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To cite this article: M Martin et al 2020 J. Phys.: Conf. Ser. 1669 012030

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Identification and prioritization of low performing wind turbines using a power curve health value approach

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1669 (2020) 012030

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Abstract. Since operational managers often monitor large numbers of wind turbines (WTs), they depend on a toolset to provide them with highly condensed information to identify and prioritize low performing WTs or schedule preventive maintenance measures. Power curves are a frequently used tool to assess the performance of WTs. The power curve health value (HV) used in this work is supposed to detect power curve anomalies since small deviations in the power curve are not easy to identify. It evaluates deviations in the linear region of power curves by performing a principal component analysis. To calculate the HV, the standard deviation in direction of the second principal component of a reference data set is compared to the standard deviation of a combined data set consisting of the reference data and data of the evaluated period. This article examines the applicability of this HV for different purposes as well as its sensitivities and provides a modified HV approach to make it more robust and suitable for heterogeneous data sets. The modified HV was tested based on ENGIE's open data wind farm and data of on- and offshore WTs from the WInD-Pool. It proved to detect anomalies in the linear region of the power curve in a reliable and sensitive manner and was also eligible to detect long term power curve degradation. Also, about 7% of all corrective maintenance measures were preceded by high HVs with a median alarm horizon of three days. Overall, the HV proved to be a promising tool for various applications.

1. Introduction

In the past decade, the global wind industry experienced an extensive growth and continuously decreasing levelized cost of energy (LCOE). Subsidies are rapidly declining or are not necessary anymore, e.g., bids of 0 ct/kWh [1] in offshore wind power tenders. In this cost-driven and highly competitive environment, operation and maintenance (O&M) costs account for about 25% to 35% [2, 3, 4, 5] of the LCOE. O&M strategies aim at high energy yields and low O&M costs at the same time. Predicting downtimes and detecting energy losses as well as degradation is, therefore, of increasing importance for operational managers.

Operational managers of wind turbines (WTs) often monitor large numbers of WTs remotely without in situ observations. In this digitalized environment, they depend on reliable tools to identify and prioritize low performing WTs, schedule preventive maintenance measures and detect long term degradation. Examples for frequently used tools are key performance Content from this work may be used under the terms of the Creative Commons Attribution 3.0 licence. Any further distribution

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1669 (2020) 012030 doi:10.1088/1742-6596/1669/1/012030

indicators (KPIs) [6, 7] to monitor the long-term performance of WTs or condition monitoring systems (CMS) [8, 9, 10] to monitor specific components. Many research activities focus on methods to detect abnormal operational behavior (anomalies) of WTs based on data of the supervisory control and data acquisition system (SCADA) without a need for additional measurements/sensors [11, 12, 13, 14]. Also, long-term performance degradation remains an essential issue in performance monitoring, as studies [15, 16, 17] indicate annual degradation rates of 0.1% to 1%.

Nevertheless, power curves remain a frequently used tool by operational managers to monitor the operational behavior and performance of WTs. Compared to more sophisticated monitoring tools, the main advantage is their simplicity and applicability in case the data basis is small, a fact which is particularly crucial for older WTs. For operational WTs, power curves are usually derived according to the IEC standard 61400-12-2 [18], but many more modeling approaches exist as Sohoni et al. [19] showed. Recent studies showed the broad applicability of power curves as a reference for intended operational behavior and to detect deviations. Ciulla et al. [20] modeled power curves using Artificial Neural Networks (ANN) to identify faulty conditions with higher reliability. Astolfi et al. [21] combined power curves and measurements of the relative wind direction to detect WT misalignment. Guo and Infield [22] used a Gaussian Process to construct a power curve model and used it to identify abnormal operation and for fault identification. He and Kursiak [23] followed the copula approach instead for the same purpose. In combination with vibrational data, power curves can also be used to trace down icing events, as Skrimpas et al. [24] showed.

Instead of modeling a reference power curve Jia et al. [25] pursued a different approach by introducing the power curve health value (HV). In order to identify abnormal measurements they performed a principal component analysis (PCA) to compare a reference data set for the linear region of power curves to sample data sets. The results of the HV approach were encouraging but based on only one WT and just two years of operational data and have not been validated against a more extensive data set yet.

