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RESEARCH ARTICLE

Modelling the Effects of Environmental Conditions on Wind Turbine Failures

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Abstract

Operation and maintenance (O&M) is one of the main cost drivers of modern wind farms and has become an emerging field of research over the past years. Understanding the failure behaviour of wind turbines (WT) can significantly enhance O&M processes and is essential for developing reliability and strategic maintenance models. Previous research has shown that especially the environmental conditions, to which the turbines are exposed to, affect their reliability drastically. This paper compares several advanced modelling techniques and proposes a novel approach to model WT system and component failures based on the site specific weather conditions. Furthermore, in order to avoid common problems in failure modelling, procedures for variable selection and complexity reduction are discussed and incorporated. This is applied to a big failure data base comprised of eleven wind farms and 383 turbines. The results show that the model performs very well in several situations such as modelling general WT failures as well as failures of specific components. The latter is exemplified using gearbox failures.

KEYWORDS:
wind turbine, failure, weather, reliability, operation and maintenance, zero-inflated models

1 | INTRODUCTION

Wind energy generation has evolved to one of the most important renewable energy sources worldwide. In order to compete with conventional energy sources, however, the overall cost of wind energy must yet be lowered significantly. Being a main cost driver of modern wind farms (WFs), operation and maintenance (O&M) has become an emerging field of research. Operators can profit substantially by shifting from corrective towards predictive maintenance strategies.

Understanding the failure behaviour of wind turbines (WTs) and their components plays an important role in this transition. Sophisticated reliability models are used to anticipate failures and to establish cost effective O&M strategies.

Reliability models usually take into account the operational life of the system or component using so-called lifetime distributions. These are probability density functions defined over a usage parameter, such as time, distance, cycles, etc.

Weibull distributions are the most widely used lifetime distributions in reliability engineering, see e.g. O'Connor *et al.*[1]. When modelling the failure rates over time, these are resulting in the famous bathtub curve.

The latter is divided into three phases - early, useful life and ageing phase. The early life is characterised by a decreasing failure rate over time and modelled with a Weibull parameter $\beta < 1$. Ageing or wear-out is represented by an increasing failure rate with $\beta > 1$. During the whole useful life period the failure rates are assumed to be constant ($\beta = 1$).

For WF operators, the failure rates on relatively short time intervals e.g. on a monthly basis are of high interest when setting up their maintenance strategies. Assuming constant failure rates (e.g. during the entire useful-life period) can lead to wrong conclusions and higher O&M expenses. Furthermore, lifetime models are meant for situations where the operational life is the only measurable driver of the subject's reliability degradation and they do not account directly for the effect of the surrounding meteorological conditions. Wind turbine systems are highly exposed to weather phenomena, and as stated by Kuik *et al.*[2], apart from the system's operational life, reliability degradation of wind turbine components is often related to complex combinations and sequences of operational and environmental conditions. This can result in highly varying component degradation processes throughout the year, which still need to be fully understood. Much research effort has been dedicated to analysing failure data of wind turbines and their components; examples can be found in literature.[3–7] Also the environmental conditions before WT failures have been analysed in previous research.[8–14] These studies have shown that not only the turbine age, but also certain combinations of weather conditions can affect their life-time negatively.

Fewer studies have been carried out on actually modelling the failure behaviour with respect to the environmental conditions the wind turbines are exposed to. A work by Wilson *et al.*[15] uses artificial neural networks with the aim of analysing the effects of rainfall, pressure, relative humidity, temperature, wind direction, wind speed and gust speed at ground level on different WT components. Wilson *et al.*[16] subsequently present a non-parametric mixture model to compare the distributions of weather conditions including relative humidity, temperature and wind speed, in the presence of failures to normal site conditions. Further, Wilson *et al.*[17] establish a Markov Chain Monte Carlo (MCMC) model to analyse the effects of wind speed on O&M cost. A work presented by Faulstich *et al.*[18] proposes an additive Weibull failure rate model for WT rotor blades based on their age, as well as the hours of full load and wind speed (overload). A recently published study by Slimacek *et al.*[19] uses a Poisson-Gamma model for modelling the rate of occurrence of failures (ROCOF) with a time-constant ROCOF as base function. A proxi-covariate indicating the number of stops caused by external natural factors was used to represent the harshness of the environmental conditions. They conclude that the latter is the most significant factor for modelling WT reliability and should be considered in further studies. Nonetheless, their data base did not permit to include environmental covariates directly.

Previous studies have successfully shown that correlations between environmental parameters and WT failures exist and models describing their effects on the component degradation were established. However, in most cases the environmental parameters were not included directly as covariates. In other cases, the influence of different weather variables on the WT failure behaviour is only modelled separately for each weather variable.

This paper proposes a novel approach to model monthly wind turbine failures directly incorporating complex combinations of six on-site environmental parameters, as well as five turbine specific and operational variables. The performance of several different multivariate regression models is compared using a large failure data base including various turbine technologies. With increasing model complexity, more sophisticated parameter estimation and variable selection techniques have to be considered in order to account for common problems related to e.g. over-dispersed failure data, heterogeneity, optimal covariate sub-sets and multicollinearity. The best combination of regression model, parameter estimation and variable selection techniques is determined and proposed for further use in the field.

The remainder of this paper is organised as follows. Section 2 describes in detail the data set and model covariates. Section 3 discusses the challenges of recent regression modelling and parameter estimation techniques. Additionally, the objectives and the novelty of this study in the context of the discussed literature are presented. Section 4 gives the mathematical formulations of the used models. The results and discussions are presented Section 5. Finally, the conclusions and future objectives are given in Section 6.

2 | DATA

The data used in this work are comprised of historical failure logbooks, WT SCADA data and the WFs' measurement tower (met mast) data. Additionally, measurements obtained at meteorological stations close to the respective WFs are used. Figure 1 presents the composition of the used data regarding the failed main components. It is shown that the gearbox contributed to a very high number of failures and will be used to test the model performance on component level. The gearbox has been identified as one of the most critical WT components.[7,20] Furthermore, although being embedded within the nacelle, it is highly affected by environmental conditions.[15,21,22]

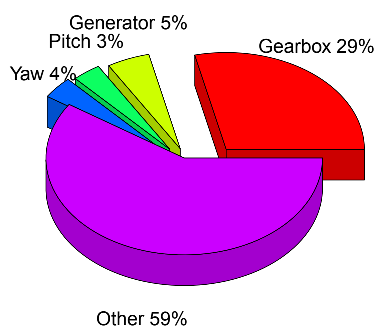


FIGURE 1 Failure data composition for this study

2.1 | Wind farm specifications and historical failure data

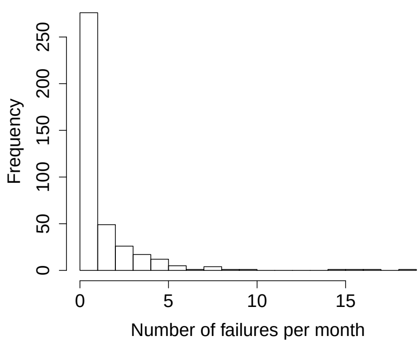
Table 1 summarises the wind farm characteristics and failure data. The observation period is three years (January 2013 to December 2015), resulting in 1149 operational WT years for eleven wind farms and in total 383 turbines. All farms are located on-shore in different areas of Spain and operate three bladed, geared-drive and pitch-regulated turbines. For confidentiality reasons further specification on WF names, turbine models, and locations cannot be made. The data were chosen intentionally to represent several WT age groups, rated capacities and different site terrain types, classified according to the IEC 61400-12-2 [23] standard.

TABLE 1 Wind farm specifications and historical failure data.

Wind Farm	Rated Capacity (kW)	Age (years)	Nb. of Turbines	Hub Height (m)	IEC Terrain Class	Total Nb. of Failures	Failure/Turb./Month	Nb. of Gearbox Failures	Failure/Turb./Month Gearbox
WF-A	2000	5	30	67	4	121	0.112	11	0.010
WF-B	1800	5	21	80	3	40	0.053	14	0.019
WF-C	800	8	36	55	5	86	0.066	16	0.012
WF-D	660	12	43	45	5	59	0.038	30	0.019
WF-E	660	14	25	45	2	36	0.040	16	0.018
WF-F	660	9	32	45	3	36	0.031	14	0.012
WF-G	660	11	74	45	3	32	0.012	12	0.005
WF-H	660	14	21	45	4	23	0.030	8	0.011
WF-I	330	4	16	30	2	35	0.061	14	0.024
WF-J	330	16	40	30	2	29	0.020	10	0.007
WF-K	300	15	45	30	4	44	0.027	10	0.006

Table 1 further shows the number of WT system and gearbox failures registered during the observation period, as well as the failures per turbine and month.

