Detection of Wind Turbine Power Performance Abnormalities Using Eigenvalue Analysis

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Abstract

Condition monitoring of wind turbines is a field of continuous research and development as new turbine configurations enter into the market and new failure modes appear. Systems utilising well established techniques from the energy and industry sector, such as vibration analysis, are commercially available and functioning successfully in fixed speed and variable speed turbines. Power performance analysis is a method specifically applicable to wind turbines for the detection of power generation changes due to external factors, such as icing, internal factors, such as controller malfunction, or deliberate actions, such as power de-rating. In this paper, power performance analysis is performed by sliding a time-power window and calculating the two eigenvalues corresponding to the two dimensional wind speed - power generation distribution. The power is classified into five bins in order to achieve better resolution and thus identify the most probable root cause of the power deviation. An important aspect of the proposed technique is its independence of the power curve provided by the turbine manufacturer. It is shown that by detecting any changes of the two eigenvalues trends in the five power bins, power generation anomalies are consistently identified.

1. Introduction

Nowadays, condition monitoring of wind turbines is directly connected to the predictive maintenance strategy employed by numerous operators in order to increase the availability, minimize the maintenance expenses, reduce the downtime and therefore the cost of energy (CoE) (Butler, Ringwood, & O'Connor, 2013). As many countries in Europe and worldwide have set high goals for the renewable energy penetration on their systems, CoE constitutes an important parameter for the competitiveness of wind power compared to the conventional energy sources (Lu, Li, Wu, & Yang, 2009).

Techniques such as vibration, temperature and oil analysis have been extensively applied for the mitigation of the unexpected operation and maintenance expenses over the past years focusing mainly on the drive train components. Continuous data trending is an essential part of condition monitoring in order to identify the commence of a faulty state and its progression in time. A typical example is the trending of speed related narrowband filtes, such as running speed harmonics and tooth mesh frequencies, and not speed related broadband measurements in vibration analysis (Marhadi & Hilmisson, 2013).

As the power rating of modern turbines is continuously increasing reaching 8MW in prototype installations, it is a requirement that their condition monitoring is performed holistically combining various techniques. Power performance analysis can be used as an assisting tool along with the established methods, such as vibration analysis. Its utilization as power generation abnormality detector and general indicator of the overall health of the turbine is based on analysing standard collected supervisory control and data acquisition (SCADA) system information and extracting useful features (Uluyol, Parthasarathy, Foslien, & Kim, 2011).

The theoretical input power obtained from wind can be expressed by the following equation:

$$P = 0.5\rho A C_p(\lambda, \beta) u^3 \tag{1}$$

where P is the power captured by the wind turbine rotor, ρ is the air density, A is the swept rotor area, C_p is the power coefficient, β is the blade-pitch angle, λ is the tip-speed ratio and u is the wind speed (Lydia, Selvakumar, Kumar, & Kumar, 2013). Furthermore, the air density ρ is equal to:

$$\rho = \frac{p}{RT} \tag{2}$$

where p is the absolute air pressure and R is the specific gas constant; these two parameters are functions of altitude and humidity (Schlechtingen, Santos, & Achiche, 2013). Finally, the air density ρ is also influenced by the ambient temperature T.

The above equations suggest that the input wind power depends on the weather conditions (seasonality) and the site of erection. Other factors, such as terrain, park topology, and wake effects contribute on the unique power production profile of every turbine (Mchali, Barthelmie, Frandsen, Jensen, & Rthor, 2006). Therefore, utilization of the nominal power curve applicable to each turbine type enhances a number of challenges which may complicate the identification of abnormalities.

In addition to the above, the wind turbine power production can be affected by external factors, such as icing and dirt on blades; internal factors, such as pitch system defect or control system malfunction; or by deliberate actions, such as power de-rating or application of specific operation modes (Park, Lee, Oh, & Lee, 2014). The aforementioned conditions yield power generation deviations which can be observed in different power production states.