The present paper investigated the applicability of the HV as a holistic indicator of performance and degradation information. It evaluated its strengths and weaknesses based on both on- and offshore WTs. Therefore, we implemented and modified the approach to work for different data sets, even if only minimal measurements were available. Besides, we performed a sensitivity analysis to identify the importance of different information and data-preprocessing. The presented modified approach incorporates the gained insights.

The scope of this work was to validate the usefulness of the HV to detect both, short-term power curve anomalies as well as long-term degradation, and to investigate its potential to predict downtime. To allow for replicability of the results, data from ENGIEs open data wind farm "La Haute Borne" [26] was used for an initial evaluation of the approach and a sensitivity analyses. The wind farm comprises four Senvion MM82 WT with a rated power of 2 MW each and is located in the department Meuse in northeast France. For each WT, operational data over about six years with a resolution of 10 minutes was available. Data from the Wind Energy Information Data Pool (WInD-Pool) [27] was used for more detailed investigations based on German on- and offshore wind farms. Due to confidentiality restrictions, further details on the WInD-Pool-Data cannot be provided.

2. Methodology

2.1. The health value approach and its implementation

The power curve of a WT represents its electrical power output as a function of the wind speed. In the case of intended operation, the operational data of a WT should match the expected power curve. Thus, deviations to the power curve can indicate technical issues. Although it is not a typical KPI, it is an essential and frequently used tool for O&M to investigate the

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performance characteristics of WTs [6]. The HV approach focuses on the linear region (see Figure 1a) of power curves as a holistic indicator to evaluate the performance and degradation of WTs since performance issues are particularly evident in the partial load range. It compares the evaluated sample data to preselected reference data (baseline). Technical issues and, as a result, reduced rotor power coefficients or deterioration of mechanical or electrical efficiency affect the performance in the linear region but are likely to become concealed as soon as the rated power is reached [28].

As for all power curve approaches, proper preprocessing of the SCADA-data was crucial to obtain sound results, see Section 2.1.1. The HV was calculated using the PC2-Dev algorithm initially introduced by Jia et al. [25], which performed a PCA on the quasi-linear region of power curves to identify anomalies, see Section 2.1.2. An overview of the implementation of the modified HV approach is given is Section 2.1.3.



Figure 1: Combined power curve before (a) and after projection into the PC-space (b).

2.1.1. Data-preprocessing and selection of the linear region. Data-preprocessing removed unnecessary or invalid information from the SCADA data before the HV investigation. Several steps were required, such as wind speed correction, eliminating downtime and derated operation, selecting the quasi-linear region, and removing outliers and noise - see Figure 1a.

For power curve assessments, it is best practice to correct power curves due to the influence of air density and wind speed turbulence according to the IEC 61400-12-2 [18]. These corrections are supposed to improve the comparability of data obtained under varying environmental conditions and to eliminate seasonal effects. In the present work, both corrections complemented the data-preprocessing of the HV approach. The air density correction of the wind speed strictly followed the IEC 61400-12-2 [18]. If air density data was missing, the air density could be derived from air pressure measurements or approximated based on the ambient temperature and altitude. The turbulence correction, as described by IEC 61400-12-1 [29] and the Power Curve Working Group [30], could not be used for the HV approach since it directly corrects the resulting power curve instead of its underlying measurements.

Alternatively, a zero turbulence effective wind speed was introduced. This metric represents the constant wind speed needed to obtain the same wind power density as that achieved by a lower averaged wind speed with turbulence over an averaging period of five or ten minutes. It makes average wind speeds with differing turbulences comparable. Following the IEC 61400-12-2 [18], this correction assumed normally distributed wind speeds over the averaging period

of 10 minutes. The normal distribution is defined by the average wind speed and its standard deviation (turbulence). Equation (1) weighs the wind speed distribution according to the cubic relation between wind speed and power to calculate the zero turbulence effective wind speed. For the present work, the integration interval was set from 0 m/s to 50 m/s, but could be further decreased in other cases to reduce computation time.

$$v_{\sigma=0} = \sqrt[3]{\int_{v=0}^{50} v^3 f(v) dv}$$
(1)

where

 $v_{\sigma=0}$ = zero turbulence effective wind speed, f(v) = wind speed distribution within 10-minute period.

Modern WTs are equipped with active power control to ensure that the rated power and corresponding design limitations are not exceeded even at high wind speeds. In most cases, power control is implemented by adjusting the rotor blade pitch angles. Since the HV approach focuses on the linear region of the power curve, periods of rated and derated operation were not of interest. Thus, periods in which the WT was operated with pitched rotor blades were excluded from the data set. Alternatively, operational modes can be used to exclude periods of derated operation when pitch angle measurements are not available, provided they comprise this information.

