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Reliability analysis of wind turbines considering seasonal weather effects

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Abstract

The failure rate of wind turbines shows obvious fluctuation due to seasonal environmental factors. However, few efforts have been devoted to modeling the seasonal failure rate. This paper develops a novel model that consists of a baseline failure rate function, seasonal indices, and a residual term to describe the monthly failure rate of wind turbines. A two-stage procedure is developed to estimate the 16 unknown parameters in the model. The first stage explores the relationship between the parameters in the baseline function and the monthly coefficients by maximum likelihood estimation and then integrates the properties into the genetic algorithm to estimate the main parameters. In the second stage, the variance of the residual term is estimated based on the analysis of the differences between the observed and predicted failure rates. The failure history of 48 months has been used to illustrate the proposed approach. The results show that the monthly failure rate function can well fit the real failure history of wind turbines, and it outperforms the traditional reliability model.

Keywords

Wind turbine, three-parameter Weibull, seasonal failure rate, reliability modeling, monthly coefficient

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Introduction

The great impacts of global warming have underscored the importance of renewable energy applications .[1] As part of the most available renewable sources, such as wind, solar, and ocean power, have played a vital role in generating clean electricity within modern power systems. Among them, wind energy is considered as one of the most promising and encouraging alternatives for power generation.[2] Large-scale wind farms have been installed across the globe in recent years. According to a survey conducted by the World Wind Energy Association (WWEA), the total capacity of installed wind turbines has reached 923 GW by the end of 2022. The data from the Global Wind Energy Council (GWEC) state that 680 GW of new capacity will be added over the next 5 years, bringing the cumulative total to 1586 GW by 2027.

Reducing operation and maintenance (O&M) costs has become a top priority in wind turbine management. O&M costs typically make up 20% to 25% of the total levelized cost of electricity in wind power systems.[3] Over a 20-year operating lifespan, maintenance costs may account for 15% and 30% of total income for onshore and offshore wind farms, respectively.[4] Several types of O&M decisions, including reliability enhancement, maintenance planning, and spare parts management, are made to mitigate maintenance costs.[5–9] Reliability modeling of wind turbines usually acts as a fundamental step of O&M decision making.[10] The accuracy of reliability models plays a significant role in the effectiveness of obtained decisions.

Existing work typically uses traditional reliability models to describe the failure data of wind turbines. Li and Guedes Soares[11] propose a framework to assess the failure rate of floating offshore wind turbines based on the data of onshore wind turbines. Kang et al.[12] utilize fault tree analysis to qualitatively and quantitatively assess the failure characteristics of semi-submersible floating offshore wind turbines. Li and Coolen[13] use the fault tree analysis and Markov chain methods to quantitatively assess the reliability of the entire system of wind turbines. El-Naggar et al.[14] perform a reliability analysis for the components of wind turbines using the Weibull model. Spinato et al.[15] employ the power law

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process to describe the failure rate functions of generator, gearbox, and converter in a wind turbine. Arabian-Hoseynabadi et al.[16] analyze wind turbine assembly reliability using a two-state Markov model. Guo et al.[17] applied a three-parameter Weibull distribution to analyze the failure rate of wind turbines with incomplete data.

Aforementioned reliability models only consider the effect of age on the failure time of wind turbines. As a typical outdoor working equipment, the reliability of wind turbines is greatly influenced by various environmental factors. The relationship between the reliability of wind turbines and wind speed has received considerable attention.[18–20] It has been well recognized that there is a strong correlation between the failure rate of wind turbines and wind speed.[21–25] Various methods, such as time series analysis, Bayesian networks, and copula functions, are used to analyze the correlation.[26–30] Zheng et al.[31] apply the proportional hazards model to integrate the effects of wind speed into the failure rate of wind turbines and then develops a preventive maintenance model considering maintenance window and power production during downtime. Moreover, the other environmental factors, such as temperature, humidity, and lighting, are also able to affect the failure rate of wind turbines to some extent.[32–37]

However, to the best of our knowledge, few models have been proposed to describe the seasonal features of failure rate. It is thus the objective of this paper to develop a seasonal failure rate function that can be used to characterize the seasonally fluctuating failure rate of wind turbines.

