FAULT PREVENTION AND DIAGNOSIS THROUGH SCADA TEMPERATURE DATA ANALYSIS OF AN ONSHORE WIND FARM

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Abstract

Wind turbines, due to the distribution of the source, are an energy conversion system having low density on the territory, whose operational behaviour and production on the short term strongly depends on the stochastic nature of wind. They therefore need accurate assessment prior installation and careful condition monitoring in the operative phase. In the present work, smart post processing of Supervisory Control And Data Acquisition (SCADA) control system data sets is employed for fault prevention and diagnosis through the analysis of the temperatures of the machines. Automatic routines are developed for monitoring the evolution of all the temperature SCADA channels against power production. The methods are tested on an onshore wind farm sited in southern Italy, where nine turbines with 2 MW rated power are installed. The tests are performed both ex post and in real time: it is shown that in the former case, a major mechanical problem is detected, and in the latter case a significant problem to the cooling system is identified before compromising turbine functionality.

Keywords: wind energy, wind turbines, SCADA control system, fault diagnosis.

INTRODUCTION

Wind turbines are a technology for converting wind kinetic energy into dispatchable electric energy. The availability of the source, together with environmental or jurisprudential limitations, causes wind turbines to have a low density on the territory. Further, the stochastic nature of the wind source on the short term strongly drives the operational behaviour and the quality of the power output.

For these reasons, wind farms need careful assessment on site before installation and sophisticated control systems during the operative phase. Supervisory Control And Data Acquisition (SCADA) control system has therefore become widely diffuse in wind turbine technology. It stores on 10 minute time basis minimum, maximum, average and standard deviation of several measurement channels: some of the most relevant involve the wind flow (intensity and direction) at nacelle, nacelle position, active or reactive power and details of the conversion of wind kinetic energy into electrical energy, vibrational and mechanical aspects, temperatures in proximity of meaningful machine components. In order to extract explanatory information from the evolution of SCADA measurements and to prevent faults, sophisticated methods are required to smear out the noise and highlight the "treasure" encrypted in the evolution of SCADA channels. SCADA data analysis and statistical techniques have therefore become a fertile subject in the scientific literature.

In [1] a set of anomaly-detection techniques is built and a multi-agent system architecture is used to interpret: it is shown that such approach is capable of early fault detection. In [2] historical fault data are elaborated and classified in category, severity and type and are employed for modelling and predicting fault incoming one hour before they occur. In [3] a solid, although not very recent, review is provided on condition monitoring and fault diagnosis: attention is devoted to gearbox and bearing, rotor and blades, generator and power electronics, as well as system-wise turbine diagnosis. A survey on model based reasoning algorithms for fault detection is also provided. In [4] a more recent review is provided, in which methodologies for condition monitoring and fault detection are revised. Further, approaches based on physics, statistics and data mining for wind speed prediction on different time scales are reviewed. In [5] robust statistical techniques, as Least Median of Squares, are employed for smearing out low quality data and feeding reliable models, which are useful for fault predictions. Adaptative Neuro-Fuzzy Interference Systems (ANFIS) is a fertile technique for wind turbine condition monitoring through SCADA data mining [6, 7]. In [6] a three step strategy is set up: first normal behaviour models are used, by training Neural Networks, for detecting anomalies on appropriate SCADA data. Subsequently, occurred anomalies are related to reported faults, and relations are obtained to implement a knowledge database used by the Fuzzy Interference System to output diagnosis. In the following Paper [8], four data mining approaches based on the ANFIS methods are applied and their performances are compared. In [9] SCADA measurements are filtered for decorrelating them and subsequently statistical estimators of outliers related to anomalous behaviour are built. It is further shown that the approach is capable of catching incipient wind turbine blade and drive train faults and tracing wind turbine deterioration. In [10] state dynamics is analysed for ex post monitoring of wind turbine behaviour and for real time operational evaluation, through the formulation of two Malfunctioning Indices.

