 DOI: 10.1051/e3sconf/20172200024

Comparison of power curve monitoring methods

Philippe Cambron[1,*], *Christian* Masson[1], *Antoine* Tahan[1], *David* Torres[2], and *Francis* Pelletier[2]

[1]École de Technologie Supérieure, 1100 Notre-Dame O, Montréal, QC, Canada
[2]Arista Renewables Energies, 2648 Desjardins, Montréal, QC, Canada

Abstract. Performance monitoring is an important aspect of operating wind farms. This can be done through the power curve monitoring (PCM) of wind turbines (WT). In the past years, important work has been conducted on PCM. Various methodologies have been proposed, each one with interesting results. However, it is difficult to compare these methods because they have been developed using their respective data sets. The objective of this actual work is to compare some of the proposed PCM methods using common data sets. The metric used to compare the PCM methods is the time needed to detect a change in the power curve. Two power curve models will be covered to establish the effect the model type has on the monitoring outcomes. Each model was tested with two control charts. Other methodologies and metrics proposed in the literature for power curve monitoring such as areas under the power curve and the use of statistical copulas have also been covered. Results demonstrate that model-based PCM methods are more reliable at the detecting a performance change than other methodologies and that the effectiveness of the control chart depends on the types of shift observed.

1 Introduction

The reliability and availability of Wind Turbines (WT) are two key aspects used to improve and insure the development and integration of wind energy in current grids. The development of robust monitoring is a way of contributing to this objective. Interesting works have been published lately on various monitoring condition techniques for WT [1, 2]. Among the monitoring methods, some authors proposed approaches to monitor the production of a WT using Power Curve Monitoring (PCM) [4–9].

The power curve of a WT is the relationship between the wind speed and the power output. It is also viewed as the performance of the WT. Therefore, any performance degradation will be reflected in the power curve: less power will be produced for a given wind speed. In the past years, various methods for PCM have been developed, and each one of them reported interesting results. Nowadays, these methods are receiving more attention from wind farm operators as their WT are starting to age. It is now common to encounter

* Corresponding author: philippe.cambron.1@ens.etsmtl.ca

DOI: 10.1051/e3sconf/20172200024

wind farms that have been in operation for more than ten years. As a wind farm ages the performance of its WT degrades with time as reported in [3].

However, these PCM methods were developed using data from different industrial wind farms. Therefore, it is not possible to clearly establish the potential of each PCM method. The objective of the current work is to compare some PCM with a common dataset. Two case studies from industrial WTs will serve as the basis for comparison.

Four different PCM methodologies will be compared. The first one from [4] uses data mining methods for the power curve model together with a Shewhart control chart for the monitoring. This approach will be in direct comparison with the one proposed by [5] which is based on the binning method defined in the IEC 64100-12-1 standard. For this second PCM method, an Exponentially Weighted Moving Average (EWMA) control chart is use to establish if the power curve sustained a change. These firsts two PCM can be classified as model-based monitoring methods since they rely on difference between the observed and the predicted behavior to determine the presence of any anomaly. Two other PCM approaches discussed are the use of the Performance Index (PI) proposed by [6] and the monitoring of power curve copulas developed by [7].

2 Data Source

2.1 Power Curve of a Wind Turbine

The power curve of a WT is the relationship between the wind speed and the output power. It is also a function of the WT operating modes. Figure 1 from previous work presents the power curve of a WT and illustrates the four zones corresponding to the operating modes [5]. Zone I is where the wind speed is lower than the cut-in speed. In this region, the power of the WT is null, since there is not enough power in the wind to move the rotor. Between the cut-in speed and the rated speed, the power of the WT is a function of the cubic wind speed. The rated speed is where the power reaches its nominal value. In Zone III, which is between the rated speed and the cut-out speed, the power of the WT is maintained to a constant value corresponding to the nominal power by varying the blade pitch angle. For a wind speed greater than the cut-out speed (Zone IV), the WT is shut down to protect its structure and components from extreme loads.

Since in Zone III the WT power is imposed, performance degradation will not be noticeable. So as recommended by [8] and done in [5], values with wind speed greater than the rated wind speed will be removed from the dataset.

