Article citation info:
Bartolini N, Scappaticci L, Garinei A, Becchetti M, Terzi L. Analysing wind turbine state dynamics for fault diagnosis. Diagnostyka. 2016;17(4):19-25.

DIAGNOSTYKA 2016, Vol. 17, No. 4

ISSN 1641-6414
e-ISSN 2449-5220

ANALYSING WIND TURBINE STATE DYNAMICS FOR FAULT DIAGNOSIS

Nicola BARTOLINI[1], Lorenzo SCAPPATICCI[2], Alberto GARINEI[2], Matteo BECCHETTI[1], Ludovico TERZI[3]
[1]University of Perugia, Department of Engineering, Perugia, Italy, nicola.bartolini@hotmail.it
[2]DSI, University Guglielmo Marconi, Roma, Italy
[3]Renvico srl, Via San Gregorio 34, Milano 20124, Italy

Abstract

Supervisory Control And Data Acquisition (SCADA) systems have recently become ubiquitous in wind energy technology. SCADA data analysis actually can provide considerable performance improvement at low cost. This also boosts wind energy exploitation, because it enlarges short and long term economic sustainability of investments. Nevertheless, SCADA data analysis poses several scientific and technological challenges, mostly related to the vastness of the data sets required for significant analysis. Separating the signal from the noise is therefore a complex task. In the present work, this issue is tackled by the point of view of state dynamics of wind turbines. SCADA control systems often record superabundant and ambiguous information. Therefore, in this work it is shown that hierarchical classification of information and time discretization of the continuous motion of states are powerful tools. The time-discretized state dynamics is processed in the formulation of several indices for performance evaluation and fault diagnosis. The method is tested on the data set of a wind farm owned by Renvico s.r.l. and sited in Italy.

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

INTRODUCTION

The age of information is revolutionizing energy production and transport. An idea is spreading: that we are in the middle of an infrastructure revolution, driven by data, similar to those that generated the Industrial Revolutions, and projecting us into the zero marginal cost society [1]. May this vision be overoptimistic, what is certain is that data are guiding our society towards a greener and smarter energy production. The efficiency of renewable energy generation is growing, the economic sustainability of green investment is growing too, the environmental expectations about green energy are becoming easier to fulfil. This picture involves also wind energy, despite its peculiarities due to the stochastic nature of the source: wind is very variable in time and space, and extreme phenomena can occur [2]. About time variability, wind farm owners are usually charged with penalties if they don’t predict with accuracy the energy they will dispatch into the grid 24 hours later. About space variability, the conjunction of numerical tools [3] and data analysis has vastly improved our capability of understanding wind flow behaviour at micro-scales and this has considerable impact on site assessment and investments. In [4, 5, 6], wind flow at micro-scales in complex terrain is analysed in the context of IEA Task-31 Wakebench Project. In [7], time and space variability of the wind energy source are addressed jointly, with a hybrid of statistical and deterministic methods for power forecast. The turning point for facing all these issues is the information provided by Supervisory Control And Data Acquisition (SCADA) systems. They record, commonly on 10-minute time basis, a comprehensive picture of wind conditions and of wind turbine behaviour: mechanical response (orientation, pitch adjustment, revolutions per minute, vibrations), power output, thermal conditions at relevant parts of the turbine, and so on. For some reviews on SCADA data analysis and its possible applications, we refer to [8, 9, 10]. The main objectives are two, but the border between them is of course fleeting: fault diagnosis and performance evaluation. Nevertheless, in the literature it is possible to distinguish methods aimed at specific fault diagnosis (in particular about gearboxes and bearings) because they are based on the processing of the most symptomatic information. For example, in [11] it is shown that monitoring temperatures is useful for detecting incoming mechanical failures. In [12, 13], oil temperature rises are used for detecting incoming gearbox failures. In [14], a survey of SCADA-based condition monitoring techniques is presented, and the capability of each method in preventing drivetrain faults is discussed. In [15], the focus is on the diagnosis of bearing faults through Artificial Neural Network techniques. As concerns long-term fault diagnosis, the issue of performance evaluation can’t be disregarded: degraded performances can be symptom of incoming faults, or can be due to load and functioning conditions affecting the health of the wind turbine. There is a vast literature on these topics, as they concern non-trivial phenomena like wakes and the mechanical response of the wind turbine. For some references, see [16-28]. The present work is at the crossroad between the two themes above: fault diagnosis and performance optimization. The general idea is that wind turbine state dynamics is a complex motion, which might be ambiguous or superabundant: not rarely, a lot of information about error, warnings and errors is provided by the SCADA supplier, and it is non-trivial to reconstruct the connection between the information itself and what's actually going on. For this reason, the philosophy of the present work is simplifying the information through the hierarchization and the discretization of the continuous motion of wind turbine states. This leads to post-processed discrete data set, which can be further elaborated through the formulation of some meaningful indices. Some glimpses of this approach have been developed in [29, 30, 31]: on these grounds, in this work a consistent and versatile approach is formulated for fault analysis and for wind farm management evaluation. The methods are tested on the data set from a wind farm owned by Renvico s.r.l. and sited in southern Italy. The structure of the paper is the following: in Section 1 the test case wind farm is briefly described, and subsequently Section 2 is devoted to the detailed discussion of the structure of the data set and of the methods. Section 3 is devoted to the presentation of some meaningful results, and finally in Section 4 the conclusions are drawn and some further research direction is indicated.