SCADA data mining techniques are not only useful for fault detection, but are also crucial for optimizing performances in the operative phase, quantifying and explaining energy losses, plan optimum maintenance. Actually, previous research of the authors [11, 12] shows that carefully investigating the operative phase and the relation between performance degradation and mechanical aspects provides useful insight for preventing faults. Optimizing performances passes through deep knowledge of wake interactions and their effects in deteriorating turbine functionality: at this aim, SCADA data mining techniques and numerical methods are widely exploited. In [13] power losses due to wakes are investigated for offshore wind farms of Horns Rev and Nysted in Denmark. In [12] the issue is addressed for onshore wind farms on complex terrains sited in southern Italy and it is shown that orography effects force to define efficiency of the farm in a novel and more consistent way, with respect to the offshore case [14]. In [15] post processing techniques are developed for quantifying wake power deficit and considerable attention is devoted to misalignment and yawing under downstream angles. In [16] the test case of Horns Rev is addressed and dependency of farm efficiency on wind rose, wind speed, turbulence intensity and stability of the atmosphere is quantified.

Ongoing research of the authors focuses on quantifying power production degradation, due to wakes, in relation to mechanical behaviour: anomalous nacelle blockage while the wind meanders and misalignment between wind direction and nacelle position. The lesson is that careful performance monitoring provides insight on turbine functionality degradation and stresses suffered from the machine, and thus is crucial to prevent faults.

In the present work, this philosophy is applied to the analysis of SCADA data from the temperature sensors of an onshore test case wind farm during the operative phase. The structure of the Paper is as follows: in Paragraph 1 the SCADA database, the post processing technique and the methods are described. In Paragraph 2 the wind farm, owned by Sorgenia Green and sited in southern Italy, is described. In Paragraph 3 the results are shown and it is demonstrated that the proposed methods for monitoring the history of temperature against power of single turbines and for comparing "horizontally" one turbine against the other, are capable to identify performance degradation leading to future faults and allow to intervene before traumatic machine stops. The methods are applied both ex post, on the historical SCADA data set of the wind farm, and in real time: in the former case, a major mechanical problem is individuated. In the latter case, a significant problem at the cooling system is found and resolved before leading to turbine degradation severe enough to stop and compromise machine functionality. Finally some concluding remarks are included, which summarize the results and sketch further directions of the present work.

1. The SCADA database and the method for temperature analysis

The data set at disposal is built as follows: the SCADA system stores data on 10 minute time basis, including minimum, maximum, average and standard deviation for each channel. The database provides a complete picture of machine functionality: it records details of the wind flow at nacelle (direction and intensity), of the conversion of wind kinetic energy into electric energy (active and reactive power and so on), of the mechanical status (nacelle position, blade pitch, rotor revolutions per minute etc.), of the electric behaviour, of the vibrations, of the temperatures in meaningful parts of the machine.

Further a landmark for atmospheric conditions is available thanks to a meteorological station, which stores in the same time basis as above the details of the wind flow (direction and intensity at multiple sensors), temperature, pressure, humidity and so on.

For the present work, data from the state dynamics of each machine have heavily been exploited for post processing SCADA data sets. These demarcate basically in two types: Operating States and Status Codes. The former are mutually exclusive states, resulting in a series of entries providing at which time stamp what each turbine starts doing (producing output, awaiting enough wind strength, testing, resting for Brake Programs and so on). While the Operating States basically provide "what" each turbine does, the Status Codes provide a sketch of "why": they are not mutually exclusive, and they are classified in order of severity (info, warning, error). They are stored with associated time stamp and the indication if the state is incoming or phasing out.

The Operating States database has been employed for the present work as a read only tool for filtering "raw" SCADA measurement, as depicted in Figure 1. Since the aim is preventing faults and detecting machine degradation before traumatic stops, the zoom is focused on the regime of power output production. Further, since comparison of one machine against the other inside the wind farm is a precious tool for early fault prevention, data have actually been filtered on the condition of unison power output production of the whole farm.

The temperature sensors analysed for the present work are the following:

- Converter Inlet
- Gearbox Inlet
- Gearbox Bearing (2 sensors)
- Generator Bearing (2 sensors)
- Rotor Bearing
- Oil Sump
- Stator Wind
- Top Box

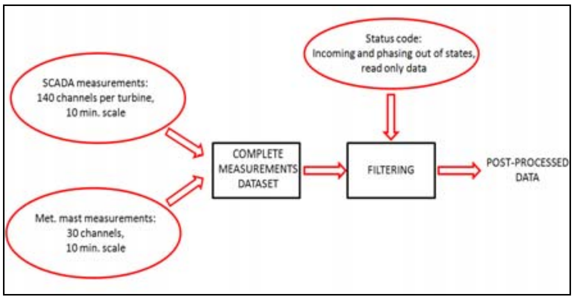

Figure 1. The structure of the data set.

