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DEVELOP THE FEED-FORWARD NEURAL NETWORKS FOR THE PREDICTION OF WIND TURBINE BLADE FATIGUE LOADS

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ABSTRACT

There has been a lot of interest in the use of machine learning in the wind power business in recent years. Artificial neural networks have been used to predict the fatigue loads of wind turbine components like rotor blades, with mean absolute percentage errors (MAPE) of 0.78% and 9.31% for the flap wise and edgewise directions, respectively, for a model trained and tested on the same turbine. One possible explanation for the discrepancy in question is a lack of data covering all possible edgewise moments. When NEWA data is used, the model's accuracy increases by 10% compared to MAPE values. The fact that the model did not improve when trained under varying wake situations indicates that the input characteristics adequately reflect the wake effects. When applied to data from other turbines, the model's generalization performance suffered in the flap-wise direction. It was shown that increasing the number of turbines used to train the model improved its ability to accurately anticipate loads on other turbines.

Keywords: Machine Learning, Feed-Forward Artificial Neural Network, Wind Power, Damage Equivalent Loads

1. Introduction

Wind power is a relatively new addition to the global energy scene, but it is gaining favor due to its benefits as a sustainable, ecologically friendly energy choice. As the world's foremost renewable energy producer, China puts a premium on wind power as part of its vigorous campaign to achieve carbon peaking and carbon neutrality. The International Energy Agency predicts that by 2020, China will have around 69GW of onshore wind

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generating capacity deployed. The broad adoption of wind power has given exciting new opportunities for the development of the free market, but it has also posed a number of challenging barriers, such as safeguarding the infrastructure, lowering prices, and guaranteeing enough energy supply. A wind turbine's drive train is especially susceptible to damage because of the wind's instability and temporal variability, which creates a challenging operating environment. The bearings are the beating heart of the drive train of a wind turbine, and their proper operation is essential to the machine's efficiency. In addition, the cost of maintenance may rise if a malfunction in the bearings caused a breakdown in the drive system or equipment downtime. However, this might be due to the limitations imposed by wind turbines' tall stature, sluggish speed, and large load in operation. Bearings are a pain to remove and examine, which adds complexity and expense to the operation and maintenance of wind generating equipment. Real-time fault diagnostics of wind power bearings are, hence, essential for enhancing the efficacy of wind power generation and preventing premature failures.

2. Literature Review

The focus of this study is on reducing the weight of retracted telescoping blades without sacrificing their efficiency. This one-of-a-kind telescopic Savonius turbine's torque, power, and rotor thrust are evaluated in an open jet wind tunnel. The extended and folded designs' dynamic and static characteristics are determined after the experimental data is corrected for wind tunnel blockage. An first numerical study looks at the variation of the drag coefficient with regard to the bucket thickness. The proposed telescoping turbine has a maximum power coefficient of 0.14 at a tip speed ratio of 0.7, resulting in a 72.4% decrease in thrust load compared to an extended operating configuration characteristic of Savonius turbines. For the same cost as other high-speed rotors, such as Darrieus or horizontal axis wind turbines, the telescoping Savonius turbine has the potential to produce more power.

Fernando Porté-Agel et.al (2020) Renewable energy, including wind power, is expected to grow rapidly over the next decades, playing a key role in mitigating climate change and achieving energy sustainability. As a result of multiscale, bidirectional interactions between wind farms and the turbulent atmospheric boundary layer (ABL), performance predictions for wind farms are notoriously challenging. Because of this, optimizing wind farm layout, operations, controls, and grid interconnection is challenging. From a fluid mechanical perspective, these interactions are complicated by the ABL flow's high Reynolds number, its inherent unsteadiness due to the diurnal cycle and synoptic-forcing variability, the pervasive nature of thermal impacts, and the diversity of the terrain. The effect of ABL turbulence on wind-turbine wake flows and their superposition is crucial because of the large power losses and fatigue loads they produce in wind farms. There are repercussions for the ABL structure and the turbulent momentum and scalar fluxes from these interactions. This article will cover the advances in our knowledge and ability to predict the effects of ABL flow on wind turbines and wind farms that have resulted from recent experimental, computational, and theoretical investigations.

Han Peng, Hai Zhang et.al (2022) A significant portion of the new renewable energy industry is made up of wind power due to its infinite regenerative capacity. Premature failure of essential components of wind turbines is a major issue in the wind energy

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industry, and the problem can be traced back to wind power bearings. The bearing in a wind turbine is crucial because it determines the transmission efficiency and the work performance of the whole machine. Bearing failure is the most common cause of wind turbine breakdowns, and insufficient lubrication is typically to blame. The issue of increasing the longevity and accuracy of bearing motion in wind turbines is becoming increasingly urgent as the wind power industry expands. This study compares and contrasts a variety of wind turbine bearing configurations. The most frequent causes of wear and lubricant failure were also investigated. In addition, the latest discoveries from research and development in lubrication technology and other domains, as well as other elements of wind turbine bearings, have been compiled. The study concludes with a summary of its results and suggestions for further research.

