Estimation of Wind Turbine Performance Degradation with Deep Neural Networks

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ABSTRACT

In this paper, we estimate the age-related performance degradation of a wind turbine working under Norwegian environment, based on a deep neural network model. Ten years of high-resolution operational data from a 2 MW wind turbine were used for the analysis. Operational data of the turbine, between cut-in and rated wind velocities, were considered, which were pre-processed to eliminate outliers and noises. Based on the SHapley Additive exPlanations of a preliminary performance model, a benchmark performance model for the turbine was developed with deep neural networks. An efficiency index is proposed to gauge the age-related performance degradation of the turbine, which compares measured performances of the turbine over the years with corresponding bench marked performance. On an average, the efficiency index of the turbine is found to decline by 0.64 percent annually, which is comparable with the degradation patterns reported under similar studies from the UK and the US.

1. INTRODUCTION

With the current emphasis on clean and secure energy supply, the global wind power sector is growing significantly in the recent years. From the cumulative wind power installations of 743 GW in 2020 (Global Wind Energy Council, 2021), the global wind capacity may reach up to 6044 GW by 2050 (International Renewable Energy Agency, 2019). This could make wind to be one of the major energy resources, contributing more than one-third of the total global energy demand. Hence, wind energy would play a significant role in the future clean energy scenarios.

Power generated from the turbines over its life span is one of the most important factors deciding the technical feasibility and economic viability of any wind energy project. The normal life span of a turbine could vary from 20 to 25 years, depending on the design features and operational environments (Adedipe, & Shafiee, 2021; Ziegler, Gonzalez, Rubert, Smolka, & Melero, 2018). Some of the recent studies have reported longer life span for different wind energy projects, ranging from 25 to 40 years and averaged to 29.6 years (Wiser, & Bolinger, 2019). Performance of the wind turbines decline gradually during this life period. There are several reasons for this age-related performance degradation. The mechanical wear and tear of various components over time could affect the turbine's performance, reliability, as well as efficiency (Hamilton, Millstein, Bolinger, Wiser, & Jeong, 2020; Pan, Hong, Chen, Feng, & Wu, 2021). Another major reason for this declining performance is the reduction in aerodynamic efficiency due to material erosion over the blade tips (Sareen, Sapre, & Selig, 2014; Zweiri et al., 2022).

Despite its significant influence on the techno-economic viability of wind energy projects, the age-related efficiency reductions in these systems are not systematically analyzed extensively. As reported by Staffell and Green (2014), most of the earlier studies focused on the component level system reliability and availability.

One of the earliest studies addressing the age-related efficiency degradation was by Hughes (2012), where ten years of operational data from windfarms in the UK and Denmark were used. Performance degradation was represented as the variations in normalized load factor (capacity factor) over the years. The normalized load factor was computed based on monthly productions from the windfarms and the corresponding indices on average wind speeds. The load factor for the UK onshore windfarms declined by 13% within 15 years of its life, whereas the corresponding decline reported for Danish turbines was 4%. Offshore farms showed faster degradation compared to the onshore systems. Similar results were also reported by Staffell and Green (2014) in which 282 windfarms in the UK were considered. The ideal power curve of the turbines in windfarms, along with the corresponding wind speed simulated using the NASA model, were used to compute the theoretical power production. This is then compared with the reported monthly load factors to estimate the performance decay. Under this study, turbines were found to lose 1.6 ± 0.2% of their output per year.

In later years, studies on Swedish wind turbines were conducted by Olauson, Edström and Rydén (2017). They found that the turbines could suffer 6 % reduction in capacity factor during their lifetime. Similar performance reduction is reported in the case of German turbines as well (Germer, & Kleidon, 2019). In a more comprehensive analysis involving 917 plants, Hamilton et al. (2020) quantified the age related performance changes in the US windfarms, interestingly, in a policy perspective as well. Under this study, the capacity factor point percentages were reported to decline by 0.53% and 0.17% for older and newer projects respectively.

