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Failure probability prediction based on condition monitoring data of wind energy systems for spare parts supply

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ABSTRACT

The feasibility of maintenance processes relies on the availability of spare parts. Spare part inventory planning is capital intensive. It is based on demand forecasting, which possesses a high potential in reducing inventories. Even if condition monitoring systems are installed in technical systems, condition monitoring information is barely used to predict the failure probability of units. Therefore, an enhanced forecast model, which integrates SCADA information, has been developed. This leads to more accurate spare part demand forecasts. The approach presented in the paper is based on data mining, the proportional hazards model (PHM) and a binomial distribution. It has been validated with maintenance data of wind energy systems.

1. Introduction

Spare parts availability is essential for efficient maintenance repair and overhaul processes. These are necessary to ensure an economic machine operation. Long lead times of spare parts lead to the necessity of stock keeping, which ties a lot of capital because of high acquisition costs. Spare parts stocking is based on demand forecasting that possess high potential in reducing the amount of spare parts in stock. Even if online condition monitoring systems are installed in complex technical systems like wind energy systems (WES, Table 1), condition monitoring information is barely used to predict spare parts demand. The varying loads on wind energy system components and technically different system concepts of wind energy systems in general (e.g. rotational characteristics, load regulation, or generator type), varying operating conditions regarding the WES location, and components constructed the same way but from different suppliers, result in varying survival times of units and wide scattered results of the failure analysis [1]. In order to extract usable information about the failure probability for specific components, operational data, event, failure and damage descriptions have to be comprised and analyzed systematically. Therefore, an enhanced forecast model that considers condition information, has been developed. The example in Fig. 1 illustrates the availability of the research WES of the University of Bremen in its first year of operation.

For example, during May the elevator rope system failed and influenced the total availability of the wind turbine due to a repair cycle lasting 10 days. Fig. 1 highlights how this single event

Table 1
Acronyms and abbreviations.

Abbreviation	Augmentation
α	Shape parameter of Weibull distribution
β	Regression coefficient
CMS	Condition monitoring system
g	Density function of binomial distribution
$h_0(t)$	Baseline hazard function
$h_i(t)$	Hazard function
k	Number of spare part demands
λ	Scale parameter of Weibull distribution
n	Number of units
p	Failure probability
PHM	Proportional hazards model
$p(t)$	Density function of Weibull distribution
SCADA	Supervisory control and data acquisition
t	Time
T	Survival time of Weibull distribution
Temp	Temperature
WES	Wind energy systems
WT	Wind turbine
x	Covariate
CBM	Condition based maintenance
WONDER	Wind farm management system (brand name)
LWK	Chamber of agriculture Schleswig–Holstein
WMEP	Scientific measuring- and evaluation programme

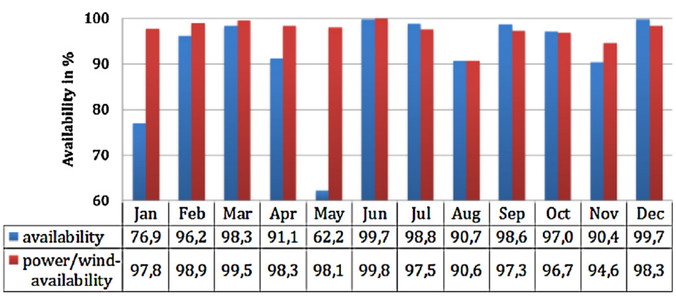

Fig. 1. Monthly availability (blue) and power output availability (red) of the research WES of the University of Bremen in (1st year of operation).

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reduced the availability of the research WES significantly in contrast to the "power/wind-availability".

2. State of the art

2.1. Preventive and corrective maintenance processes

The two most prevalently applied maintenance strategies are corrective and preventive maintenance processes. Corrective maintenance is carried out unscheduled in case of component failures or if faults are detected in WES components during the recurring inspection [2]. It is the most expensive strategy and operators strive for minimizing the number of these events, because of a high risk of unavailable spare parts and prolonged downtimes, caused by conditions that prohibit maintenance activities. By contrast preventive maintenance aims at repairing or replacing components before they fail. This can be achieved by scheduled maintenance activities, also known as time based (or planned) maintenance, which involves repair or unit replacements at regular time intervals, as recommended by the supplier, and regardless of its condition. Time based maintenance reveals the possibility of planning maintenance resources and the instant of maintenance [3], thus minimizing downtime. This advantage is contrary to the drawback that unnecessary frequent maintenance tasks increase the maintenance cost, because the lifespan of units is not entirely utilized. An alternative to preventive and corrective maintenance is the condition based maintenance strategy, in which specific components are monitored and maintenance tasks are determined ahead of failures [4]. Today, maintenance technicians manually perform failure detection with the help of condition monitoring systems (CMS).