R. Fuentes et.al (2020) Faulty bearings are likely to blame for many issues with Winds Turbine (WT) gearboxes and, by extension, significant amounts of downtime for WTs throughout the globe. Since the rolling surface shape does not vary, damage to rolling element bearings starts below the surface, making it hard to detect with conventional vibration monitoring. Once the damage to the bearings has reached the surface, spalling occurs, and debris enters the oil system, the gearbox quickly deteriorates. It is critical that any damage be detected far before it reaches the bearing surface. Using Acoustic Emission (AE) data, we propose a method for locating subsurface damage in this investigation. It is widely established that AE measurements may identify developing damage. However, owing to noise and operational variations inside a bearing, damage diagnosis requires a rigorous statistical method. In this piece, we take a probabilistic approach to addressing this problem, namely using Gaussian mixture models. The procedures are proven effective by testing them on a full-size WT bearing setup. The bearings are deliberately seeded with faults at both the sub-surface and early-stage surface levels to assess the changes in detectability throughout the phases of a fault's propagation.

Ahmed N-s Abufroukh et.al (2018) As demand for wind turbine technology increases, the government of the United Kingdom has announced a variety of incentives to encourage the fast expansion of the wind turbine business. By 2023, the United Kingdom plans to have installed roughly 806MW of small and medium turbines, saving the equivalent of 0.8 million tonnes of pollutants in the process. Eventually, a turbine's primary shaft, bearings, gearbox, and generator will all wear down, therefore it's necessary to plan for their upkeep. The bearing is one of the most common sources of failure. Due to the large range of potential reasons, including pollution, inadequate lubrication, and harsh operating conditions, bearing element failure may take many forms and occur anywhere. However, they are ignored by the recommended ISO281 rated life (L10) computation. Therefore, the bearing's lifespan is notoriously hard to estimate. By reviewing the available literature, we were able to identify the most often encountered issues with bearings, generators, brakes, and main shafts in small wind turbines. The next step, reciprocal condition monitoring, is what we use now to identify failure. Finally, we spoke about a few innovative strategies that may be used to increase the efficiency of the machinery. Tools used to construct the test bench for this investigation and interconnected sensors and controllers used to develop the IHMS are shown as examples of the hardware and software developments in the next chapter.

3. Data and Methodology

First, the framework and provenance of the data utilized in this analysis are published here. The correlation between DEL results and other characteristics is investigated. After that, the data is analyzed to shed further light on the situation by depicting the available data under various wake conditions and power curves. Following this, the technique that was used in order to utilize the data for the study's intended purpose is detailed. Two feed-forward neural networks were trained using data from the Lillgrund wind farm to provide fatigue load predictions for the blade root in flapwise and edgewise directions.

Evaluation Of the Effect of Different Features on The Moment Values

We start by analyzing the effect of several variables on the DEL values for turbine B8 to see which ones, if any, contribute to the projections. Because of its proximity to the wind farm's boundary, our knowledge of its loading patterns, and the fact that it need not be shut down, this turbine was selected. We may examine the effect of the waking state without thinking about how the use of other power curves may have affected the observation. However, the effect of using different power curves is determined separately for each kind of turbine. Since gaining a better understanding of the current database is the primary objective of this study, qualitative methods predominate. First, using what we know about the physical loads we see (Figure 1 and Figure 2), we assess the eight most influential variables on the DEL values. Table 1 provides a concise summary of the outlier filtering procedure to avoid ambiguity and misinterpretation.

Table 1 The summary of applied filters on data

Variable	Considered range
Mean wind speed	3.5-25 m/s
Mean power	$Power > 0$
M_{eq} $edgewise\ blade$ 2	$150 - 3000\ kN.m$
M_{eq} $flapwise\ blade$ 2	$500 - 1500\ kN.m$

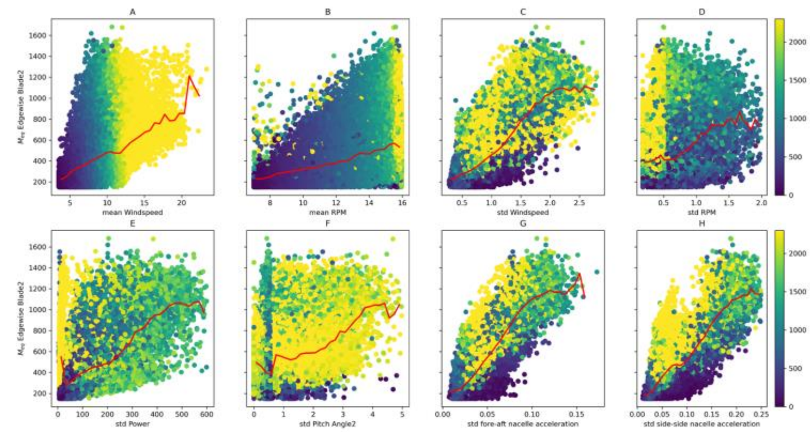

Figure 1: The Meq edgewise blade 2 [kN.m] values vs features values, mean power coloured [kW], redline is the Meq mean value for each bin of the studies features

