system, in that after the failed system is repaired, the previously scheduled PM plan should be updated treating the restored components to be as good as new.

The optimization model is tested in three numerical case studies. The first study addresses the illustrative case of a single component system. The second study analyzes the case of seasonal variations of mobilization costs, as compared to the constant mobilization cost setting. Among other things, this analysis reveals a dramatic cost reduction achieved by the optimization model as compared to the pure CM strategy. In these two case studies, the costs are reduced by around 35%. The third case study compares the NextPM model with PMSPIC. This comparison demonstrates that the NextPM model is accurate and much more effective.

8.2 Paper II: Mathematical optimization models for long-term maintenance scheduling of wind power systems

In this article, the planning of corrective and preventive maintenance is investigated under different types of contracts between the wind farm owner and a maintenance or insurance company, and during different phases of the turbines' lives and the contract periods.

The optimization model MICPM is a simplification of the models presented in this article. While MICPM focuses on a n-component system, the models in this article represents a wind farm comprising m wind turbines each of which has n (identical) component types. In this article, a mathematical model of

preventive maintenance scheduling is combined with corrective maintenance strategies. The combined strategies are then applied to four relevant combinations of the phases of the turbines' lives and the contract types.

Our case studies show that even with the same initial criteria, the optimal maintenance schedules differ between different phases of time as well as between contract types. One case study reveals a $40\ \%$ cost reduction and a significantly higher production availability—$1.8\ \%$ points—achieved by our optimization model as compared to a pure corrective maintenance strategy.Another study shows that the number of planned preventive maintenance occasions for a wind farm decreases with an increasing level of an insurance contract regarding reimbursement of costs for broken components.

8.3 Paper III: Optimal maintenance schedule for a wind turbine with aging components

In this article, the optimization model NextPM^{MIC} is developed using the renewal-reward theorem. In the multi-component setting, a new concept virtual replacement is introduced, which allows us to treat each replacement event as a renewal event, even if some components are not replaced by new ones.

NextPM^{MIC} is applied to a four-component model of a wind turbine and the optimal maintenance plans are computed for various initial conditions. In this article, compare to the two articles above, one clear difference of the parameters is that the actual PM replacement cost is not a constant value any more, it is assumed to depend on the component's age. The modelling results show clearly the benefit of PM planning compared to pure CM strategy (about 8.5% lower maintenance cost). Then the optimization model is compared with another state-of-art optimization model, it shows a similar scheduling with a much faster CPU time. The comparison demonstrates that the proposed optimization model is both fast and accurate.

Compare to paper 1, the scale parameter is in a different parameterization which is also commonly used [17]. Suppose the scale parameters in [67, Table 4] are α_j, the shape parameter is β_j, then the relationship between α_j and the scale parameter in this paper θ_j is $\theta_j = \alpha_j^{-\beta_j}$.

8.4 Paper IV: Optimal preventive maintenance scheduling for wind turbines under condition monitoring

In this article, we further develop NextPM^{MIC}. We use the data from SCADA system to update the Weibull parameters of the model. Our optimization criterium takes into account the current ages of the key components, the major maintenance costs including eventual energy production losses as well as the available data monitoring the condition of the wind turbines. To illustrate how the optimization algorithm works, a case study is presented based on data

collected from several wind farms located in Sweden. The results show that PM planning gives some effects, if the wind turbine components in question live significantly shorter than the turbine itself.

9 Conclusions

In this thesis, we introduce new modelling frameworks for the maintenance scheduling of the wind turbines. Our long-term scheduling optimization model, taking into account the prospective ages of the major components, allows to estimate the reasonable price of a full service maintenance contract or an insurance contract for the wind farm owner.

The short-term maintenance scheduling approach developed in this thesis results in much faster computational algorithms compared to accurate long-term scheduling algorithms. This effect is achieved without compromising the accuracy of the planning of the next preventive maintenance action.

Among other things, our analysis shows that if preventive replacements are not sufficiently cheaper than the corrective maintenance replacements (which may be true for the onshore wind farms with low mobilization costs), then the optimal solution is to manage the wind farm without preventive maintenance planning.