The method we propose is a plot of the measurements of each temperature sensors against the percentage of power with respect to the rated. In order to highlight the trends, this is done by averaging on intervals with amplitude of 10% of the rated power. It has been observed that the results do not sensibly depend on the amplitude of the binning interval and this threshold has therefore been chosen for compromising necessity of capturing the details of temperature evolution against machine functionality and representativeness, i.e. adequate population, of the intervals.

The plots above are done "horizontally" along the wind farm, for each turbine, and using the SCADA mean value measurement for each temperature sensor: this, as shall be shown later, allows to highlight massive deviations of single machines from the main trend of the farm. This tool is applied ex post on the historical data and in real time on the test case wind farm and it is shown that is capable to isolate temperature trends, which are evolving into traumatic stops of the machine. Therefore the method is extremely useful as alarm signal for intervention on the machine before incoming of serious damage.

Further, the same plots are performed on variable time scale, from monthly to daily, and using the data set of minimum and maximum values on 10 minutes time basis. This allows to single out potentially dangerous spikes and short term anomalies. On the other way round, the dominant trend of the each turbine is also analysed by smearing out anomalies, and plotting the median of temperature values for each interval of percentage of rated power.

2. The wind farm

The present work deals with an onshore wind farm, owned by Sorgenia Green and sited in southern Italy on a terrain with gentle slopes. On site nine turbines are installed with a rated power of 2 MW each. The main features of the turbines are summarised in Table 1.

Table 1: Main turbine characteristics

Nominal Power	2 MW
Rotor Diameter	82 m
Hub height	80 m
Tower	Tubular

The layout of the farm deserves attention: as shown in Figure 2, the slopes are gentle and the dynamics is therefore mainly driven by wake interactions. The distance between turbines is such as resulting in considerable wake effects: the closest turbine are T53 and T55; T58 and T59 can be affected by multiple wakes in the east-west direction, which is far the most populated of the wind rose in the period under examination.

Wake interactions affect the mechanical behaviour of the turbines: due to meandering wind, anomalous nacelle blockages and misalignments with respect to the wind direction occur. Due to other expected phenomena (anomalous rotor revolutions etc.), when the wind blows mainly from sectors which give rise to wakes, a close watch to temperature effects is needed, in order to prevent turbine degradation.

The turbine T42 is isolated from the main cluster of turbines, at more than 13 diameters from the other aerogenerators. Therefore its SCADA data should be treated with care, when comparing it with the other machines of the wind farm.

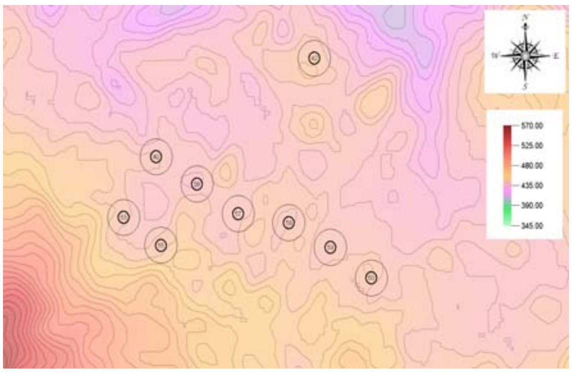

Figure 2. The layout of the wind farm

3. The results

The first application of the proposed method is on the historical data of the year 2013. Figure 3 shows the plot of Rotor Bearing temperature against relative power output, averaged as discussed in

Paragraph 2, for the test period of two spring months during 2013. Figure 3-(a) shows mean, with standard deviation, mode and maximum for each power bin of turbine T53. Figure 3-(b) is the same plot for turbine T60, whose functionality has been normal. Comparing the two plots, the massive anomaly of turbine T53 is highlighted: it reflects also on the other temperature sensors of the drive train, omitted for brevity. Figure 3-(c) displays a bird's eye view of the mean Rotor Bearing temperature for all the wind farm: it shows that the farm behaviour has been homogenous, except for the anomalous turbine T53. The turbine has actually undergone the substitution of the main shaft immediately after the period plotted in Figure 3, due to a major mechanical problem.

