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Modeling the Effect of Environmental and Operating Conditions on Power Converter Reliability in Wind Turbines with Time-Dependent Covariates

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In wind turbines, the power-electronic converters used for connection to the power grid are among the most frequently failing subsystems. For root-cause analysis and a subsequent development of effective countermeasures, it is an important task to identify influences having a significant effect on the converter reliability. Based on data from a large fleet of wind turbines spread across five continents, the failure behavior of power converters is modeled by means of a nonhomogeneous Poisson process (NHPP) regression model in the present work. Besides constant covariates characterizing design-related aspects, site-specific environmental and operating conditions of the wind turbines are included in the analysis as time-dependent covariates. As suggested by seasonal and load-dependent patterns observed in the failure behavior, the analysis results confirm that both humidity and the electrical load of the turbines have a significant effect on the reliability of the converter core components and allow for a quantification of these effects.

Keywords: reliability, field data, regression models, time-dependent covariates, humidity, power electronics, converter, wind turbines

1. Introduction

A considerable portion of the levelized cost of wind energy is related to operation and maintenance (O&M) of wind turbines (WTs). Herein, a major part accounts for repairs and replacements after failures. In addition, failures cause turbine downtime and with that revenue losses. Enhancing reliability is therefore key to achieve further cost reductions. Understanding the failure behavior and relevant factors driving failure is essential to develop effective countermeasures and establish cost effective O&M processes.

As different reliability surveys have shown, e.g. Lin et al. (2016); System Performance, Availability and Reliability Trend Analysis (2017); Dao et al. (2019), power converters are among the most frequently failing subsystems of wind turbines. Despite considerable progress during the past years, the knowledge about the mechanisms and causes can still be improved. This publication aims at extracting further insights from field reliability data to support root-cause analysis.

WTs in the field are exposed to environmental and operating conditions differing between regions and varying with seasons. Hence, reliability models should include environmental and operating conditions to account for different climatic conditions and particularly for seasonality. This paper presents results from reliability analysis which directly incorporates both constant and time-dependent covariates. The analysis is based on an extensive field-data collection of more than 6,000 turbines worldwide.

The remainder of this paper is structured as follows: Section 2 reviews previous work regarding reliability modeling including constant and time-dependent explanatory variables in the context of wind energy. Section 3 describes the data basis. Sections 4 and 5 introduce the mathematical framework and its implementation. The results are presented and discussed in Section 6. The paper closes with conclusions in Section 7.

2. Reliability Modeling Including Constant and Time-Dependent Explanatory Variables

Field reliability data is not necessarily limited to failure data. It may also contain (or be complemented with) concomitant variables that can be useful in gaining a better understanding of the underlying failure causes. Regression-based reliability models are capable of including a set of covariates to investigate the effect of these potential influencing variables. In the area of reliability analysis for wind turbines, only few previous field-data-based reliability studies have investigated the impact of site conditions on the failure behavior of wind turbine components by means of regression models.

Slimacek and Lindqvist (2016) presented results from a Poisson regression model including, among other covariates, a proxy variable capturing the harshness of the environment. This turbine-specific covariate indicated the number of stops caused by external natural factors, but did not include environmental covariates directly. Ozturk et al. (2018) investigated the reliability of wind turbines using survival analysis models incorporating different operational, geographical and environmental factors as covariates, e.g. climatic regions, distance to coast or the mean annual wind speed. The analysis was based on data from 109 turbines in Germany operating for a period of 19 years.

Climatic and wind conditions vary with time and season. More advanced reliability models take into account the variation of such environmental quantities over time. A study by Jiang et al. (2016) explored the effect of environmental conditions based on monthly averaged covariates in a multiplicative model. The effects of temperature, humidity, rainfall, and wind speed on reliability were investigated at turbine-system level. However, the size of the evaluated dataset covering 33 turbines limits the conclusiveness of the obtained results. Based on data of 383 wind turbines, Reder and Melero (2018) proposed different reliability models incorporating monthly-averaged time series of six on-site environmental variables taken from nearby weather stations as well as operating data from the Supervisory Control and Data Acquisition (SCADA) system. The models were applied using failure data on turbine-system level as well as on subsystem level (gearbox). The study was intended to compare different regression model approaches (including e.g. Poisson, negative binomial and zero-inflated models) and to determine the best combination of models and variable selection.