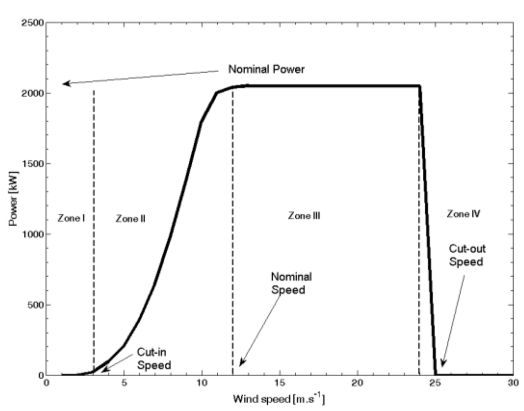

Fig. 1. Power Curve and operating modes of a WT. From [5].

DOI: 10.1051/e3sconf/20172200024

2.2 Case Studies

The PCM methodologies will be compared using data from an industrial wind farm located in Canada. The WTs are MW class and pitch regulated. This wind farm has been in service since 2005 and data is archived at frequency of 1 Hz. However, as suggested by the IEC standard, 10-minute averages are use rather than the high frequency data to reduce the noise and the effect of autocorrelation. Data have been filtered for outliers caused by events such as sensor malfunctions, database unavailability or malfunction and icing with the method proposed in [9]. The timestamp of the date is the beginning of the time period.

Two cases of WT performance degradation will provide the common reference for the comparison of the PCM methods. The first case is an example of an erroneous activation of a curtailment algorithm of a WT resulting in a sudden underperformance of the WT. The second case presents a small and progressive performance degradation caused by blade leading edge erosion.

The nacelle wind speed will be use because met masts are not available for these two WTs. This wind speed will also be corrected for the effect of air density has suggested by the IEC standard (all further mention of wind speed take account of the air density correction).

3 Power Curve Monitoring Methodologies

Each PCM method will be briefly introduced. References to the original work are included for more details on each one of them. All PCM methods will be compared on their ability to detect a small change in the power performance and on the time needed for the detection of the behaviour change presented by the two different case studies. The first case is a sudden shift corresponding caused by a control algorithm change. For the second case, which is about a progressive degradation, it is not possible to clearly define when the issue started. Therefore, the date of detection will be use as a PCM performance metric.

3.1 Model-Based Monitoring

In model-based monitoring, the energy output coming from the WT is predicted with a model. Then, the residuals (differences between the prediction and the observation) are analysed. For a valid model, and without any on-going under-performance, the residuals should be ergodic (same statistical behaviour in time). However, a change of energy output coming from the WT will result in a significant change or trend in the residuals. Thus, the power residuals will be monitored for any occurrence of under-performance. Two different models will be compared, the bins method and the random forest.

3.1.1 Bins Model

The bins model consists of splitting wind speed data by an interval of 0.5 $m.s^{-1}$. The power curve is obtained by taking the average of the power in each bin. This model is widespread in the industry since it is recommended by the IEC standard. This model is used in [7].

The power residuals are normalized using the average and the standard deviation of the power in the respective bin, allowing treating all the bins simultaneously rather than bin by bin. For more on this transformation, the reader should consult [7].

3.1.2 Random Forest

In [4], a model using a random forest is use to predict the WT power. Random Forest is a non-parametric data mining methods constructed by an ensemble of randomly generated regression trees that can be used for prediction. See [10] for more on random forest. The random forest used for the prediction of the power will have the wind speed and the air density as inputs factors. The power residuals $R(t)$ in this case are transformed to normalized residuals:

$$R(t) = \frac{P(t)-\hat{P}(t)}{P(t)} = \frac{\Delta P(t)}{P(t)} \tag{1}$$

where $P(t)$ is the observed power and $\hat{P}(t)$ the expected power.

3.1.3 Control Charts

Control chart are use in Statistical Process Control (SPC). They act in a way like a continuous statistical testing. A statistical property of the process is plotted trough time (individuals, sample average, range, sample standard deviation, etc.) If the data of the control chart is outside of the control limits, the process is reported as statistically different. A $\bar{X}$ Shewhart chart is use in [4] and a EWMA chart is use in [5]. The process monitored here is the power residuals. The residuals are averaged on a three-day period to reduce the effect of noise as discussed in [5]. The EWMA chart smoothes the residuals, acting as a high frequency filter. The smoothing parameter (λ) is adjustable and takes values between 0 and 1. If $\lambda = 0$ the smoothing is at its highest possible point and if $\lambda = 1$, there is no smoothing. A complete definition of control charts is included in [11]. Here, as recommended in [5], $\lambda = 0.2$ will be use.