In this paper, we propose a monthly failure rate function consisting of three components: a baseline failure rate function, several seasonal indices, and a residual function. The baseline failure rate represents the expected failure rate under designated environmental conditions, and it is modeled using a three-parameter Weibull distribution. The seasonal factor serves as a coefficient for each month, capturing the seasonal variations. Additionally, we assume that the residual function, capturing the difference between predicted and observed failure rates, follows a normal distribution. We develop a two-stage procedure to estimate the unknown parameters in the model. In the first stage, we explore the relationship between the parameters of the baseline function and the monthly coefficients by Maximum Likelihood Estimation (MLE) and then integrate the properties into the Genetic Algorithm (GA) to estimate the parameters. In the second stage, we analyze the differences between the observed and predicted failure rates and estimate the variance of the residual term. Finally, the failure history of 48 months has been used to illustrate the proposed approach. Results show that the proposed model is able to fit the real failure data properly. It outperforms the traditional three-parameter Weibull distribution. We also provide several possible applications of the proposed model in the O&M management of wind turbines.

The remainder of this paper is organized as follows. Section 2 describes the monthly failure rate model for wind turbines. Section 3 presents a two-stage procedure to estimate the 16 unknown parameters in the model. Section 4 demonstrates the application of the proposed model and estimation method using field data from a batch of wind turbines in a Chinese wind farm. Some conclusions and extensions are provided in Section 5.

Monthly failure rate function

The following notation is adopted in this paper:

$\mathbf{t}$	**Age of wind turbine**
$\boldsymbol{\lambda}(\mathbf{t})$	Monthly failure rate function
$\boldsymbol{\lambda}_0(\mathbf{t})$	Baseline failure rate function
$\boldsymbol{k}_i$	Seasonal factors
$\boldsymbol{\omega}$	Residual term
$\boldsymbol{\beta}$	Shape parameter of Weibull distribution
$\boldsymbol{\eta}$	Scale parameter of Weibull distribution
$\boldsymbol{\gamma}$	Position parameter of Weibull distribution
$\boldsymbol{N}(\mathbf{t})$	Expected failure number of a wind turbine in age t
$\boldsymbol{\lambda}_\alpha(\boldsymbol{j})$	Observed failure rate of wind turbine in the jth month
$\mathbf{N_w(j)}$	Failure number of wind turbine w in time interval $(j-1, j)$
$\boldsymbol{W}$	Total number of wind turbines

The failure rate of wind turbines is influenced by seasonal environmental factors. In this paper, we develop a novel model to describe monthly failure rates of wind turbines. Assume now that the age of a wind turbine is $t \geqslant 0$ (months). Its failure rate is given as follows:

$$\lambda(t) = \lambda_0(t) \cdot k_{S(t)} + \omega, \tag{1}$$

where $\lambda_0(t)$ is the baseline failure rate function, k_i ($i \in \{1, 2, \cdots, 12\}$) is a monthly coefficient that represents the effect of each month on failure time, and the residual term $\omega \sim N(0, \sigma^2)$ represents the difference between the predicted value and the actual value. In equation (1), $S(t)$ is used to determine the monthly coefficient for any time t and it is given by

$$S(t) = \lfloor t - 12\lfloor t/12 \rfloor + 1 \rfloor, \tag{2}$$

where $\lfloor x \rfloor$ derives the largest integer that is no greater than x. For example, if the age of a wind turbine is $t = 14.5$ months, its monthly coefficient is $S(t) = 3$. It is also worth mentioning that $S(t) = i$ does not necessarily mean the i th month of a year.

We describe the baseline failure time by a three-parameter Weibull model. In particular, $\lambda_0(t)$ has the following expression:

$$\lambda_0(t) = \frac{\beta}{\eta}\left(\frac{t+\gamma}{\eta}\right)^{\beta-1}, \tag{3}$$

where $\beta > 0$ is the shape parameter, $\eta > 0$ is the scale parameter, and γ is the position parameter. It is obvious that when $\gamma = 0$, the three-parameter Weibull model reduces to a two-parameter Weibull model. We select the more generalized model because, in many practical situations, there exists a time gap between the starting time of failure data history and the installation time of wind turbines.

According to the reliability theory, the reliability function of a wind turbine at time $t \in [i, i+1]$, where $i \in \mathbb{N}$, is given by

$$R(t) = exp\left(-\int_0^t \lambda(x)dx\right) = exp\left\{-\sum_{j=0}^{i-1} k_{S(j)}[\Lambda_0(j+1) - \Lambda_0(j)] - k_{S(i)}[\Lambda_0(t) - \Lambda_0(i)]\right\}, \quad (4)$$

where

$$\Lambda_0(t) = \left(\frac{t+\gamma}{\eta}\right)^{\beta}. \quad (5)$$

From equation (4), the reliability function of wind turbines is a piecewise function, which distinguishes our model from most previous ones.