1. THE WIND FARM

The present work deals with an onshore wind farm, owned by Renvico s.r.l., and sited in southern Italy on a terrain with gentle slopes. The main features of the turbines are summarized in Table 1 and the layout is sketched in Figure 1. This peculiar wind farm has been selected as test case for several reasons. The first is that some turbines (T58 and T59) suffer from multiple wakes when the wind blows from West, a direction very frequent in the wind rose of the site. This determines a certain degree of variability of wind farm operating behaviour, especially at wind intensities near the cut-in. Further, the analysis through the method of [11] shows that there are some wind turbines (particularly T40, T42, T57) undergoing some gearbox problems. Further, vast data sets are available for this test case.

Table 1: Main turbine characteristics

Number of turbines	9
Rotor diameter	82 meters
Hub Height	80 meters
Rated Power	2 MW
Terrain	Flat

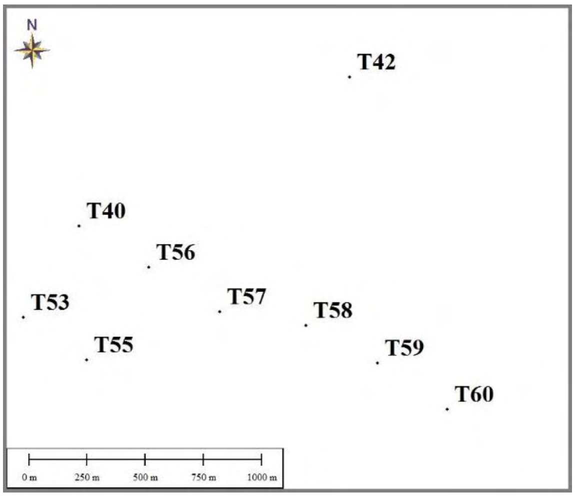

Fig. 1: The layout of the wind farm

2. THE DATA SET AND THE METHOD

As briefly discussed in the introduction, the philosophy of the present work is converting the continuous dynamics of wind turbine states into a discretized data set. At the cost of introducing some coarse-graining effect, discretization provides simpler and more powerful data sets, acting on which with simple statistical methods leads to very meaningful indicators. The time basis of the discretization is selected as the same time interval of SCADA sampling: 10 minutes. This is done in order to provide parallel data sets, which can be put in connection. Each SCADA supplier has its own codifying procedure for recording wind turbine states and alarm logs. Nevertheless, the inspiring philosophy is the same. In particular, the structure of the data set for the selected test case is the following:

- Wind turbine states: they provide the basic information about what the turbine is doing (producing output, being in fault, and so on). They are mutually exclusive: in every moment one and only one state can be activated. For this reason, they are recorded as a series of entries with associated state and time stamp, because the incoming of a state automatically means the phasing out of the state previously activated.
- Status codes: they are classified according to the degree of severity (error, warning, info) and they are not mutually exclusive: more than one of them can be activated at a given time. For this reason, the status codes data set is recorded as a series of entries with associated status name, time stamp and state (activating or phasing out).

The status codes constitute the building block for extracting why the wind turbine is behaving as described by the parallel wind turbine states data set.

The inspiring idea is trying to build a connection between what each turbine does and why, i.e. between the wind turbine states and the status codes: this is achieved by crossing the discretized data sets, rather than the complete continuous dynamics. For this reason, status codes are considered in their severity hierarchy and the most urgent ones (errors) are employed in the following. The discretized data sets are built through a sort of number map, one for the wind turbine states and one for the error status codes. To each wind turbine state (or error) a digit in the corresponding map is associated, turning from 0 to 1 if the state (or error) activates during the 10-minute time interval. This is done for each 10-minute interval and, doing so, one ends up with two data sets made of binary numbers, having the same time sequence, which is also parallel to the SCADA measurements. The only exception to the rule for building the number map is the wind turbine state associated to power output production: actually a 10-minute interval should be considered productive if the production time exceeds a fairly high threshold. For the present work, this threshold has been chosen at 80%. First of all, the discrete wind turbine states number map is meaningful on its own, once one has a criterion for demarcating good states from bad states. This can be done through an absolute and relative classification: the former relates to turbine being productive or not, the latter relates to the turbine deviating or not from the dominant wind farm behaviour. We consider a time step good if the turbine has produced, or has been potentially but not actually productive due to inadequate wind strength. We consider a time step bad otherwise. Similarly, we consider a time step anomalous if the turbine has deviated from the wind farm mode. Therefore each time step for each wind turbine classify in one of these four categories: good and not anomalous, good and anomalous, bad and anomalous, bad and not anomalous. With this classification at hand, two indices can be defined for any given time period. In Equation 1, the Global Malfunctioning Index is defined as the ratio of the number of not productive time steps to the number of anomalous time steps.