Recent work by the authors, Pelka and Fischer (2022); Fischer et al. (2023), has investigated the effect of constant covariates such as design-related variables, site-specific mean absolute humidity and mean capacity factor on converter reliability in wind turbines. In that analysis limited to constant covariates, regional differences regarding humidity level and load regimes have been captured and their effects on converter reliability have been quantified. Other field-data analyses of the authors, Fischer et al. (2018, 2019), have revealed pronounced seasonal patterns in the failure behavior of WT power converters. A correlation with the seasonally varying ambient absolute humidity at the WTs was visually observed but the effect was not investigated by means of reliability models so far. Achieving this step is the subject of the present work.

3. Data Description

3.1. *Field failure data*

The comprehensive field failure data forming the basis of the present work are summarized in Table 1. The data set covers converter-specific data of 6,121 wind turbines of different manufacturers. Only turbines with a power converter are included and their data are investigated. The operating sites include onshore and offshore sites and are distributed over five continents, see Fig. 1. For details on the turbines and their power converters as well as on data processing, please refer to Pelka and Fischer (2022).

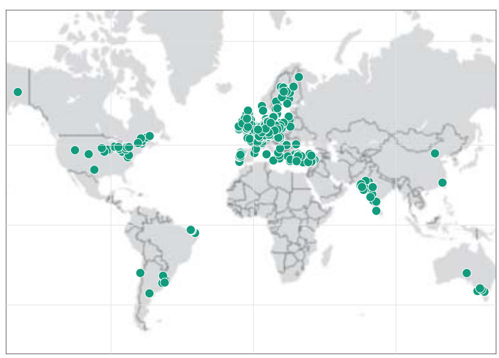

Fig. 1. Locations of the wind farms included in the analysis

The present analysis focuses particularly on the component category 'phase module' comprising the core components of the converter (power-semiconductor modules, their driver units, DC-link components) as this category was identified as the main driver of downtime and repair cost within the main converter system in previous analyses (Fischer et al. (2019)). Only failures of the 'phase module' category are considered in the following.

As a previous study by the authors, Fischer et al. (2021), has revealed different seasonal failure patterns for air-cooled and liquid-cooled converters, models including time-dependent environmental covariates should distinguish between the converter cooling system. The set of turbines evaluated in the following contains only liquid-cooled converters.

Table 1. Converter-specific failure data set and characteristics of wind turbines under consideration

Number of turbines covered by the analysis	6,121 WTs
Total number of evaluated WT operating years	15,490 years
Year of WT commissioning	2000–2020
Converter-specific failure data from years	2006–2020
Rated power of WTs	850–6150 kW

3.2. *Supplementary environmental data*

For every wind farm location, time series describing the site-specific environmental conditions have been extracted from the publicly available ERA5 reanalysis data set provided by the European Centre for Medium-Range Weather Forecasts (ECMWF (2022)). The ERA5 data set covers a large number of atmospheric and oceanographic variables at an hourly resolution and with an approx. 30 km $\times$ 30 km grid spacing with global coverage.

The variables of the ERA5 reanalysis data set used in this study are the temperature, dew-point temperature and the wind speed, the latter adjusted to the average hub heights of the investigated turbine types. Based on temperature and dew-point temperature, the absolute humidity is calculated. In a study based on comprehensive climatic field-measurement data and ERA5 reanalysis data by Fischer et al. (2021), ERA5 has proven to be a suitable and valuable source for site-specific WT-ambient climatic time series. For use as covariates, time series corresponding to the data-collection period of the individual turbines have been extracted.

It is important to note that for an analysis of climatic effects on converter reliability, the climatic conditions inside the power-converter cabinet are relevant, not those in the ambient air of the WT. However, we can make use of the fact that the absolute humidity inside the converter cabinet of WTs typically follows the ambient absolute humidity very closely and with only a short time delay ($<$1h), as shown in Fischer et al. (2021) and Fischer and Göhler (2022). We may therefore use the absolute-humidity time series from the ERA5 data set as a good approximation of the cabinet-internal humidity condition.

3.3. *Power time series estimation*

Due to wind speed variation, the turbines in the field are exposed to very diverse operating conditions. To be able to characterize and include the site-specific load regime of all WTs in spite of the fact that SCADA operating histories are available only for some of the turbines, we approximate the potential power output fed to the grid: The turbine-specific power curve provided by the manufacturers (see Fig. 2 for an example) gives the ideal output power of a turbine at a specific wind speed. Based on the power curve and ERA5 wind-speed time series, which are adjusted to hub height using the power law (with different exponents for onshore and offshore sites), power output time series for every investigated turbine are calculated. An example of a wind-speed time series and the resulting WT active-power time series is presented in Fig. 3. As power curves are only available at 1 m/s or 0.5 m/s resolution, linear interpolation is used, which provides sufficient accuracy for our case. Moreover, for wind-speed values below cut-in wind speed (typically between 3 and 5 m/s) and wind-speed values above cut-off wind speed, the power is set to zero (cf. Fig. 2). Each turbine's power time series generated in this way is normalized with its rated power.