3.2 Copulas Monitoring

Copulas are coming from probability theory and statistics. They are a multivariate probability distribution for which the marginal probability distribution of each variable is uniform. According to Sklar's theorem, any joint distribution can be transformed to a copula with uniform marginal distribution. The copula is an illustration of the dependence structure between the variables [7].

Copulas have been use for PCM by [7]. The power curve can be considered as a multivariate probability distribution function of the wind speed (v) and the power (P). It is therefore possible to transform this multivariate distribution to a copula by transforming the random variables v and P into two new random variables with uniform marginal distribution $u \sim U[0,1]$ and $w \sim U[0,1]$. Figure 2 presents the multivariate distribution of the wind speed and power and its transformation to a copula. Since the copula represents the dependence structure between the wind speed and the power, any change in the WT performance will be reflected in the copula. As shown in Figure 2, the copula of a power curve has a linear aspect. A reference copula is first constructed, and this transformation from the original probability distribution to the new probability distribution is use afterwards with date from the test periods. Therefore, a change on the energy output coming will be easily detected in the copula. The advantage of the use of copula in PCM is that no model is required, hence limiting the uncertainty inherent in the use of a model.

The residuals between the baseline period copula and the copula of the period under evaluation ($\tilde{R}$) is used as the metric to determine if there is a change in the WT behaviour. The suggested threshold for the determination of a behaviour change of are $|\tilde{R}| > 0.02$.

 DOI: 10.1051/e3sconf/20172200024

Authors suggested a two-month baseline period and a month of data for each evaluation period.

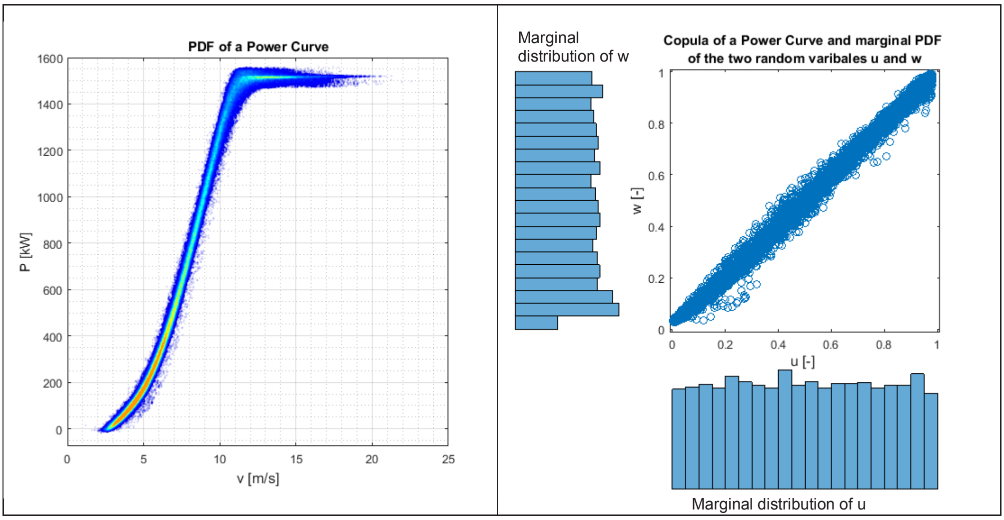

Fig. 2. On the left: Kernel density estimate of the joint probability of wind speed and power output with the colour in function of the probability (blue for 0, red for 1). On the right: Copula of a Power Curve along with the uniform marginal distribution of the random variable u and w.

3.3 Performance Index

The Performance Index (PI) for the performance assessment of a WT was proposed for the performance assessment of a WT in [6]. The power curve is separated in n different wind speed regions. In their original work, the authors proposed two different regions (below and above the nominal wind speed). Its calculation is based on the area under the power curve is the following way:

$$PI_i = \frac{S_i^T - S_i^R}{S_i^R} \tag{2}$$

where PI_i is the performance index in the region i, S_i^R is the area under the power curve in the region i during the reference period and S_i^T is the area under the curve for the period under evaluation. The final PI is obtained with a weighted sum of all the PI_i with the weight corresponding to the wind distribution. The calculation is the following:

$$PI = \sum_{i=1}^{n} WD_i \cdot PI_i \tag{3}$$

where WD_i is the percentage of wind distribution in the region i for the period under evaluation. The use of the PI for PCM implies the use of a power curve model. In the original work, a linear hinge model was used. However, the effect of a different model on the PCM will be covered by the comparison between the bin model and the random forest. Also, to isolate the results of the PI as a metric for PCM, the PI will be used with the bin model. As in [6], the PI will be calculated monthly.

