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

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Introduction

Power curves are a frequently used tool to assess the performance of wind turbines. The power curve health value proposed by Jia et al. [1] is supposed to detect power curve anomalies since small deviations in the power curve are not easy to identify. Our work evaluates the applicability of this health value (HV) for different purposes as well as its sensitivities and recommends modifications to make it more robust and suitable for various data sets.

We tested whether the HV is applicable to:

- detect low performing wind turbines
- detect long term degradation
- predict downtimes

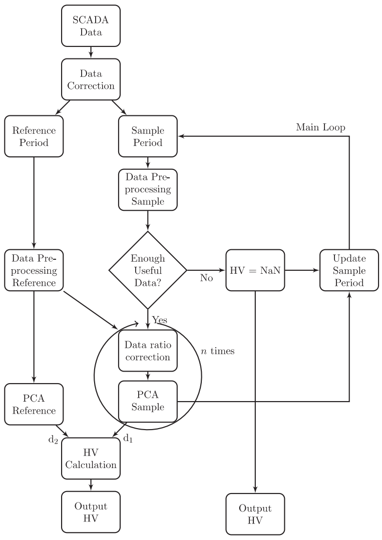


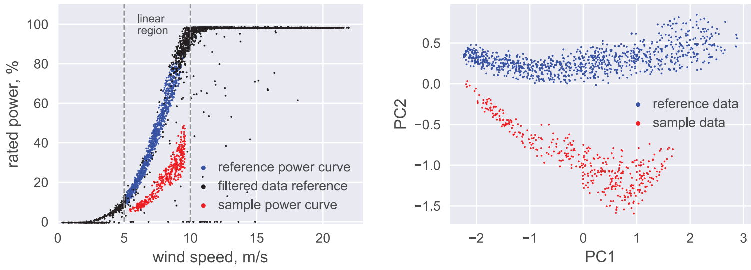
Figure 1: Flow chart of the health value calculation.

Method

The power curve HV assesses deviations in the linear region of power curves by performing a principal component analysis (PCA), see Fig. 2. To calculate the HV, the standard deviation in the PC2 direction 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.

We complemented the original HV approach by an automated detection of the linear region, a turbulence and air density correction [2] of the wind speed and a compensation for varying data ratios between the reference and sample data set, see Fig. 2.

We tested the modified HV based on ENGIE's open data wind farm [3] and data of on- and offshore wind turbines from the WInD-Pool [4].



(a) Data-preprocessing. (b) Principal component analysis.

Figure 2: Projection of the linear region of an exemplary power curve (a) into the PC-space (b) for a reference and sample data set. The health value is derived by comparing the standard deviation in the PC2 direction of the reference data to the standard deviation of the combined reference and sample data.

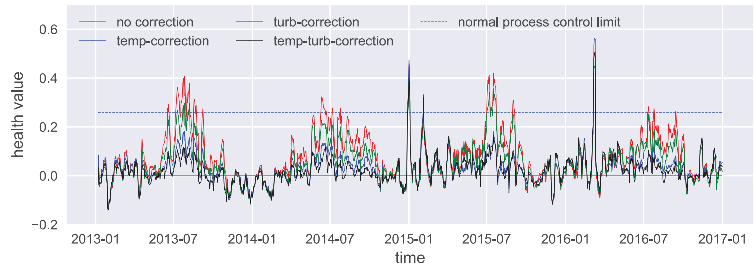


Figure 3: Daily health values of wind turbine "R80736" of ENGIE's open data windfarm over four years. The figure compares health values for uncorrected data to health values based on corrected wind speeds (temperature-based density correction and/or turbulence correction). At this location, a seasonal pattern is evident but can be mostly corrected.

Results

The power curve HV proves to detect anomalies in the linear region of the power curve very well. However, several requirements have to be met to reduce the number of false alarms.

Known periods of abnormal operational behavior, such as derated operation, should be removed from the data set. Pitch angles are the preferred indicator to do so but can be replaced by operational states. DBSCAN- or k-means-filters help with noise reduction.

The seasonal dependence of the power curve also extends to the HV, see Fig. 3. Thus, we recommend the correction of the wind speed for air density and turbulence.

The HV is also eligible to detect long term power curve degradation, which we could prove based on 16 years of operational data of an onshore wind turbine from the WInD-Pool. A linear regression of the daily HVs to the number of operational days showed a positive correlation, see Fig. 4.

Over a period of two years, about 7 % of all corrective events at the evaluated offshore wind farm were preceded by high HVs with an average alarm horizon of 7 days. These events accounted for 20 % of all HV events.

Thus, the HV seems to be able to predict some downtimes, but most technical issues do not foreshadow in the power curve.

Conclusion

Overall, the power curve HV proves to support operational managers in prioritizing their work, focus on critical WTs, and use their limited resources efficiently.

Since the approach can be implemented based on as little data as wind speed and power measurements, it can be applied to almost all available data sets.

While the HV proves 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.

Figure 4: Long term power curve degradation of a German onshore wind turbine over 16 operational years. A linear regression highlights a trend in daily health values. Health values above the normal process control limit were deleted from the data set to exclude temporary technical issues.

References:

[1] Jia et al., Wind turbine performance degradation assessment based on a novel similarity metric for machine performance curves, Renewable Energy, 2016

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[3] ENGIE, Welcome to ENGIE's first open data windfarm, https://opendata-renewables.engie.com, 18.10.2019

[4] Fh IEE, Wind Energy Information Data - Pool, www.wind-pool.de, 2019

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