Simulation of wind turbine faulty production profiles and performance assessment of fault monitoring methods

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ABSTRACT

Wind turbines being one of the fastest growing sources of renewable energy have garnered significant scientific interest for the monitoring and fault analysis using SCADA (supervisory control and data acquisition) data. Various monitoring approaches using power curves, i.e. industry wide characteristic curves expressing produced power as a function of wind speed, have been proposed in the literature. However, an objective comparison of the performance of these methods is difficult. The difficulty comes from (i) the variability in operational and environmental conditions taken into account; (ii) the nature, size and type of data-sets used and (iii) the type and signatures of faults considered for validation. To solve this problem, an approach with a twofold contribution is proposed in this work: 1) an original procedure to generate realistic and controlled simulations of 10 minutes SCADA data, simulating situations when the wind turbine is operating in normal or faulty conditions, is presented; 2) a framework for objective performance assessment of the fault detection methods, based on the proposed controlled and standardized simulation scheme is presented. Objective performance evaluation metrics, such as detection probability and false alarm rates are computed and represented as characteristic receiver operating curves (ROC). The proposed simulation approach is shown to provide a useful global framework for objective performance analysis. A number of realistically simulated and controlled data streams are used to compare and discuss the performances of two fault detection methods referenced in the literature.

1. INTRODUCTION

The global installed capacity of wind power production has seen significant increase in recent years, from around 432 GW reported at the end of 2015 to 539 GW at the end of 2017 (Global Wind Energy Council, 2017). This growth also reported by Beiter & Tian, 2016 is a result of increased global efforts for environmental protection, to combat greenhouse effects and to address climate change.

With an increasing number of wind turbines installations, wind turbine operations and maintenance teams need reliable health indicators and monitoring tools for condition monitoring and predictive maintenance. At the same time, increasingly competitive market has driven renewable energy producers to become more efficient and cost effective in terms of operational maintenance.

The typical cost of operation and maintenance (O&M) as a percentage of the total asset cost can be 12% for onshore wind turbines and can go as high as 18% - 23% for offshore installations (Tavner, 2012). The O&M cost for European offshore installations can be as high as 45 Euros/MWh (Röckmann, Lagerveld, & Stavenuiter, 2017).

These costs have encouraged both manufacturers and operators to be more intelligent with the monitoring of wind turbine (WT) state of health, generally referred to as condition monitoring (CM). A number of 'add-ons' in the form of so-called condition monitoring systems (CMS) have been developed by manufactures to monitor key wind turbine components. Although early fault detection capabilities for these systems resulting in financial benefits has been shown (Yang, Tavner, Crabtree, Feng, & Qiu, 2014) but a major deterrent for operators is the installation cost. For example, the vibration analysis based CMS's usually cost more than 11,000 Euros/turbine (Yang, Court, & Jiang, 2013).

On the contrary, all large utility scale WTs already have a standard supervisory control and data acquisition (SCADA) system installed that is principally used for performance monitoring. SCADA systems provide a wealth of data normally at 10 minutes resolution with records for various parameters. These parameters can be sectioned into four major categories of variables, including environmental measurements (e.g. wind speed, direction, ambient temp.) electrical characteristics (e.g. active power), component temperatures (e.g. gearbox bearings) and control variables (e.g. pitch angle, rotor speeds).

Due to the easy availability and accessibility of SCADA data, it can be interesting to investigate the extent to which they can be used for finer monitoring and fault detection purposes. Hence, various methods have been proposed in the literature when it comes to wind turbine monitoring using SCADA data. The approaches can be globally classified into measured temperature based methods and produced power based methods. (Lydia, Kumar, Selvakumar, & Prem Kumar, 2014). Power Curve is the official performance indicator that is often used to calculate the performance of a wind turbine. This curve, expressing the power output of wind turbine as a function of wind speed is an industrial standard and is used to calculate contractual performance guarantee by the manufacturers.

The relationship between the power produced by a wind turbine and wind speed recorded is expressed by a curve as shown on Figure 1. Based on the produced power, this relationship can be further divided into different modes of operation shown in terms of Zones I-IV. For wind speeds that are below the cut-in value (Zone I on Fig. 1), there is no power produced, since the wind does not have enough energy to move the rotor. At wind speeds above the nominal speed (Zone III), the power reaches its nominal value. Mechanisms such as pitch angle attenuation for active control turbines are used in order to maintain power at its nominal value. At extreme wind speeds, the wind turbine is stopped in order to ensure the structural integrity of the wind turbine (Zone IV). The cubic relationship between wind speed (v) and produced power (P) is only observed between the cut-in speed and the nominal speed as shown by Zone II of Figure 1. (Cambron, Lepvrier, Masson, Tahan, & Pelletier, 2016).This cubic relationship is given by Eq. (1) below

$$P = \frac{1}{2}\rho c_p A v^3 \qquad (1)$$

with ρ the air density; A the area swept by the rotor; and c_p the power coefficient of the wind turbine generator.