The above studies have significantly contributed in identifying and understanding the age-related performance issues in wind turbines. Different rates of degradation reported in these studies highlights the regional and site-specific nature of the issue. Nevertheless, these studies are based on the cumulative data from several windfarms, collected from public sources. With the site-specific nature of the degradation pattern, an analysis based on the data from a specific farm/turbine could give a better insight in to the issue. With the extensive deployment of SCADA systems in windfarms, time series performance data from the turbines are available which can be used to develop data driven degradation models as suggested by Astolfi, Castellani, Lombardi and Terzi (2021). Compared to the monthly averaged information used in some of the previous studies, analyses based on the high-resolution SCADA data can bring out more precise understanding on the issue.

In view of this, Dai, Yang, Cao, Liu and Long (2018) analyzed the aging pattern of wind turbines based on SCADA data. However, to eliminate the effects of weather conditions and turbine's operational parameters on the results, the power variations above the rated speed were only considered in the analysis. As the effect of power deficits are more prominent from cut-in to rated wind speeds, inclusion of data from this dynamic operating region of the turbine is essential for such analysis. Study by Kim and Kim (2021), based on the SCADA data, uses the turbine's power curve for performance comparison. As discussed in Veena, Mathew and Petra (2020), limitations of manufacturer's power curve in understanding the site specific dynamics of the velocity-power response of the turbines has been well established in several previous studies. Further, the analysis is based on four years performance of the turbines, which may not be sufficient to capture the time series performance degradation. Other significant studies based on SCADA data, focused on same turbine model installed at Irish and Italian sites, can be seen in Byrne, Astolfi, Castellani and Hewitt (2020) and Astolfi, Byrne and Castellani (2021). The turbine at the Italian site showed an efficiency reduction of 1.5% over 12 years, whereas the corresponding degradation at the Irish site was 8.8%. These studies further reinstate the site dependencies of the performance degradation phenomena.

To the best of the authors' knowledge, studies on the age-related degradation pattern in turbines working under the Norwegian environment have not yet been reported. In this paper, we present such a first-time analysis based on the time series performance of a 2 MW wind turbine installed at a Norwegian site.

One of the distinct features of this study is the deep neural network (DNN) based site specific benchmark model. The strength of neural networks is that it can approximate any Borel measurable function from a finite dimensional space to another, if sufficient amount of hidden neurons are present in the network (Goodfellow, Bengio, & Courville, 2016). Compared to conventional machine learning (ML) algorithms, neural networks perform extremely well in learning non-linear relationships between variables (Somers, & Casal, 2009). DNNs improve on neural networks with the presence of two or more hidden layers between the input layer, and the output layer. Furthermore, traditional ML algorithms require feature engineering i.e., features must be extracted from the data to learn its relationship with the target. However, DNNs extract the necessary features from the data based on the learning task at hand. This allows the model to be trained with raw input data to learn the underlying representations (Janiesch, Zschech, & Heinrich, 2021).

Other features of the study are the improvement and explainability of the DNN models through SHapley Additive exPlanations (SHAP) analysis and the proposed performance deficit index based on the overall efficiency ratio of the turbine.

After this introductory section, the paper is arranged as follows. Initially, the description of the data used for the analysis and its preprocessing methods are discussed. This is followed by the details of a preliminary DNN based performance model and its SHAP analysis. Architecture of the proposed DNN bench marking model is then introduced along with the model performance analysis based on different error metrics. The efficiency index for quantifying the age-related performance deficit is then defined and the performance degradation of the turbine over the years, estimated based on the efficiency index, is presented.

2. DATA DESCRIPTION AND PREPROCESSING

A pitch-controlled wind turbine with 2 MW rated capacity, installed in a Norwegian site, was chosen for the study. The turbine has cut-in, rated and cut-out wind speeds of 3.5 m/s, 15 m/s, and 25 m/s respectively. The turbine has a rotor diameter of 82.4 m, and the system is installed over a tower