There are many unknown parameters in the failure rate function, such as β, η, γ, $k_1, \cdots, k_{12}$, and σ. It is important to estimate these parameters according to the failure history of wind turbines. We consider that a batch of W wind turbines are installed in a wind farm simultaneously. We note that the maximum useful time of a wind turbine usually reaches 20 years, which is much longer than a month. It is thus reasonable to assume that the failure rate of $t \in [j-1, j)$, where $j \in \mathbb{N}$, can be approximated by $\lambda(j)$. Thus, the observation of $\lambda(t)$ for $t \in [j-1, j)$, denoted by $\lambda_\alpha(j)$, is

$$\lambda_\alpha(j) = \frac{\sum_{i=1}^{W} N_i(j)}{W}, \quad (6)$$

where $N_i(j)$ is the failure number of wind turbine i over the time interval $[j-1, j)$. The objective is to estimate the unknown parameters by minimizing the difference between the predicted failure rate and the observed failure rate.

Parameter estimation

In this section, we propose a two-stage procedure to estimate the unknown parameters in the monthly failure rate function. For notational convenience, let $\theta_1 = \{\beta, \eta, \gamma\}$ be the set of parameters of baseline failure rate function, and $\theta_2 = \{k_1, \cdots, k_{12}\}$ be the set of parameters of monthly coefficients. In stage 1, we investigate the relationship between θ_1 and θ_2 by the MLE, and the properties are integrated into a GA to derive the estimates of θ_1 and θ_2. Then in stage 2, the residual parameter σ^2 is estimated with residual analysis.

Stage 1

This section is to estimate the parameters so that the predicted failure rate $\lambda(t|\hat{\theta}_1, \hat{\theta}_2)$ can fit the observed failure rate $\lambda_\alpha(t)$. Assuming that each failure of wind turbines is minimally repaired and the repair time is negligible, the failure number in each month follows a homogeneous Poisson process (HPP). Therefore, the probability that the failure number of a wind turbine over the j th month is equal to k is given by

$$P(\lambda_\alpha(j) = k) \propto exp(-\lambda(j)) \cdot (\lambda(j))^k = exp\left[-\frac{\beta(j+\gamma)^{\beta-1} \cdot k_{S(j)}}{\eta^\beta}\right] \cdot \left[\frac{\beta(j+\gamma)^{\beta-1} \cdot k_{S(j)}}{\eta^\beta}\right]^k. \quad (7)$$

We assume that the failure data are collected from J continuous months. As mentioned before, the expected failure numbers of a wind turbine over these months construct a sequence $\{\lambda_\alpha(1), \cdots, \lambda_\alpha(J)\}$. The likelihood function is given by

$$L(\theta_1, \theta_2) = \prod_{j=1}^{J} P(N(t)) \propto exp\left[-\prod_{j=1}^{T} \frac{\beta(j+\gamma)^{\beta-1} \cdot k_{S(j)}}{\eta^\beta}\right] \cdot \prod_{j=1}^{T} \left[\frac{\beta(j+\gamma)^{\beta-1} \cdot k_{S(j)}}{\eta^\beta}\right]^{\lambda_\alpha(j)}. \quad (8)$$

The log-likelihood function is then given by

$$\ln L(\theta_1, \theta_2) \propto -\frac{\beta}{\eta^\beta} \sum_{j=1}^{J} (j+\gamma)^{\beta-1} \cdot k_{S(j)} + \sum_{j=1}^{T} \{\ln \beta + (\beta - 1)\ln(t+\gamma) + \ln k_{S(j)} - \beta \ln \eta\}. \quad (9)$$

The partial derivatives with respect to k_i $(i = 1, 2, \ldots, 12)$ derives

$$\frac{\partial \ln L}{\partial k_i} = -\frac{\beta}{\eta^\beta} \sum_{j=1}^{J} (j+\gamma)^{\beta-1} \cdot \mathbb{I}_{\{S(i)=i\}} + \sum_{j=1}^{J} \lambda_\alpha(j) \cdot \frac{1}{k_i} \mathbb{I}_{\{S(i)=i\}}, \quad (10)$$

where the indicator function $\mathbb{I}_{\{\cdot\}}$ is equal to 1 if the condition $\{\cdot\}$ is satisfied, and it is equal to 0 otherwise.