Figures 2 a and 2 b display histograms for the monthly WT system and gearbox failures, respectively.



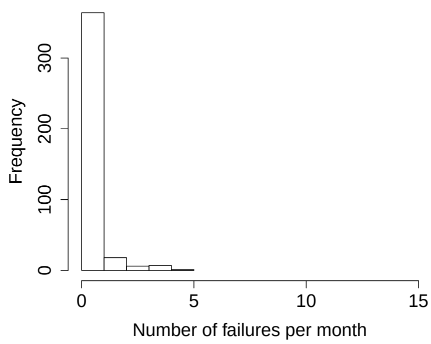


FIGURE 2 Histograms for the recorded (a) wind turbine and (b) gearbox failures per month.

2.2 | Weather and operational data

This work considers six environmental parameters. These were identified in literature [12,16] as the most critical ones influencing the WT failure behaviour negatively. The monthly mean wind speed (WS), turbulence intensity (TI), and monthly maximum wind speed (MaxWS) were measured at a met-mast height of 45 meters. The monthly mean relative humidity (RH), ambient temperature (Temp) and total monthly precipitation (Rain) are taken from closely located weather station. Figures 3 a to 3 f show histograms of the measured environmental covariates. The turbulence intensity is only available for *WF-A* and *WF-C*, and does not enter in the model for all WT technologies. But the influence of TI on the outcome is discussed separately for *WF-C* in Section 5.5.

As operational indicator the covariate *PWR* is introduced, which is defined as the average monthly active power (taken from the SCADA system) in percent of the turbines' rated capacity. This covariate indicates indirectly how long and with how much capacity the turbines are operating on average during each month. The hub-height, rated capacity and turbine diameter also enter the models to distinguish between the different WT technologies. In order to avoid problems due to distinct covariate magnitudes, all inputs are standardised: centred to a mean of 0 and divided by their standard deviation (scaled). This allows the relative comparison of the variable importance within the context of the respective model.[24]

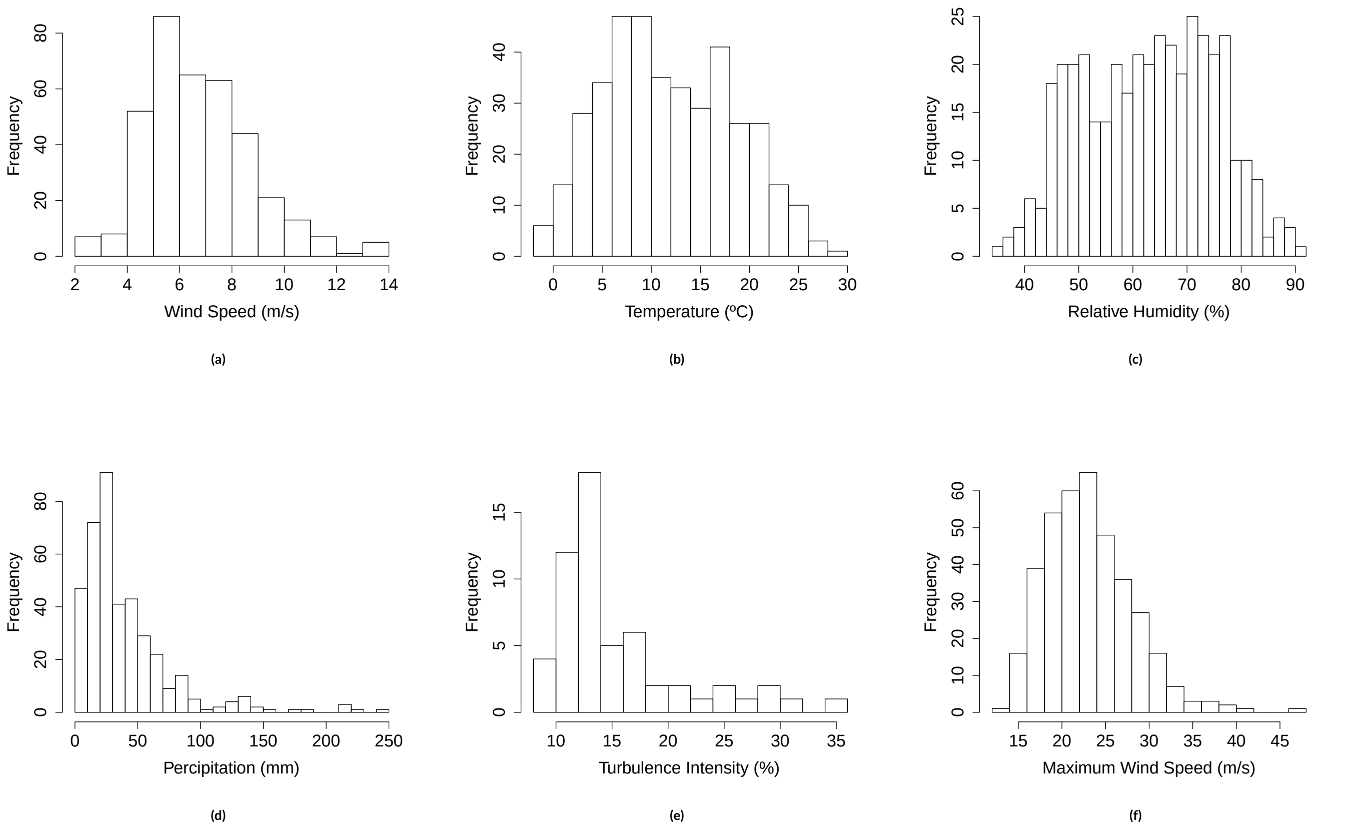


FIGURE 3 Histograms for the measured environmental data.

Figure 4 shows the correlation between the input variables. *TI* is excluded, as it was only available for two WFs. Red indicates negative and blue positive correlation. Although only pairwise correlation is displayed, it can be seen that many environmental variables are correlated to each other.

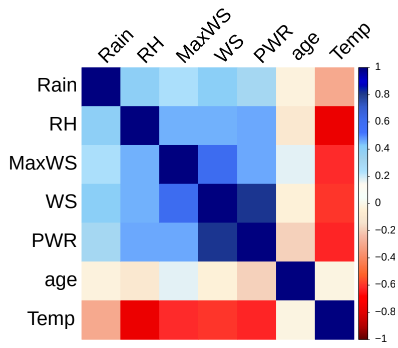


FIGURE 4 Correlation between the input variables.

2.2.1 | Model memory

Previous studies [14] have shown that the weather conditions can have a delayed and/or cumulative effect on the WT components. Thus, the environmental covariates of the previous month will be included in the model. This is further referred to as model memory and the additional covariates are indicated with a suffix *.mem*. With this, the total number of covariates rises from 11 to 17. The effects of this extension are discussed in Section 5.3.

3 | BACKGROUND AND PROBLEM STATEMENT

Modelling failures based on the environmental conditions can be realised in several ways. For continuous responses such as the time to failure of non-repairable systems with externally induced stresses, accelerated life models [25] or proportional hazard (PH) models [26], may be alternatives to the Weibull models.

These, however, are not appropriate when modelling discrete responses, such as the rate of occurrence of failures.

The latter are often modelled using Poisson regression, which is very similar to applying the PH model. Nevertheless, Poisson models have shown to perform poorly in certain situations causing several problems. The following Section 3.1 discusses the problems that come along with the Poisson regression and introduces three advanced alternatives. The latter result in increased model complexity and more sophisticated parameter estimation and variable selection (PEVS) methods must be considered, as shown in Section 3.2. The presented models in connection with the estimation techniques will be applied to the data and the most appropriate combination will be determined, as discussed in Section 3.3.

3.1 | Failure models

The Poisson distribution dictates that its mean is equal to its variance. Serious problems can arise with over-dispersed count data, having a larger variance than the Poisson distribution permits. Over-dispersion can occur due to a variety of reasons, such as e.g. the presence of unobserved effects (heterogeneity) and/or an abundance of zero counts in the data. Especially, when modelling the actual monthly failure observations (not the average of a typical year), the distributions of the latter are usually highly right-skewed. This was shown in Figures 2 a and 2 b of Section 2, where the number of zeros is significantly larger than the non-zero counts. In these cases Poisson models are likely to overestimate the number of failures.

The Poisson model is often extended to the negative-binomial regression model (NegBin), a mixture of the Poisson and a gamma distribution accounting for the unobserved effects.

In WT reliability modelling, Slimacek *et al.* [19] use a Poisson-Gamma model and maximum likelihood estimation (MLE) for estimating the model coefficients.