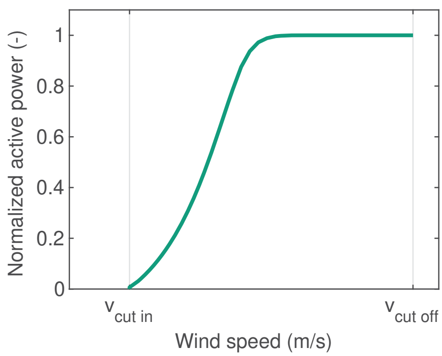

Fig. 2. Example power curve of a wind turbine

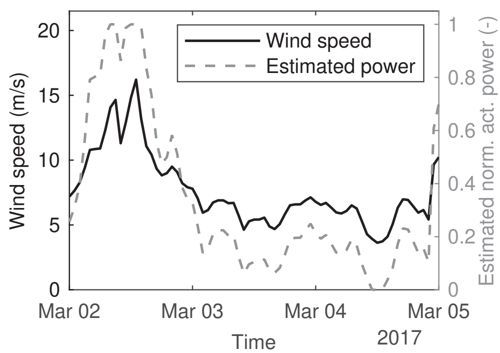

Fig. 3. Illustration of power time series estimation from hub-height wind speed

To validate the methodology and quantify the estimation error, more than 700 turbines have been used for which SCADA operating data and thus measured active power time series are available. These include turbines of a variety of different types and locations. An evaluation of the deviations and root mean squared errors between the SCADA operating data and the estimated power time series has shown that the proxy time series adequately represent the dynamic site- and turbine-specific load conditions: Comparing the daily mean values of measured and estimated power time series, the deviation remains below 10% in 84% of all days. Only 4% of the daily mean values show a deviation of 20% or more. Note that within the proxy time series characterizing the operating condition, effects of downtime, curtailment and site-related performance losses (wake effects) are neglected and the maximum possible yield is considered. This leads inevitably to some deviation between measured and estimated values. In view of the results of the above described validation procedure, the estimated power time series are nevertheless considered a suitable measure for characterizing the WT-individual time-variant operating conditions in the present study.

4. Mathematical Framework

Reliability theory categorizes systems into non-repairable and repairable systems. In this work, the power converter is considered to be a repairable system, which consists of a large number of components including at least one phase module.

After a phase-module failure, this phase module is repaired or replaced and the power converter is restored to satisfactory performance. Hence, failures are observable recurrent events in time and we model these with Poisson processes (Ascher and Feingold (1984)).

Let $N(t)$ be the number of events occurring in the time interval $[0, t]$ and let $N(a, b]$ denote the number of events occurring in $(a, b]$. A counting process $\{N(t), t \geq 0\}$ is called Poisson process if it satisfies (Ascher and Feingold (1984)):

(1) $N(0) = 0$
(2) For any $a < b \leq c < d$, the random variables $N(a, b]$ and $N(c, d]$ are independent.
(3) There exists a function such that

$$\lambda(t) = \lim_{\Delta t \to 0} \frac{P(N(t, t + \Delta t] = 1)}{\Delta t}.$$

The function is called the intensity function of the Poisson process.

(4) For each $t > 0$ holds

$$\lim_{\Delta t \to 0} \frac{P(N(t, t + \Delta t]) \geq 2)}{\Delta t} = 0.$$

Poisson processes can be fully characterized by their intensity function $\lambda(t)$, which is at time t a measure of the unconditional probability that the repairable system will fail in a small time interval $(t, t + \Delta t]$. A frequently used parametric form of the intensity function in applications to repairable systems is the power-law intensity (Ascher and Feingold (1984))

$$\lambda(t) = \left(\frac{\delta}{\nu}\right)\left(\frac{t}{\nu}\right)^{\delta\text{-}1}, \tag{1}$$

where $\nu > 0$ is the scale parameter and $\delta > 0$ is the shape parameter.

The power-law intensity corresponds to the minimal repair assumption: The system is repaired to the state it had immediately before the failure. In practice, the concept of minimal repair corresponds to the repair or replacement of only a small part of the system. This is a reasonable assumption also for the modeling of power converter systems.