A failure or loss in performance is identified when the produced power deviates from the normal power curve. Several failures can reduce and impact the power production capabilities of a wind turbine. These include but may not be limited to Down-rating, pitch control malfunction, icing on turbine blades, erosion, and wind speed under reading, dirt or bugs on blades and so on etc. (Park, Lee, Oh, & Lee, 2014). Figure 2 shows some of the fault cases having peculiar signatures on the power curve.

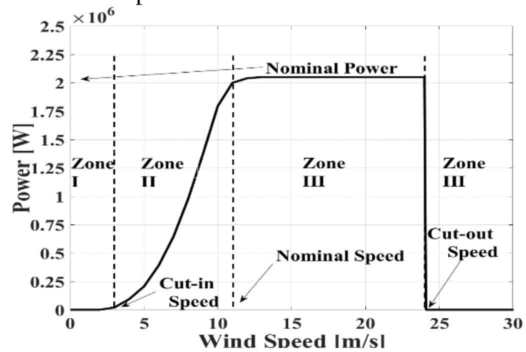

Figure 1. Example of a power curve

Based on this observation various monitoring approaches using power curves have been proposed in the literature. (Kim, Ra, & Kim, 2012)), (Bi, Zhou, & Hepburn, 2017) (Kusiak & Verma, 2013), (Kusiak, Zheng, & Song, 2009), (de Andrade Vieira & Sanz-Bobi, 2015), (Cambron et al., 2016).

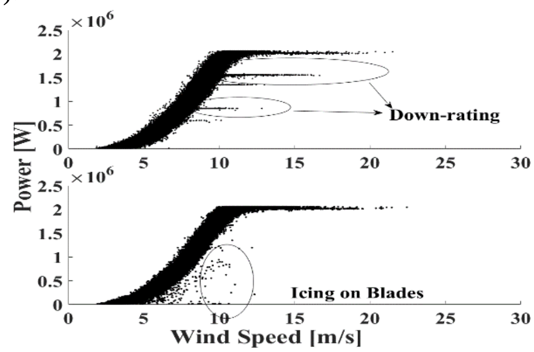

Figure 2.Types of power curves in various failures (a) Down-rating & (b) Icing on blades

While performing a literature review and analysis, a major obstacle can be observed while comparing the research discussing the wind turbine monitoring approaches using power curves. The general lack of a comparative benchmark and difficulty in selection of the most appropriate approach become evident. The problem comes from the fact that there is a huge variation in terms of the operational conditions, environmental factors and geographical locations of the wind turbines on which different methods proposed are developed. Additional factors include the type and resolution of the data sets being used in case of real data or in case of simulations, the over-simplifying assumption of Gaussian noise. And finally the variation in performance evaluation techniques make it difficult to compare the proposed methods in the domain of fault monitoring using power curves.

To solve this problem, an approach with a twofold contribution is proposed. First an original procedure to generate realistic and controlled simulations of 10 minutes SCADA data is presented. This method is used to model realistic faulty and normal behavior data sets. Secondly, the framework for performance assessment of various methods proposed in the literature is presented. The suggested framework is also used to explore performance comparison of two methods presented in literature and the results are summarized.

The work presented in this paper provides the ability to create power profiles of desired lengths. The conditions to generate the data streams are controlled and the faults can be injected at desired time period (winter, summer) and for desired lengths. This enables the opportunity of rigorous testing and extensive comparative analysis.

2. PROPOSED APPROACH

2.1. Overview

As explained earlier, a problem is faced due to the lack for an efficient, controlled and standardized comparison framework for the methods using power curves. In order to compare methods using power curves as performance monitoring tools, a two-step approach is presented. First a realistic simulation creation method based on the real dispersion of wind turbine data is devised.

This simulation procedure has two significant sub-stages.

a) First, various realistic and useful reference fault power curve patterns, replicating multiple practical faults scenarios are identified and created.

b) Secondly, a realistic dispersion profile is added around the fault models to create practical simulations of fault scenarios.

A framework for performance analysis is also presented. The performance analysis is done by creating ROC (Receiver Operating Characteristic) curves that express the relationship between probabilities of fault detection and probabilities of false alarms. (Van Trees, 2001)

2.2. Simulation Process

The first step in order to create a realistic simulation of power curve is to model the normal behavior for reference.