The key modelling innovations of this thesis are

- the development of the modified interval cost function, which improves the initial definition based on heuristic argument, and provides a mathematical justification for the modified formula,
- the introduction of the virtual replacement concept arising from the renewal-reward argument, which takes account of hidden future costs associated with positive ages of components treated by the model as being as good as new,
- a systematic implementation of the Cox's proportional hazard method for updating the Weibull parameters of the components based on condition monitoring data.

9.1 Performance of different optimization models

In this thesis, we introduce three optimization models of maintenance scheduling: $\text{NextPM}^{\text{MIC}}$, $\text{NextPM}^{\text{VR}}$, and MICPM. Our models treats the objective function as the total maintenance cost of a preventive maintenance schedule, which takes into account the corrective replacement costs associated with the eventual component failures as well as the expected preventive replacement costs.

The MICPM modelling framework allows evaluating different kinds of contracts covering different phases of the lifetime of the wind farm. In a related case study we demonstrate how the MICPM algorithm can be used for rescheduling the long-term maintenance plan following eventual component failures. Through this case study we demonstrate that our approach gives a robust estimate of the total maintenance cost: after each rescheduling the total cost goes either up or down compared to the cost of the initial plan, depending on the consecutive times of the component failures.

The main idea behind the $\text{NextPM}^{\text{MIC}}$ and $\text{NextPM}^{\text{VR}}$ models is to drastically reduce the computational time by focusing on the next preventive maintenance planning. We suggest two different approaches to this problem and compare their performance through a case study dealing with a wind turbine viewed as a four-component system. According to this case study, the latter algorithm, based on the new idea of virtual replacement, is much faster producing very similar results. Both algorithms are much faster than the long-term scheduling algorithms MICPM and PMSPIC.

The fast model $\text{NextPM}^{\text{VR}}$ is further enhanced by adding a parameter updating step, allowing the maintenance scheduling optimization algorithm to take into account the real time data from the SCADA condition monitoring system. A case study using the historical data from a Swedish wind farm illustrates how our rescheduling algorithm may work in practice. The case study clearly demonstrates that our algorithm may result in appreciable savings due to smart scheduling of preventive maintenance activities by monitoring the ages of the components in use as well as available real time data, which supervising the condition of the wind turbines in a wind farm.

9.2 Further research

The optimization models of maintenance scheduling for wind turbines are based on several assumptions concerning the functioning of the wind turbine and different maintenance actions. In the future, one can build new models upon the optimizations models developed in this thesis by allowing for

- deferred corrective maintenance actions, define as "corrective maintenance which is not immediately carried out after a fault detection but is delayed in accordance with given rules" [66];
- preventive maintenance actions other than full replacement, like inspection, minor or major repair;
- secondary damage of components connected to the components experiencing the prime failure.

Bibliography

[1] The Swedish Wind Power Technology Centre at Chalmers University of Technology in Gothenburg, Sweden.

[2] AMPL IDE (2018). V. 12.1,. http://www.ampl.com. AMPL Optimization LLC.

[3] Guidance document on wind energy developments and EU nature legislation. Brussels, 18.11.2020.

[4] CPLEX Optimizer v. 20.1. https://www.ibm.com/analytics/cplex-\optimizer. IBM ILOG.

[5] Matlab R2019b. https://www.mathworks.com/products/matlab.html. MathWorks.

[6] Wind in Europe. 2020 Statistics and the outlook for 2021-2025.

[7] Energy transition outlook 2020. Annual report, DNV GLAS, 2020.

[8] Adiel Teixeira de Almeida. Multicriteria decision making on maintenance: spares and contracts planning. *European Journal of Operational Research*, 129 (2):235–241, 2001.

[9] Joachim Arts and Rob Basten. Design of multi-component periodic maintenance programs with single-component models. *IISE Transactions*, 50(7): 606–615, 2018.

[10] Huy Truong Ba, Michael Cholette, Pietro Borghesani, Yifan Zhou, and Lin Ma. Opportunistic maintenance considering non-homogenous opportunity arrivals and stochastic opportunity durations. *Reliability Engineering & System Safety*, 160:151–161, 2017.