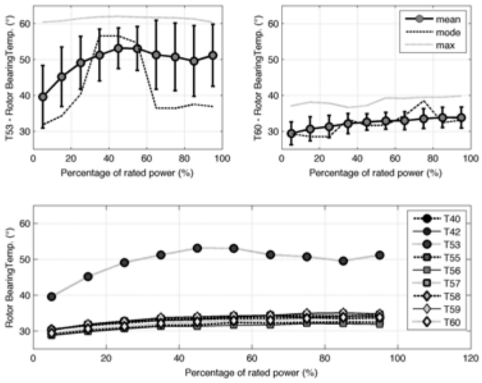

Figure 3: Mean, mode and minimum of Rotor Bearing Temperature for turbine T53 (a), T60 (b). Mean of Rotor Bearing Temperature for all the turbines (c). Sample spring period in 2013.

During the period of Figure 3, alarm status codes were activated and therefore our analysis has been shifted to the beginning of year 2013, in order to inquire if our method is capable of catching incoming faults before the control system of the machine signals them. The method is thus applied on a shorter time scale: weekly. Figure 4 below shows the behaviour during the third week of 2013 and Figure 5 shows the fifth week of 2013, which is the first period of alarm activation. From the figures it is evident that the anomaly of turbine T53 is sharper during week 5, but it is nevertheless very clear also during week 3. We therefore infer that our method is a useful "wake-up call" for monitoring wind turbines and identifying suspect incoming faults.

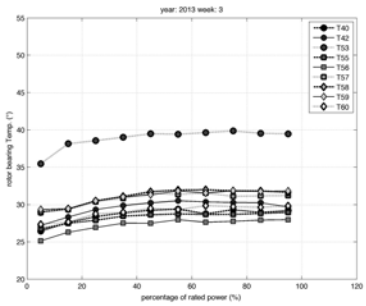

Figure 4. Mean Rotor Bearing Temperature for weekly test period: week 3 of 2013.

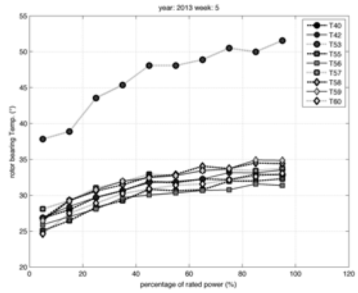

Figure 5. Mean Rotor Bearing Temperature for weekly test period: week 5 of 2013.

The test case above allows to inquire if the method is capable of encoding also when the turbine turns back to its normal thermal behaviour after a huge maintenance. This has been analysed through a weekly map, which crosses the maintenance period, of the main shaft temperatures of turbine T53. Figure 6 and 7 below therefore show the weekly history of Rotor Bearing Temperature from the 2nd to the 17th week of 2013 for turbine T53, and it appears that during week 17, which is posterior to the maintenance, the temperature goes back to the expected behaviour, which is analogous to the one of Figure 3-(c), which is the milestone for normal functionality. We therefore argue that our method is also useful for monitoring machines after massive maintenance.

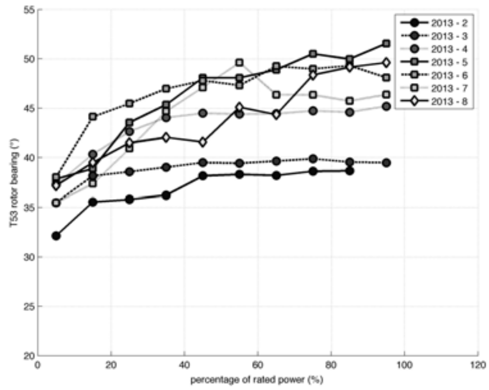

Figure 6. Mean Rotor Bearing Temperature for weekly test periods of turbine T53

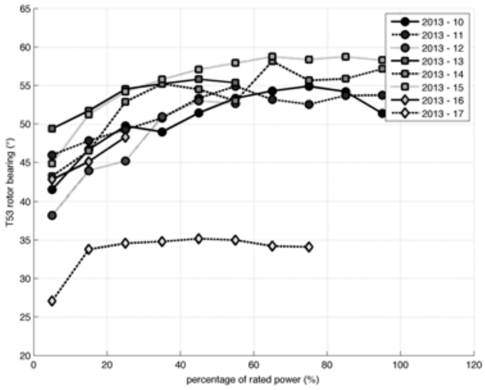

Figure 7. Mean Rotor Bearing Temperature for weekly test periods of turbine T53

Figure 8 shows the same analysis of Figure 3, on a different monthly test period: a worrying anomaly on the temperatures related to the generator is highlighted for turbine T59.