2.2.1. Reference Power Curves (PC)

Reference power curves can be created in two ways. A manufacturer provided power curve can be used as a nominal reference to depict the production behavior of a wind turbine or more practically a measured reference power curve can be calculated. (IEC 61400-12-1, 2005) provides a method to calculate mean reference power curve. The mean power curve is determined by applying the "method of bins" for the measured data sets. Using 0.5 m/s as the size of a single bin, the data set is divided into corresponding wind bins. The mean values of the measured wind speed and measured power output for each wind speed bin is calculated. This results in the assignment of one mean reference power value per wind speed bin.

2.2.2. Faulty and Fault Free PC

As referred to in Figure 2, different failures can have different fault patterns. Based on the literature review (Park et al., 2014), expert knowledge and using the method presented by (IEC 61400-12-1, 2005) several fault free and faulty power curve references are created. Figures 3a & 3b show the power curves replicating behavior of a wind turbine power curve under faults like icing on the blade and down rating of a power turbine. The choice of these two faults is a result of their fault signatures on the Power Curve. These faults have a direct impact on the link of produced power as a result of observed wind speed. The ability to isolate the source and impacts of these faults makes them the suitable candidate for comparison of Power Curve based methods.

These realistic reference curves for icing on the blades and down rating can now be used to replicate and simulate the behavior of real data experiencing these faults.

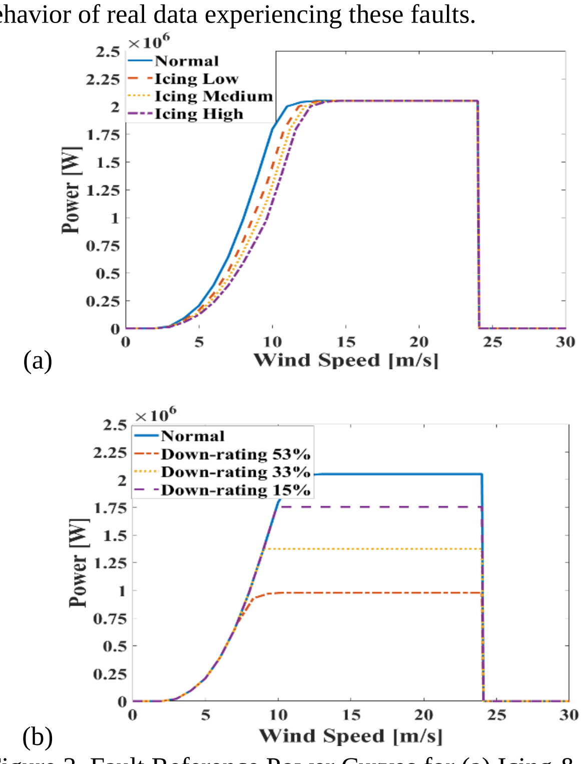

Figure 3. Fault Reference Power Curves for (a) Icing & (b) Down-rating

2.2.3. Dispersion Profile

2.2.3.1 Learning Phase

In order to achieve a realistic fault model, a realistic data dispersion profile needs to be replicated. To simulate the dispersion profile, real 10 minutes SCADA data from real wind turbines operated by VALEMO, operating in normal conditions during several years is used. Figure 4 shows the power curve data from a 2 MW wind turbine operating under normal conditions for the year 2014-2017. It also shows the mean power curve calculated using IEC binning method.

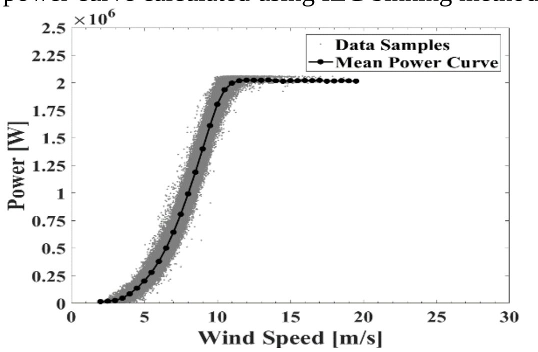

Figure 4. Real Power Curve Data for dispersion learning

This normal behavior data set is used to calculate a large number of dispersion residuals. The residuals referred to here are the difference between the power produced (measured data) and the mean wind turbine power curve (IEC Mean Curve). They express the data dispersion around the mean power curve. Figure 5 shows the dispersion of the residuals calculated as a function of wind speed and corresponding temperature values.

These dispersion residuals calculated are then further grouped into 2 dimensional bins according to their corresponding wind speeds and external temperature values. Within a certain range of wind speeds and external temperatures, these further grouped samples serve as wind/temperature reference subsets. Based on the amount of reference data available, each Wind/Temperature bin can have several data samples.