In this paper, the application of eigenvalue analysis for monitoring of power performance deviations due to external factors and deliberate actions is presented and analysed. There are two special points on the proposed performance assessment method. Firstly, the power curve is divided in discrete power classes deviating from the conventional approach of having wind bins (Park et al., 2014). The power classification is followed in order to obtain finer resolution so as to discriminate between different performance deterioration factors. Furthermore, eigenvalue analysis is an unsupervised method meaning that the objective is to calculate a number of features from the distribution under consideration rather than explicitly defining relations between sets of variables, e.g. condition distributions in the form $p(output|input)$. Hence, prior knowledge of the power curve suggested by the wind turbine manufacturer or employment of power curve learning are not required.

The paper structure is as follows. Section 2 provides a short description to the mathematical background of eigenvectors and eigenvalues. In section 3, the method description is presented based on the analysis of a turbine subjected to ice build-up. The trending behaviour of the calculated eigenvalues is illustrated in section 4 for the cases of icing, power de-rating and operation under noise reduction mode. Finally, sections 5 and 6 present the discussion and conclusions respectively.

2. EIGENVECTORS AND EIGENVALUES BACKGROUND

The statistical characteristics of a given data set can be represented by the covariance matrix, its eigenvalues, and the corresponding eigenvectors. The following analysis is classified as an unsupervised learning method which can be used to discover correlation among patterns as well as intrinsic directions where the data patterns change most (with maximum variance).

$\mathbf{R_{xx}}$ is defined as the covariance matrix of the power curve data set, with dimension $N = 2$. The two orthonormal eigenvectors $\mathbf{e_1}$ and $\mathbf{e_2}$, corresponding to the eigenvalues λ_1 and λ_2 of the data covariance matrix $\mathbf{R_{xx}}$ are called eigenvectors.

$$\mathbf{R_{xx}} \cdot \mathbf{e}_i = \lambda_i \cdot \mathbf{e}_i \quad , \quad i = 1, 2 \tag{3}$$

These eigenvectors show orthogonal directions in the pattern space where data change is maximum (maximum variance) (Cios, Pedrycz, Swiniarski, & Kurgan, 2007). The latter feature is used to explore any abnormal deviations of the power curve which could potentially correspond to power production anomalies.

Providing a two dimensional data set (wind speed and power production), the number of eigenvectors is two. However, if more data related to the wind turbine operation are taken into consideration, such as the blade pitch angle, the rotor running speed, the ambient temperature and the nacelle direction, then principal component analysis could be employed to extract only the most informative factors. This reduction of dimensionality is usually applied on classification problems for data compression (Bishop, 2006).

3. WIND TURBINE POWER PERFORMANCE MONITORING VIA EIGENVALUES VARIATIONS

Figure 1 depicts the power production and wind speed s function of time for Turbine#14 for a period of approximately two years along with the derived power curve. The power production - wind speed data are sampled every one hour. The negative power values correspond to periods where the turbine is set to local mode due to performed maintenance activities or inspection of potential faulty components.

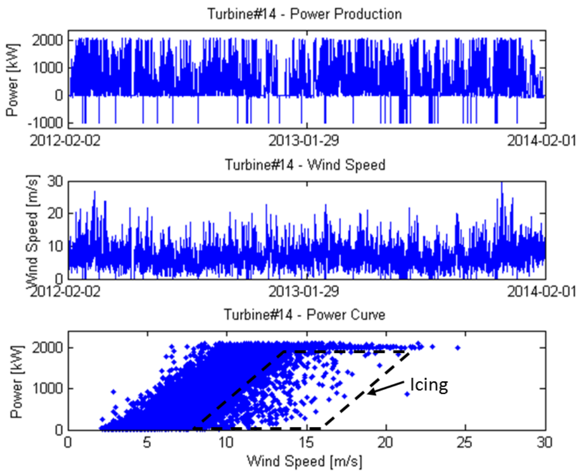

Figure 1. Turbine#14 - Power Production, Wind Speed and Power Curve - Case: Ice build-up on blades.