Figure 2 shows that the flapwise moment increases with increasing wind speed up to the set value. Once it reaches the rated power range, it lowers and stabilizes, showing that the control system's regulation is having the desired effect. This agrees with the observation that the thrust coefficient decreases with increasing wind speed.

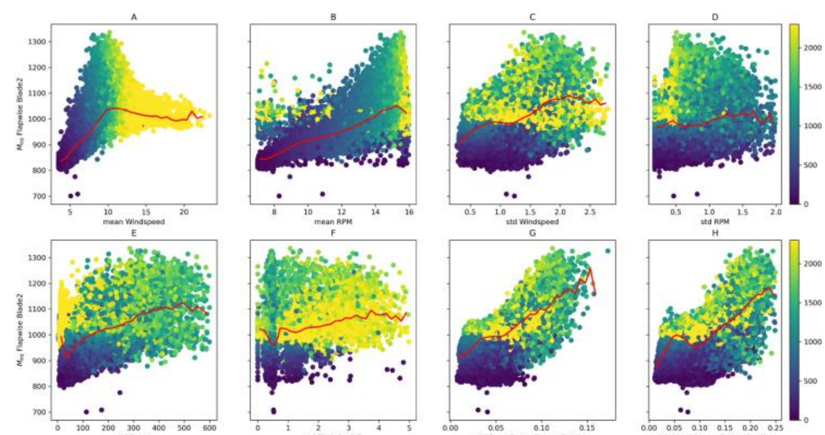

Figure 2: The Meq Flapwise blade 2 [kN.m] values vs features values, mean power coloured [kW], redline is the Meq mean value for each bin of the studies features

The original dataset is provided in a unique format that may be foreign to the user and need extensive explanation. Thus, initially, data from many months are compiled into a single file, data for individual turbines are clustered together, and column titles are assigned. The simplified database design is shown in Figure 3.

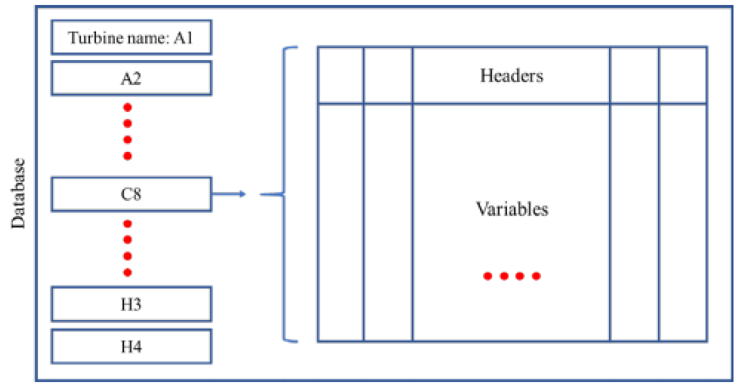

Figure 3: The structure of the reorganized database

The information gained from analyzing the data for the relevant factors is then used to filter the results, removing any anomalies. Furthermore, only operational data has been used. This means that the average wind speed is only considered at those locations in the dataset that fall between the turbine's cut-in and cut-out speeds. Extraneous details are eliminated as well. The status flag of the turbine is not utilized, but the electrical output is.

Base Model's Performance

In order to train the data from turbine B8 using the fundamental model outlined in 4.3, we first choose 14 attributes. This will be used as a yardstick against which the final models may be judged. The results are summed up in Table 2.

Table 2 The performance indicators for ANN trained on B8 Turbine using 14 features

	$MAPE$	$NRMSE$	R	R^2
M_{eq} $edgewise\ blade$ 2	11.57	16.57	0.96	0.93
M_{eq} $flapwise\ blade$ 2	1.21	2.46	0.95	0.91

The accuracy of the model's label regeneration is shown on the test dataset by comparing normalized prediction values to normalized actual values, as shown in Figures 3 and 5. Distributions of MAPE values for different numbers of test datapoints are shown in Figures 5 and 6, respectively. The distribution of errors often looks like a bell curve, with a peak at zero. Error values are higher for the edgewise bending moment than the flap wise bending moment. Figures 7 and 8 show that after 10 iterations, the loss value on the training and validation datasets has stayed stable, indicating that the model has converged. Training and validation sets' loss values are so similar that overfitting is impossible.