Below the cut-in wind speed, the WT does not operate, and above the rated wind speed, no effect of degradation can be expected due to adaptation of the plant control system. Therefore, it was essential to limit the data set to this quasi-linear region of the power curve to obtain useful degradation information. Only with a correct selection of the quasi-linear region, the PC2-Dev algorithm using PCA could provide proper results since PCA is restricted to linear or quasi-linear data sets [31]. For this reason, the present work complemented the HV by a dynamic selection of the linear region based on the reference data set for every WT. The linear region was determined in an iterative process which assessed the linearity of the data by the correlation coefficient of linear regressions. It decreased the range of the linear region step-by-step until the correlation coefficient was stable or worsened.

Depending on the quality of the data set, outlier detection and elimination were not always necessary but increased the accuracy of the approach and are thus recommended. The DBSCAN algorithm [32, 25] or other methods such as the K-Means clustering algorithm provided by the NREL OpenOA Library [33] can be used for this purpose.

2.1.2. Health value calculation. PCA is one of the most popular dimensional reduction methods. It is generally used as a multivariate statistical technique to convert data sets with many quantitative dependent inter-correlated variables into a data set of linearly uncorrelated variables, the so-called principal components (PCs) [34]. The PC2-Dev algorithm described by Jia et al. [25] served less dimensional reduction; instead, it utilized PCA as a technique for axis transformation. The following procedure was required to apply the PCA [31]:

- create a covariance matrix of normalized data set;
- calculate eigenvectors and eigenvalues of the covariance matrix;
- project the data set into the PC space (Figure 1b).

The first PC corresponded to the eigenvector with the highest eigenvalue, thus the direction with the most significant variation. In contrast, the secondary PC was orthogonal to the first PC and contained information on the variation in the power curve. The variation in PC2 direction

was represented by its standard deviation, and the standard deviation of the reference data served as a benchmark for variation at normal conditions.

To quantify the quality of the sample data, the standard deviation in PC2 direction of the combined data set d_1 , which consists of the reference data and the sample data, was calculated. The HV compared the standard deviation in PC2 direction of the combined data d_1 , to the standard deviation of the reference data d_2 . For better visualization and comparability of results, the HV was normalized using Equation (2).

$$HV = \frac{d_1}{d_2} - 1 \tag{2}$$

where

HV = health value, $d_1 =$ standard deviation in PC2 direction of the combined data, $d_2 =$ standard deviation in PC2 direction of the reference data.

In the context of detecting anomalies in WT power curves, the expected HV was zero, and a rising HV indicated an increasing criticality. Since d_1 represented a combined data set of reference and sample data, it was vital to ensure a consistent ratio between both data sets. Changing data ratios affected the weighting of the data sets and thus the HV and its comparability throughout an extended period. Therefore, we modified the combined data set by adding additional random samples out of the original data sets to ensure a constant data ratio. The error caused by the randomness of the selected samples was mitigated by resampling the data multiple (n) times and averaging the resulting d_1 , see Section 3.1.

2.1.3. Implementation. The modified HV approach implemented in this work was compatible with both on- and offshore wind farms, and could be adapted to different extends of SCADAdata. The procedure depicted in the implementation flowchart (Figure 2) required wind speed and power measurements as minimum data requirements. Pitch angles should be available to eliminate derated operation [25]. In case of recommended air density and turbulence correction, additional information on the temperature at hub height, the air pressure, and the wind speed turbulence indicated by its standard deviation were required.

In a first step, a reference or baseline period was selected. Jia et al. recommended a duration of three weeks for the baseline data set and reselected the baseline after each extended downtime. This procedure, however, hindered the detection of long-term degradation and was only valid if the WTs were repaired to a state as good as new. Since this assumption is not generally valid and does not account for long term degradation, we recommend choosing a period as early as possible in which the WT shows excellent performance. A period between five and seven days for the sample data set provided, in most cases, a sufficient sample for the HV calculation. Shorter sample periods were more likely to cover the linear region insufficiently, while longer periods decreased the sensitivity of the HV. In any case, the sample period had to be consistent throughout all experiments. The default length of the sample data was set to one week, as recommended by Jia et al. [25].