4 Results

4.1 Model-Based Monitoring

4.1.2 Shewhart Control Chart

Figure 3 reports the results of the two model-based PCM when used with a $\bar{X}$ Shewhart chart. The normalized residuals for the bins method are expressed by $\|R\|$. For case study A, both power curve model-based PCM could easily detect the shift in the power curve; by 2012-05-08 for the random forest and by 2012-04-15 for the bin model. However, neither of the two model-based PCM methods can detect the performance degradation in Case B, which is therefore not presented. Also, both methods return a false positive around 2010-02-14.

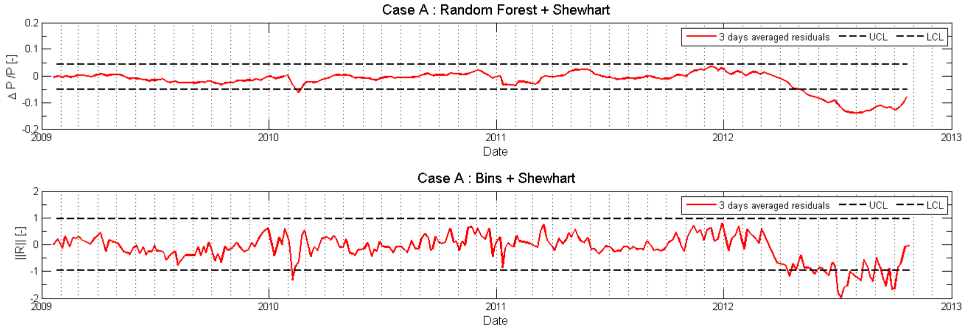

Fig. 3. Power Curve Monitoring with the $\bar{X}$ Shewhart chart for both models.

4.1.2 EWMA Control Chart

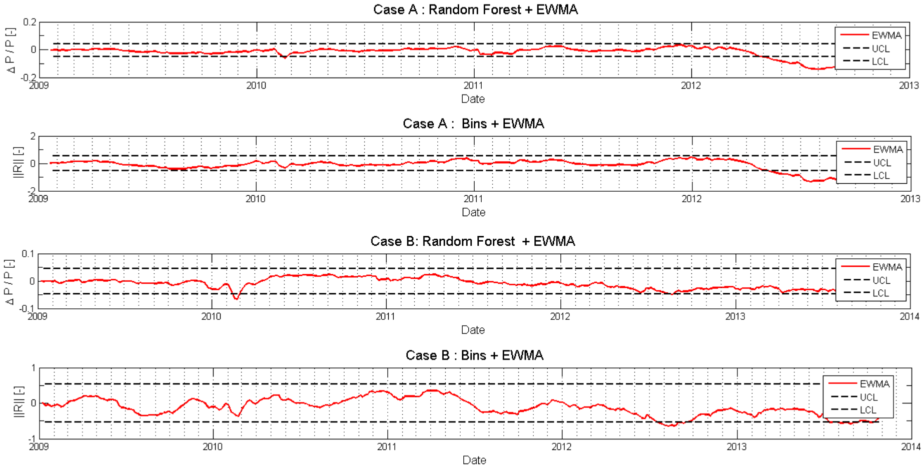

Fig. 4. Power Curve Monitoring with the EWMA chart for both models.

DOI: 10.1051/e3sconf/20172200024

Figure 4 presents the results of the two model-based PCM when use this time with an EWMA chart. For Case A, both power curve models could detect easily the shift in the power curve; by 2012-05-02 for the random forest and by 2012-05-13 for the bins model. However, for the case study B, the PCM method based on the bins model performed better than the one based on the random forest. The bins + EWMA method found the change of behaviour on 2012-07-21 while the random forest + EWMA reported the change a month later, on 2012-08-22.

The false positive in Case A is no longer observed, due to the smoothing effect of the EWMA. It was expected in Case A that the Shewhart chart performed better than the EWMA chart. The smoothing of the EWMA is known to enhance the detection of small shifts while reducing the reactiveness to sudden variations [11].

4.2 Copula Monitoring

The results of PCM with copula are presented in Figure5. This method could detect the shift in power curve in the dataset observed in Case A. The detection date is 2012-05-01. This result is like the one obtained with the use of the random forest with the EWMA and the bins method with the EWMA. The need for a full month of data to calculate the copula, since it requires a large sample, is a drawback for copula monitoring. However, the use of a rolling window of a month for the evaluation period with a daily calculation of the copula might be able to overcome this issue.