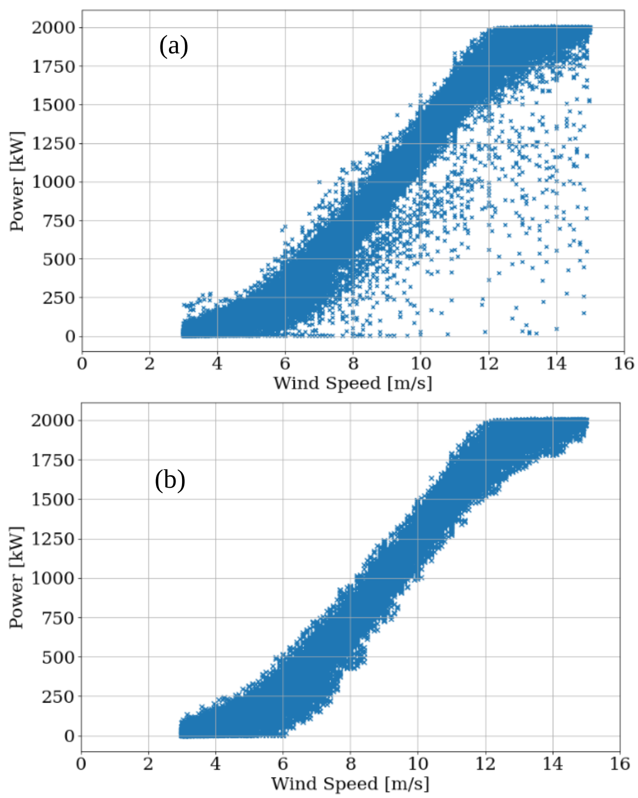

Figure 1. (a) Raw performance data of the turbine between the cut-in and rated wind speeds. (b) data after cleaning the outliers using DBSCAN

Table 1. Details of the SCADA data used for the study

No	Measurements
1	Wind speed
2	Standard deviation of wind speeds
3	Pitch positions of the blades and the pitch reference
4	Yaw position
5	Generator RPM
6	Main shaft RPM
7	Power

of 70 m height. SCADA data from the turbine during the period 2007 to 2017, at 10 min temporal resolution, were collected for the study (Under the non-disclosure agreement, the data cannot be shared with this paper). Various measurements related to the operational and control settings of the turbine were available out of which the most relevant parameters (see Table 1) were considered for the analysis.

Wind turbines have two distinct operational regions viz. the dynamic region corresponding to the cut-in to rated wind velocities, and the deterministic region corresponding to the rated to cut-out velocities (Veena et al., 2020). Out of these, performance of the turbine between the cut-in and rated wind velocities were considered for this study. This is because the performance degradation of the turbine is expected to be prominently observable between the cut-in to rated velocities. Above the rated velocity, output is regulated to rated power by the control system and hence the degradation would be masked.

The data corresponding to the cut-in to rated region as above contains outliers and noises as shown in Figure 1 (a). These outliers are caused by various reasons like malfunctioning of sensors and logs, downtime of the turbine, power curtailments, weather related factors like icing etc. To eliminate these anomalies, the data has been filtered using density-based spatial clustering of applications with noise (DBSCAN), proposed by Ester, Kriegel, Sander and Xu (1996). DBSCAN is a clustering method which efficiently identifies the arbitrary-shaped clusters and noises in the dataset and thereby filters and cleans the undesired data outliers. Figure 1 (b) shows the performance data from the turbine over the study period, cleaned using DBSCAN.

3. PRELIMINARY MODEL AND SHAP ANALYSIS

Data on various operational parameters were available in the dataset. Out of these, features listed in Table 1 were chosen for the analysis based on the Pearson and Spearman correlations of these variables with the power generated by the turbine.

With these input features, a preliminary performance model for the turbine was developed based on the data from 2007. Purpose of this model was to enhance the model interpretability through explainable AI (XAI) (in contrast to the black box approach in traditional AI methods). The datasets were divided into three groups for training (60%), validation (20%), and testing (20%). The preliminary model was developed using the deep neural network architecture with back propagation of errors for training. Under the error analysis, the preliminary model showed an MAE, RMSE, and MSE of 27.76 and 31.90, and 1017.76 respectively on the test data previously not seen by the model. With this acceptable accuracy, the model was further analyzed using SHAP, introduced by Lundberg and Lee (2017). SHAP, which is a unified approach to interpret the model's predictions, is used here to explain the prediction of power generated at an instance by calculating the respective contribution from each of the features selected for the model development. SHAP unified seven different methods in explainable AI to provide a framework to interpret the predictions made by a machine learning model, both locally (for a single instance) and globally (across N number of instances). SHAP is based on Shapley values (Shapley, 1952), a collaborative game theory method that involves fairly distributing both gains and costs to actors working in a coalition. The mathematical

