A novel method for obtaining a wind turbine performance curve

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Abstract. The precise knowledge of the wind turbine (WT) performance during the operation and maintenance (O&M) phase is of primary importance. The most widely used approach is utilising WT supervisory control and data acquisition (SCADA) data to derive a reference power curve, showing the relation between the wind speed and the power during normal operating conditions. WT performance degradation is then detected by analysing the residual between the predicted and observed power values. This paper explores a new method to obtain a WT performance curve, based on the idea that a WT converts kinetic energy into electric power. High frequency SCADA data from a small wind farm is used to develop and test the proposed methodology. Unsupervised machine learning techniques are used to automatically detect performance deviations that are then filtered out. Finally, a reference performance curve and a related threshold is obtained, allowing to characterise the behaviour of WT under normal operating conditions. The promising results suggest that the methodology is valid for tracking the performance of a WT and could be exploited for optimising the O&M phase.

Keywords: Wind Turbine, Power Curve, SCADA, Operation & Maintenance, Wind Turbine Performance, Data filtering

1. Introduction

The precise knowledge of the wind turbine (WT) performance during the operation and maintenance (O&M) phase is of primary importance. The most widely used approach is utilising WT supervisory control and data acquisition (SCADA) data to derive a reference power curve, showing the relation between the wind speed and the power during normal operating conditions. The main objective for modelling the power curve is twofold: monitoring the global condition of the wind turbine and predictive control and optimisation of the performance, through fault diagnosis. Indeed, the presence of outliers and abnormal values might be due to several reasons: environmental issues, faulty anemometers, downtime due to maintenance or power curtailment, control system issues, blade damage, etc.

The dependency of the performance on environmental factors has been studied in [1], [2] and [3]. However, including the effect of these parameters in the power curve modelling requires accurate measurements of the free wind speed at several heights. This inevitably entails the installation of a met mast or a remote sensing instrument, which is not common during the O&M phase. This can be overcome by the use of the data from the SCADA system.

Over the last decade, many important contributions have been made to the study of WT power curves based on SCADA data. Butler et al. [4] considered the nacelle wind speed and air density to derive a power curve using a gaussian process for regression. Cutler et al. [5]

explored the influence of the wind direction on the power curve obtained by the method of bins. Finally, Kusiak et al. [6] produced a set of performance curves based on the SCADA records of power, rotor speed and blade pitch angle. These examples prove that exploiting SCADA data is a cost-effective approach to monitor the performance of a WT.

In this context, two shortcomings can be highlighted. On one hand, most research studies are based on the use of 10-min SCADA data. However, many SCADA systems also record data at higher frequency. The benefit of using these data lies, as an example, in the reduction of the period-of-record to obtain an accurate reference power curve. Although high frequency SCADA data show a very high variability, these data demonstrate the WT dynamic behaviour and avoid the smoothing effect due to averaging process. On the other hand, to the present authors' knowledge, the concept of a kinetic power curve has not been explored yet. Indeed, a WT converts the wind kinetic energy into electric power. The performance curve showing the relation between these two parameters can be therefore understood as a measure of the efficiency of the energy conversion. Moreover, the linear relation between input and output facilitates the modelling process.

From this standpoint, the objective of this work aims to explore this new concept of performance curve by using SCADA data of high frequency (0.1 Hz).

2. Approach

The general principle of the approach is to obtain a reference performance curve and a related threshold allowing to characterise the behaviour of WT under normal operating conditions.

The proposed methodology includes several phases. First, several parameters measured by the SCADA system at a high frequency are analysed and processed. Then, a preliminary kinetic power curve is obtained but abnormal data are still needed to be filtered out. For that purpose, an automatic filtering algorithm is applied, based on unsupervised machine learning techniques as suggested in [6]. The resulting reference curve is deemed to be representative of the normal operating conditions and can be therefore used as a benchmark to evaluate the WT performance.

3. Main body of abstract

3.1. Data processing

Historical 10-second SCADA data were collected from a small wind farm. A scheme of the data processing methodology is shown in Figure 1. The considered parameters are wind speed, wind direction, ambient temperature and power. As mentioned previously, since the wind kinetic power depends on the air density, it is derived from the ambient temperature by applying the International Standard Atmosphere (ISA) [7] model. Then, an exploratory analysis of the data is conducted in order to reveal the need of a directional approach, that is, separate performance curves for different sectors. Finally, input and output parameters are normalised to feed the model. All the presented results will be with normalised values.

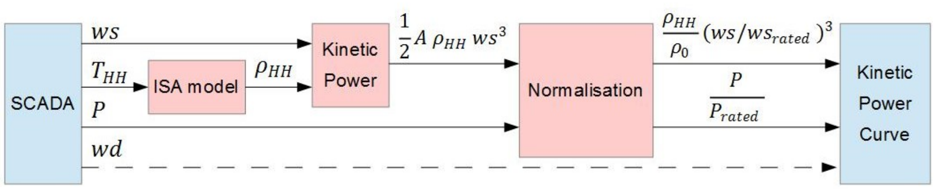

Figure 1: Scheme of the methodology for SCADA data processing

3.2. *Outlier detection*

The kinetic power curve prior to the filtering process for a winter month M and one of the sectors is shown in Figure 2. As can be seen, several outliers need to be filtered out for the clear depiction of the WT normal operation. Robust filtering techniques has been explored in [8] whereas Kusiak et al. [6] use a multivariate outlier detection approach based on k-means clustering and Mahalanobis distance. Due to its flexibility of application, this approach has been applied to the kinetic power curve in order to obtain the optimal number of clusters and to remove the outliers in each cluster. Data clustering and the refined performance curve for the same period are illustrated in Figure 4 and Figure 3 respectively.