[11] Pramod Bangalore and Michael Patriksson. Analysis of scada data for early fault detection, with application to the maintenance management of wind turbines. *Renewable Energy*, 115:521–532, 2018.

[12] Pramod Bangalore, Simon Letzgus, Daniel Karlsson, and Michael Patriksson. An artificial neural network-based condition monitoring method for wind turbines, with application to the monitoring of the gearbox. *Wind Energy*, 20(8):1421–1438, 2017.

[13] Dragan Banjevic and Andrew Jardine. Calculation of reliability function and remaining useful life for a markov failure time process. *IMA journal of management mathematics*, 17(2):115–130, 2006.

[14] François Besnard, Katharina Fischer, and Lina Bertling Tjernberg. A model for the optimization of the maintenance support organization for offshore wind farms. *IEEE Transactions on Sustainable Energy*, 4(2):443–450, 2012.

[15] Frangois Besnard, Michael Patriksson, Ann-Brith Strömbergt, Adam Wojciechowskit, and Lina Bertling. An optimization framework for opportunistic maintenance of offshore wind power system. In *2009 IEEE Bucharest PowerTech*, pages 1–7. IEEE, 2009.

[16] Om Prakash Bharti, Kumari Sarita, Aanchal Singh S Vardhan, Akanksha Singh S Vardhan, and Ram K. Saket. Controller design for DFIG-based wt using gravitational search algorithm for wind power generation. *IET Renewable Power Generation*, 2021.

[17] Adrian Colin Cameron and Pravin Trivedi. *Microeconometrics: methods and applications*. Cambridge university press, 2005.

[18] Sofía Carlos, Ana Sánchez, Sebastián Martorell, and Isabel Martón. Onshore wind farms maintenance optimization using a stochastic model. *Mathematical and Computer Modelling*, 57(7-8):1884–1890, 2013.

[19] AH Christer. Modelling inspection policies for building maintenance. *Journal of the Operational Research Society*, 33(8):723–732, 1982.

[20] AH Christer and WM Waller. Delay time models of industrial inspection maintenance problems. *Journal of the Operational Research Society*, 35(5): 401–406, 1984.

[21] Ángel M. Costa, José A. Orosa, Diego Vergara, and Pablo Fernández-Arias. New tendencies in wind energy operation and maintenance. *Applied Sciences*, 11(4):1386, 2021.

[22] David Roxbee Cox and David Oakes. *Analysis of survival data*, volume 21. CRC Press, 1984.

[23] Cuong D. Dao, Behzad Kazemtabrizi, Christopher Crabtree, and Peter J. Tavner. Integrated condition-based maintenance modelling and optimisation for offshore wind turbines. *Wind Energy*, 2021.

[24] Fangfang Ding and Zhigang Tian. Opportunistic maintenance optimization for wind turbine systems considering imperfect maintenance actions. *International Journal of Reliability, Quality and Safety Engineering*, 18(05): 463–481, 2011.

[25] Fangfang Ding and Zhigang Tian. Opportunistic maintenance for wind farms considering multi-level imperfect maintenance thresholds. *Renewable Energy*, 45:175–182, 2012.

[26] Elhoussine Ech-Chhibat, Lhoucine Bahatti, Abdelhadi Raihani, and Omar Bouattane. Implementation of a maintenance plan: case of wind turbines. *International Journal of Mechanical Engineering and Technology*, 9:1130–1145, 2018.

[27] Asier Erguido, Adolfo Crespo Márquez, Eduardo Castellano, and Juar Francisco Gomez Fernández. A dynamic opportunistic maintenance model to maximize energy-based availability while reducing the life cycle cost of wind farms. *Renewable Energy*, 114:843–856, 2017.

[28] Katharina Fischer. Maintenance management of wind power systems by means of reliability-centred maintenance and condition monitoring systems. *Chalmers University of Technology*, 2012.