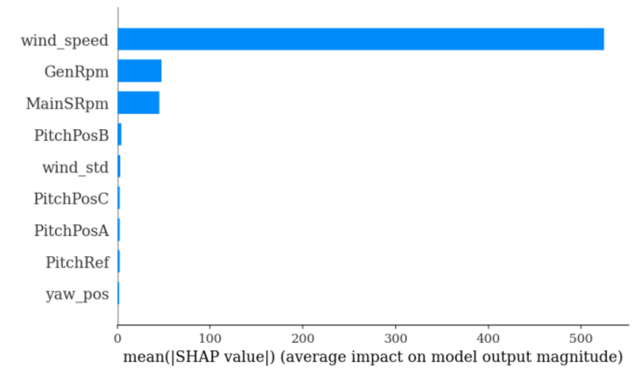

Figure 2. The average SHAP values for various input features for the preliminary model

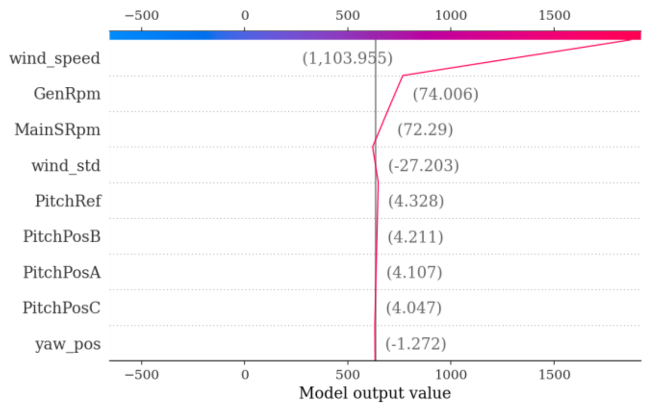

Figure 3. SHAP values for the preliminary model corresponding to a single sample

formulations for computing the SHAP values can be found in Lundberg, and Lee, 2017 as well as Molnar, 2020. For robust calculation of the contributions from each feature and to verify how the model uses these features as a whole for making predictions, 100 random samples were passed on to the model and their corresponding SHAP values has been calculated using the Kernel SHAP method, which is a model-agnostic method and is detailed in Lundberg and Lee (2017). The mean absolutes of the SHAP values, corresponding to each feature, were computed, and are shown in Figure 2. The wind speed has the highest mean absolute value of SHAP, which is then followed by generator and rotor shaft RPMs respectively.

Similar result is observed in the SHAP values in local explainability (in case of a single sample) as well, which is presented in Figure 3. The figure shows how each feature contributes towards pushing the prediction away from the base value. The base value or the expected value is the average of the model outputs over the samples. The red bars indicate an increase in power prediction over this base value corresponding to a particular feature and the blue shows a decrease in prediction. Here also, wind speed and generator & rotor shaft RPMs form the significant contributions towards the power prediction.

Though the SHAP analysis do not imply causalities explicitly, it helps in interpreting the model's predictions by explaining the contribution of each feature towards the model output and hence in finding the feature saliency in a model prediction.

4. BENCHMARK MODEL

A site-specific performance model for the turbine, based on its operational data in 2007, was developed for bench marking the turbine's performance. This benchmarked performance can be compared with the turbine's productivity in later years for identifying the age-related performance degradations.

From the SHAP analysis, it is evident that the predictions made by the preliminary model is mostly explained by the wind speed, followed by speeds of the generator and the main shaft. Contributions from other features are relatively low.