Both data sets underwent data-preprocessing, which was followed by a usability check. If the remaining data amount of the linear region was below a threshold of 10 % of the total timestamps, no HV was calculated (NaN), and the algorithm continued with the next day. A consistent data ratio of 3:1 (reference to sample) was ensured through filling data gaps by randomly selected data, see Section 2.1.2. After performing a PCA for the reference and combined data, the HV was calculated using Equation (2). A HV alarm was triggered if the HV exceeded a defined normal process control limit, which can be set according to user-specific needs (sensitivity vs.

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alarm frequency). For the present work, a limit of three-sigma (d_2) was used, as recommended by Jia et al. [25].



Figure 2: Modified implementation flowchart of the PC2-Dev algorithm.

2.2. Sensitivity analysis

In order to test the robustness of the HV approach to different data sets and alternative datapreprocessing procedures, a sensitivity analysis was carried out as part of the present work. This analysis was also intended to evaluate the modifications to the original HV approach described in Section 2.1.3.

In particular older WTs and data management systems do not provide the full extent of measurement data expected for modern WT. While wind speed and power measurements are commonly available, pitch angles are not available. Multiple tests were carried out to determine whether pitch angles were indispensable during data-preprocessing or whether they could be substituted by alternative information like the operating status or even neglected in specific cases. Section 3.1.1 provides a short qualitative summary of the gained insights.

According to IEC 61400-12-2 [18], power curves are affected by seasonal changes of the air density and varying wind speed turbulences. Our work investigated whether the HV showed the

same dependency on meteorological conditions and whether their influence could be mitigated through air density and turbulence corrections. The mentioned corrections required additional information like air temperature, air pressure, and the standard deviation of the wind speed measurement. Correlation coefficients were calculated and different long term HV comparisons were performed for this purpose, see Section 3.1.2.

Due to the wind speed distribution and data-preprocessing, the number of data points in the linear region differed from sample to sample. For this reason, the influence of changing reference/sample data ratios on the HV was also investigated in the present work, see Section 3.1.3. A generic reference data set with a reference/sample ratio of 3:1 was created by adding additional random samples out of the original data set. By gradually decreasing the data quantity of the sample data set, its effect on the HV was observed. To account for the impact of deleting random data, the HV for each data quantity was calculated in a total of 100,000 experiments. The implemented approach to ensure constant data ratios (see Section 2.1.2) and the required number of iterations were evaluated in numerous experiments.

2.3. Identification and prioritization of low performing wind turbines

In order to validate the applicability of the HV to detect both short-term power curve anomalies and long-term degradation, as well as its potential to predict downtime, different data sets were analyzed. To test the ability to detect low performing WTs by analyzing power curve deviations, we applied the HV approach on a large scale offshore wind farm, included in the WInD-Pool, and three years of operational data per WT. This data set also included pitch angles, operational modes, ambient temperatures, air pressure measurements, and standard deviations of the wind speed. Additionally, service reports on reactive maintenance measures for two years were available.

We defined HV events to consist of at least three consecutive days having critical HVs to compare maintenance measures to HV alarms and to reduce the number of false or irrelevant alarms. Deviating definitions are also possible but the selected duration of three days led to good results and was chosen for the present work. A selected sample of HV events was reviewed in detail and compared to corresponding service reports to evaluate the HV approach for its ability to detect power curve deviations, see Section 3.2.

An application of the HV for downtime prediction was assessed by matching as many HV events and reactive maintenance measures as possible, see Section 3.3. For matching events, the HV alarm horizon was determined and used as a first indicator for the ability of the HV approach to predict critical behavior or malfunction of WTs - the share of matched reactive measures on the total number of reactive measures served as a second indicator.

The ability of the HV to detect performance degradation trends was evaluated based on 16 years of operational data of an onshore WT from the WInD-Pool and the corresponding daily HVs. HVs above the normal process control limit were considered to be caused by temporary technical issues and excluded. The long-term trend was assessed through a linear regression based on the remaining daily HVs. To validate the results, in a second approach the linear regression was based on yearly HV medians, which are robust to outliers and thus didn't require filtering critical health values. Compared to shorter periods, like monthly HV medians, a yearly HV median has the advantage to be robust to seasonal variation. Annual updates can be sufficient since long-term degradation is not expected to require short-term action. Daily HVs are still necessary to detect temporary technical issues.