[29] Katharina Fischer, Francois Besnard, and Lina Bertling. A limited-scope reliability-centred maintenance analysis of wind turbines. In *Scientific Proceedings of the European Wind Energy Conference & Exhibition EWEA 2011, 14-17 March 2011, Brussels, Belgium*, pages 89–93, 2011.

[30] Katharina Fischer, Francois Besnard, and Lina Bertling. Reliability-centered maintenance for wind turbines based on statistical analysis and practical experience. *IEEE Transactions on Energy Conversion*, 27(1):184–195, 2011.

[31] Alireza Ghasemi, Soumaya Yacout, and M-Salah Ouali. Evaluating the reliability function and the mean residual life for equipment with unobservable states. *IEEE Transactions on Reliability*, 59(1):45–54, 2009.

[32] Geoffrey Stirzaker Grimmett et al. *Probability and random processes*. Oxford university press, 2020.

[33] Emil Gustavsson, Michael Patriksson, Ann-Brith Strömberg, Adam Wojciechowski, and Magnus Önnheim. Preventive maintenance scheduling of multi-component systems with interval costs. *Computers & Industrial Engineering*, 76:390–400, 2014.

[34] Zafar Hameed and Jørn Vatn. Role of grouping in the development of an overall maintenance optimization framework for offshore wind turbines. *Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability*, 226(6):584–601, 2012.

[35] Edward Hart, Benjamin Clarke, Gary Nicholas, Abbas Kazemi Amiri, James Stirling, James Carroll, Rob Dwyer-Joyce, Alasdair McDonald, and Hui Long. A review of wind turbine main bearings: design, operation, modelling, damage mechanisms and fault detection. *Wind Energy Science*, 5(1):105–124, 2020.

[36] Herbert L. Hess, N. A. Abdul Melek, and E. Muljadi. Power converter for wind turbine application. In *2000 Power Engineering Society Summer Meeting (Cat. No.00CH37134)*, volume 2, pages 1275–1276 vol. 2, 2000. doi: 10.1109/PESS.2000.867570.

[37] Leila Jafari, Farnoosh Naderkhani, and Viliam Makis. Joint optimization of maintenance policy and inspection interval for a multi-unit series system using proportional hazards model. *Journal of the Operational Research Society*, 69(1):36–48, 2018.

[38] Andrew K.S. Jardine and Albert HC Tsang. *Maintenance, replacement, and reliability: theory and applications*. CRC press, 2005.

[39] Andrew K.S. Jardine, Daming Lin, and Dragan Banjevic. A review on machinery diagnostics and prognostics implementing condition-based maintenance. *Mechanical systems and signal processing*, 20(7):1483–1510, 2006.

[40] JRC. Facts and figures on offshore renewable energy sources in europe. 2020.

[41] Salman Kahrobaee and Sohrab Asgarpoor. A hybrid analytical-simulation approach for maintenance optimization of deteriorating equipment: Case study of wind turbines. *Electric Power Systems Research*, 104:80–86, 2013.

[42] Szilard Kalosi, Stella Kapodistria, and Jacques AC Resing. Condition-based maintenance at both scheduled and unscheduled opportunities. *arXiv preprint arXiv:1607.02299*, 2016.

[43] Madjid Karimirad. *Offshore energy structures: for wind power, wave energy and hybrid marine platforms*. Springer, 2014.

[44] A Karyotakis and R Bucknall. Planned intervention as a maintenance and repair strategy for offshore wind turbines. *Journal of Marine Engineering & Technology*, 9(1):27–35, 2010.

[45] Radouane Laggoune, Alaa Chateauneuf, and Djamil Aissani. Opportunistic policy for optimal preventive maintenance of a multi-component system in continuous operating units. *Computers & Chemical Engineering*, 33(9): 1499–1510, 2009.

[46] Ji Ye Janet Lam and Dragan Banjevic. A myopic policy for optimal inspection scheduling for condition based maintenance. *Reliability Engineering & System Safety*, 144:1–11, 2015.

[47] Hyunju Lee and Ji Hwan Cha. New stochastic models for preventive maintenance and maintenance optimization. *European Journal of Operational Research*, 255(1):80–90, 2016.