However, this could also be handled using more advanced modelling techniques. For example by considering two separate processes to model the failure counts and the zeros.

One process generates the structural zeros using a binary distribution, the other one is governed by a regular count process, such as the Poisson or even better the negative binomial distribution that generates counts including occasional zeros and takes into account heterogeneity. These types of models are often referred to as zero-inflated Poisson (ZIP), and zero-inflated negative binomial (ZINB) and have successfully been applied in many different research areas. [27] Having two separate processes, these models tend to have a very high number of regressors and are sometimes avoided for this reason. In combination with a suitable parameter estimation other than MLE and advanced variable selection methods, however, they can lead to much better results than other modelling techniques.

3.2 | Parameter estimation and variable selection (PEVS)

When dealing with high dimensional regression problems, two of the most serious issues are over-fitting (e.g. a model with too many input variables) and strongly correlated covariates (multicollinearity). Variable selection and regularisation are methods applied during the parameter estimation with the aim of reducing the number of model covariates to the most relevant ones. They often provide remedy for the mentioned issues.

Parameter estimation is usually carried out via maximum likelihood estimation (MLE), a popular procedure of finding the set of model parameters that maximizes a known log-likelihood function. MLE, however, does not provide any variable selection criteria and can lead to over-fitting and high variance of the coefficient estimates when including more model covariates.

Also, for small sample sizes and in the presence of high multicollinearity, MLE can be heavily biased. To avoid over-fitting and to select the best subset of input variables, several manual, forward, backward and stepwise model selection approaches have been developed. These techniques, however, received much criticism and are said to be quite unstable. Furthermore, multicollinearity is still a remaining issue.[28,29] Penalised likelihood estimation such as LASSO ℓ_1 (least absolute shrinkage and selection operator)[29] and ridge ℓ_2 (Tikhonov)[30] regularisation accomplish the same goal in an automatic, more stable, and computationally efficient manner. Additionally, they account for multicollinearity and LASSO is able to perform variable selection.

Nonetheless, besides having other excellent properties, LASSO has shown to be a highly biased estimate.[31] Thus, to overcome bias issues, further penalised regression techniques have been developed. Among these are the smoothly clipped absolute deviation (SCAD) penalty[31] and the minimax concave (MCP) penalty.[32] Both, SCAD and MCP initially apply the same penalisation rate as LASSO, but relax it towards zero with increasing coefficient values. Hence, they apply less shrinkage to the non-zero coefficients and with this reduce the bias. Still, LASSO, SCAD and MCP have certain limitations in the presence of collinearity, as they assume the independence between penalty and correlation among predictors.

The ridge ℓ_2 regularisation often performs better in the presence of highly correlated inputs.[33] But, since it does not perform variable selection, Zou *et al.*[33] proposed the elastic net (Enet) method combining the ℓ_1 and ℓ_2 penalties. With a similar objective, a combination of the MCP and ℓ_2 penalties called Mnet was proposed by Huang *et al.* [34]. Both, have the ability of eliminating correlated covariates as a group. Thus, there are very sophisticated alternative parameter estimation techniques to *MLE*, such as *Enet* and *Mnet*, which help to avoid bias in the regression coefficients, reduce multicollinearity and over-fitting, and guarantee an effective variable selection.

3.3 | Methodology and objectives

The objective of this paper is to extend existing research by developing models that directly consider the environmental conditions and are able to capture their combined effect on the failure behaviour of WTs and their components. As the weather significantly changes throughout the year, the failures are modelled on a monthly basis. Previously used regression techniques and parameter estimation methods, have not been found to entirely accomplish the objectives. Advanced alternatives need to be applied. Due to the very high numbers of (correlated) input covariates the latter, however, might require PEVS techniques other than MLE.

In order to find the most suitable modelling technique, four regression models, namely Poisson, NegBin, ZIP and ZINB in combination with three PEVS methods such as *MLE*, *Enet* and *Mnet*, are compared. To the authors' knowledge, these types of models and variable selection methods have not been applied in the field of wind turbine failure modelling yet.

To cover the most relevant aspects the following steps are carried out and will be presented in this order in the results section:

1. **Evaluating the model performance with MLE:** WT system failures and gearbox failures are modelled via Poisson, NegBin, ZIP and ZINB models in combination with MLE. The latter is a standard procedure for parameter estimation, does not delete input covariates and serves to understand the model performance when including all input variables. The gearbox was chosen to test the performance on component level as it is a critical sub-system and one of the most expensive and highly maintenance intensive components causing the highest downtime.[4,7]

2. **Effect of the model memory:** The benefits of including the environmental covariates of the previous month are shown.

3. **Performance of the PEVS methods:** This is evaluated by combining each of the four regression models with either Enet or Mnet regularisation and comparing the results with the ones of step 1. Figure 5 visualises this process. Due to limited space in this paper, this is carried out only for the gearbox failure data. WT components have shown to react differently to certain weather conditions and in some situations establishing separate models for each component is more useful for operators than modelling the whole WT system without further distinguishing between the failed components.

4. **Model Performance on data of a single wind farm:** Operators often need separate models for each WF to plan O&M actions properly. The combinations of environmental conditions can vary strongly at each site and affect the turbines differently. Thus, the capability of the proposed models for establishing separate WF models will be assessed in a final step.

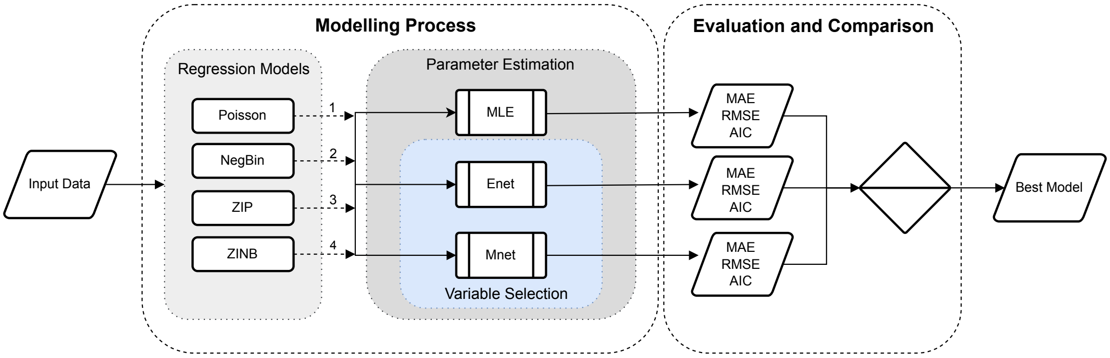


FIGURE 5 Modelling process for gearbox failures

4 | MATHEMATICAL FORMULATION OF THE MODELS

In Section 3 different models have been explained. Problems of current WT failure models including over-fitting, over-dispersion, excess zeros in the response variable, variable selection, heterogeneity and multicollinearity have been discussed. Possible solutions to these problems were presented. Their mathematical formulations are introduced in this section. To account for the different numbers of turbines per WF, the failure counts are modelled with an offset of the number of turbines. This is essentially the same as modelling the failures per turbine over a certain time interval (ROCOF).

4.1 | Regression models

This study uses four regression models: Poisson, NegBin, ZIP and ZINB; which are based on different probability distributions. The probability distribution for the Poisson model is given by:

$$\mathrm{Pr}(y_i|x_i) = \frac{\mu_i^{y_i}}{y_i!} e^{-\mu_i}, \tag{1}$$

where y is the response variable of non-negative integer values. The mean and variance are $E(y_i|x_i) = Var(y|x_i) = \mu_i = \exp(x_i\beta_i)$, with the estimation coefficients β_i. The covariates x_i for each observation i include the variables described in Section 2.2:

$$x_i = \begin{bmatrix} \text{age} \\ \text{Max.WS} \\ \vdots \\ \text{Rain.mem} \\ \text{RH.mem} \end{bmatrix}_i . \tag{2}$$

As previously discussed, the Poisson model can be extended to the negative-binomial (NegBin) model with the probability distribution:

$$\mathrm{Pr}(y_i|x_i, \theta) = \frac{\Gamma(y_i + \theta)}{y_i!\Gamma(\theta)} \left(\frac{\theta}{\theta + \mu_i}\right)^{\theta} \left(\frac{\mu_i}{\theta + \mu_i}\right)^{y_i}, \tag{3}$$

where $\mu_i = \exp(x_i\beta_i)$ and θ is a dispersion parameter adjusting the model regarding the degree of over-dispersion. The NegBin model is a Poisson mixture model, with mean $E(y_i|x_i) = \mu_i\tau_i = \exp(x_i\beta_i + \epsilon_i)$ and variance $Var(y|x_i) = \mu_i + \mu_i^2/\theta$, taking into account the unobserved effects $\tau_i = \exp(\epsilon_i)$, which follow a Gamma distribution.