In order to detect any power performance changes, a sliding time window is used. The time window length selection is a compromise between computational cost and capability of extracting useful information. A reasonable choice is between one to three weeks, as a too long window would result in smoothing phenomena and a too short window would generate noisy results. The sliding time window can be overlapping for finer time resolution. The overlapping selection is also a function of the computational cost and desired time step. The analysis in the following sections is based on time window of two weeks and time step of one hour.

In order to proceed to the recognition of any patterns efficiently, the sliding time window is further divided into five power bins (classes). The classification into five bins follows Brüel and Kjær Vibro's vibration based condition monitoring scheme (Andersson, Gutt, & Hastings, 2007). The five classes are evenly distributed in general terms, but they might alter for different turbine models. The power classification is implemented so as to distinguish between various factors influencing the power production.

Figure 2 presents the power curve points of Turbine#14 under normal and abnormal power production for two weeks in late September 2013 and mid January 2014, along with the nominal power curve provided by the turbine manufacturer (black dashed line). The abnormal operation is due to ice build-up on the turbine blades, which was verified by the park operator. For better illustration, figure 3 presents the contour plot of the two dimensional histogram corresponding to the data shown in figure 2. The red lines correspond to high probability density function (pdf) values whereas the blue lines indicate low pdf values.

The data distribution of the right subplot in low to mid power production is significantly shifted to the right compared to the left subplot as well as compared to the power curve provided by the manufacturer. However, it should be noted that the ideal power curve should not be fully trusted as it is a function of the air density and consequently of the ambient temperature, which is not available for this turbine. Furthermore, it should be emphasized that the performance of a wind turbine is also influenced by site related factors and thus any discrepancies are not necessarily indicators of abnormal behaviour.

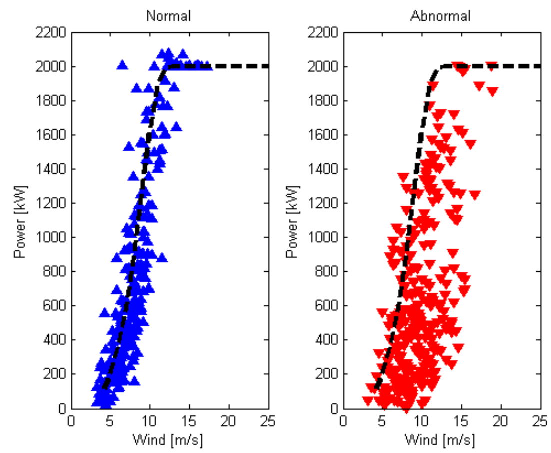

Figure 2. Turbine#14 - Power curve points under normal and abnormal (icing) power production.

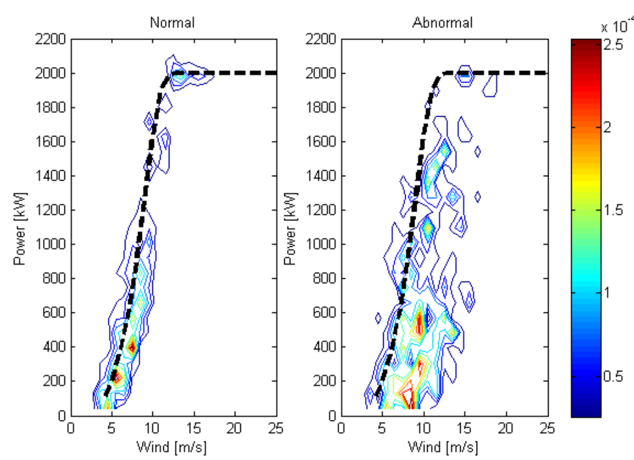

Figure 3. Turbine#14 - Contour plot of two dimensional histogram under normal and abnormal (icing) power production.