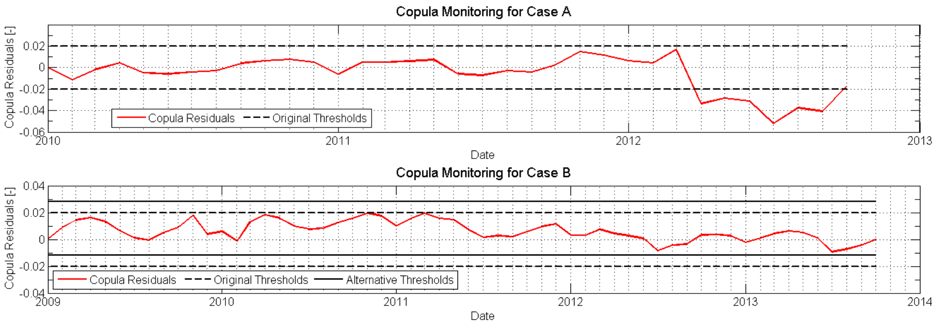

Fig. 5. Power Curve Monitoring with Copula Monitoring.

However, the copula method was not able to detect the change in the power curve for the case study B using the threshold provided in the original work ($|\tilde{R}| > 0.02$). The choice of this threshold is based under the assumption that, in absence of any issue, the value of $\tilde{R}$ will remain close to 0. However, it can be seen on Figure 5 that the value of the copulas residuals $\tilde{R}$ is above 0 at the beginning of the reference period, pointing toward a systematic bias. We suggested that the thresholds should be defined with regard of the average copula residuals from a reference period of a year. Using these alternative thresholds, the copula PCM method would almost have could detect the under-performance by 2012-07-01.

4.3 Performance Index

The result of PCM with the PI is reported on Figure 6. It is difficult to identify if the PI detected the behaviour changes in the two case studies as it is unclear what threshold to use. For Case A, a change in the PI can be observed by 2012-04-01. However, it is not possible to tell if the PI has detected the change of behaviour in Case B.

DOI: 10.1051/e3sconf/20172200024

Fig. 6. Power Curve Monitoring with the Performance Index.

5 Conclusion

Four different PCM methods were compared using common set of data. The dataset consisted of two case studies from WT in industrial wind farms that suffered a performance change. The model-based PCM used with a EWMA control chart was the only approach able to detect both behaviour changes. However, model-based PCM along with the Shewhart chart and the copula PCM provided better results for case A. The smoothing effect of the EWMA chart is enhancing the ability to detect small shifts while reducing the reactiveness to sudden important shifts. Here, both models studied presented similar results. A combination of both control charts could be an interesting SCADA monitoring strategy.

Not all PCM methodologies present in the literature have been covered in this work and new PCM approaches are still interesting as results may be improved. Further work on the benchmarking of other PCM methods would be a logical follow-up to the current work.

This research was made possible with the help of the National Science and Engineering Research Council of Canada (NSERC) and Quebec's Nature and Technology Research Fund (FRQNT) joint Industrial Innovation Scholarships Program. Special thanks go to the participating industrial partner.

References

1. Z. Hameed, Y.S. Hong, Y.M. Cho, S.H. Ahn, C.K. Song, JRESER **13**,1–39 (2009)
2. F.P. Garcia Marquez, A.M.Tobias, J.M. Pinar Perez, M.Papaelias, JRENE **46**, 94–101 (2012)
3. I. Stafell, R. Green, JRENE **66**, 775–786 (2014)
4. A. Kusiak, H.Zheng, Z.Song, JRENE **34**, 1487–1793 (2009)
5. P. Cambron, R. Lepvrier, C. Masson, A.Tahan, F. Pelletier JRENE, **94**, 126–135 (2016)
6. R. de Andrade Viera, M. Sanz-Bobi, S. Kato ICRERA, 31–36 (2013)
7. S. Gill, S. Bruce, S. Galloway, JSE **3**, 94–101 (2012)
8. S. Butler, J. Ringwood, F. O'Connor, Sys. Tol. 389–394 (2013)
9. J. Park, J. Lee, K. h, J. See, IEEE Trans. Energy Convers **29**, 119–128 (2014)
10. L. Breiman, JMLR **45**, 5–32 (2001)
11. D. Montgomerry, Introduction to statistical quality control (2007)