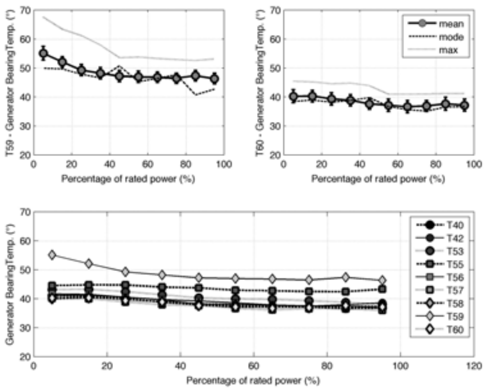

Figure 8. Mean, mode and minimum of Generator Bearing Temperature for turbine T59 (a), T60 (b). Mean of Rotor Bearing Temperature for all the turbines (c). Sample spring period in 2014.

Therefore the focus is shifted on turbine T59 on a shorter time scale: Figure 9 shows the same plot as Figure 8-(c), but each line represents the data of a different week of 2014 (with its numbering) only for turbine T59, during the month before the period of Figure 8.

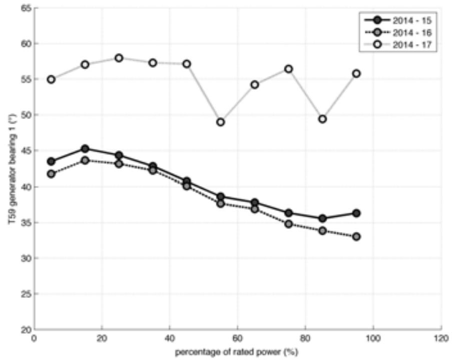

Figure 9. Mean of Generator Bearing Temperature for turbine T59. Sample weekly periods immediately before Figure 6.

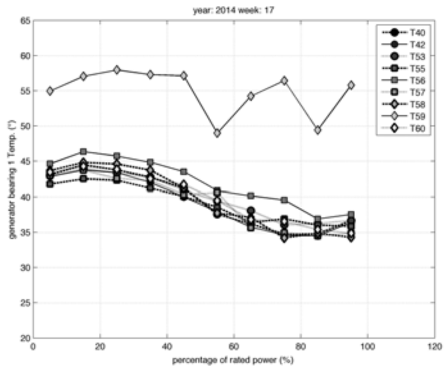

Figure 10. Mean Generator Bearing Temperature for weekly test period: week 17 of 2014.

From Figure 9 several considerations arise: firstly, temperature behaviour mildly varies from period to period due to outside temperature conditions. Secondly and most importantly, a significant anomaly peaks far more sharply with respect to normal temperature fluctuations: Figure 9 actually shows that the anomaly begins in during the 17^{th} week of 2014. Therefore, in Figure 10 a bird's eye view of the whole farm, during the same week 17 of Figure 9, is provided and it appears very sharply that the Generator Bearing Temperature of turbine T59 is massively anomalous.

Thanks to this analysis, a problem to the generator fan of turbine T59 has been individuated and solved before producing serious damages to the machine. Comparing Figure 8 to Figure 3, it also arises that in the case of turbine T53 the functionality appears so degraded that not only the mean of Rotor Bearing temperature anomalously peaks with respect to the rest of the farm, but also the standard deviation of the measures inside each bin is anomalously large. In the case of turbine T59 depicted in Figure 6, the standard deviation is of the same order of magnitude as the other turbines. This is an interesting difference, which might encode details of the severity of the temperature anomaly.

The approach above is useful not only for detecting urgent incoming faults, but also for monitoring fluctuations which are suspect of evolving into faults on a longer time scale. Figure 11 shows indeed another monthly test period in Fall 2013, during which turbine T42 shows an anomalous fluctuation, not as massive as the cases above but significant, of Rotor Bearing and other drive train temperatures.