Following the power classification approach, figure 4 presents the contour plot of the two dimensional histogram in low production, i.e. from 0% to 30% of the nominal power output, for both normal and abnormal operation. It can be noticed that two orthonormal vectors are included for the two cases under investigation. The two vectors are further described by two quantities, direction and magnitude. The direction is defined by the eigenvector and the magnitude by the corresponding eigenvalue. The eigenvalues represent the variances of the data set in directions specified by the eigenvectors. Given that the direction does not vary significantly, the eigenvalues provide essential information about the scatter of the distribution and consequently the power performance of the wind turbine. Hence, figure 4 suggests that the distribution presented in the right subplot is drawn from a wind speed - power production data set where the performance of the turbine is influenced by an external factor. Bearing in mind that the right set corresponds to two weeks in January 2014 and that the turbine is installed in cold climate location, it can be concluded that icing is the most likely root cause of the detected power curve deviation.

The naming convention wind and power variation is adopted for the two eigenvalues. The virtual unit for wind variation is in m/s and for power variation is in kW.

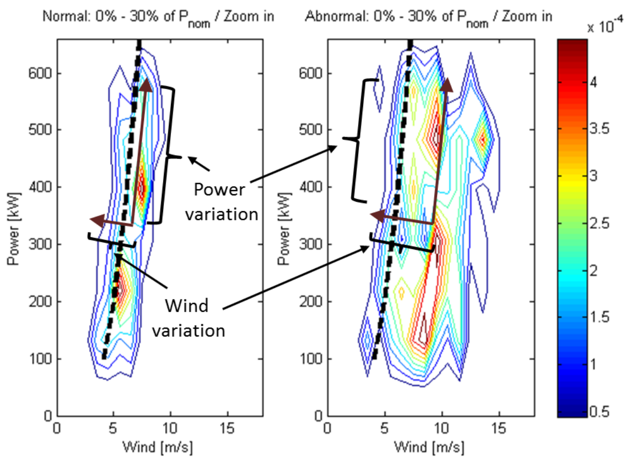

Figure 4. Turbine#14 - Zoom in low power production contour plot of two dimensional histogram under normal and abnormal (icing) power production.

4. DETECTION OF WIND TURBINE POWER PERFORMANCE ABNORMALITIES

Figures 5 and 6 show the trending behaviour of the square root of the two eigenvalues for two power classes, 0%-30% and 30%-50% of the rated power output. The sliding window length is two weeks and the time step is set to one hour.

It can be observed that the wind variation shows increased trends in both power bins in winter seasons. The increase in the trends shows that the scatter of the two-week sets is wider, indicating potential performance deterioration. Especially in winter 2012-2013, one can notice several hills and

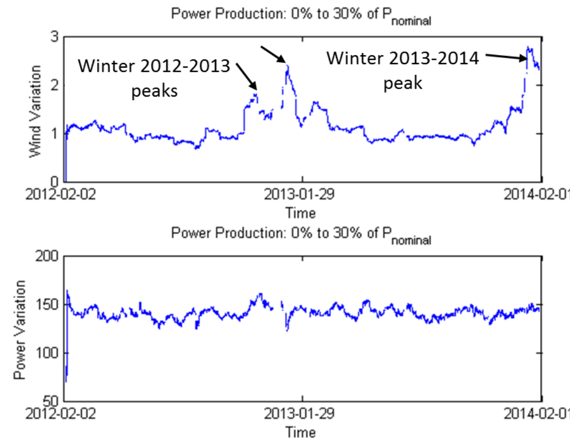

Figure 5. Turbine#14 - Icing - Trending behaviour of eigenvalues in low power production.

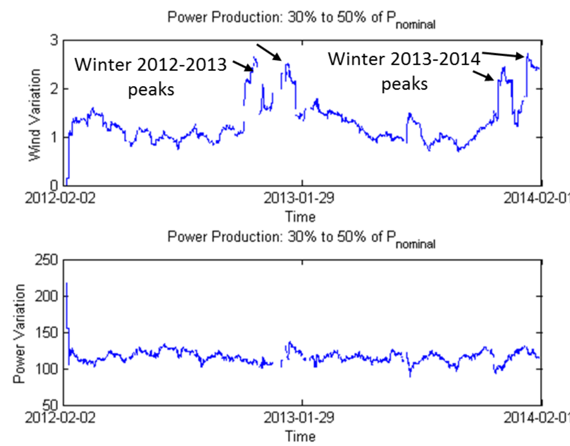

Figure 6. Turbine#14 - Icing - Trending behaviour of eigenvalues in low to mid power production.

valleys. The cause was ice formation on the turbine blades in December 2012, which was successfully removed by the turbine operator. However, the turbine was subjected to icing again a few days later resulting in emergency stop. The same phenomenon was repeated in winter 2013-2014, where again the wind variation behaviour presents clear increasing trends.