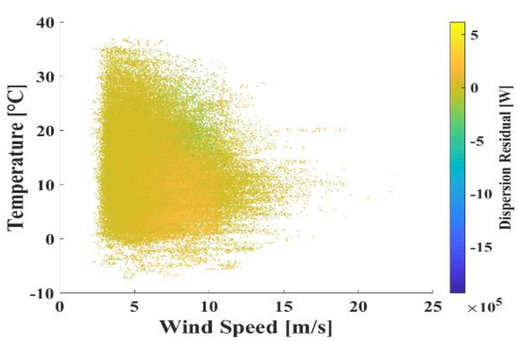

Figure 5. Learnt Dispersion Residual (w.r.t wind speed &Temperature)

The resolution of these 2D bins is chosen to be 0.5 m/s for the wind and 1 °C for the temperature. The dispersion observed here is realistic to the behavior of a wind turbine in operation and not simply Gaussian.

2.2.3.2 Simulation Phase

In order to create new 10 minutes power profiles, yearly recordings of wind speed and external temperature measured on different wind farms are used. These new wind farms are geographically distant from the one used to build the dispersion residuals data set. Figure 6a & b show the wind and temperature profiles recorded for a separate 2 MW wind turbine over a period of 4 years (2014-2018) used for creating new simulations of power data.

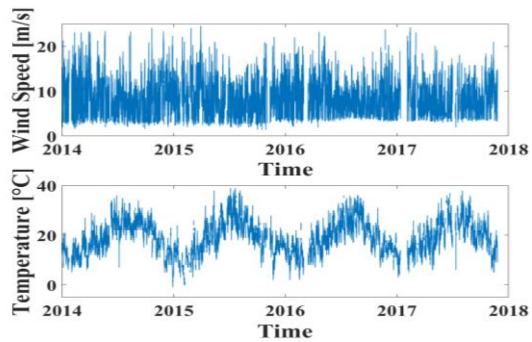

Figure 6. Input Profiles (Real data) (a) Wind and (b) Temp.

For each new (Wind, Temperature) pair of 10 minutes data sample, a residual is randomly drawn from the corresponding wind speed and temperature subset. Since there are several corresponding dispersion residuals in each reference (W, T) bin, the process is randomized as a residual sample is drawn at random for each new sample data pair.

The randomly selected dispersion value is then added to the reference power curves (Figures 3a &b) for the normal and faulty behavior modelling. This is done in a bootstrap-like approach using the real wind and temperature profiles shown in (Figures 6a &b). The normal behavior simulated power data as a result of input wind profile is shown in **Figure 7** for a short duration of time. (15th April 2015- 1st May 2015).

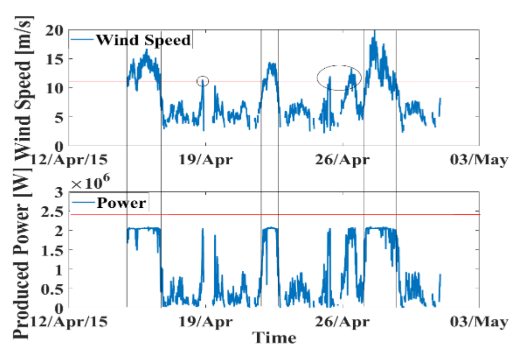

Figure 7. (a) Input Real Wind Profile & (b) Corresponding Simulated Power Profile

Based on the relationship of wind speed and produced power for a 2MW turbine as shown in Figure1, the produced power is stalled at 2MW for wind speeds greater than nominal speeds. Figure 7 shows the same relationship for simulated power with red line indicating the nominal wind speed, at which the produced power reaches nominal power. The same process is used to generate multiple simulation streams (normal and faulty) through various iterations to further randomize the process, which allows to build a realistic simulated data set with controlled faulty behaviors that can be used for performance analysis of the fault detection methods.

New normal or faulty power profiles can be created at length, in totally controlled conditions for the mean pattern of the power curve, with data dispersion replicating the dispersion observed in the real world.

2.3. Framework of Performance Analysis

Objective performance analysis is done by the selection of appropriate evaluation metrics. Receiver operating characteristic curves are used to compare the performance of the different methods. The ROC curve plots probability of detection (PD) for each method tested as a function of varying probabilities of false alarms (PFA). (Van Trees, 2001).

For one set of measured wind speed and temperature data, 10 randomized and realistic power profiles are created. For each simulated data stream, desired fault data is inserted at the desired locations and for the desired durations. Methods using power curves for monitoring as presented in literature (Uluyol, Parthasarathy, Foslien, & Kim, 2011) , (Cambron et al., 2016) etc. can then be used to calculate residuals.