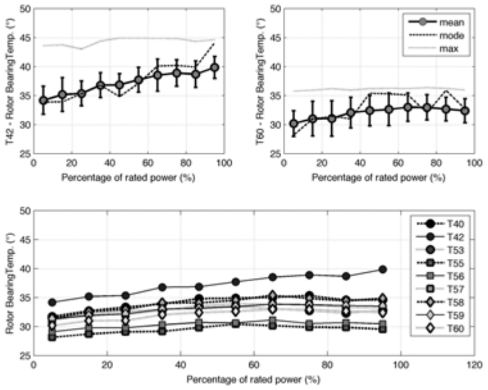

Figure 11. Mean, mode and minimum of Generator Bearing Temperature for turbine T42 (a), T60 (b). Mean of Rotor Bearing Temperature for all the turbines (c). Sample period in Fall 2013.

Yet, crossing against Operating State and Status Codes data sets, it arises that turbine T42 has shown the best productive time and the best production of the farm during the test period plotted in Figure 9. Therefore the analysis has been pushed further to a comparison between different monthly samples of the history of turbine T42. The behaviour is anomalously floating in time, more than expected due to mere outside temperature seasonality.

Performances have not been affected by these fluctuations for long time. Yet, recently temperatures have evolved to a worrying range of deviation, which resembles the test cases described in Figures 3 and 8, and is currently under analysis by the wind farm owner.

For this reason, the weekly analysis has been carried on during the weeks immediately before the appearance of warning signals and is plotted in Figures 12 and 13. Figure 12 shows the 20th week of 2014, during which a considerable anomaly for Rotor Bearing temperature of turbine T42 appears. Not negligible is also the worrying trend of T40. Figure 13 shows the analysis of three sample weeks, during spring 2014, of Rotor Bearing temperature for turbine T42: a considerable increase is highlighted, which actually further evolved in anomaly so massive to be individuated also by the control system of the machine.

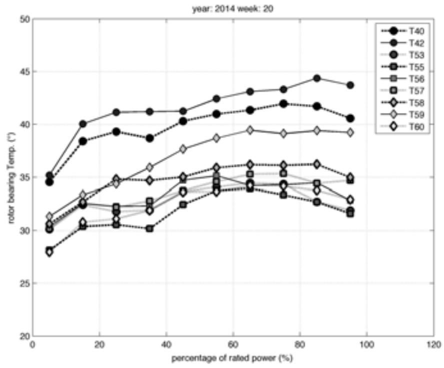

Figure 12. Mean Rotor Bearing Temperature for weekly test period: week 20 of 2014.

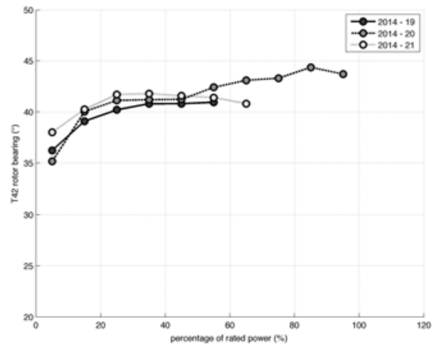

Figure 13. Mean of Rotor Bearing Temperature for turbine T42. Sample weekly periods during Spring 2014.

The lesson, from the test cases shown above, of turbines T42, T53 and T59 during different periods, is therefore that the proposed method allows not only to prevent urgent incoming faults and make diagnosis before the control system alerts about it, but also to monitor long-term trends of temperatures, which are suspect to evolve in warning and error situations.