As stated in Section 3, zero-inflated models use one process governed by a binomial distribution and a second one governed by a count distribution such as Poisson or negative binomial. The probability distribution for the zero-inflated Poisson (ZIP) model is:

$$\mathrm{Pr}(y_i|x_i) = \begin{cases} \sigma_i + (1 - \sigma_i)e^{-\mu_i} & \text{for } y_i = 0 \\ (1 - \sigma_i)\frac{\mu_i^{y_i} e^{-\mu_i}}{y!} & \text{for } y_i \geq 1 \end{cases}, \tag{4}$$

with mean $E(y_i|x_i, z_i) = \mu_i(1 - \sigma_i)$, variance $Var(y_i|x_i, z_i) = E(y_i|x_i, z_i)[1 + \mu_i\sigma_i]$ and $\mu_i = \exp(x_i\beta)$. The term σ_i is the zero-inflation probability and is given by the logistic link function $\sigma_i = \exp(\gamma_i z_i)/(1 + \exp(\gamma_i z_i))$, with the zero-inflated regressors z_i and parameters γ_i.

The probability distribution for the zero-inflated negative binomial (ZINB) model is denoted by:

$$\mathrm{Pr}(y_i|x_i, \theta) = \begin{cases} \sigma_i + (1 - \sigma_i)\left(1 + \frac{\sigma_i}{\theta}\right)^{-\theta} & \text{for } y_i = 0 \\ (1 - \sigma_i)\frac{\Gamma(y_i+\theta)}{\Gamma(y_i+1)\Gamma(\theta)}\left(\frac{\theta}{\theta+\mu_i}\right)^{\theta}\left(\frac{\mu_i}{\theta+\mu_i}\right)^{y_i} & \text{for } y_i \geq 1 \end{cases}, \tag{5}$$

with the logistic link function given above. The mean is $E(y_i|x_i, z_i) = \mu_i(1 - \sigma_i)$ and the variance $Var(y_i|x_i, z_i) = E(y_i|x_i, z_i)[1 + \mu_i(\sigma_i + \theta^{-1})]$, with x_i as defined in Eq. 2.

4.2 | Parameter estimation and variable selection (PEVS)

The PEVS techniques *MLE*, *Enet* and *Mnet* are used in this paper, as explained in the following.

Maximum likelihood estimation aims at finding the values for β that maximize the log-likelihood function $L(\beta|x_i) = \ln(\mathcal{L}(\beta|x_i))$ with the covariates shown in Eq. 2. As maximizing the log-likelihood is equivalent to minimizing the negative log-likelihood (loss-function), the MLE estimators are given by:

$$\hat{\beta}_{MLE} = \underset{\beta}{\operatorname{argmax}}\Big\{L(\beta|x_i)\Big\} = \underset{\beta}{\operatorname{argmin}}\Big\{-L(\beta|x_i)\Big\}. \tag{6}$$

In penalised regression, instead of minimising the loss-function, the objective function $M(\beta)$ is minimised:

$$\hat{\beta}_{pen} = \underset{\beta}{\operatorname{argmin}}\Big\{M(\beta)\Big\} = \underset{\beta}{\operatorname{argmin}}\Big\{-L(\beta|X) + \lambda P(\beta)\Big\}, \tag{7}$$

where $P(\beta)$ is the penalty function and λ is a parameter that controls the trade-off between the penalty and the fit. Subtracting the penalty introduces sparsity and shrinks the coefficients. The penalty function for the regularisation depends on the used technique. The *Enet* regularization penalty [33] is given as:

$$\lambda P(\beta, \alpha) = \lambda\left(\alpha||\beta||_1 + \frac{1}{2}(1-\alpha)||\beta||_2^2\right) \quad \text{with} \quad \lambda \geq 0, \tag{8}$$

where $\alpha \in [0, 1]$ controls the mixture between the ℓ_1 and ℓ_2 penalties. For $\alpha = 1$ a pure LASSO regression is obtained, penalizing the sum of the absolute values of the model coefficients $||\beta||_1 = \sum_{k=1}^{p} |\beta_k|$, where p is the number of model covariates. For $\alpha = 0$ the ridge penalty for model coefficients $||\beta||_2^2 = \sum_{k=1}^{p} \beta_k^2$ is applied. In this study an Enet with equal share of ℓ_1 and ℓ_2 penalty is used ($\alpha = 0.5$). The Enet estimates are defined as:

$$\hat{\beta}_{Enet} = \underset{\beta}{\operatorname{argmin}}\Big\{M(\beta; \lambda, \alpha)\Big\} \tag{9}$$

In contrast to *Enet*, which uses the ℓ_1 penalty in the first term, *Mnet* uses the *MCP*, which is given by [32]:

$$\lambda P(\beta, \gamma) = \sum_{j=1}^{p} \rho(|\beta_j|; \lambda_1, \gamma) + \frac{1}{2}\lambda_2||\beta||_2^2 \quad \text{with} \quad \lambda = (\lambda_1 \geq 0, \lambda_2 \geq 0), \tag{10}$$

with a regularisation parameter γ and:

$$\rho(\beta; \lambda_1, \gamma) = \begin{cases} \lambda_1\beta - \frac{\beta^2}{2\gamma} & \text{, for } \beta \leq \gamma\lambda_1 \\ \frac{1}{2}\gamma\lambda_1^2 & \text{, for } \beta > \gamma\lambda_1. \end{cases} \tag{11}$$

The Mnet estimator is defined as [34]:

$$\hat{\beta}_{Mnet}(\lambda, \gamma) = \underset{\beta}{\operatorname{argmin}}\Big\{M(\beta; \lambda, \gamma)\Big\} \tag{12}$$

For more detailed explanations of the three regularisation techniques, reference is made to the respective literature.[32–34] In all cases a K-fold cross validation (with $K = 10$) is carried out before fitting the models in order to find the appropriate shrinkage parameter λ that minimises the mean squared error.

4.3 | Model evaluation metrics

The proposed models will be fitted to the data and compared via the evaluation metrics: mean absolute error (MAE), root mean square error (RMSE) and the Akaike information criterion (AIC). The MAE and RMSE are given by:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\hat{y}_i - y_i)^2} \quad , \tag{13}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\sqrt{(\hat{y}_i - y_i)^2} \quad , \tag{14}$$

where $\hat{y}$ is the modelled and y the original data value. Both metrics express the average model error reaching from 0 to ∞. However, the RMSE is more sensitive to occasional large errors than the MAE. Furthermore, the width of the confidence intervals is proportional to the RMSE.

Additionally, the models will be compared using the AIC,[35,36] a measure of the relative quality of statistical models that have been applied to the exact same data set. It is defined as:

$$\mathrm{AIC} = 2k - 2\ln(\hat{\mathcal{L}}) \quad , \tag{15}$$

with the maximum value of the likelihood function $\hat{\mathcal{L}}$ and the number of estimated parameters k. For small data samples the AIC has been refined with a correction factor as[37] :

$$\mathrm{AICc} = \mathrm{AIC} + \frac{2k(k+1)}{n-k-1} \quad , \tag{16}$$

with the sample size n. The AIC and AICc account for the complexity of the models and increase with a higher number of model parameters.

According to literature,[38,39] the AIC and AICc have several advantages over the *F-Test*, and are supposed to find the most suitable model more reliably.

5 | RESULTS AND DISCUSSIONS

In this section the results of the evaluation steps explained in Sections 3.3 are presented. In order to facilitate the model interpretation some comments will be made firstly.

5.1 | Comments on the model interpretation

Several things need to be considered when analysing the effect of each regressor on the dependent variable. The latter can only be investigated when simultaneously assuming the other covariates to be constant. This, however, is very unlikely considering the dynamics of meteorological parameters. One has to keep in mind that due to the naturally high correlation between many weather parameters, the covariates that are deleted by *Enet* and *Mnet* estimations still need to be considered in the interpretation. Thus, the results have to be interpreted by combining the information for all of the meteorological parameters. This can be done by looking at the correlations between the different variables in Figure 6 . This graph shows the pairwise Pearson correlation values on the upper right triangle, the histograms and density functions of the data in the diagonal, and the data scatter-plots with smoothed lines (LOESS) on the lower left triangle. The following observations can be made:

- With increasing temperatures the WS and MaxWS decrease. Thus, these variables are highly negatively correlated.
- Temperature and RH are also negatively correlated.
- WS and RH are positively correlated.
- PWR is highly positively correlated with wind speed and maximum wind speed; and negatively correlated to temperature.
- Precipitation is not significantly correlated with the other input parameters.
- As RH is defined as the percentage of moisture held in the air in relation to the possible maximum moisture content at a given temperature, lower RH can be caused by both, higher temperatures and/or less precipitation. However, as shown in Figure 6 there is nearly no significant correlation between RH and precipitation. Whereas, the temperature seems to be more important for the RH changes.