The approach for performance analysis of these methods is as follows:

Step 1: A four-year long data set is generated: where one year is to learn the threshold for desired PFA, one year to validate PFA, and one year is for PD estimation.

Step 2: Each desired probability of false alarm (PFA_D) is used to calculate the corresponding threshold (Th) on first year of fault free residual data.

Step 3: The calculated threshold (Th) is then validated on the second year of fault free residual data and the estimated probability of false alarms is calculated (PFA_{EST}).

$$PFA_{EST} = \frac{No.\ of\ data\ points\ below\ threshold\ (Th)}{Total\ No.\ of\ data\ points\ in\ validation\ period}$$

Step 4: The estimated probability of detection (PD_{EST}) is calculated on the faulty data stream of residual data (year three).

$$PD_{EST} = \frac{No.\ of\ data\ points\ above\ threshold\ (Th)}{Total\ No.\ of\ data\ points\ in\ fault\ period}$$

Step 5: Steps 1-4 are repeated for all 10 iterations of simulated data streams and averaged to compute $\overline{PFA_{EST}}$ & $\overline{PD_{EST}}$

Step 6: This averaged value gives one data sample of PD as a function of PFA on the ROC curve.

The method explained above is used to calculate PDs for all desired PFAs, for all fault types and to create a ROC curves for all the considered fault detection methods.

3. RESULTS

3.1. Experimental setup

As referred to earlier, a four year (2014-2018) long simulated data stream is used to calculate residuals based on different methods. One year of fault period was introduced as year three of the overall stream. For the performance evaluation, first year is taken as the learning period, year two as validation and year three being the faulty period is for testing. Two major groups of faults of various intensities (icing: low, medium, high) and Down-rating (15%, 33% and 53% of the nominal power) are simulated and inserted as fault periods (year three).

3.2. Methods Comparison

The simulation procedure is used to assess the performance and compare two different methods. These two methods of residuals calculations are tested for the faults implemented. These normal behavior model based methods applied to power curves include a simple residual method using method of bins (IEC 61400-12-1, 2005) and a method proposed by (Cambron et al., 2016) referred to hereafter as EWMA (exponentially weighted moving average) Residual Method.

3.2.1. Simple Residual Method

The simple residual method calculates, for each wind bin of 0.5 m/s resolution, a difference between the simulated power data samples and mean power curve calculated on normal behavior period using method of bins (IEC 61400-12-1, 2005). Figure 8a shows the simple residual and Figure 8b shows the same residual with a moving average of 1 day for smoothing.

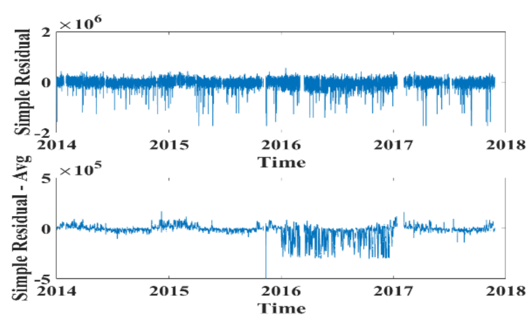

Figure 8. Simple Residual for: Down-rating15% (a) Unprocessed and (b) Moving Averaged

The example fault shown is Down-rating15% (ref. Figure 3b).

3.2.2. EWMA Residuals

The EWMA residual method as presented by (Cambron et al., 2016) is implemented with varying parameters and has following three main stages:

a) Pre-processing

i. *Density Correction*: Wind speed values are corrected to reference density (1.225 kg m^{-3}) (IEC 61400-12-1, 2005).

b) Residual Creation

ii. *Reference Creation*: Average of the data points per wind bin (0.5 ms^{-1}) is calculated. (IEC 61400-12-1, 2005)

iii. *Data Translation*: Translation of data samples within a wind bin towards the center of the bin is done.

iv. *Residual Calculation*: the difference between the translated data and the reference value within a wind bin is calculated. (Translated Data – Reference)

v. *Residual Normalization*: The residuals are then normalized with mean & standard deviation of reference data.

c) Post Processing

vi. *Post Processing °1* = Simple Moving Average is calculated to reduce noise.

vii. *Post Processing °2* = Exponentially Weighted Moving Average (λ =0.1, 0.069)

Figures 9 a & b show the residuals calculated for the example fault type Down-rating 15% using the described method with (λ = 0.001).