4 Final remarks further directions

The present Paper has dealt with the analysis of temperatures during the operational phase of a test wind farm sited in southern Italy (Figure 2). On site nine turbines are installed with a rated power of 2 MW. The method is based on the post processing of SCADA data sets, through the read-only information contained in the state dynamics. The focus is on the operative phase of the wind farm, because the aim is furnishing methods for early fault detection far before traumatic machine stops. The main tool is a plot of average temperature for each interval of power output in units of the rated power. This is automatically performed for each turbine of the farm, allowing “horizontal” comparison between the machines, on multiple time scales, and for each temperature sensor included in the SCADA system (see Paragraph 1 for the list). As shown in Paragraph 3, the approach is tested both on historical data of year 2013 and in real time. It is demonstrated that the method is capable to highlight anomalies evolving into faults: for turbine T53 a mechanical problem, which led to the substitution of the main shaft, is individuated. For turbine T59, a problem to the generator fan is individuated in real time, through the analysis on multiple time scales: this has led to the substitution of the component before major problems occurred. The method has not only been used as a sentinel for early detection of incoming traumatic situations, but also for long-term analysis. The test case of turbine T42 has actually been investigated: drive train temperatures are seen to be significantly floating, yet not enough to be qualified as urgent anomalies. It has yet been observed that, for turbine T42, the amplitude of fluctuations has increased with time and finally reached alert level. The lesson is therefore that the proposed method is useful both for early fault detection and for long term monitoring of turbine functionality. Several are the further directions of the present work: wake effects commonly affect power performance and are associated mechanical stress, as anomalously protract nacelle blockage while the wind meanders and nacelle misalignment with respect to wind direction. It is planned to increase the level of post processing complexity, zoom into the regimes most suspect of being affected by wakes and inquire if peculiar temperature effects arise. This is indeed an ambitious task, because temperature behaviour of the machines is affected by multiple agents and it is therefore complicated to single out peculiar thermic effects associated to wakes. Yet, wakes can be clearly put in relation with mechanical stress, as the following Figures 14 and 15 show. In Figure 14 the percentage standard deviation of rotor revolutions per minute is plotted against the percentage of rated power, for all the turbines in the wind farm. Measures are averaged on 10 intervals of power percentage, as in the Paragraph above. Figure 15 instead zooms in the regime most expected to result in wake effects: data are filtered in 270° sector, according to the criterion of nacelle position being between 240° and 300°, as measured by turbine T55, which is upstream, and therefore taken as reference when the wind blows in this direction sector.

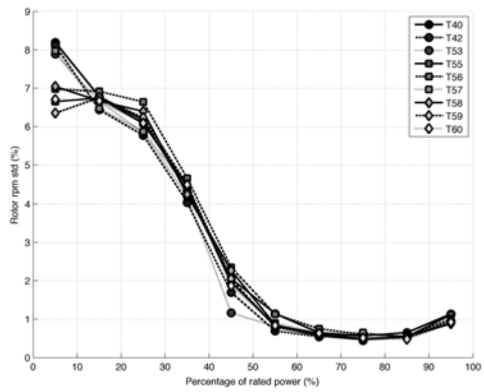

Figure 14. Mean percentage of rotor revolutions per minute standard deviation. Sample period in Spring 2013.

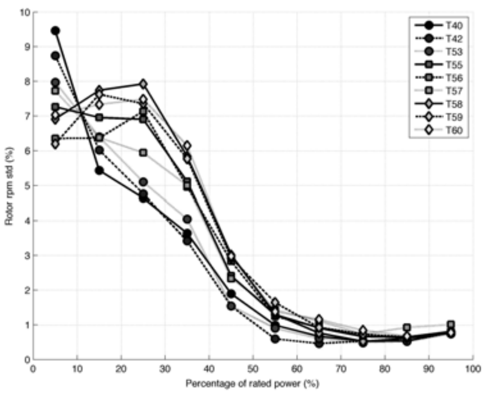

Figure 15. Mean percentage of rotor revolutions per minute standard deviation: 270° sector. Sample period in Spring 2013.

The shapes of the plots of Figures 14 and 15 are considerably different: it is evident that the plot of Figure 15 is smeared in the regime of low powers, which corresponds to low wind intensity, high turbulence, maximum influence of wakes. In this regime, actually, the turbines affected by wakes show a remarkably higher rotor revolutions per minute standard deviation with respect to the turbines upstream. The plot in Figure 14 shows instead that the average mechanical behaviour of the farm is homogeneous. Thus, the emergence of wakes is clearly identified by a mechanical point of view. Since relating wakes directly to temperatures is expected to be a complex task, it might be useful to use the peculiar wake mechanical effects as a trait d'union for the analysis.

This approach might indeed be very useful for planning optimum maintenance programs, in order to minimize as possible the stress to the machine. It is also planned to apply the methods of the present Paper to test case wind farms on very complex terrains, with slopes up to 60% in proximity of the turbines, in order to investigate if temperature trends in the operational phase and fault occurrence sensibly depend on terrain complexity. Finally, the method can be pushed further for investigating if temperature trends can be correlated to mechanical aspects and if incoming faults can be interpreted in terms in such framework, as suggested in [9] and modelled in [17].