[48] Lin Li, Zeyi Sun, Xinwei Xu, and Kaifu Zhang. Multi-zone proportional hazard model for a multi-stage degradation process. In *International Manufacturing Science and Engineering Conference*, volume 55461, page V002T02A013. American Society of Mechanical Engineers, 2013.

[49] Anatoly Lisnianski, Ilia Frenkel, Lev Khvatskin, and Yi Ding. Maintenance contract assessment for aging systems. *Quality and Reliability Engineering International*, 24(5):519–531, 2008.

[50] Kamran S Moghaddam and John S Usher. Sensitivity analysis and comparison of algorithms in preventive maintenance and replacement scheduling optimization models. *Computers & Industrial Engineering*, 61(1):64–75, 2011.

[51] S.M. Muyeen. *Wind power*. BoD–Books on Demand, 2010.

[52] Jannie Jessen Nielsen and John Dalsgaard Sørensen. On risk-based operation and maintenance of offshore wind turbine components. *Reliability Engineering & System Safety*, 96(1):218–229, 2011.

[53] Julia Nilsson and Lina Bertling. Maintenance management of wind power systems using condition monitoring systems—life cycle cost analysis for two case studies. *IEEE Transactions on energy conversion*, 22(1):223–229, 2007.

[54] Peter Fogh Odgaard, Jakob Stoustrup, and Michel Kinnaert. Fault-tolerant control of wind turbines: A benchmark model. *IEEE Transactions on control systems Technology*, 21(4):1168–1182, 2013.

[55] Minjae Park and Hoang Pham. Cost models for age replacement policies and block replacement policies under warranty. *Applied Mathematical Modelling*, 40(9-10):5689–5702, 2016.

[56] Ying Peng, Ming Dong, and Ming Jian Zuo. Current status of machine prognostics in condition-based maintenance: a review. *The International Journal of Advanced Manufacturing Technology*, 50(1-4):297–313, 2010.

[57] Hong Thom Pham, Bo-Suk Yang, Tan Tien Nguyen, et al. Machine performance degradation assessment and remaining useful life prediction using proportional hazard model and support vector machine. *Mechanical Systems and Signal Processing*, 32:320–330, 2012.

[58] Ashok Prajapati, James Bechtel, and Subramaniam Ganesan. Condition based maintenance: a survey. *Journal of Quality in Maintenance Engineering*, 18(4):384–400, 2012.

[59] Qingan Qiu, Lirong Cui, Jingyuan Shen, and Li Yang. Optimal maintenance policy considering maintenance errors for systems operating under performance-based contracts. *Computers & Industrial Engineering*, 112:147–155, 2017.

[60] Nora Tangen Raknes, Katrine Ødeskaug, Magnus Stålhane, and Lars Magnus Hvattum. Scheduling of maintenance tasks and routing of a joint vessel fleet for multiple offshore wind farms. *Journal of Marine Science and Engineering*, 5(1):11, 2017.

[61] José G. Rangel-Ramírez and John D. Sørensen. Risk-based inspection planning optimisation of offshore wind turbines. *Structure and Infrastructure Engineering*, 8(5):473–481, 2012.

[62] Zhengru Ren, Amrit Shankar Verma, Ye Li, Julie JE Teuwen, and Zhiyu Jiang. Offshore wind turbine operations and maintenance: A state-of-the-art review. *Renewable and Sustainable Energy Reviews*, 144:110886, 2021.

[63] Leonard Rose. Motorcoach maintenance. *SAE Transactions*, pages 659–670, 1929.

[64] Mahmood Shafiee. Maintenance logistics organization for offshore wind energy: Current progress and future perspectives. *Renewable Energy*, 77: 182–193, 2015.

[65] Payam Teimourzadeh Baboli, Davood Babazadeh, Amin Raeiszadeh, Susanne Horodyvskyy, and Isabel Koprek. Optimal temperature-based condition monitoring system for wind turbines. *Infrastructures*, 6(4):50, 2021.