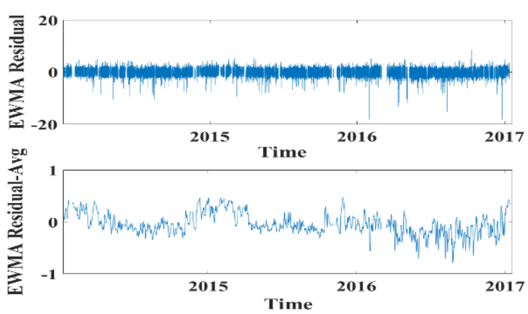

Figure 9. EWMA Residual for: Down-rating15% (a) Unprocessed and (b) Moving Averaged

3.3. Performance Evaluation

Both methods explained above are used to calculate residuals for all fault types and for 10 iterations of data. The real input wind and temperature profiles from the same wind turbine were used to generate these data streams. Performance analysis of the fault detection by thresholding the calculated residuals is done adopting the framework explained in Section 2.3. Note that different tests have been performed with various iterations of data with multiple cases and combinations of post processing techniques like moving mean, median, variance, kurtosis, standard deviation and various values of smoothing parameter λ of exponentially weighted moving average (EWMA). Post-processing the residuals or the filtered residuals with "statistic" filters such as median, variance, kurtosis did not improve the fault detection performance, but varying valued of smoothing parameter (λ) had significant impact on the results.

3.4. Receiver Operating Characteristic Curves

The receiver operating characteristic curves showing the relationship between the probability of false alarms (false positive rate) and the probability of detection (true positive rate) are shown for each type of fault. These curves compare the detection capability of both methods with varying smoothing parameter λ for EWMA residual method. The area of interest in terms of false alarm rates is restricted to 50% and the results are presented for various fault types.

3.4.1. Fault Type: Low Icing

Figure 10 shows the ROC Curves calculated for the low icing type faults. All configurations except simple residual reach close to optimal detection 100% for a false alarm rate of <5%

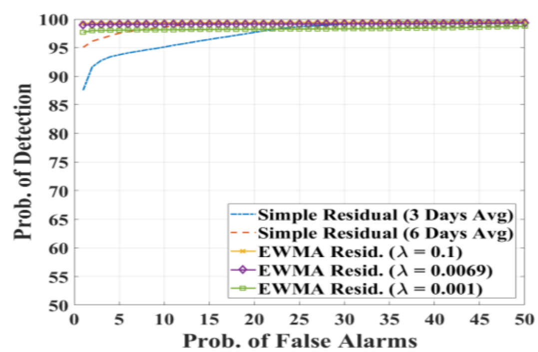

Figure 10. ROC Curve: Icing Low

3.4.2. Fault Type: Medium Icing

The fault type medium icing is efficiently detected by both methods and high true detection rates are reached for low false alarm rates. Figure 11 shows the ROC Curves calculated for the medium icing type faults.

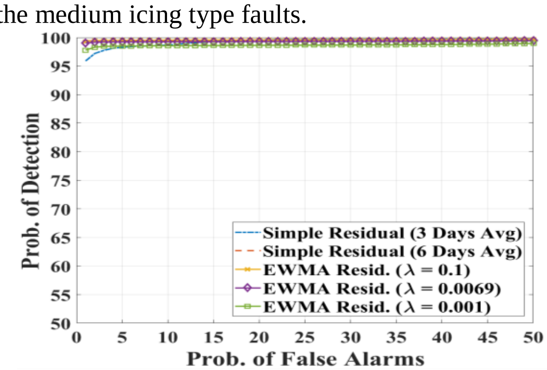

Figure 11. ROC Curve: Icing Medium

3.4.3. Fault Type: High Icing

Similar to fault types low and medium icing, both methods were able to optimally detect the high impact icing fault type. Figure 12 shows the ROC Curves calculated for the high icing type faults using simple residual calculation method and EWMA Method for varying smoothing parameter λ.

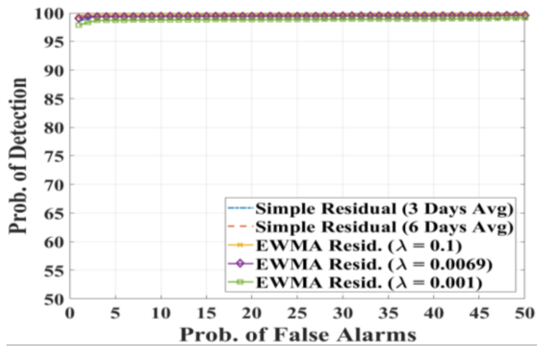

Figure 12. ROC Curve: Icing High

3.4.4. Fault Type: Down-rating 15%

The fault signature and hence the behavior of down rating fault types is different than the icing faults hence the performance of detection is visibly different as well. Figure 13 shows the ROC Curves calculated for the Down-rating 15% type faults. Due to the nature of this fault (only visible for wind speeds > ~9m/s) the overall performance of both methods is low. Only EWMA method with smoothing parameter λ=0.001 achieved a true detection rate of 60% for false alarm rate of 15%.