Setting the partial derivatives of $\ln L$ to zero, we can get the following set of equations:

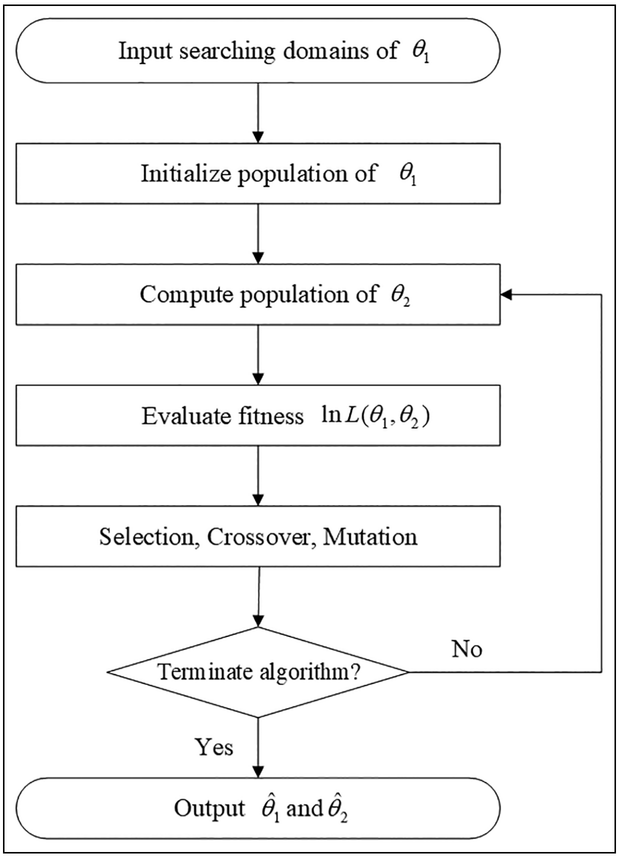

Figure 1. The procedure of the hybrid method.

$$\hat{k}_i = \frac{\hat{\eta}^{\hat{\beta}} \cdot \sum_{j=1}^{J} \lambda_\alpha(j) \cdot \mathbb{I}_{\{S(j)=i\}}}{\hat{\beta} \cdot \sum_{j=1}^{J} (j + \hat{\gamma})^{\hat{\beta}-1}}. \tag{11}$$

Thus, we can derive the estimate of θ_2 if the estimate of θ_1 is known.

However, it is well-known that the estimation of the parameters in the three-parameter Weibull distribution cannot be derived by MLE. To address this issue, we develop a hybrid algorithm that combines GA and the obtained properties to derive the estimates of θ_1 and θ_2. The flow chart of the hybrid algorithm is shown in Figure 1. In this paper, we do not introduce the details of GA such as initialization, selection, crossover, mutation, as they are quite standard. Here, we just mention the following two modifications that are made to improve the efficiency of the GA.

(1) The GA just needs to optimize θ_1, because θ_2 can be obtained from equation (11). In this case, the number of parameters to be optimized is reduced which diminishes the computation burden.
(2) We use the log-likelihood function given in equation (9) as the fitness function.

After obtaining $\hat{\theta}_1$ and $\hat{\theta}_2$, we perform the Chi-square test to verify their goodness of fit. The null hypothesis is H_0: $\hat{\lambda}(t)$ follows $\lambda\left(t|\hat{\theta}_1, \hat{\theta}_2\right)$, which is against H_1: $\hat{\lambda}(t)$ does not follow $\lambda\left(t|\hat{\theta}_1, \hat{\theta}_2\right)$. The Chi-square test statistic is

$$Q_1 = \sum_{j=1}^{J} \frac{\left(\hat{\lambda}(j) - \lambda\left(j|\hat{\theta}_1, \hat{\theta}_2\right)\right)^2}{\lambda\left(j|\hat{\theta}_1, \hat{\theta}_2\right)}. \tag{12}$$

Under H_0, Q_1 in (11) is approximately distributed as $\chi^2(k)$, where the degree of freedom k can be obtained by $k = J - 15 - 1 = J - 16$. Given a significance α, if $Q_1 < \chi^2_\alpha(k)$, we can accept H_0 and conclude that $\lambda\left(t|\hat{\theta}_1, \hat{\theta}_2\right)$ is adequate to model the failure times. Otherwise, $\lambda\left(t|\hat{\theta}_1, \hat{\theta}_2\right)$ is rejected as an adequate model.