2.2. Condition monitoring

Wind farm management or supervisory control and data acquisition (SCADA) systems acquire condition monitoring, as well as operation data. For example, the wind farm management system WONDER by Deutsche WindGuard records 10-min mean values of operation and condition data of a WES and transfers them to a data acquisition server. Data of that system have also been processed to validate the approach presented in this paper. Current and new emerging maintenance strategies for WESs depend on condition parameters and measurements. Those are either supplied by component specific CMS (designed e.g. for gearboxes or bearings) or manufacturer related, plant wide CMS (e.g. GE or Nordex).

For the maintenance of WES, emphasis is put on the gearbox and the main bearing as a direct consequence of the long machine downtimes caused by failures of these components (Fig. 2).

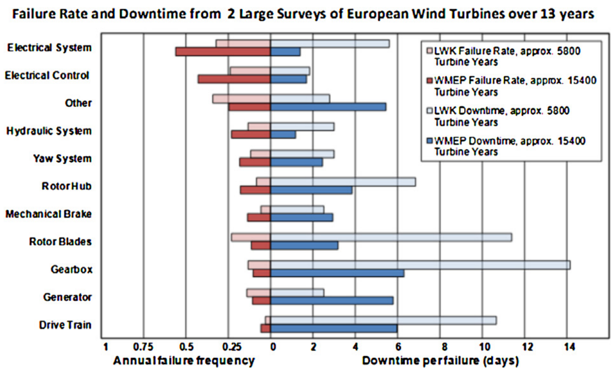

Fig. 2. Failure rate and downtime per failure of WES units for two surveys including over 20,000 turbine years of data as published in [5].

Today, parameters like oil, gearbox or bearing temperature, power output, wind speed, wind directions as well as vibrations are monitored online. The majority of available CMS focus on vibration characteristics [6] as defined by DIN ISO 10816. However, physical models are not available for failure forecasting because of complex interactions between WES components and the superposition of signals.

Despite the large amount of data, condition monitoring information is not used systematically to predict failures as well as spare parts demands and manual inspection of data becomes impractical with the increasing number of WES per operator.

SCADA data on the other hand are readily available [7] and systems like WONDER collect and store large amounts of data, which give indications about the WES status. At present, SCADA-systems are the most cost effective way of implementing a CMS [8]. Kusiak and Verma show that component failures can be predicted 5 to 60 min in advance [9,10]. This short period can be used to prevent further damages on the WES, but it is not suitable for a reasonable demand forecasting.

2.3. Demand forecasting of spare parts

Spare parts demand forecasting requires failure forecasting of units. It is either performed on the basis of historical data or based on hazard functions [11]. In case of demand prediction by means of historical data, time series analysis approaches, such as Crostons method is applied to predict intermittent and lumpy spare part demands. Crostons method has been modified by Syntetos, who hereby achieved the lowest forecast-error in demand prediction, compared to other well known time series analysis methods, like exponential smoothing or moving average [12]. These algorithms need a very large amount of historical data, which do not exist within the comparably young WES industry. Historical data are missing due to short innovation cycles of units, high WES growth rates and a lack of profound data recordings. Furthermore, condition monitoring data and characteristics of maintenance processes, applied for different machines, as well as wear or aging processes, are only considered indirectly in time series based approaches. Hence, observations of changing values of these parameters cannot be implemented in these methods.

In contrast to this, spare parts demand prediction with the help of hazard functions offers the opportunity of considering varying stress or machine loads. Lanza, for example, implemented a shape parameter into the Weibull distribution that varies with the machine load. Thereby, the author is able to consider different operating modes of machine tools [13]. More specific details of operating modes or condition monitoring data, like temperature values or oil conditions cannot be integrated into the approach.

Oil conditions have been implemented by Louit [14]. The model proposed there is a single unit system that investigates the impact of age and oil condition on the remaining useful lifetime of a unit with the help of a proportional hazards model (PHM). Consideration of external influences is not possible in his approach. The PHM has been proposed by Cox in 1972 and is capable of integrating factors influencing the survival time [15]. Originally the PHM has been applied in the field of biology to investigate the impact of various medical treatments. A comprehensive literature review about PHM applications is presented by Kumar and Klefsjö [16].

Ghodrati showed that the PHM can be used in technical applications, but neglected time dependent variables. The author applied the algorithm to predict spare part demands of mining machines by implementing external influences, like operating conditions and operator behaviour [17].

One single time dependent internal variable has been considered by Louit (oil condition), so it is not possible to utilize comprehensive operational and online condition monitoring data, which are available in most technical systems, today. Therefore, SCADA data are investigated in this paper in order to predict failures of critical units more accurately. In contrast to existing applications, internal as well as external time dependent influences will be integrated into an enhanced forecast model. Data are processed and applicability of time dependent SCADA data to a PHM is proven. The approach proposed is verified with SCADA data of WES. This ensures that failures of units are predicted