Further, some of these measurements were not consistently available during the later years in which the turbine performance is to be compared with the benchmarked performance. In view of these, wind velocity, generator speed (as the speeds of the main shaft and generator are correlated through the gear ratio), and the yaw position were chosen as input features of the proposed benchmark model. These chosen model inputs were further tested for multi-collinearity using the variation influence factor (VIF) analysis and found to be within acceptable limits (Sulaiman et al., 2021). The data were then divided in to three groups for training (60%), validation (20%) and testing (20%). As in the preliminary model, the benchmark model was also developed using deep neural network with back propagation of errors for training. He-Normal initialization (He, Zhang, Ren, & Sun, 2015) has been done for the kernel and rectified linear unit (ReLU) was used for the activation functions. L2 regularization was used for the kernels and adaptive moment estimation (Adam) optimizer was used for the model development. The model architecture was optimized through iterations taking MAE as the principal error measure while RMSE and MSE were also monitored. The model was trained and validated under 100 epochs and the best performing model across the three monitored errors was chosen. Caution was taken to avoid any over or under fitting of the model by tracking the errors in training and validation during the model development, as shown in Figure 4. As evident from the figures, both training and validation errors are under reasonable limits, which rules out the possibility of underfitting. Further, it can also be seen that the model does not overfit to the training dataset as the training and validation errors closely follow each other.

The structure of the benchmark model is shown in Figure 5. The model consists of an input layer with three nodes, two

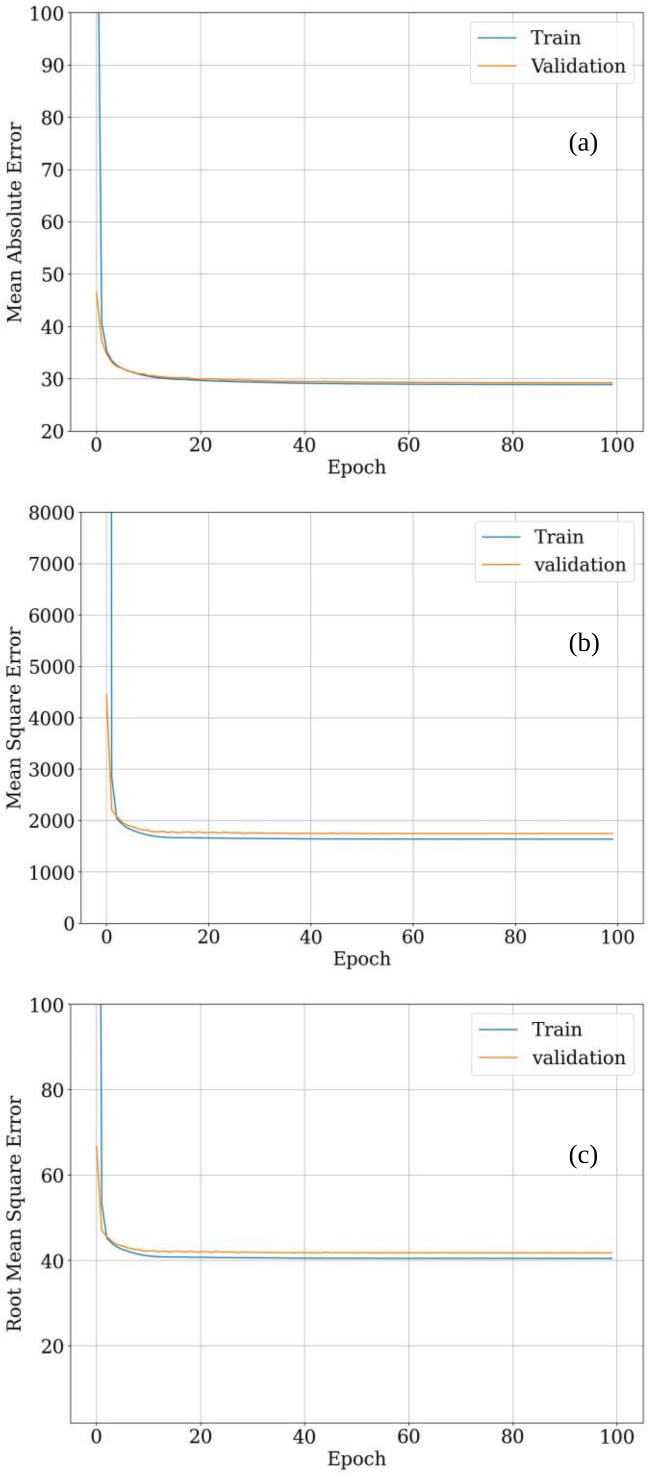

Figure 4. Variations in various error measures across epochs during the training process (a) MAE, (b) MSE, (c) RMSE

fully connected hidden layers with 16, and 32 neurons, respectively, and an output layer with a single neuron.