The above example focuses on icing detection, which can be classified as a condition which needs to be addressed by the turbine operator. However, many reasons, such as power derating or enabling of certain operation modes, can change power production from expected. If these actions are not communicated properly between the involved parties (park supervisor and technicians, performance centre, condition monitoring supplier) or the information flow has a delay of several days, unnecessary processes may initiate from either party.

Figure 7 presents the power production, wind speed time series and power curve of Turbine#09. The power output has been de-rated two times over the past two years due to grid issues. The power curve subplot validates the above as a cluster of points is centred at 1.5MW for wind speed above $12m/s$.

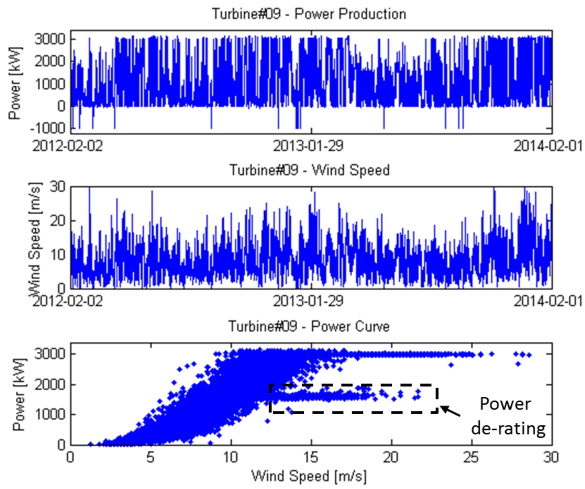

Figure 7. Turbine#09 - Power Production, Wind Speed and Power Curve - Case: Power output de-rating.

By inspecting the power production over time, one could identify that the generated power was restricted to approximately 50% in the beginning of 2013 until middle of the year. Although the wind speed could be advised to verify the above, the procedure is time consuming as data of at least a few days shall be available for confirmation. Figures 8 and 9 present the variation of the two eigenvalues in low (0% to 25%) and mid (45% to 65%) power classes. The power de-rating is clearly present in both eigenvalues in figure 9, whereas no change is seen for the low power class (figure 8). These observations lead to the the conclusion that the performance is influenced only in certain power bins and thus the most probable root cause is a deliberate control action by the turbine operator. The result from a vibration-based condition monitoring point of view is positive step changes on the gearbox speed related measurements during these periods. The latter can be considered as a sign of sudden changes in the drive train dynamics denoting a faulty operation of one or more components. Hence the eigenvalue trending can be used to detect any changes in the performance of the turbine which coincide with changes in the vibration data.

Two different control actions have caused power production variations on Turbine#07. Firstly, the power was de-rated to 1/3 of P_n for a short period of time in mid 2012. This action yielded changes to both eigenevalues as it was seen for Turbine#09 in figure 9. Then, a noise reduction mode was enabled for the current wind turbine (and for the vast majority of the turbines in the park) many times in 2012 and 2013. The noise reduction mode corresponds to the mitigation of the aerodynamic noise emitted by the blades by reducing the

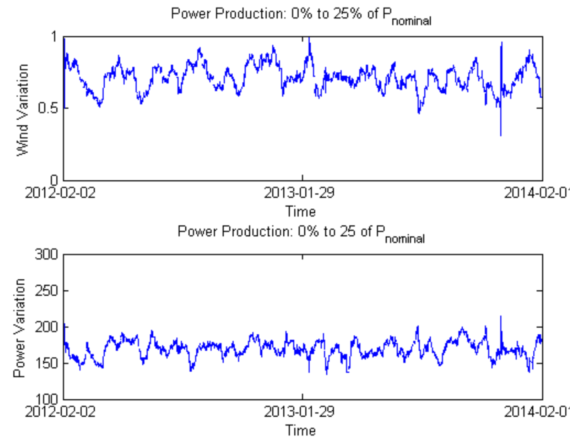

Figure 8. Turbine#09 - Power de-rating - Trending behaviour of eigenvalues in low power production.