Stage 2

After estimating the parameters of θ_1 and θ_2, in this stage, we estimate σ^2 in the residual term. First, we derive the residuals of observations as follows:

$$\omega_j = \lambda\left(j|\hat{\theta}_1, \hat{\theta}_2\right) - \lambda(j), \tag{13}$$

for $j = 1, 2 \cdots, J$.

Based on the assumption $\omega \sim N\left(0, \sigma^2\right)$, the estimate of σ^2 is given by sample variance, that is,

$$\hat{\sigma}^2 = \frac{\sum_{j=1}^{J} \omega_i^2}{J - 1}. \tag{14}$$

We again perform a Chi-square to test an overall model adequacy. The goodness-of-fit test statistic is given by

$$Q_2 = \sum_{j=1}^{J} \frac{\Phi\left(\omega_j/\hat{\sigma}\right) - \gamma(\omega_j)}{\Phi\left(\omega_j/\hat{\sigma}\right)}, \tag{15}$$

where $\Phi(x)$ is the cumulative distribution function of the standard normal distribution, $\gamma(\omega_j)$ calculates the experiential cumulative probability of the observation ω_j. Here, $\gamma(\omega_j)$ can be calculated as follows: (1) Order observations ω_j from small to large. (2) Calculate the median rank $\gamma(\omega_j) = \left(J\left(\omega_j\right) - 0.3\right)/(J + 0.4)$, where $J\left(\omega_j\right)$ is the order number of ω_j in the ordered series. Under the null hypothesis that $\omega \sim N\left(0, \sigma^2\right)$, the test statistic Q_2 is chi-squared distributed with degree of freedom $J - 1$. Given a significance θ, if $Q_2 < \chi^2_\theta(J - 1)$, we can accept the null hypothesis and reject it otherwise.

Numerical example

In this section, the field failure history of 61 wind turbines installed in a wind farm is used to verify the proposed approach. The wind farm is located in Jiangsu province, southeast China, which lies in a humid subtropical monsoon climate zone. In summer, the temperature reaches approximate 40°C, and the

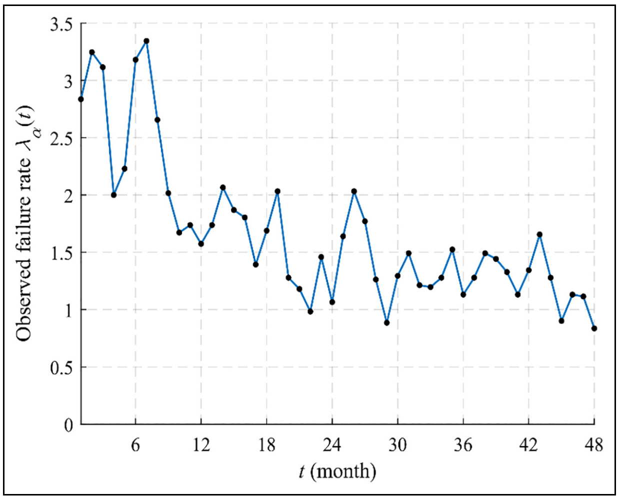

Figure 2. Observed failure rates of wind turbines.

temperature in winter is lower than $-10°C$. Thus, the local temperature has obvious seasonal features. The major configurations of these wind turbines are as follows: horizontal axis rotor with three blades, 77 m of rotor diameter, 61.5 m of hub height, power control by pitch system and variable rotational speed, doubly fed induction generator coupled with gear, rated power of 1.5 MW, and rated wind speed of 12 m/s.

The failure history was collected by a supervisory control and data acquisition (SCADA) system. The SCADA system records the shutdown time and restart time of all wind turbines in the farm. The shutdown causes are also recorded by the system or by technicians afterwards. After data preprocessing, we omit the data not associated with failures, and the left data are used for modeling.

The failure rate observations are presented in Figure 2, where the first month is June. As illustrated in the figure, the failure rate of the wind turbines has obvious seasonal features. It is relatively high in summer (June and July, e.g. $t = 1, 2$) and winter (November and December, e.g. $t = 6, 7$) due to the harsh weather conditions, while low in spring (April and May, e.g. $t = 11, 12$) and autumn (September and October, e.g. $t = 4, 5$) when the weather is desirable. We also note that the failure rate of this batch of wind turbines has a descending trend. It means that these wind turbines are in the infant mortality period. The results follow the fact that the data are recorded from the fifth month after the initial operation of the wind turbines.