5.2 | Performance of the regression models

Table 2 shows the model evaluation metrics for the four modelling techniques with *MLE* applied to the WT system failures. Table 3 displays the results for the gearbox failures. In both cases, the *ZINB*-models have a substantially better fit to the data indicated by the lowest values for all evaluation metrics. Furthermore, when comparing these results to other studies,[18] the error metrics for both models are significantly lower.

Figures 7 and 8 display hanging rootograms[40,41] of the models (with MLE) for WT and gearbox failures, respectively. Rootograms are useful methods to show the model fit to the data, and are able to display issues such as over-dispersion and problems with excess zeros. The distance between the bars and the reference line highlights the dissimilarity between expected and observed frequencies.[41] Figure 7 a and 8 a indicate

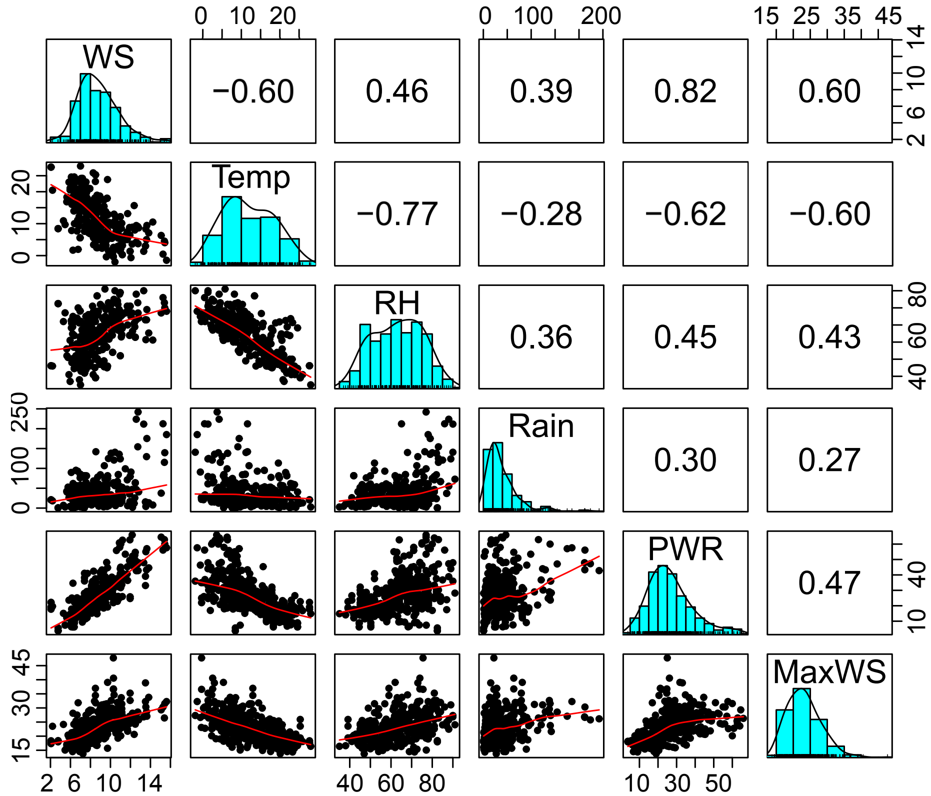


FIGURE 6 Correlation plots of the meteorological inputs.

TABLE 2 Evaluation metrics for the wind turbine failure models with MLE.

Measure	Poisson	NegBin	ZIP	ZINB
AIC	1144.73	1004.02	1056.88	991.45
AICc	1146.92	1006.21	1065.94	1000.51
MAE	1.226	1.206	1.242	1.137
RMSE	1.903	1.848	1.883	1.812

TABLE 3 Evaluation metrics for the gearbox failure models with MLE.

Measure	Poisson	NegBin	ZIP	ZINB
AIC	557.18	532.34	542.74	523.52
AICc	559.37	534.53	551.80	532.58
MAE	0.6005	0.6126	0.6430	0.5733
RMSE	0.7749	0.7827	0.7830	0.7572

that the Poisson model has problems with high over-dispersion and the zero counts. Figures 8 c and 7 c display the ZIP models, which still shows some degree of over-dispersion, but a significantly better fit for the zeros. Figure 7 b and7 d as well as 8 b and 8 d present almost identical results: NegBin and ZINB models handle over-dispersion and excess zeros significantly better than Poisson and ZIP.

Consequently, the *ZINB*-models show the best overall performance for both, the whole WT system and the gearbox failures. Comparing Tables 2 and 3 one can observe that the gearbox models have much lower errors. The WT system data contain any failed component during the observation period, and their failure behaviour is substantially harder to capture by models. Hence, as each component is affected differently by weather conditions the components should be modelled separately. Therefore in the following sections, only the results for the gearbox failure models will be displayed.

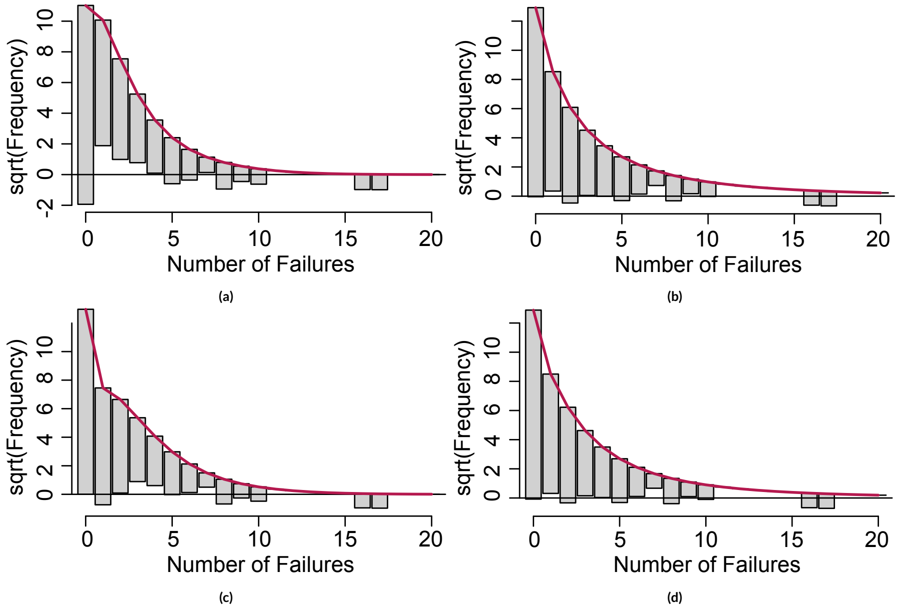


FIGURE 7 Rootograms for WT system failure models: (a) Poisson, (b) NegBin, (c) ZIP, (d) ZINB models.

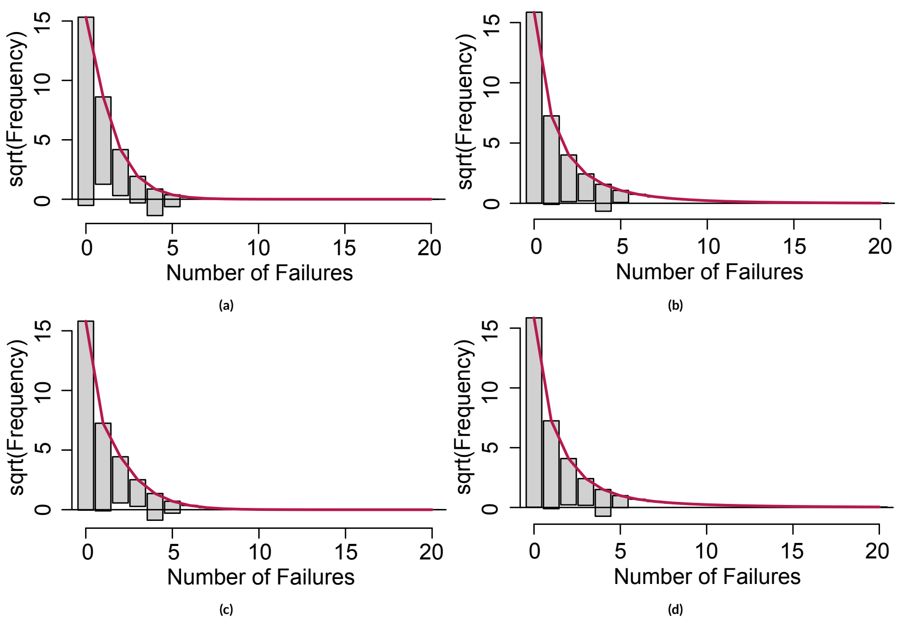


FIGURE 8 Rootograms for gearbox failure models: (a) Poisson, (b) NegBin, (c) ZIP, (d) ZINB models.