3. Results

3.1. Sensitivities

3.1.1. Available inputs for data-preprocessing. During data-preprocessing, pitch angles could be replaced by operational modes to delete periods of derated operation. Even based on wind

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Journal of Physics: Conference Series	1669 (2020) 012030	doi:10.1088/1742-6596/1669/1/012030

speed and power measurements only, the HV approach provided excellent results for the ENGIE wind farm since it did not experience derated operation in the evaluated period. Short periods of derated operation were also classified as outliers by the DBSCAN and K-Means algorithms. However, it is crucial to consider that additional information can significantly decrease the risk of false alarms, and its use is therefore highly recommended, especially when WTs are down-regulated frequently.

3.1.2. Seasonal behavior. The HV showed a strong correlation to the air density, represented by the temperature in Figure 3a, and a smaller but still recognizable correlation to the turbulence of the wind speed, see Figure 3b. The blue regression lines visualize the correlations. A clear trend of increasing HVs with rising temperatures and decreasing HVs with increasing turbulence is visible. The correlation coefficient between HV and temperature was calculated to be 0.45, and 0.04 for the correlation coefficient between HV and turbulence. A significant reduction of the correlation between the measured variables and the HV was possible by an air density and turbulence correction of the wind speed. Even though no pressure measurements were available for the ENGIE data, and the air density calculation was based on temperature measurements, the correlation coefficients after correction were close to zero.



(a) Correlation between temperature and HV. (b)



Figure 3: Correlation of the HV to meteorological conditions resulting in a seasonal behavior.

Figure 4 shows a clear seasonal pattern in the HVs calculated for ENGIEs onshore WT "R80790" over four years. For the presented case, the normal process control limit (see Section 2.1.3) was set to 0.26. Periods having HVs above the normal process control limit were considered critical. Without any corrections the HV graph has a seasonal trend represented by the red line with a total number of 98 days of critical HVs and an average HV of 0.080 ± 0.103 . The temperature based correction of wind speed (blue line) led to a significant reduction of the mean HV from $0.080 \text{ to } 0.033 \pm 0.064$ and 14 days of critical HVs. Performing a turbulence correction reduced the average HV to 0.056 ± 0.085 (green line) and resulted in 27 critical HVs. The combination of both corrections resulted in a significantly flattened course of the HV. Most of the time, the WT showed unremarkable behavior, represented by a mean HV of 0.024 ± 0.059 after the combined correction (black line).

The three remaining periods of high HVs resulted in a total of 11 critical days and were due to significant deviations to the power curve. Since the reference period was chosen in the winter months, the corrections during the winter months hardly affected the HVs. The minor remaining seasonal behavior of the HV might have been caused by an imperfect correction

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of the wind speed regarding temperature and turbulence or by other seasonal factors such as humidity or changing wind shear. Even though the consideration of additional environmental measurements also resulted in an increased amount of inaccurate data points and calculation errors, the presented results emphasize the importance of air density and turbulence corrections for the HV calculation.



Figure 4: HVs of Engies onshore WT "R80790" for different data correction procedures.

3.1.3. Data quantity. The ratio of the reference data to the sample data in the combined data set had a significant impact on the calculation of the standard deviation (d_1) . More significant variations in the data ratio led to a stronger or lesser weighting of the sample data and thus to more or less sensitive HVs. As exemplarily shown in Figure 5a, a decrease in the data quantity of the sample data set caused a change in the data ratio and had thus a substantial impact on the HV. The shaded error band visualizes the standard deviation of the results of multiple experiments.



(a) Influence of decreasing sample data. (b) Error reduction by multiple averaging of d_1 .

Figure 5: Influence of varying data ratios and their correction on the HV.

Filling the data gaps to maintain a constant data ratio, however, led to an error in the HV calculation, which is indicated by the variation coefficient as the ratio of the standard deviation in the HV of multiple experiments, to the expected value, see Figure 5b. This issue was solved

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Journal of Physics: Conference Series	1669 (2020) 012030	doi:10.1088/1742-6596/1669/1/012030

by filling the data gaps multiple times in independent experiments and averaging the resulting d_1 . Since the variation coefficient flattened after 30 iterations and further iterations led to longer computation time, 30 iterations were selected for the HV calculation. Therefore, the coefficient of variation was reduced from about 6% to 1%.