Derive the model

We use the monthly failure rate function to fit the seasonal failure rate of wind turbines. To increase the efficiency of our algorithm, we need to determine an appropriate searching domain for θ_1. It is normally believed that the baseline failure rate of wind turbines is that in modest weather. We first choose some baseline failure rates when $t = 4, 10, 12, 17, 22, 24, 29, 33, 36, 41, 45, 48$. Based on these selected data, we obtain crude estimates of θ_1 by the graphic method,[38] and then set the search domain of θ_1 around the crude estimates. We run the hybrid algorithm to derive the following more precise parameter estimates: $\hat{\theta}_1 = (0.5458, 0.0142, 4.9618\ )$, and $\hat{\theta}_2 = (1.21, 1.49, 1.43, 1.15, 1.04, 1.42, 1.65, 1.28, 1.07, 1.04, 1.22, 0.98)$. According to equation (12), $Q_1 = 1.12 < \chi^2_{0.01}(32) = 53.49$, so we accept the obtained estimates $\hat{\theta}_1$ and $\hat{\theta}_2$.

The obtained shape parameter $\hat{\beta} = 0.5458 < 1$ shows that the wind turbines are in the infant mortality period. The position parameter $\gamma = 4.9618$ indicates that the failure history starts about 5 months after the initial operation of wind turbines, which is in line with the actual situation. According to the parameters of $\hat{\theta}_2$, the monthly effects on the failure rate can be divided into three categories as shown in Table 1. As the failure rate in severe influence months is very high, we recommend wind farm owners to pay more attention to the operation and maintenance of wind turbines in these months.

We draw the observed failure rate $\lambda(t)$ and the predicted failure rate $\hat{\lambda}(t)$ in Figure 3 for a comparison. As can be seen, the observed and predicted failure rate curves show a relatively close consistency. Therefore, the obtained failure rate function can be used to predict failure rates in the future.

It is shown in Figure 3 that there exist gaps between $\lambda(t)$ and $\hat{\lambda}(t)$, which can be fitted by the residual term ω. Following equation (14), we obtain $\hat{\sigma}^2 = 0.04$. According to equation (15), $Q_2 = 35.33 < \chi^2_{0.01}(47) = 72.44$, so we accept the parameter estimate.

We compare our model with the traditional three-parameter Weibull distribution. We use a similar procedure given in Figure except setting all seasonal coefficients to 1. The obtained parameter estimates of the traditional model is $\hat{\beta} = 0.9415$, $\hat{\eta} = 1.2266$, and $\hat{\gamma} = 5$. We use the root mean squared error (RMSE) to measure the predictive accuracy, which is given by

Table 1. Categories of each month in a year.

Categories	Standards	Months
Severe influence month	$k_i \geqslant 1.4$	July, August, November, and December
Medium influence month	$1.2 < k_i < 1.4$	January, April, and June
Soft influence month	$k_i \leqslant 1.2$	February, March, May, September, and October

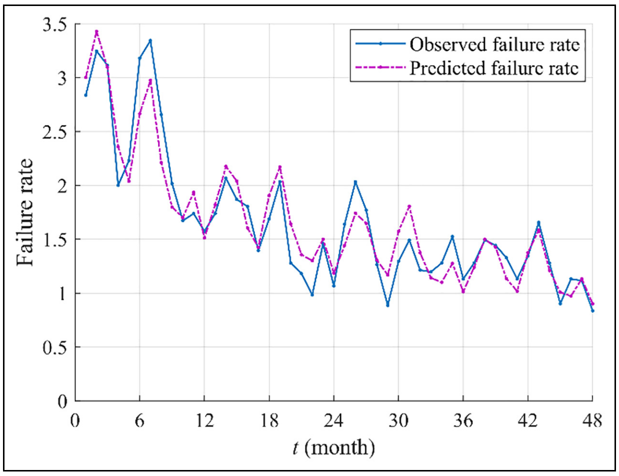

Figure 3. Comparison of observed and predicted failure rates.

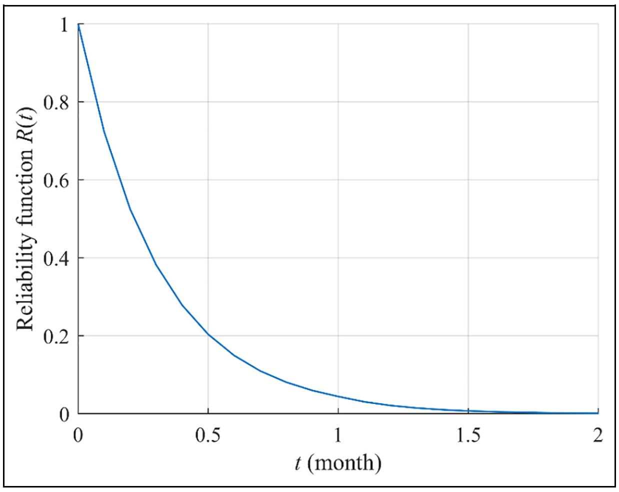

Figure 4. Reliability function of wind turbines.