5.3 | Model memory

As the *ZINB*-model has shown the best results, it will be used to display the effects of including a model memory. For the present case MLE will be used in order to emphasize the effects of the model memory without eliminating covariates, as Mnet and Enet would do.

It can be seen in Table 4 that including a model memory significantly decreases the MAE and RMSE about approximately 9%. Although, the model with memory has more covariates, the AIC and AICc show lower values. This leads to the assumption that certain input covariates of the model memory are important and need to be included in the failure model. As introducing a memory results in a higher number of model covariates, previously discussed variable selection techniques should be considered for reducing model complexity by selecting the relevant covariates, as discussed in the following.

TABLE 4 Comparing *ZINB*-models with and without memory.

MLE		
Measure	ZINB without memory	ZINB with memory
AIC	542.63	523.52
AICc	544.82	532.58
MAE	0.6702	0.5733
RMSE	0.7936	0.7572

5.4 | Variable selection method

In this section the *ZINB*-model in combination with the *Enet* and *Mnet* penalty will be applied to the gearbox failure data. The resulting evaluation metrics are presented in Table 5 . It can be obtained, that the zero-inflated models out-perform the *Poisson* and *NegBin* models in both cases. *ZINB* again showed the best results. There is only approximately a 1% difference in *MAE* and *RMSE* for *ZINB-Enet* and *ZINB-Mnet*. However, the values for the AIC and AICc are in favour of the *ZINB-Mnet* model. Compared to Table 3 , *Mnet* also outperforms *MLE*.

TABLE 5 Evaluation metrics for the models with Enet and Mnet.

	Enet				Mnet			
Measure	**Poisson**	**NegBin**	**ZIP**	**ZINB**	**Poisson**	**NegBin**	**ZIP**	**ZINB**
AIC	554.19	530.85	512.36	508.32	552.43	527.39	503.27	494.45
AICc	555.34	532.18	513.88	510.80	553.76	528.72	504.42	495.43
MAE	0.6047	0.6103	0.6035	0.5468	0.6012	0.6090	0.5936	0.5503
RMSE	0.7776	0.7812	0.7768	0.7394	0.7754	0.7804	0.7704	0.7419

Tables 6 and 7 show the standardised model coefficients, standard errors and 95% confidence intervals for *ZINB-Mnet* and *ZINB-Enet* models respectively. As discussed in Section 4, θ is the model specific dispersion parameter.

The coefficients that were eliminated by the penalised regressions are not displayed, as they are not included in the resulting models.

TABLE 6 Results of the estimation of the ZINB models with Mnet.

Variable	Coefficient (β)	Standard Error	95% Confidence Interval
Intercept	-0.321	0.159	(-0.582, -0.060)
Rated Capacity	-0.327	0.160	(-0.591, -0.063)
Age	-0.430	0.137	(-0.655, -0.205)
Temp	-0.288	0.204	(-0.622, 0.047)
Rain	0.209	0.101	(0.043, 0.376)
RH.mem	-0.929	0.225	(-1.299, -0.559)
Log(θ)	1.139	0.777	–

The *Enet* model has 13 coefficients; the *Mnet* model has only six, while having a very similar fit (RMSE and MAE). Additionally, the *Mnet* model shows lower AIC and AICc values.

As most input variables are highly correlated (see Figure 6), *Mnet* successfully eliminated as many of the latter as possible in order to prevent collinearity. The *Enet* model tends to include most of them. Thus, the *Mnet* model is able to describe the data very well by only using very few of the input variables.

Furthermore, as the model with less complexity shall be preferred, the *Mnet* model results will be discussed further.

TABLE 7 Results of the estimation of the ZINB models with Enet.

Variable	Coefficient (β)	Standard Error	95% Confidence Interval
Intercept	-0.395	0.189	(-0.706, -0.085)
Rated Capacity	-0.336	0.158	(-0.596, -0.077)
Age	-0.314	0.173	(-0.599, -0.029)
WS	0.176	0.234	(-0.208, 0.560)
Temp	-0.512	0.255	(-0.932, -0.092)
PWR	-0.112	0.250	(-0.523, 0.300)
RH	-0.372	0.263	(-0.805, 0.060)
Rain	0.286	0.120	(0.089, 0.484)
WS.mem	-0.187	0.259	(-0.614, 0.239)
RH.mem	-0.704	0.288	(-1.177, -0.230)
Rain.mem	-0.097	0.138	(-0.323, 0.130)
PWR.mem	0.214	0.233	(-0.170, 0.598)
MaxWS.mem	-0.240	0.197	(-0.564, 0.084)
Log(θ)	1.294	0.895	–

5.4.1 | Interpreting the model covariates

By analysing the estimated coefficients of the *ZINB-Mnet* model given in Table 6 one can interpret the effect of each covariate on the model response. The following observations were made for non-environmental covariates:

- *Age:* The negative model coefficient for the covariate *age* suggests that the gearbox failures occur mainly in younger wind turbines. This is consistent with literature, where premature gearbox failures are often considered a principal problem of wind turbines. Although being designed for a life-time of 20 years, literature states that gearboxes frequently suffer from major damages within the first 2-11 years [42] or commonly fail at least once within the first 5 years [43] of their life-time. The most common cause of premature gearbox failures are problems with the gear bearings. [44,45]

- *Rated Capacity:* The negative coefficient for the model covariate *Rated Capacity* suggests that turbines with lower rated capacity suffer from more gearbox failures. This, however, could be also because the data base itself includes more WTs with lower rated capacity.

The coefficients of the meteorological covariates, show the following behaviour:

- *Rain:* The precipitation covariate has a positive coefficient, indicating that with more precipitation the gearboxes fail more frequently.

- *Temperature (Temp):* The model states that more gearbox failures occur for lower monthly mean temperatures. This is consistent with earlier findings. [14] Furthermore, during months with colder mean temperatures (winter), usually the mean wind speeds are higher. This causes increased wear on the gearbox.

- *Relative Humidity (RH.mem):* The negative coefficient for the model memory covariate *RH.mem* suggests that for lower mean relative humidities during the month prior to the gearbox failures, the latter occur more often.

As discussed in Section 5.1, some of the model covariates are highly correlated. For this reason combinations of the latter need to be interpreted while taking into consideration the failure modes of the component.

Failure Mode

Wind turbine gearboxes can fail in a variety of different ways. However, according to the National Renewable Energy Laboratory (NREL) gearbox failure data base, [46] more than 60% of all gearbox failures are directly related to the gear bearings. The principal reasons for WT gearbox bearing failures are oil degradation and contamination. Additionally, temperature related changes in oil viscosity can affect the gearbox. Oil contamination is caused by moisture, particles and entrained air (foam), which can result in high vibrations and wear. These contaminations can enter the gearboxes in a variety of ways. They could be introduced during manufacturing or maintenance or generated internally. Additionally, they can be ingested through air exchange with the ambient air. The latter occurs often during warmer months or due to diurnal temperature variations, which cause air to be sucked into the gearbox through the seals and "breathers". The typical breather systems in WT gearbox housings are usually not sufficiently preventing the contaminants from entering the system. The model suggests that the gearbox failures occur in the presence of these temperature variations, as discussed in the next two paragraphs.

The Month before Failure

The model indicates that the month before the failure is characterised by lower relative humidity and thus higher temperatures, lower mean wind speeds and less PWR. Although, the relative humidity might be lower at higher temperature, the increased air exchange contributes to a higher risk of contamination inside the gearbox. As the effect of these contaminations usually occurs time-delayed, the component might only fail after a certain period of time or when the operational conditions change due to higher wind speeds and/or increased operational time.

The Month of Failure

The month of failure is defined by lower temperatures. This is consistent with earlier studies carried out by the authors.[14] As the previous month was rather characterised by higher temperatures, this is likely to indicate a transition month from warmer to colder seasons. Especially, the daily temperature swings during these months can cause wear due to oil viscosity changes, which are resulting in less oil flow.[47] Additionally, temperature variations due to heavy rain facilitate further air exchange between the ambient air and the interior of the gearboxes through the breathers. Along with lower temperatures, usually higher mean wind speeds are registered, causing more WT shut-down and start-up events and higher times in operation. Under these conditions the gearboxes are mechanically challenged and possible damages due to previously entered oil contaminations can lead to a component breakdown. So, a combination of degraded and contaminated lubricant due to previous air exchange with the surroundings and problems with oil viscosity and higher loads during the failure month are affecting the gearbox life time behaviour negatively.