3.2. Detecting power curve deviations

The power curve HV detected anomalies in the linear region of the power curve reliably. 3,227 days of critical HVs were revealed during the analyzed period. According to the definition of HV events, this resulted in a total number of 319 HV events. Since the HV is normalized, it is possible to create criticality rankings to prioritize low performing WTs, as well as to benchmark turbine types, locations, or wind farms.



Figure 6: Exemplary power curve deviations.

Using service reports several HV events could be related to specific technical problems. Figure 6 shows four examples of deviations in the power curve, which were due to different technical issues. Since the examined WTs were of the same turbine type, the same location, and the same reference period, the HV normal process control limits for all WTs were about 0.4. The first example (Figure 6a) shows a period in which an issue with the rotor blade pitch system occurred. Due to not optimally aligned rotor blades, the performance of the WT in the

linear section of the power curve deteriorated and shifted to a negative PC2 direction. This deviation in the power curve caused a critical HV of about 0.61. Due to technical problems in the data transmission for the whole wind farm, a significant deviation of power curves occurred in the second example (Figure 6b) with a corresponding HV of 3.54. During this period a pattern of clustered data points is visible, which resulted from a deviating resolution of the measured wind speed. Since the measured wind speed was an essential variable for the HV approach, technical problems of the environmental measuring equipment showed up as visible deviations to the power curve, as seen in Figure 6c. The reason for this deviation leading to an HV of 0.99 was a malfunctioning anemometer which was replaced afterward. The consequence of the erroneous wind measurement was a scattering of the data points. In the last example, a defective electrical fuse caused a control system error, which is displayed in Figure 6d. It is theorized that the electrical power was reduced to avoid damage to the WT. Consequently, a critical HV of 1.05 was determined.

This well working detection of power curve deviations could be applied to further systems if more detailed data is available. Kim et al. [35], for example, investigated further characteristics of individual system components. With the help of the statistical methods Q-statistics and T^2 , technical faults related to the transmission system of WTs were detected. In addition to the application of a PCA, Self-Organizing Feature Maps (SOFM) were applied as a further automated approach for fault detection.

3.3. Predicting failures and downtimes

Over two years about 7% of all corrective measures at the evaluated offshore wind farm were preceded by critical HVs with a median alarm horizon of 3 days and a maximum alarm horizon of 27 days. These events accounted for 20% of all HV events. Even if the detection rate appears to be small, these results are still encouraging since only a fraction of all technical issues are likely to affect the power curve. In particular, critical HV preceded more malfunctions in systems that were likely to affect the wind speed measurement or the power output of the WT, see Figure 7. For example, about 27% of the errors in the environmental measurement system were detected with a median alarm horizon of 10 days and a maximum alarm horizon of 19 days, as well as 23% of the malfunctions in the generator transformer system with a median alarm horizon of 5 days and a maximum alarm horizon of 27 days. Nevertheless, the ability of the HV approach to predict downtime is limited and can only complement other tools and strategies.

Based on more detailed SCADA data and error codes, other publications show higher prediction rates. Wang et al. [36], for example, used a Laplacian Eigenmaps (LE) algorithm in combination with a Linear Mixture Self-Organizing Maps (LMSOM) algorithm for the detection of anomalies in the power of WTs. With the help of the cumulative trend difference method, almost 58% of the occurring faults could be predicted. Kusiak and Verma [37] used a more comprehensive range of parameters for the prediction of faults, such as the blade reference angles, the generator and gearbox speed, and the temperature in the rotor hub. Using data mining algorithms, 78 - 98% of the individual defect categories in the sample could be predicted. A direct comparison of the different results is misleading since the tested data sets, as well as the data requirements of the single approaches, are differing..

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Figure 7: Detection of service events based on HV events.

3.4. Power curve degradation

Besides the detection of short term deviations in the power curve due to temporary technical issues, the HV also proved eligible to detect long term power curve degradation, as seen in Figure 8. A linear regression of the daily HVs to the total number of operational days in Figure 8 shows a positive correlation with a gradient of about 0.004/year. Over the analyzed period of 16 years, the degradation resulted in a displacement of the expected HV by 0.064 and made HV alarms more likely. This result was verified by a linear regression based on the annual median HVs with a corresponding gradient of about 0.005/year and a resulting displacement of the expected HV by 0.08. A direct comparison to the annual degradation rates of 0.1% to 1% indicated by [15, 16, 17] is not possible since the HV gradient can not be easily translated to a degradation rate. In future work, visualization and quantification of degradation trends could enable plant managers to identify WTs with high degradation and to schedule corresponding inspections and maintenance measures (e.g., blade repair).