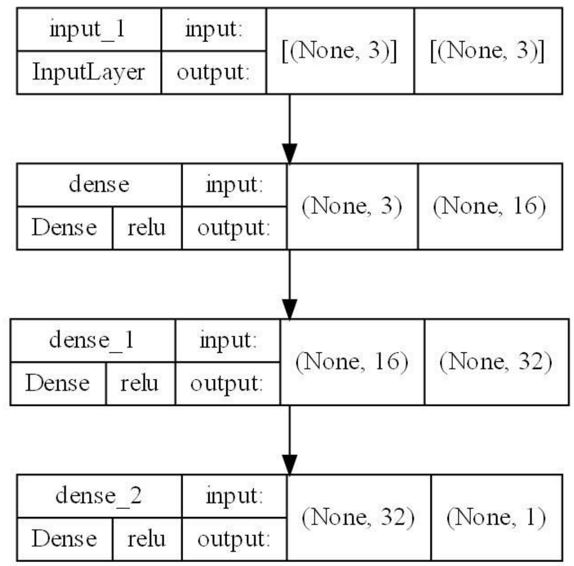

Figure 5. Architecture of the DNN benchmark model

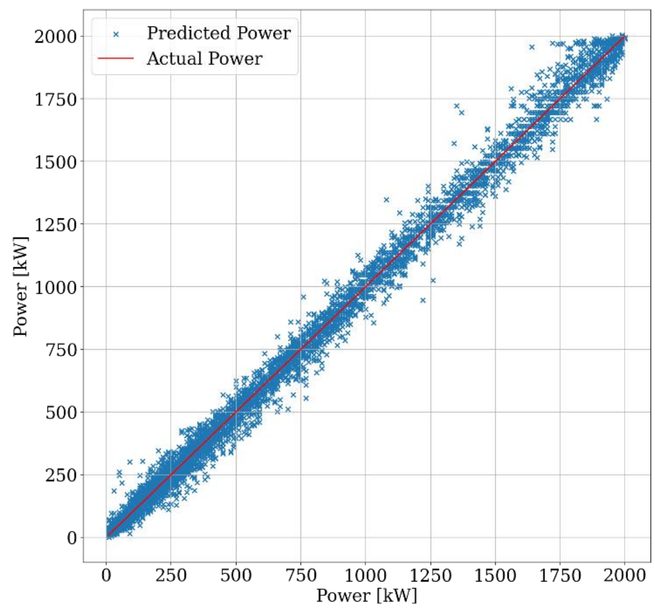

Figure 6. Comparison between the model predictions and the measured power

The model thus finalized was tested with the test dataset which was not seen by the model previously. The power predicted by the model (scattered points) is compared with the corresponding measured power (represented by the red line) from the turbine as represented in Figure 6. With an R squared value of 0.996, the proposed benchmark model could efficiently capture the performance variations of the turbine under various operating conditions. This is further evident in Figure 7, where the monthly averaged predictions and measurements over the study period are compared.

Performance of the benchmark model on the test dataset is further quantified with various error metrics like MAE,

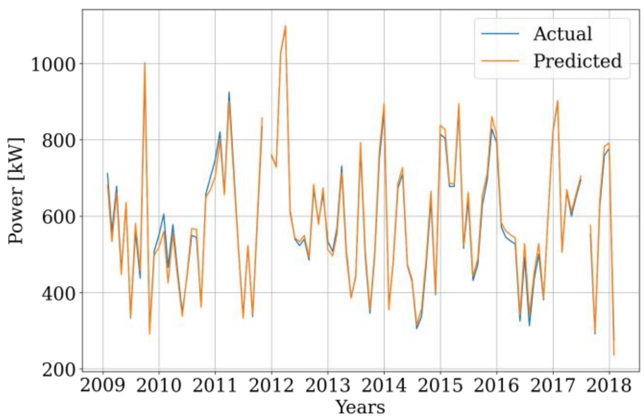

Figure 7. Comparison between the power predicted by the model and the actual power on monthly basis

RMSE, and MSE which were found to be 29.30, 41.37, and 1711.43 respectively.