5.5 | Application of the model to a single wind farm

In Sections 5.2 to 5.4 it was shown that the *ZINB*-models with Mnet penalty perform significantly better than other combinations of modelling techniques. The latter has lead to very satisfying results when applied to a large data set containing several different WFs and turbine technologies. As distinct technologies can react differently to combinations of environmental conditions, operators might prefer modelling each technology separately. In order to test the model performance on a data set containing only one technology, a single WF taken from the data set presented in Section 2 is tested. As *WF-C* contained information for the turbulence intensity and with an age of 8 years represents a WF that is well into its useful life without being very old, the latter was chosen for the analysis. The results are expected to show slightly different model coefficients than for the whole data set. Figures 9 a and 9 b display the modelled versus the original monthly failures for *ZINB-Mnet* with and without the covariate TI. Furthermore, the constant failure rate that is usually assumed during the useful lifetime is displayed. Figure 10 displays the kernel density plots for the two set-ups. It is shown that the *ZINB-Mnet* model including TI performs best. Additionally, one can see that assuming a constant failure rate throughout the year leads to quite wrong assumptions and can delay the repair and maintenance processes for months.

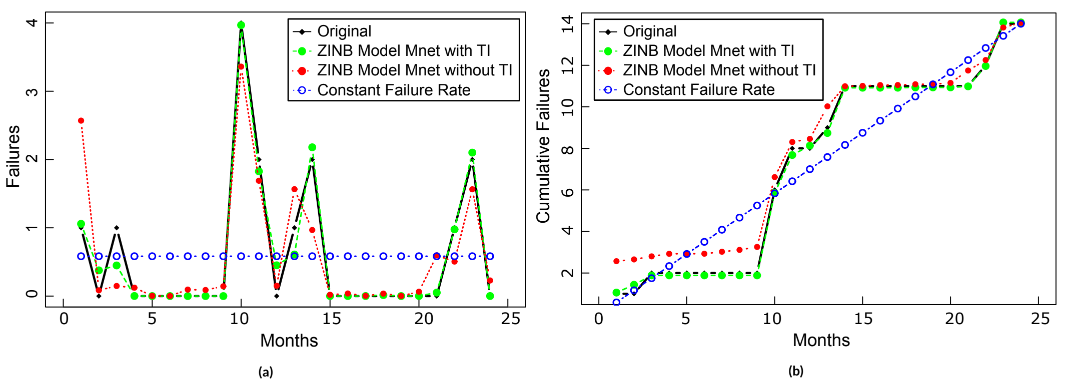


FIGURE 9 *WF-C* gearbox failure model with and without TI: (a) failures per month, (b) cumulative failures

As shown in Table 8 , including TI substantially increases the model performance. Significantly lower AIC, MAE and RMSE values were recorded when TI was included. As the model has one additional covariate, the difference between AIC and AICc for the model with TI is slightly higher. Nonetheless, its value is lower than for the model that does not include TI. When comparing the evaluation metrics to the results presented in Table 5 of Section 5.4, much lower errors were recorded when modelling a WT technology separately. This was an expected result, as the failure behaviour of distinct technologies and different sites varies.

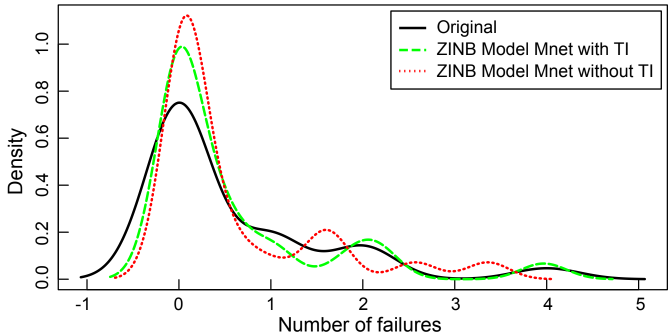


FIGURE 10 *WF-C*: kernel density plots of the original and modelled gearbox failures with and without TI

TABLE 8 Comparing the models with and without TI.

	ZINB-Mnet	
Measure	without TI	with TI
AIC	43.43	39.83
AICc	47.85	44.25
MAE	0.331	0.100
RMSE	0.485	0.192

In section 5.4.1 the terrain class was eliminated by both variable selection algorithms for modelling the gearbox failure data of all WT technologies. However, as the terrain complexity affects wind conditions such as the turbulence intensity, which has lastly shown to play quite a big role when modelling gearbox failures, the terrain complexity is entering indirectly into the model.

Table 9 displays the results for the estimation process of the *ZINB-Mnet* model with TI. Six environmental parameters were selected by the *Mnet* algorithm. Again, the combination of low temperatures and high precipitation raise the failure frequency. Additionally, increasing *TI* and *MaxWS* during the month of failure lead to more failures. The *Mnet* algorithm did not eliminate the *TI* covariate, showing that it is an important parameter for modelling the gearbox failures in this WF.

TABLE 9 *WF-C*: Results of the estimation of the ZINB model with Mnet including TI.

Variable	Coefficient	Standard Error	95% Confidence Interval
Intercept	-2.528	1.672	(-5.806 , 0.750)
Temp	-2.920	1.769	(-6.387 , 0.548)
Rain	2.154	0.845	(0.498 , 3.811)
TI	1.375	0.765	(-0.123 , 2.874)
MaxWS	4.286	2.021	(0.324 , 8.248)
WS.mem	0.746	0.542	(0.316 , 1.808)
TI.mem	0.518	0.312	(-0.095 ,1.130)

As the data set for *WF-C* was rather small, the coefficients show wider confidence intervals than the results of Section 5.4. Bigger data bases (longer observation periods) would be needed to obtain lower confidence intervals, which is likely to slightly affect the selection of the model coefficients. Nonetheless, it has been shown that for modelling one WT technology separately, the *ZINB-Mnet* model also performs very well, having even lower errors than when modelling several turbine technologies at the same time.

6 | CONCLUSIONS AND OUTLOOK

This paper presents a novel approach to model wind turbine failures based on the meteorological conditions the turbines are exposed to. Several regression models have been tested on the data. Suitable parameter estimation and variable selection techniques to reduce issues with high dimensional regression problems have been implemented and evaluated. To the authors' knowledge this is the first work of this type in the context of modelling WT failures based on environmental conditions.

The use of Zero-Inflated Negative Binomial models with Mnet penalty is proposed. The model takes into account unobserved effects (heterogeneity) with a Gamma distribution. It handles the excess numbers of zeros by using a separate process that generates the structural zeros, which is governed by a binomial distribution. The *Mnet* penalised regression has shown to be capable of selecting the most important input covariates very efficiently. Using the proposed model in combination with the penalised regression, helps to prevent several problems such as over-dispersion, overfitting, multicollinearity, etc. Including a model memory with the meteorological covariates of the previous month enhances the model performance significantly.

The proposed model has shown to perform well for modelling WT system failures of different turbine technologies without specifying the failed component. When considering the different components separately instead of modelling the whole system, the models performed even better, as the environmental conditions affect the components' reliability differently. This has been shown using a sub-set of the data containing only gearbox failures, which is one of the most critical WT components. The model reveals that low temperatures, high maximum wind speeds and precipitation affect the gearbox failure behaviour negatively. The findings related to wind speed are consistent with earlier studies.[15,21] However, this study extends the latter by developing a more thorough model with further environmental variables and including a model memory.

Furthermore, the model performance was tested on the failure data of a single wind farm. Different WT technologies behave differently when exposed to certain weather conditions. Consequently, operators frequently use separate models for each turbine technology. Modelling the different technologies and their components separately has shown to lead to the best results and is recommended for future studies in this context. However, in order to analyse WFs separately, further work shall consider bigger data bases. Model improvements could also take into account noise in the input variables by using e.g. error-in-variable models. Additionally, the authors will extend this study by modelling other WT components and including further operational SCADA data.