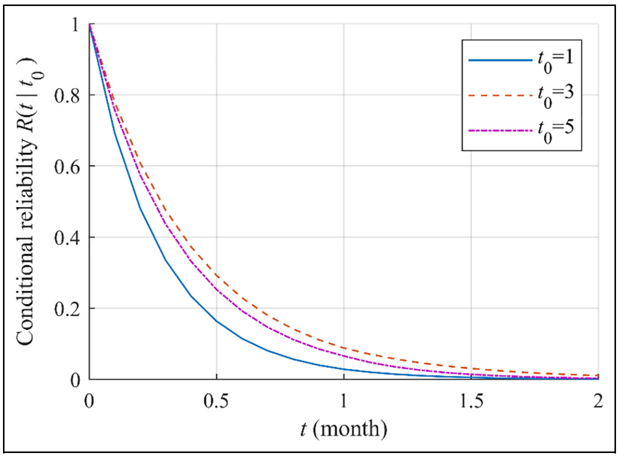

Figure 5. Conditional reliability functions under varying current ages.

Table 2. The RMSE under different model.

Model	Proposed model	Traditional model
RMSE	0.2	1.2

$$RMSE = \sqrt{\frac{\sum_{i=1}^{J} \left(\lambda_p(t_i) - \lambda_\alpha(t_i)\right)^2}{J}}, \tag{16}$$

where $\lambda_p(t)$ and $\lambda_\alpha(t_i)$ is the predicted and the observed failure rates at age t, respectively. Table 2 presents the RMSE of the proposed model and the traditional model. The RMSE of the proposed model is close to 0, and much smaller than that of the traditional model.

Based on the parameter estimation results, we can derive the reliability function, as shown in Figure 4. It can be seen that the reliability of the wind turbine gradually decreases with the increase of time, which is intuitive. However, it is worth mentioning that the curve is piecewise.

Possible applications

In this section, we provide several possible applications of the proposed monthly failure rate function such as conditional reliability, mean residual life, and expected failure number, which are supportive for maintenance decision making and performance evaluation.

(1) Conditional reliability

Assume now the age of a wind turbine is t_0. The conditional reliability of the wind turbine is

$$R(t|t_0) = Pr(\xi > t_0 + t|\xi > t_0) = \frac{R(t_0 + t)}{R(t_0)}, \tag{17}$$

where $R(t_0 + t)$ and $R(t_0)$ can be calculated by equation (4).

Figure 5 presents the conditional reliability $R(t|t_0)$ when t_0 is misspecified. It is interesting to notice that the conditional reliability $R(t|t_0)$ is not monotone in t_0. Actually, both t_0 and the monthly coefficient affect the conditional reliability. In particular, $R(t|5) > R(t|1)$ mainly follows the fact that the larger t_0 indicates a lower failure rate due to the infant mortality period. The seasonal effects are negligible because the first coefficients for $t_0 = 1$, $k_2 = 1.49$, is similar to that of $t_0 = 5$, $k_6 = 1.42$. The reason for $R(t|5) < R(t|3)$ is that $k_6 = 1.42 > k_4 = 1.15$, leading to a higher failure rate.

(2) Mean residual life

Table 3. The MRL under different age t_0.

t_0	1	2	3	4	5
MRL	0.40016	0.36375	0.48299	0.41021	0.3479

Assume now the age of a wind turbine is t_0. The mean residual life of the wind turbine is given by

$$MRL(t_0) = \int_0^{+\infty} R(t|t_0)dt. \tag{18}$$

Table 3 presents the MRL of a wind turbine under different current ages t_0. The result may seem counter-intuitive in the sense that one would typically expect a monotone MRL with respect t_0. The reason is that the failure rate function of a wind turbine is not only dependent on age but also on the month of the age. In other words, the failure rate of the same age in different months can vary each other.