In Veena et al. (2020), four different algorithms have been used to estimate the performance of a similar wind turbine of 2 MW size in a different location. Artificial neural network (ANN), support vector machine (SVM), k-nearest neighbors (k-NN), and multivariate adaptive regression splines (MARS) algorithms were used for this purpose. Even though the SVM performance is found to be better by the authors, the benchmark model developed using the DNN architecture outperforms all these algorithms. The MAE of the SVM model was found to be 91.10 while in our study, the MAE is 29.30. Thus, with a significant improvement in the monitored metrics, the use of DNN for model development is justified.

To explain the power prediction by the benchmark model, SHAP analysis has been conducted as discussed in the previous section. The results are shown through Figure 8 and Figure 9. As in the preliminary model, the output power prediction for the turbine is significantly contributed by the wind speed followed by generator RPM and yaw position. The explainability of this model helps in identifying the feature contributing to each individual prediction. Such an explanatory analysis, in contrast with the black box approach of the traditional AI models, could help windfarm operators and system managers in understanding the model better and thereby adopting it for decision making during the day-to-day operations. Further, explainable AI could also be used to identify problems the model may run into and can help in debugging the issues. With these high accuracies and explainability, the benchmark model was used for estimating the age-related performance degradation of the turbine as discussed in the next section.

5. Efficiency Index

In most of the previous studies, age related performance decline of windfarms was estimated based on the data from several farms, considering the aggregated changes in

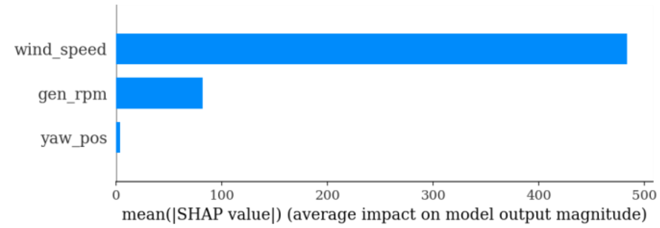

Figure 8. The average SHAP values for various input features of the benchmark model

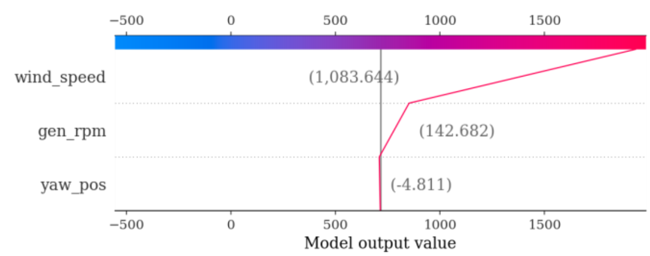

Figure 9. SHAP values for the preliminary model corresponding to a single sample

normalized capacity factor over the years. In this study on a specific turbine which is based on the high-resolution data collected from the SCADA system, the performance decline is measured through the time series drop in the turbine's overall efficiency The power input from the wind to the turbine (P_{in}) is given by:

$$P_{in} = \frac{1}{2} \rho_a \, A_T \, V^3 \tag{1}$$

where ρ_a is the density of air, A_T is the area of the wind turbine's rotor and V is the incoming wind velocity. Whereas the power developed by the turbine at this wind velocity is given by:

$$P_T = C_P \, \eta_{tran} \, \eta_{gen} \frac{1}{2} \rho_a \, A_T \, V^3 \tag{2}$$

where C_P is the power coefficient of the turbine, η_{tran} is the combined efficiency of the drivetrain and η_{gen} is the generator efficiency.