[66] Terminology Maintenance. Swedish standard ss-en 13306. *European Standard EN editor*, 2017.

[67] Zhigang Tian, Tongdan Jin, Bairong Wu, and Fangfang Ding. Condition based maintenance optimization for wind power generation systems under continuous monitoring. *Renewable Energy*, 36(5):1502–1509, 2011.

[68] Zhigang Tian, Bairong Wu, and Mingyuan Chen. Condition-based maintenance optimization considering improving prediction accuracy. *Journal of the Operational Research Society*, 65(9):1412–1422, 2014.

[69] Vestas. V236-15.0 MW. .

[70] Vestas. 4MW platform. .

[71] PJ Vlok, Jasper Coetzee, D Banjevic, Aandrew Kennedy Jardine, and V Makis. Optimal component replacement decisions using vibration monitoring and the proportional-hazards model. *Journal of the operational research society*, 53(2):193–202, 2002.

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

[73] Jinhe Wang, Xiaohong Zhang, Jianchao Zeng, and Yunzheng Zhang. Optimal dynamic imperfect preventive maintenance of wind turbines based on general renewal processes. *International Journal of Production Research*, 58 (22):6791–6810, 2020.

[74] Lu Wang, Li Zhang, and Xue-zhi Wang. Reliability estimation and remaining useful lifetime prediction for bearing based on proportional hazard model. *Journal of Central South University*, 22(12):4625–4633, 2015.

[75] Sylwia Werbińska-Wojciechowska et al. Technical system maintenance. *Delay-time-based modelling (in rev., Springer)*, 2019.

[76] Xiang Wu and Sarah M Ryan. Optimal replacement in the proportional hazards model with semi-markovian covariate process and continuous monitoring. *IEEE Transactions on Reliability*, 60(3):580–589, 2011.

[77] Hsu-Hao. Yang, Mei-Ling Huang, Chun-Mei. Lai, and Jhih-Rong Jin. An approach combining data mining and control charts-based model for fault detection in wind turbines. *Renewable Energy*, 115:808–816, 2018.

[78] Lingjian Ye, Yi Cao, Xiushui Ma, and Zhihuan Song. A non-optimality detection technique for continuous processes. *IFAC Proceedings Volumes*, 47 (3):7616–7621, 2014.

[79] Ruey Huei Yeh and Cheng-Kang Chen. Periodical preventive-maintenance contract for a leased facility with Weibull life-time. *Quality and Quantity*, 40(2):303–313, 2006.

[80] Ming-Yi You and Guang Meng. Updated proportional hazards model for equipment residual life prediction. *International Journal of Quality & Reliability Management*, 2011.

[81] Chen Zhang, Wei Gao, Sheng Guo, Youliang Li, and Tao Yang. Opportunistic maintenance for wind turbines considering imperfect, reliability-based maintenance. *Renewable energy*, 103:606–612, 2017.

[82] Rui Zheng, Yifan Zhou, and Yingzhi Zhang. Optimal preventive maintenance for wind turbines considering the effects of wind speed. *Wind Energy*, 23(11):1987–2003, 2020.

[83] Xiaojun Zhou, Lifeng Xi, and Jay Lee. Opportunistic preventive maintenance scheduling for a multi-unit series system based on dynamic programming. *International Journal of Production Economics*, 118(2):361–366, 2009.

[84] Qiushi Zhu, Hao Peng, and Geert-Jan van Houtum. An age-based maintenance policy using the opportunities of scheduled and unscheduled system downs. *Beta report, Eindhoven University of Technology*, 2016.

[85] Qiushi Zhu, Hao Peng, Bas Timmermans, and Geert-Jan van Houtum. A condition-based maintenance model for a single component in a system with scheduled and unscheduled downs. *International Journal of Production Economics*, 193:365–380, 2017.

[86] Lisa Ziegler, Elena Gonzalez, Tim Gonzalez, Ursula Smolka, and Julio J. Melero. Lifetime extension of onshore wind turbines: A review covering Germany, Spain, Denmark, and the UK. *Renewable and Sustainable Energy Reviews*, 82:1261–1271, 2018.