(3) Expected failure number

Assume that the current age is $t_0 \in \mathbb{N}$. According to the non-homogeneous Poisson process, the expected failure number over the next month is

$$N(t_0) = \int_0^1 \lambda(t|t_0)\mathrm{d}t = k_{S(t_0)}\left[\left(\frac{t_0+\gamma+1}{\eta}\right)^\beta - \left(\frac{t_0+\gamma}{\eta}\right)^\beta\right].$$

Discussions

The following discussions are made for the extensions of our seasonable failure rate function.

(1) Various studies based on the database of wind turbines, such as WMEP, LWK, and SPARTA, have shown that the failure rates of wind turbines in a wide range of areas are influenced by key weather factors, such as wind speed and temperature, and thus have seasonal features. Our model provides a potential method to quantify the seasonal features and integrate them into the failure rate function.

(2) It is also interesting to represent the seasonal influence by quarters instead of month-by-month to reduce the complexity of the model. In particular, we let $k_1 = k_2 = k_3$, $k_4 = k_5 = k_6$, $k_7 = k_8 = k_9$, $k_{10} = k_{11} = k_{12}$. We integrate these constraints into the algorithm and obtain the $\hat{\theta}_1 = (0.6905, 0.1096, 1)$ and $\hat{\theta}_2 = (1.20, 1.20, 1.20, 1.48, 1.48, 1.48, 1.53, 1.53, 1.53, 1.28, 1.28, 1.28)$. The Chi-square test statistic $Q_1 = 4.19 < \chi^2_{0.01}(40) = 63.69$, so that the obtained estimates can be accepted. Figure 6 compares the observed failure rate and the predicted failure rate under quarter coefficients. Compared with the results given in Figure 3, this quarter model, although is simpler in model structure and parameter estimation, is less accurate than the model with monthly coefficients.

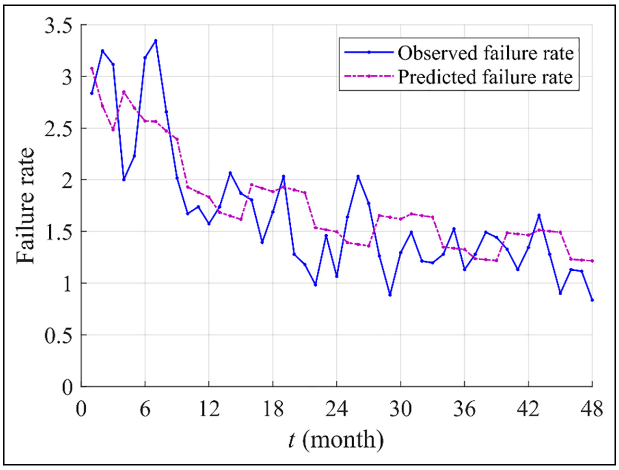

Figure 6. Comparison of observed and predicted failure rates under quarter coefficients.

Conclusions

In this paper, we have proposed a novel monthly failure rate function involving a three-parameter Weibull baseline failure rate function, 12 seasonal coefficients, and a residual term to describe the failure rate of wind turbines influenced by seasonal environmental factors. We have developed a two-stage procedure to estimate the unknown parameters. In the first stage, we explore the relationship between the parameters in the baseline function and the monthly coefficients by MLE and then integrate the properties into the GA to estimate the parameters. In the second stage, we analyze the differences between the observed and predicted failure rates and estimate the variance of the residual term. The failure history of 48 months has been used to illustrate the proposed approach. The results show that the monthly failure rate function can well fit the real failure history of wind turbines, and it outperforms the traditional three-parameter Weibull model.

The proposed monthly failure rate model encompasses a range of applications. First, it can be used to predict the failure rates and expected failure numbers of wind turbines in the future. It is worth mentioning that the obtained failure rate function is not only useful for the current wind turbines, it can be applied to wind turbines which are installed nearby with small modifications. Second, it can be applied to estimate the conditional reliability and remaining useful life, which can help wind farm owners and operators to understand their wind turbines more clearly. Third, based on the obtained failure rate function, it is convenient to predict the expected failure number in the future.

There are still some interesting topics that can be pursued in the future. First, the proposed failure rate model treats the effects of all environmental factors as a whole. It remains a problem of how to build the relationship between the reliability of wind turbines and each key environmental factor. Also, it is recognized that the environmental factors of wind turbines are by no means independent. It is thus of great importance to construct a reliability model considering dependent environmental factors. Another interesting direction is to explore the causes and effects of turbine failures, which will provide important support to identify key components of wind turbines and conceive corrections for reliability improvement. The final extension is to investigate the reliability modeling of key components of wind turbines. Such reliability models play important role in evaluating the performance of these components.

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