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References

1. O'Connor PDT, Kleyner A. *Practical Reliability Engineering*. West Sussex, United Kingdom: John Wiley & Sons, Ltd.; 5 ed.2012.
2. Van Kuik GAM, Peinke J, Nijssen R, et al. Long-term research challenges in wind energy – a research agenda by the European Academy of Wind Energy. *Wind Energy Science.* 2016;1(1):1–39.
3. Hahn B, Durstewitz M, Rohrig K. Reliability of Wind Turbines. In: Peinke J Barth S, ed. *Wind Energy: Proceedings of the Euromech Colloquium*, Springer Berlin Heidelberg; 2007; Springer Berlin, Heidelberg.
4. Wilkinson M, Harman K, Hendriks B, Spinato F, Van Delft T. Measuring wind turbine reliability, results of the reliawind project. *European Wind Energy Conference EWEC*, Brussels, Belgium, 2011.
5. Tavner PJ, Xiang J, Spinato F. Reliability analysis for wind turbines. *Wind Energy.* 2007;10(1):1–18.
6. Carroll J, McDonald A, McMillan D. Failure rate, repair time and unscheduled O&M cost analysis of offshore wind turbines. *Wind Energy.* 2015;19(6):1107–1119.
7. Reder MD, Gonzalez E, Melero JJ. Wind Turbine Failures - Tackling current Problems in Failure Data Analysis. *Journal of Physics: Conference Series.* 2016;753(072027):1–11.
8. Hahn B. Zeitlicher Zusammenhang von Schadenshäufigkeit und Windgeschwindigkeit. *FGW-Workshop Einfluss der Witterung auf Windenergieanlagen,.* 1997;.

9. Tavner P, Edwards C, Brinkman A, Spinato F. Influence of Wind Speed on Wind Turbine Reliability. *Wind Engineering*. 2006;30(1):55–72.
10. Tavner PJ, Greenwood DM, Whittle MWG, Gindele R, Faulstich S, Hahn B. Study of weather and location effects on wind turbine failure rates. *Wind Energy*. 2013;16(2):175–187.
11. Faulstich S, Lyding P, Tavner PJ. Effects of wind speed on wind turbine availability. *European Wind Energy Conference EWEC*, Brussels, Belgium, 2011.
12. Wilkinson M, Van Delft T, Harman K. The Effect of Environmental Parameters on Wind Turbine Reliability. *European Wind Energy Conference EWEC*, Copenhagen, Denmark, 2012.
13. Reder M, Melero JJ. Assessing Wind Speed Effects on Wind Turbine Reliability. *Wind Europe Summit*, Hamburg, Germany, 2016.
14. Reder M, Melero JJ. Time series data mining for analysing the effects of wind speed on wind turbine reliability. *Safety and Reliability - Theory and Applications, Proceedings of the European Safety and Reliability Conference*, Portoroz, Slovenia, 2017.
15. Wilson G, Mcmillan D, Ault G. Modelling the Effects of the Environment on Wind Turbine Failure Modes using Neural Networks. *International Conference on Sustainable Power Generation and Supply*, 2012.
16. Wilson G, McMillan D. Modeling the relationship between wind turbine failure modes and the environment. *Safety, Reliability and Risk Analysis: Beyond the Horizon - Proceedings of the European Safety and Reliability Conference*, 2014.
17. Wilson G, McMillan D. Assessing Wind Farm Reliability Using Weather Dependent Failure Rates. *Journal of Physics: Conference Series*. 2014;524(1):1–10.
18. Faulstich S, Berkhout V, Mayer J, Siebenlist D. Modelling the failure behaviour of wind turbines. *Journal of Physics: Conference Series*. 2016;749:1–11.
19. Slimacek V, Lindqvist BH. Reliability of wind turbines modeled by a Poisson process with covariates, unobserved heterogeneity and seasonality. *Wind Energy*. 2016;19(11):1991–2002.
20. Tavner P. J., Spinato F., Bussel G. J. W., Koutoulakos E.. Reliability of Different Wind Turbine Concepts with Relevance to Offshore Application. *European Wind Energy Conference, Brussels*. 2008;(April).
21. Reder Maik, Melero Julio J.. Modelling Wind Turbine Failures based on Weather Conditions. *Journal of Physics: Conference Series*. 2017;926:012012.
22. Reder Maik, Yürüşen Nurseda Y., Melero Julio J.. Data-driven learning framework for associating weather conditions and wind turbine failures. *Reliability Engineering & System Safety*. ;:554–569.
23. International Electrotechnical Commission . *IEC 61400-2: Wind turbines - Part 2: Power performance of electricity-producing wind turbines based on nacelle anemometry*. Geneva, Switzerland; 2013.
24. Denis DJ. *Applied Univariate, Bivariate, and Multivariate Statistics*. Hoboken, New Jersey: John Wiley & Sons Inc.; 2016.
25. Escobar LA, Meeker WQ. A Review of Accelerated Test Models. *Statistical Science*. 2006;21(4):552–577.
26. Cox DR. Models and Life-Tables Regression. *Journal of the Royal Statistical Society. Series B (Methodological)*. 1972;34(2):187–220.
27. Greene W H. *Econometric Analysis*. Pearson Education Limited: Pearson Education Limited; 7 ed.2012.
28. Whittingham MJ, Stephens PA, Bradury RB, Freckleton RP. Why do we still use stepwise modelling in ecology and behaviour?. *Journal of Animal Ecology*. 2006;75(5):1182–1189.
29. Tibshirani R. Regression Shrinkage and Selection Via the Lasso. *Journal of the Royal Statistical Society, Series B*. 1994;58:267–288.
30. Tikhonov A N, Arsenin V Y. *Solutions of Ill-Posed Problems*. Winston Washington, DC; 1977.
31. Fan J, Li R. Variable Selection via Nonconcave Penalized Likelihood and its Oracle Properties. *Journal of the American Statistical Association*. 2001;96(456):1348–1360.

32. Zhang C-H. Nearly unbiased variable selection under minimax concave penalty. *The Annals of Statistics.* 2010;38(2):894–942.

33. Zou H, Hastie T. Addendum: Regularization and variable selection via the elastic net. *Journal of the Royal Statistical Society: Series B (Statistical Methodology).* 2005;67(5):768–768.

34. Huang J, Breheny P, Lee S, Ma S, Zhang C-H. The Mnet method for variable selection. *Statistica Sinica.* 2016;26(402):903–923.

35. Akaike H. Information theory and an extension of the maximum likelihood principle, Tsahkadsor, Armenia, USSR. In: Petrov, BN and Csáki F, ed. *2nd International Symposium on Information Theory*, :267–281; 1973; Budapest.

36. Akaike H. A new look at the statistical model identification. *IEEE Transactions on Automatic Control.* 1974;19(6):716–723.

37. Hurvich C M, Tsai C-L. Regression and Time Series Model Selection in Small Samples. *Biometrika.* 1989;76(2):297.

38. Glatting G, Kletting P, Reske S N, Hohl K, Ring C. Choosing the optimal fit function: Comparison of the Akaike information criterion and the F-test. *Medical Physics.* 2007;34(11):4285–4292.

39. Kletting P, Glatting G. Model selection for time-activity curves: The corrected Akaike information criterion and the F-test. *Zeitschrift für Medizinische Physik*. 2009;19(3):200–206.

40. Tuckey JW. Some Graphic and Semigraphic Displays. In: Bancroft TA, ed. *Statistical Papers in Honor of George W. Snedecor*, Ames, Iowa: The Iowa State University Press 1972 (pp. 293–316).

41. Kleiber C, Zeileis A. Visualizing Count Data Regressions Using Rootograms. *The American Statistician.* 2016;70(2013):1–25.

42. Liu W. Chapter 13 - A concise filtergram wear particle atlas and some case studies. In: Makhlouf Abdel Salam Hamdy, Aliofkhazraei Mahmood, eds. *Handbook of Materials Failure Analysis with Case Studies from the Chemicals, Concrete and Power Industries*, Butterworth-Heinemann 2016 (pp. 311 - 353).

43. Ragheb A, Ragheb M. Wind Turbine Gearbox Technologies. *Proceedings of the 1st International Nuclear & Renewable Energy Conference (INREC)*, Amman, Jordan, 2010.

44. Evans M-H. White structure flaking (WSF) in wind turbine gearbox bearings: effects of "butterflies" and white etching cracks (WECs). *Materials Science and Technology.* 2012;28(1):3–22.

45. Greco A, Sheng S, Keller J, Erdemir A. Material wear and fatigue in wind turbine Systems. *Wear.* 2013;302(1-2):1583–1591.

46. Sheng S. Gearbox Typical Failure Modes, Detection and Mitigation Methods. *AWEA Operations & Maintenance and Safety Seminar*, 2014.

47. Guo P, Bai N. Wind Turbine Gearbox Condition Monitoring with AAKR and Moving Window Statistic Methods. *Energies.* 2011;4(12):2077–2093.

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