References

[1] Zaher A., McArthur S.D.J, Infield D.G., Patel Y.: *Online wind turbine fault detection through automated SCADA data analysis*. Wind Energy, Volume 12, Issue 6, 574-593 (2009).

[2] Kusiak A., Li W.: The prediction and diagnosis of wind turbine faults. Renewable Energy 36 (2011) 16.

[3] Bin Lu, Yaoyu Li, Xin Wu, Yang Z.: *A review in recent advances in wind turbine condition monitoring and fault diagnosis*. Power Electronics and Machines in Wind Applications, 2009. PEMWA 2009 IEEE, 1-7.

[4] Kusiak A., Zhang Z., Verma A.: *Prediction, operations and condition monitoring in wind energy*. Energy 60 (0) (2013) 1-12.

[5] Sainz E., Llombart A., Guerrero J.J.: *Robust filtering for the characterization of wind turbines: Improving its operation and maintenance*. Energy Conversion and Management 50 (9) (2009) 2136-2147.

[6] Schlechtingen M., Ferreira Santos I., Achiche S.: *Wind turbine condition monitoring based on SCADA data using normal behavior models. Part 1: System description*. Applied Soft Computing Volume 13 January 2013.

[7] Elijorde F.I., Moon D., Ahn S., Kim S., Lee J.: *Wind turbine performance monitoring based on hybrid clustering method*. Future Information Communication Technology and Applications, Lecture Notes in Electrical Engineering Volume 235, 2013, pp 317-32.

[8] Schlechtingen M., Ferreira Santos I., Achiche S.: *Using Data-Mining Approaches for Wind Turbine Power Curve Monitoring: A Comparative Study*. Sustainable Energy, February 2013, Volume PP, Issue 99, pp. 1-9, DOI:10.1109/TSTE.2013.2241797.

[9] Yang W.,Court R., Jiang J.: *Wind turbine condition monitoring by the approach of SCADA data analysis*. Renewable Energy, May 2013, Volume 53, pp. 365-376, DOI:10.1016/j.renene.2012.11.030.

[10] Castellani F., Garinei A., Terzi L., Astolfi D., Moretti M., Lombardi A.: *A new data mining approach for power performance verification of an on-shore wind farm*. Diagnostyka 14 (4) (2013) 35-42.

[11] Castellani F., Garinei A., Terzi L., Astolfi D., Gaudiosi M.: *Improving windfarm operation practice through numerical modelling and supervisory control and data acquisition data analysis*. Renewable Power Generation, IET 8 (4) (2014) 367-379.

[12] Castellani F., Astolfi D., Terzi L., Hansen K., Rodrigo Sanz J.: *Analysing wind farm efficiency on complex terrains*. J. Phys.: Conf. Ser. 524

[13] Barthelmie R., Hansen K., Pryor S.: *Meteorological controls on wind turbine wakes*. Proceeding of the IEEE 101 (4) (2013) 1010-1019

[14] Barthelmie R., Pryor S., Frandsen S., Hansen K., Schepers J., Rados K., Schlez W., Neubert A., Jensel L., Neckelmann S.: *Quantifying the impact of wind turbine wakes on power output at offshore wind farms*. Journal of Atmospheric and Oceanic Technology 27 (8) (2010) 1302-1317

[15] Mc Kay P., Carriveau R., Ting D.S.K.: *Wake impacts on downstream wind turbine performance and yaw alignment*. Wind Energy 16 (2013) 221-234

[16] Hansen K., Barthelmie R., Jensen J., Sommer A.: *The impact of turbulence intensity and atmospheric stability on power deficits due to wind turbine wakes at Horns Rev offshore wind farm*. Wind Energy 15 (1) (2012) 183-196.

[17] Wilkinson M., Darnell B., Delft T.V., Harman K.: *Comparison of methods for wind turbine condition monitoring with SCADA data*. Renewable Power Generation, IET 8 (4) (2014) 390-397.

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- numerical simulation of wind flow and wakes on complex terrain sites;
- condition monitoring and fault diagnosis through SCADA data analysis;
- wind tunnel test of small wind turbines.