Figure 8: Long term degradation trend of an onshore WT.

4. Conclusion and Outlook

Overall, the power curve HV appeared to be a promising tool that could support operational managers of wind farms in prioritizing their work, focusing on critical WTs and using their limited resources of time efficiently. In contrast to other power curve approaches, the HV does not model power curves as a discrete function of wind speed and power to identify anomalies, but evaluates the underlying measurement data and its distribution. Thus, the uncertainty due to the choice of varying power curve modeling methods is avoided. Compared to a mere visualization of power curves and deviating operational data, the HV quantifies power curve deviations as a single value and can be presented and compared as a KPI. Compared to more sophisticated approaches, the HV can be implemented on the basis of wind speed and power measurements only. Hence, it is suitable for almost all available data sets. This is of particular advantage for older WTs even though less information can increase the risk of false alarms. Our work validated the usefulness of the power curve HV to detect both, short-term power curve anomalies as well as long-term degradation. However, assigning technical problems to individual systems or components is difficult but can be achieved using additional measurements as other approaches show. While the HV proved to be beneficial to detect low performing WTs and long term degradation, its abilities to predict downtime are limited and can only complement other approaches. In particular, the combination and application of several statistical methods to component-specific characteristic curves can improve the early detection of anomalies and the assignment of technical problems to individual components. The results also emphasize the importance of data preprocessing and data correction for the HV to obtain valid and reliable results.

Future investigations should validate the HV on more extensive event data to analyze its ability to predict downtime and abnormal operational behavior. Depending on the intended application, the normal process control limit and its effect on the sensitivity of the approach should also be investigated in more detail. Since the choice of a suitable reference period is crucial for sound results and is currently determined manually, we recommend adding an automatic selection of the reference time window to the method. For example the examination of power coefficients in the first years of operation could be a possible way. In a further step, a prototype tool should be implemented and tested in collaboration with wind farm managers to test the HV approach in day-to-day practice.

Acknowledgments

The research work of Fraunhofer IEE for this paper was funded by the German Federal Ministry for Economic Affairs through the WInD-Pool (grant No. 0324031A) project. Also, we'd like to thank ENGIE for making the operational data of their "La Haute Borne" wind farm public. Open data is of great importance for the scientific community and enables replicability.

Author Contributions

Moritz Martin and Sebastian Pfaffel defined the research question, designed the methodology and structure of the study, and wrote the paper. Moritz Martin implemented the modified HV approach, performed the experiments, and analyzed the data. Sebastian Pfaffel, Henrik te Heesen and Kurt Rohrig supervised the work. Henrik te Heesen and Kurt Rohrig performed an internal review of the paper.

References

- Kreiss J, Ehrhart K M and Hanke A K 2017 Journal of Physics: Conference Series 926 012015 ISSN 1742-6588
- [2] Stehly T J, Beiter P C, Heimiller D M and Scott G N 2018 2017 Cost of Wind Energy Review
- [3] Wiser R, Bolinger M and Lantz E 2019 Renewable Energy Focus **30** 46–57 ISSN 17550084