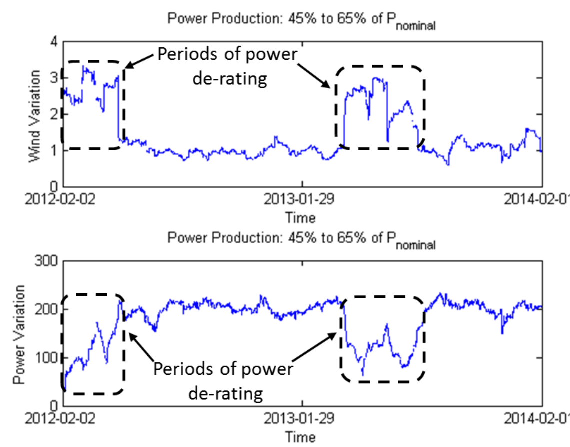

Figure 9. Turbine#09 - Power de-rating - Trending behaviour of eigenvalues in mid power production.

main rotor running speed. In this case, only the wind variation subplot presents increased trends matching the periods where this operation mode was active. It can be remarked that the wind and power variation is not affected by the operational changes in low power production. Thus, as for Turbine#09, the fact that the trends of the low power bin are stables indicates that the most likely origin of the increase in mid power production is again due to an intentional control action.

At this point, it is important to emphasize that the recognition of the power generation changes is solely based on the comparison between the normal behaviour and any decrease or increase of either the wind or power variation trends. This approach excludes the dependency from the power curve provided by the manufacturer. In addition, any site related factors influencing the power output profile of the turbine under investigation are implicitly included.

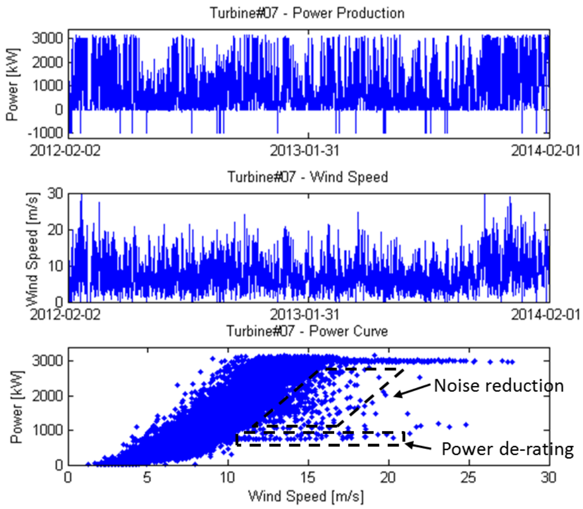

Figure 10. Turbine#07 - Power Production, Wind Speed and Power Curve - Case: Enabling of noise reduction mode.

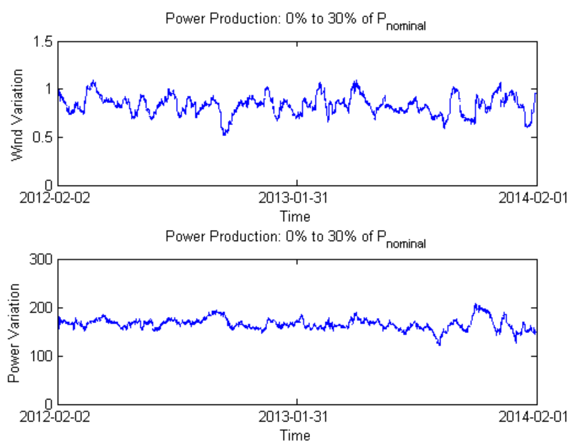

Figure 11. Turbine#07 - Noise reduction mode - Trending behaviour of eigenvalues in low power production.