Hence, the overall efficiency of the turbine η_T can be expressed as

$$\eta_T = \frac{P_T}{P_{in}} = \frac{P_T}{\frac{1}{2} \rho_a \, A_T \, V^3} = C_P \, \eta_{tran} \, \eta_{gen} \tag{3}$$

In this study, the age-related performance degradation of the turbine is proposed to be gauged through the time series decline in the efficiency index (η_I) of the turbine which is defined as

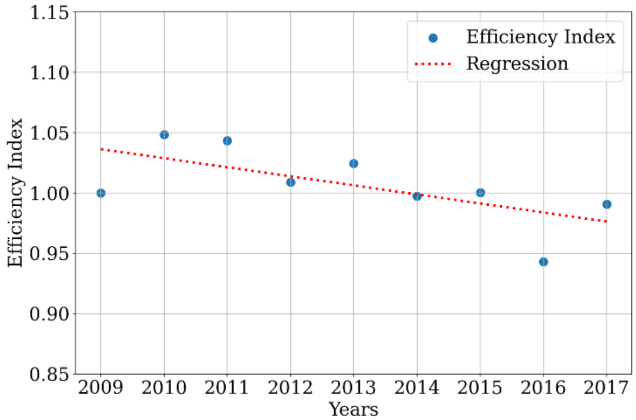

Figure 10. Decline in the efficiency index of the turbine over the years

$$\eta_I = \frac{\eta_{T_{Measured}}}{\eta_{T_{Modelled}}} \quad (4)$$

where $\eta_{TMeasured}$ is the overall efficiency of the system at a given wind velocity, estimated based on the actual measured power, and $\eta_{TModelled}$ is the corresponding system efficiency based on the power predicted by the model at the same wind velocity.

6. PERFORMANCE DEGRADATION PATTERN

The Power developed by the turbine during the years from 2009 to 2017 were predicted by running the benchmark model with the 10 min resolution input data corresponding to these years (2008 was not included due to excessive missing data points during this year). The data points were further reduced after the data filtering and pre-processing as discussed in section 2. The overall system efficiencies, corresponding to these model predictions ($\eta_{TModelled}$) were calculated using Eq. (3). Similarly, the efficiencies corresponding to the measured power ($\eta_{TMeasured}$) was also calculated. From these, the efficiency indexes (η_I) were computed using Eq. (4). These efficiency indexes were then averaged over different years and regressed as shown in Figure 10. It can be observed that the efficiency indices of the turbine decline over the years, indicating the age-related performance degradation of the system. One of the major causes of this performance degradation could be the gradual wear and tear of the turbine's power transmission components and generator.

However, these issues are usually resolved during the maintenance of the system. Another significant reason for this could be erosion of the rotor blade tips, which will adversely affect the aerodynamic performance of the rotor and thereby the power coefficient, C_p. In this context, it is worth mentioning that the site at which the turbine is installed is exposed to extreme weather events like heavy rain and snow, which will aggravate the tip erosion of the blades.

The annual average decline in the efficiency index of the turbine is 0.64 %. This value is between the reported average degradation of 0.53% per year for the US systems (Hamilton et al., 2020) and 0.87 % for turbines in the UK (Hughes, 2012). However, the degradation rate of this Norwegian turbine is less than the reported rate of 1.6% per year under another UK based study by Staffell and Green (2014). These differences in the reported degradation rates could be due to the variations in the environments under which the systems are exposed while in operation.

7. CONCLUSIONS

In this paper, we analyze the age-related performance degradation of a 2 MW wind turbine, working under the Norwegian environment. Ten years of high-resolution operational data from the turbine were used for this analysis in which the actual performance of the turbine over the years were benchmarked with the performance of the system modelled based on its initial year's performance data. For this, a DNN based preliminary performance model was developed which was interpreted through SHAP analysis. Based on this, an efficient benchmark model for the turbine's performance was developed with an optimized DNN architecture. An efficiency index has been proposed to estimate the age-related performance decline of the turbine from its expected benchmarks. The age-related performance degradation of the turbine is evident from the declining trend of the efficiency index over the years of operation. On an average, the efficiency index of the turbine was found to decline by 0.64 percent every year of its operation. In spite of the slight differences in the degradation rates, the current estimates on the performance decline of the Norwegian turbine are comparable with the results from similar studies on the US and the UK based turbines. The results of the study can give some useful indications for the timely interventions for performance enhancement of the turbine through appropriate overhauling and refurbishing. Further, the analysis can be extended for the estimation of the Remaining Useful Life (RUL) of wind turbines using efficient Recurrent Neural Network architectures like Long Short-Term Memory (LSTM).

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