- [4] Wind I 2018 Golden, Colorado: National Renewable Energy Laboratory
- [5] Arwas P, Charlesworth D, Clark D, Clay R, Craft G, Donaldson I, Dunlop A, Fox A, Howard R, Lloyd C, Lovett C, Marshall A and Wiles F 2012 Offshore Wind Cost Reduction: Pathways Study.
- [6] Pfaffel S, Faulstich S and Sheng S 2019 Journal of Physics: Conference Series 1356 012040 ISSN 1742-6588
 [7] Gonzalez E, Nanos E M, Seyr H, Valldecabres L, Yürüşen N Y, Smolka U, Muskulus M and Melero J J 2017
- Energy Procedia 137 559–570 ISSN 18766102
 [8] Stetco A, Dinmohammadi F, Zhao X, Robu V, Flynn D, Barnes M, Keane J and Nenadic G 2019 Renewable Energy 133 620–635 ISSN 09601481
- Koukoura S, Carroll J, McDonald A and Weiss S 2019 IET Renewable Power Generation 13 2549–2557 ISSN 1752-1416
- [10] Sheng S S 2014 Wind Energy 17 671–672 ISSN 10954244
- [11] Helbing G and Ritter M 2018 Renewable and Sustainable Energy Reviews 98 189–198 ISSN 13640321
- [12] Lau B C P, Ma E W M and Pecht M 2012 Review of offshore wind turbine failures and fault prognostic methods Proceedings of the IEEE 2012 Prognostics and System Health Management Conference (PHM-2012 Beijing) (IEEE) pp 1–5 ISBN 978-1-4577-1911-0
- [13] Vogt S, Otterson S and Berkhout V 2018 Multi-task distribution learning approach to anomaly detection of operational states of wind turbines WindEurope conference 2018 (Bristol: IOP Publishing) pp Art. 012040, 11
- [14] Wilkinson M, Harman K, van Delft T and Darnell B 2014 IET Renewable Power Generation 8 390–397 ISSN 1752-1416
- [15] Shin D and Ko K 2017 Energy 118 1180–1186 ISSN 03605442
- [16] Wilkinson M 2014 Long-term Performance of Wind Farms.
- [17] Staffell I and Green R 2014 Renewable Energy 66 775–786 ISSN 09601481
- [18] IEC Wind turbines part 12-2: Power performance of electricity producing wind turbines based on nacelle anemometry (iec 61400-12-2:2013).
- [19] Sohoni V, Gupta S C and Nema R K 2016 Journal of Energy **2016** 1–18 ISSN 2356-735X
- [20] Ciulla G, D'Amico A, Di Dio V and Lo Brano V 2019 Renewable Energy 140 477-492 ISSN 09601481
- [21] Astolfi D, Castellani F, Scappaticci L and Terzi L 2017 Diagnostyka Vol. 18, No. 1
- [22] Guo P and Infield D 2020 IEEE Transactions on Sustainable Energy 11 107-115 ISSN 1949-3029
- [23] He Y and Kusiak A 2018 IEEE Transactions on Sustainable Energy 9 65–73 ISSN 1949-3029
- [24] Skrimpas G A, Kleani K, Mijatovic N, Sweeney C W, Jensen B B and Holboell J 2016 Wind Energy 19 1819–1832 ISSN 10954244
- [25] Jia X, Jin C, Buzza M, Wang W and Lee J 2016 Renewable Energy 99 1191–1201 ISSN 09601481
- [26] Welcome to ENGIE's first open data windfarm. URL https://opendata-renewables.engie.com/
- [27] Faulstich S, Pfaffel S and Hahn B 2015 Performance and reliability benchmarking using the cross-company initiative WInD-Pool.
- [28] Hau E 2016 Windkraftanlagen (Berlin, Heidelberg: Springer Berlin Heidelberg) ISBN 978-3-662-53153-2
- [29] IEC 2017 Power performance measurements of electricity producing wind turbines (IEC 61400-12-1)
- [30] PCWG 2018 Power Curve Working Group. URL https://pcwg.org/
- [31] Jolliffe I 2011 Principal component analysis International encyclopedia of statistical science ed Lovric M (Berlin: Springer) pp 1094–1096 ISBN 978-3-642-04897-5
- [32] Ester M, Kriegel H P, Sander J and Xu X 1996 A density-based algorithm for discovering clusters in large spatial databases with noise Proceedings of the Second International Conference on Knowledge Discovery and Data Mining KDD'96 (AAAI Press) pp 226–231
- [33] National Renewable Energy Laboratory 2019 Open operational assessment (OpenOA). URL https://github.com/NREL/OpenOA/blob/master/operational_analysis/toolkits/filters.py
- [34] Abdi H and Williams L J 2010 Wiley Interdisciplinary Reviews: Computational Statistics 2 433–459 ISSN 19395108
- [35] Kim K, Parthasarathy G, Uluyol O, Foslien W, Sheng S and Fleming P 2012 Use of SCADA Data for Failure Detection in Wind Turbines Proceedings of the ASME 5th International Conference on Energy Sustainability - 2011 (New York, NY: ASME) pp 2071–2079 ISBN 978-0-7918-5468-6
- [36] Wang S, Huang Y, Li L and Liu C 2016 Measurement 93 178–188 ISSN 02632241
- [37] Kusiak A and Verma A 2012 IEEE Transactions on Sustainable Energy 3 150–157 ISSN 1949-3029