5. DISCUSSION

The analysis presented in the previous sections attempted to illustrate the condition monitoring capabilities of the power performance technique. As condition monitoring systems rely on alarms when an alert or danger limit is violated, the same approach can be adopted in this case as well. The authors of the present paper are currently working on setting customized alert limits for each turbine individually after a short learning period (approximately one month) and global danger limits for each turbine type.

The results of the power performance monitoring method can be also applicable to other functions related to the operation of the turbine. A potential application is the enabling of de-icing systems installed in turbines erected in cold climate lo-

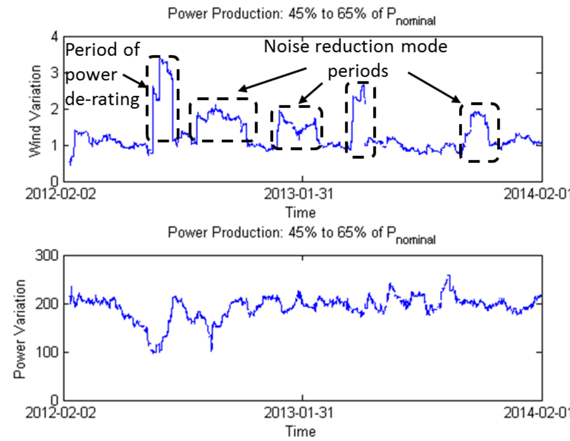

Figure 12. Turbine#07 - Trending behavior of eigenvalues in mid power production.

cations. By combining indications from the power performance analysis technique and the ambient temperature, the de-icing systems can be triggered in order to avoid long offline periods by consuming a portion of the energy production for heating the blades and the nacelle.

6. CONCLUSIONS

In this paper, changes in eigenvalues of wind speed - power production data sets are employed as power performance monitoring tools. Three cases have been analysed and presented: icing, power de-rating and noise reduction mode. The analysis has shown that detection of power production abnormalities can be achieved without necessity of the power curve provided by the turbine manufacturer, but based solely on the trending behaviour of the two eigenvectors. Furthermore, the division of the power output into discrete power classes has provided essential information regarding the identification of the most likely root cause of the power generation change. Finally, with high time resolution of the field data, the presented approach adds value to existing diagnostics, based on vibration, resulting in a comprehensive evaluation of the turbine state and consistent identification of issues during operation.

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BIOGRAPHIES

Georgios Alexandros Skrimpas was born in Athens, Greece in 1986. He received the Diploma in electrical and computer engineering from the Aristotle University of Thessaloniki, Greece, in 2009 and the M. Sc. in wind energy from the Technical University of Denmark (DTU) in 2012. He joined Brüel and Kjær Vibro in 2012 and since 2013 he is pursuing the Industrial Ph.D. degree at the Centre of Electric Power and Energy at DTU in cooperation with Brüel and Kjær Vibro. His research interests are diagnosis and prognosis of electrical and mechanical faults in wind turbines.

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Bogi Bech Jensen received the Ph.D. degree from Newcastle University, Newcastle Upon Tyne, U.K., for his work on induction machine design. He was in various engineering and academic positions in the marine sector from 1994 to 2004. He was at Newcastle University from 2004 to 2010 first as a Postgraduate, then Research Associate and finally as a Lecturer. From 2010 to 2014 he was Associate Professor and later Head of Research Group at the Technical University of Denmark (DTU), Lyngby, Denmark. He is currently Professor of Energy Engineering at the University of the Faroe Islands (UFI), where he is responsible for education and research in energy.

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Joachim Holbøll is associate professor and deputy head of center at DTU, Department of Electrical Engineering, Center for Electric Power and Energy. His main field of research is high voltage components, their properties, condition and broad band performance, including insulation systems performance under AC, DC and transients. Focus is also on wind turbine technology and future power grid applications of components. J. Holbøll is Senior Member of IEEE.