The power converters are considered to be m similar independent repairable systems that differ in design and site-specific conditions. This observable heterogeneity is incorporated by covariates, which can be constant or time-dependent. Adapting the model of Cook and Lawless (2007), the intensity function is adjusted to account for observed heterogeneity through a multiplicative model

$$\lambda(t) = \lambda_0(t) \exp(\beta_1 x_1(t) + \cdots + \beta_p x_p(t)) \tag{2}$$

where $\lambda_0(t) = (\frac{\delta}{\nu})(\frac{t}{\nu})^{\delta\text{-}1}$ is the baseline intensity function. $x_i(t)$ represents a vector of time-dependent covariates at time t. Constant covariates, namely $x_i(t) = x_i$ for all times t, are a special case of this general form. $\beta = (\beta_1, ..., \beta_p)$ is a vector of unknown coefficients corresponding to the covariates.

Apart from heterogeneity explained by the covariates, there may be other factors which affect the failure behavior but have not been measured and are not available otherwise. To account for such unobserved heterogeneity, a multiplicative frailty model is used. In this model, variation is modeled by the term z assuming that each system has its individual frailty and can be viewed as being the effect of an unobserved covariate. The unobserved frailties z are assumed to be independent and identically distributed. The most common choice of frailty distribution is the gamma distribution, which is scaled to mean 1 and variance θ for the sake of computational simplicity (see e.g., Cook and Lawless (2007)).

The model described by Eq. (2) becomes

$$\lambda(t) = z\lambda_0(t) \exp(\beta_1 x_1(t) + \cdots + \beta_p x_p(t)), \tag{3}$$

with z being the individual frailty term of each system. Note that within this multiplicative model, the effect of one covariate can only be investigated when simultaneously keeping the other covariates unchanged. The coefficients are to be interpreted with a relative effect on the baseline covariate. A negative coefficient $\beta < 0$ results in $\exp(\beta) < 1$ and therefore the baseline intensity is reduced by the effect of $\exp(\beta)$. Vice versa a positive coefficient $\beta > 0$ has an increasing effect on the baseline intensity.

The model (3) is fitted by constructing the likelihood function L for the observed failure data of the m systems and maximizing $\log L$ with respect to the unknown parameters $\beta_1, ..., \beta_p, \delta, \nu$ and θ. The likelihood function L derived for Eq. 3 can be found in Chapter 2 of Rondeau et al. (2012) as Eq. (2), where the baseline intensity function has to be adjusted to the power-law intensity used here.

Inference on the covariates is based on likelihood-ratio statistics, see (Meeker and Escobar (1998)). Additionally, the standard errors are computed and the confidence intervals are constructed using the Hessian of the log-likelihood function as described in Cook and Lawless (2007).

We use the operating age of the turbine as the time scale and only one type of event (phase-module failures) is of interest. The time-dependent covariates are incorporated with a temporal resolution of two days (i.e. with two-day average values).

5. Implementation

The results have been obtained using R Statistical Software version 4.2.2 (R Core Team (2022)).

The frailty regression models were fitted using the package frailtypack (Rondeau et al. (2012)). In comparison with the analysis with constant covariates presented in Pelka and Fischer (2022), the inclusion of time-dependent covariates increases the dataset underlying the regression by a factor of approx. 500. Data preprocessing and visualization were performed in MATLAB version R2022a.

6. Results and Interpretation

To assess the validity of assuming a power-law process as a baseline intensity for the Poisson process, the non-parametric cumulative failure intensities are plotted vs. the failure times in a double-logarithmic representation, see Fig. 4. The non-parametric cumulative intensity is estimated by means of the Nelson Aalen estimator (Ascher and Feingold (1984)). The roughly straight shape of the graph confirms that the power-law process is a suitable choice for the baseline intensity. Failures observed during the day of WT commissioning (zero-time failures, colored light grey in Fig. 4) are excluded form the analysis as they are likely to be governed by different mechanisms than the other failure events. The data set covers failures up to an WT operating age of 16 years.

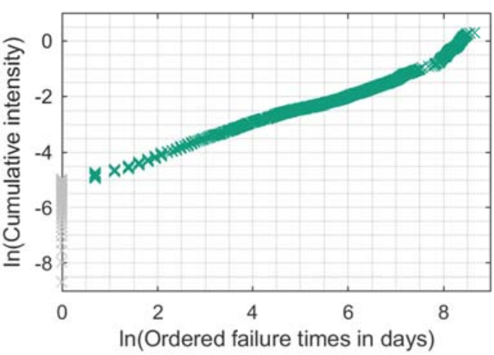

Fig. 4. Plot of natural logarithm of non-parametric cumulative failure intensities vs. logarithm of failure times for the evaluated data set (excluding zero-time failures in grey)

The model described by Eq. 3 with constant covariates and different combinations of time-dependent covariates is numerically fitted by means of the maximum likelihood method. The model quality resulting from different combinations of covariates is presented in Table 2. The included constant design-related covariates, which have been identified by means of the variable selection procedure described in Pelka and Fischer (2022), are 'turbine commissioning year' and 'converter rated power' as numerical covariates and 'IGBT-module manufacturer' as a categorical covariate. We refer to them with the abbreviation CC (constant covariates) in the following.