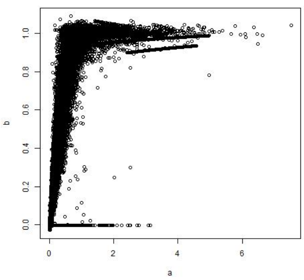

Figure 2: Raw performance curve

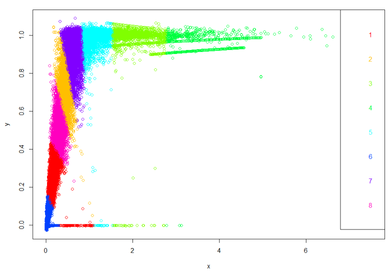

Figure 3: Clustered performance curve

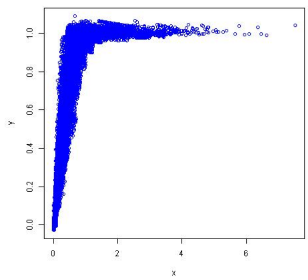

Figure 4: Refined performance curve

3.3. *Performance monitoring*

To be able to identify events of underperformance, we need to set the limits of the performance curve.An iterative algorithm has been developed, based on simple linear regression. For the considered month M, the coefficient of determination between the kinetic power (x) and the electric power (y) was found to be higher than 92%, for the region below rated speed ($x < 1$). Normal behaviour limits and a preliminary linear reference performance curve are shown in Figure 5 for the same winter month M and the same sector. Additionally, other reference performance curves are calculated by applying the method of bins. They are also shown in Figure 5 for comparison purposes. The average per bin is illustrated in yellow and green points correspond to the median per bin.

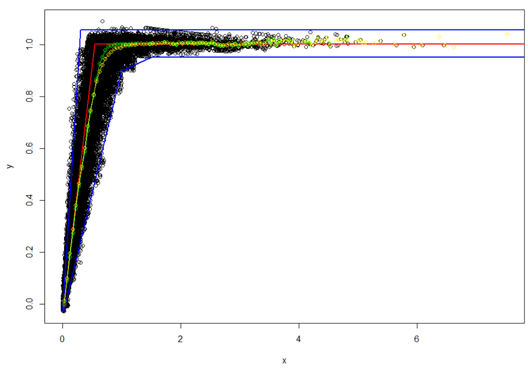

Figure 5: Reference performance curves and normal behaviour limits

3.4. Analysis of the results

The produced power curve has been tested for different months, in order to test its capability of underperformance detection. The accuracy has been evaluated through the calculation of the outliers detection percentage and false detection ratios. For the sake of simplicity, accuracy results for a different winter month $M + 1$ are presented in Table 1.

Month	Outliers (%)	FN ratio (%)	FP ratio (%)	Accuracy
M+1	0.84%	0.00%	0.59%	99.41%

Table 1: Accuracy of outliers detection for month $M + 1$

The herewith presented method is verified using data from three wind farms, with different climate conditions and turbine technologies. The results from this validation will be presented in the final version of this paper.

4. Conclusion

This paper presents an automatic methodology to process and filter high frequency SCADA data in order to derive a new concept of WT performance curve. The suggested method has shown its success in accurately filtering raw data and in monitoring the WT performance with a low level of false positives. Moreover, the concept of a kinetic power curve facilitates the curve modelling process since the relation between input and output is supposed to be linear. Besides, the use of high frequency SCADA data offers a real opportunity to understand how the WT is performing.

The promising results suggest that the methodology is valid for tracking the performance of a WT and could be exploited for optimising the O&M phase.

5. Learning objectives

The present work aims to define an effective methodology to monitor the performance of a WT relying on the new concept of a kinetic power curve and on the use of high frequency SCADA data. Future research will focus on the comparison of the suggested methodology against existing techniques in order to improve the WT performance monitoring phase.

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References

[1] Rareshide E, Tindal A, Johnson C, Graves A, Simpson E, Bleeg J, Harris T and Schoborg D 2009 *Scientific Proceedings. American Wind Energy Association WINDPOWER Conference* 1–15
[2] Vanderwende B J and Lundquist J K 2012 *Environmental Research Letters* **7** 034035
[3] Wharton S and Lundquist J K 2012 *Environmental Research Letters* **7** 014005
[4] Butler S, Ringwood J and O'Connor F 2013 *Conference on Control and Fault-Tolerant Systems, SysTol* 389–394
[5] Cutler N J, Outhred H R and MacGill I F 2012 *Wind Energy* **15** 245–258
[6] Kusiak A and Verma A 2013 *IEEE Transactions on Sustainable Energy* **4** 192–199
[7] International Organization for Standardization 1975 *Standard Atmosphere*
[8] Sainz E, Llombart A and Guerrero J J 2009 *Energy Conversion and Management* **50** 2136–2147