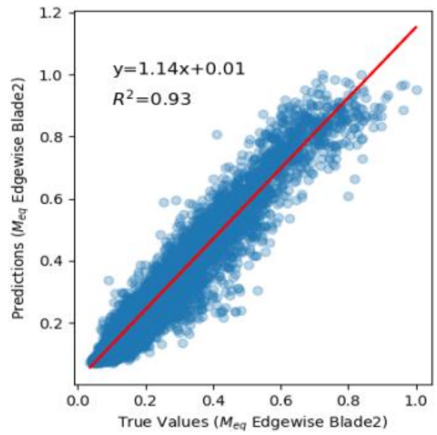

Figure 4: Normalized predictions vs Normalized true values for the Meq edgewise blade 2, redline linearly fitted to data

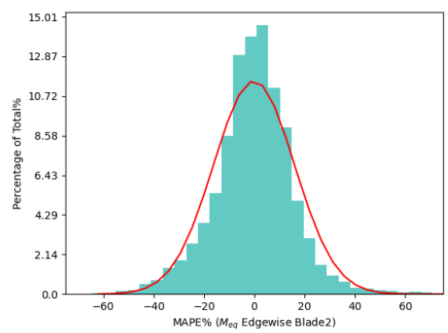

Figure 5 MAPE distribution for Meq edgewise blade 2, redline normally fitted to data: it does not represent the range of all observations to increase the readability of the figure

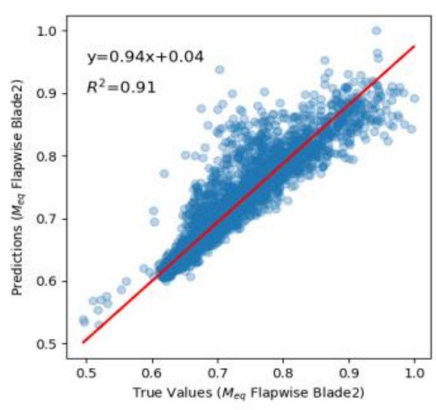

Figure 6 Normalized predictions vs Normalized true values for the Meqflapwise blade 2, redline linearly fitted to data

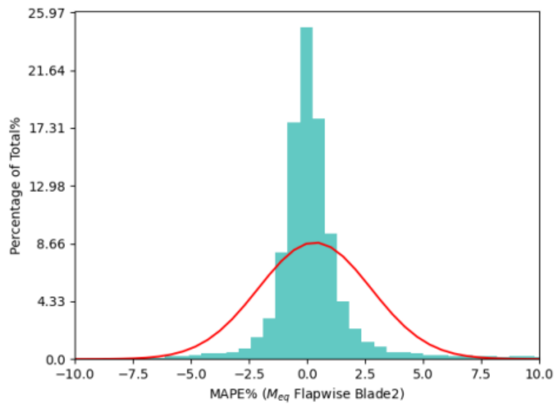

Figure 7 MAPE distribution for *M*eq flap wise blade 2, redline normally fitted to data: it does not represent the range of all observations to increase the readability of the figure

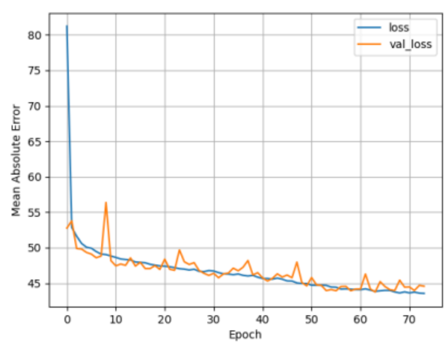

Figure 8 Convergence for the trained ANN vs Number of Epochs for *M*eq edgewise blade 2

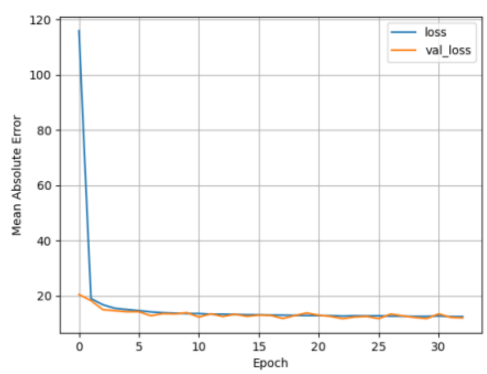

Figure 9 Convergence for the trained ANN vs Number of Epochs for Meq flap wise blade 2

5. Conclusion

The purpose of this study was to examine the viability of training a neural network on 5-minute data from the Lillgrund offshore windfarm to make damage equivalent load predictions in the edgewise and flapwise directions for wind turbine blades. Different wake circumstances and the effect of various factors, such as mesoscale NEWA data, on the model's accuracy, are investigated. The idea of using the model created in this work to forecast the DEL values for turbine blades in situations when load data are unavailable was also explored.

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