Table 2. Comparison of model quality for models with different sets of covariates

Covariates included in the model	-2 log(L)
CC (constant covariates)	24,380
CC, Estimated power	24,359
CC, Absolute humidity	24,256
CC, Estimated power, Absolute humidity	24,226

To determine the significance of the effect of the covariates, likelihood ratio tests are performed. The results show that incorporating site-specific absolute humidity improves the model significantly, indicating that this time-dependent covariate has a significant effect on the failure behavior of the investigated power converters. The same applies for the site-specific estimated power: While it benefits the model quality less than the absolute humidity, also this second time-dependent covariate is found to improve the model significantly.

For the determined set of covariates having a significant effect on converter (or more specifically: phase module) reliability, Table 3 summarizes the estimated coefficients β_i together with their 95% confidence intervals. These coefficients provide additional information on whether the corresponding covariate has a positive or a negative effect on reliability and how strong this effect is. Note, however, that the values of these coefficients may not be directly compared among each other as they refer to the individual scale of each covariate.

A higher rated power of the converter is found to have a negative effect on reliability, which is physically plausible. The negative sign of the β

Table 3. Results of parameter estimation

Covariate (if applicable: factor level)	β	exp(β)	Confidence interval
Converter rated power	0.63	1.89	[0.47,0.80]
Commissioning year	-0.19	0.82	[-0.21,-0.18]
Module manufacturer (B)	-0.36	0.70	[-0.89,0.17]
Module manufacturer (C)	0.10	1.11	[-0.09,0.29]
Absolute humidity	0.07	1.08	[0.06, 0.09]
Estimated power	0.57	1.77	[0.36, 0.79]

coefficient corresponding to the WT commissioning year indicates a higher phase-module reliability for WTs commissioned in later years (i.e. tending to contain more modern technology). Regarding the time-dependent covariates being of particular interest in the present study, the β coefficients indicate that higher absolute humidity negatively affects converter reliability: Per 1 g/m³ higher two-day averaged absolute humidity, the failure intensity increases with a factor of 1.08. Taking into account the considerable seasonal variations in absolute humidity with differences of e.g. more than 20 g/m³ between summer and winter levels in India, this explains the excessively increased failure intensities observed during the summer months in that region, but also the less extreme seasonal failure patterns in other regions (cf. Fischer et al. (2018)). Likewise, a higher electrical load has an increasing effect on the failure intensity and therefore a negative effect on the reliability: Per 25% higher electrical load of the WT (e.g. operation at 75% instead of 50% of the rated power), the intensity increases by a factor of 1.15. While this factor does not exceed 1.77 (corresponding to operation at 100% vs. 0% of the rated power), that of absolute humidity will take on higher values for humidity differences of 8 g/m³ and above. In many regions of the world, the failure behavior will therefore be influenced more strongly by variations in the climatic conditions than by variations of the electrical load.

7. Conclusions

A nonhomogeneous Poisson process (NHPP) regression model has been utilized to quantify the effect of environmental and operating conditions on the failure behavior of power converters in wind turbines. To characterize observed heterogeneity between the converter systems, both constant and time-dependent covariates have been included. In addition, random effects accounting for unobserved heterogeneity have been considered in the model. The analysis has been performed using a temporal resolution of two days.

The results show that both absolute humidity and the electrical loading level have a significant effect on the reliability of the converter core components. The higher the humidity level or the higher the electrical load, the higher is the failure intensity. The results explain and confirm the observations of seasonal patterns in the failure behavior reported in Fischer et al. (2018, 2019). In addition, the findings are in agreement with the humidity- and load-dependencies encountered during the investigation of environmental and load conditions preceding failure events for certain groups of turbines documented in the same articles. The analysis method described and applied in the present work has made it possible to investigate these effects separately and quantify them.

While regression-based reliability models intended for the identification of prevailing failure causes and failure-promoting factors as in the present case are best based on a diverse turbine fleet distributed over different climate zones, potential future models intended e.g. as input for wind-farm specific maintenance modeling and optimization are best derived using data from the WT types and region of interest.

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