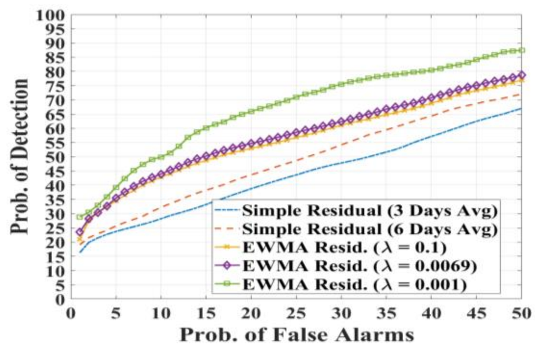

Figure 13. ROC Curve: Down-rating 15%

3.4.5. Fault Type: Down-rating 33%

The true detection rates for down-rating of 33% are generally improved for all the residuals as compared to 15% down rating. The residual with a smoothing parameter λ = 0.001 shows the best detection results for this type of fault with (85% true detection for false alarm rate of 10%). Figure 14 shows the ROC Curves calculated for the Down-rating 33% type faults.

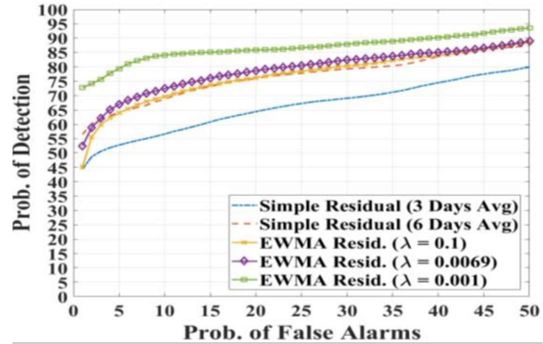

Figure 14. ROC Curve: Down-rating 33%

3.4.6. Fault Type: Down-rating 53%

The down rating of more than 50% has a significant fault signature and hence the true detection rates are increased considerably. With 4 of 5 configurations reaching a true detection rate of 85% or more for 10% false alarm rate, figure 15 shows the ROC Curves calculated for the fault type of 53% down-rating.

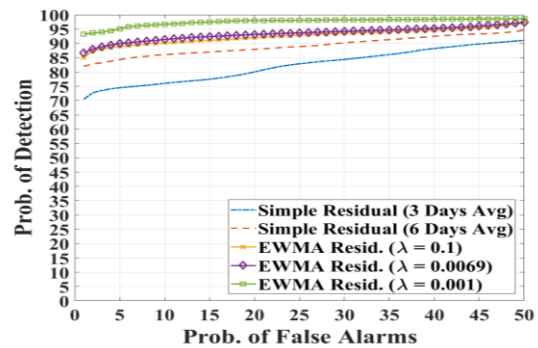

Figure 15. ROC Curve: Down-rating 53%

4. CONCLUSION

The proposed approach presented in Section 2 enables the creation of a SCADA data simulator that can be used to test fault detection methods. Section 3 uses the developed simulation procedure to generate a controlled and well-known data set to test and assess the performance of fault-detection procedures. The ideas presented in this paper were tested and used to compare two methods presented in literature for a controlled benchmarking of the detection capacity and utility of these approaches.

The overall summary and conclusions drawn through analysis are as follows:

- An overall procedure for SCADA data simulation has been developed: it allows to simulate SCADA data following a user-controlled faulty (or normal) power curve pattern, while at the same time, mimicking the real dispersion of the SCADA data]

- Two realistic faults of varying intensity levels were created and simulated namely: (icing (low, medium, high) and down-rating (15%, 33% and 53% of the nominal power)

- Computing the residuals or the filtered residuals with "statistic" filters such as median, variance, kurtosis does not improve the results (not presented here).

- Using the EWMA method on the data set, the best results are obtained with the value of smoothing parameter λ = 0.001, when the filtering effect is maximal.

- The EWMA method with smoothing parameter λ =0.001 outperforms the simple residual method for all the considered fault types.

- Icing is a fault which is easy to detect, whatever the method used. The performance of all variations were optimal for all intensities.

- The fault effect of icing is easily visible on the residuals because it is visible when the wind speed is between cut-in and nominal wind speeds (3m/s – 11.2 m/s approx.).

- Down-rating 15% is the most difficult to detect because it is visible only when the wind speed is higher than the ~9 m/s for the case taken as reference.

REFERENCES

Beiter, P., & Tian, T. (2016). *2016 renewable energy data book*. National Renewable Energy Laboratory.

Bi, R., Zhou, C., & Hepburn, D. M. (2017). Detection and classification of faults in pitch-regulated wind turbine generators using normal behaviour models based on performance curves. *Renewable Energy*, *105*, 674–688. https://doi.org/10.1016/j.renene.2016.12.075

Cambron, P., Lepvrier, R., Masson, C., Tahan, A., & Pelletier, F. (2016). Power curve monitoring using weighted moving average control charts. *Renewable Energy*, *94*, 126–135. https://doi.org/10.1016/j.renene.2016.03.031

de Andrade Vieira, R. J., & Sanz-Bobi, M. A. (2015). Power curve modelling of a wind turbine for monitoring its behaviour. In *Renewable Energy Research and Applications (ICRERA), 2015 International Conference on* (pp. 1052–1057). IEEE. Retrieved from http://ieeexplore.ieee.org/abstract/document/7418571/

Global Wind Energy Council. (2017). *Global Wind Statistics 2017*. GWEC. Retrieved from http://gwec.net/wp-content/uploads/vip/GWEC_PRstats2017_EN-003_FINAL.pdf

IEC 61400-12-1. (2005). Power Performance Measurements of Electricity Producing Wind Turbines.

Kim, S.-Y., Ra, I.-H., & Kim, S.-H. (2012). Design of wind turbine fault detection system based on performance curve. In *Soft Computing and Intelligent Systems (SCIS) and 13th International Symposium on Advanced Intelligent Systems (ISIS), 2012 Joint 6th International Conference on* (pp. 2033–2036). IEEE. Retrieved from http://ieeexplore.ieee.org/abstract/document/6505401/

Kusiak, A., & Verma, A. (2013). Monitoring Wind Farms With Performance Curves. *IEEE Transactions on Sustainable Energy*, *4*(1), 192–199. https://doi.org/10.1109/TSTE.2012.2212470

Kusiak, A., Zheng, H., & Song, Z. (2009). Models for monitoring wind farm power. *Renewable Energy*, *34*(3), 583–590. https://doi.org/10.1016/j.renene.2008.05.032

Lydia, M., Kumar, S. S., Selvakumar, A. I., & Prem Kumar, G. E. (2014). A comprehensive review on wind turbine power curve modeling techniques. *Renewable and Sustainable Energy Reviews*, *30*, 452–460. https://doi.org/10.1016/j.rser.2013.10.030

Park, J.-Y., Lee, J.-K., Oh, K.-Y., & Lee, J.-S. (2014). Development of a Novel Power Curve Monitoring Method for Wind Turbines and Its Field Tests. *IEEE Transactions on Energy Conversion*, *29*(1), 119–128. https://doi.org/10.1109/TEC.2013.2294893

Röckmann, C., Lagerveld, S., & Stavenuiter, J. (2017). Operation and Maintenance Costs of Offshore Wind Farms and Potential Multi-use Platforms in the Dutch North Sea. In B. H. Buck & R. Langan (Eds.), *Aquaculture Perspective of Multi-Use Sites in the Open Ocean* (pp. 97–113). Cham: Springer International Publishing. https://doi.org/10.1007/978-3-319-51159-7_4

Tavner, P. J. (2012). *Offshore wind turbines: reliability, availability and maintenance*. London, U.K: Institution of Engineering and Technology.

Uluyol, O., Parthasarathy, G., Foslien, W., & Kim, K. (2011). Power curve analytic for wind turbine performance monitoring and prognostics. In *Annual conference of the prognostics and health management society* (Vol. 2, pp. 1–8). Retrieved from http://72.27.231.73/sites/phmsociety.org/files/phm_submission/2011/phmc_11_049.pdf

Van Trees, H. L. (2001). *Detection, estimation, and modulation theory. Part I, Part I,*. New York; Chichester: Wiley. Retrieved from http://search.ebscohost.com/login.aspx?direct=true&scope=site&db=nlebk&db=nlabk&AN=98954

Yang, W., Court, R., & Jiang, J. (2013). Wind turbine condition monitoring by the approach of SCADA data analysis. *Renewable Energy*, *53*, 365–376. https://doi.org/10.1016/j.renene.2012.11.030

Yang, W., Tavner, P. J., Crabtree, C. J., Feng, Y., & Qiu, Y. (2014). Wind turbine condition monitoring: technical and commercial challenges: Wind turbine condition monitoring: technical and commercial challenges. *Wind Energy*, *17*(5), 673–693. https://doi.org/10.1002/we.1508