$$I_{GL} = \frac{N_{not.prod}}{N_{anom}} \tag{1}$$

In Equation 2, the Detailed Malfunctioning Index is defined as the ratio of the number of anomalous not productive time steps to the number of anomalous productive time steps.

$$I_{DET} = \frac{N_{anomnot.prod}}{N_{anom\,prod.}} \tag{2}$$

Both indices are intuitively expected to rise with increasing turbine malfunctioning, but Equation 2 is built only with relative classification and Equation 1 is built with a mixture of absolute and relative classification. Equation 2 is more responsive in capturing the details, but it is more demanding because it doesn’t capture as malfunctioning bad wind turbine behaviour on bad wind farm mode.

A first connection between wind turbine states and errors can be built through a severity classification of errors according to what the turbine has been doing during, before and after the activation of the error. This is what we call severity classification: an interval of variable amplitude, centred on the time step of error occurrence, has been considered and it has been checked if the machine is productive before, during, after the error signal has activated. For the present work, an interval of 1 hour forward and backward the activation time of the error has been considered. The classification of errors is depicted in Table 2.

Table 2: Classification of the severity of error status codes.

Degree of Severity	Prod. before	Prod. during	Prod. after
0	✓	✓	✓
1	✗	✓	✓
2	✓	✗	✓
3	✗	✗	✓
4	✓	✓	✗
5	✓	✗	✗
6	✗	✓	✗
7	✗	✗	✗

The final step to relate errors to wind turbine states (why to what), is crossing the time steps during which an error has been active against the map of states: the idea is inquiring if an error is occurring while the turbine is in mode with the rest of the farm, or not. This allows to distinguish, for example, real alarms from planned maintenance programs. Actually, if the turbine is in error and in mode with the rest of the farm, it is likely that it is due to a service program, while if it is not, it is likely that a real error occurs. We therefore formulate a Mode Index, Equation 3, as the ratio of the number of error time steps out of farm trend to the number of total error time steps.

$$I_{MODE} = \frac{N_{err.out.\mathrm{mode}}}{N_{err.tot}} \tag{3}$$

In Equation 4, further, an Error Index is formulated as the ratio of the number of error time steps to the size of the data set. It measures the amount of time of the activation of any error for a given wind turbine, relative to the total time length of the data set.

$$I_{ERROR} = \frac{N_{err}}{N_{tot}} \tag{4}$$

In Section 3, some meaningful results are reported about the use of the indices above, for inquiring the behaviour of the test case wind farm, and its reasons.

3. THE RESULTS

In Figure 2, the Global Malfunctioning Index of Equation 1 is shown on a sample month, against an historical basis. Notice that the selected wind farm is characterized, on the long term, by a very good functioning, and so the historical basis shows correspondingly low values.

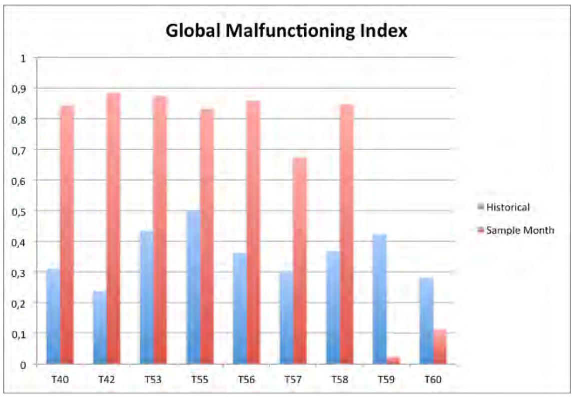

Fig. 2: Global Malfunctioning Index: sample month versus historical trend

From Figure 2, it arises that all the turbines except T59 and T60 have undergone a functioning sensibly worse than the historical. Let us now zoom more and more into details, through the methods described in Section 2. Figure 3 shows the Detailed Malfunctioning Index of Equation 2, on the same basis: sample month versus historical.

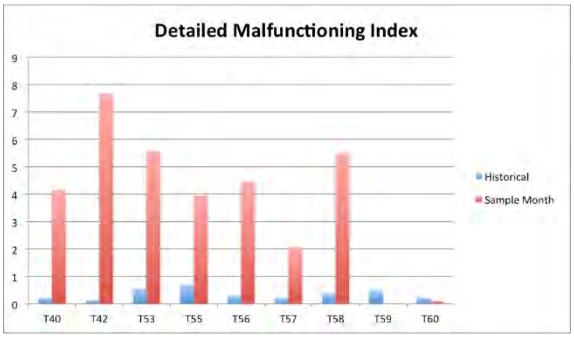

Fig. 3: Detailed Malfunctioning Index: sample month versus historical trend

Figure 3 provides almost the same information as Figure 2, but the Detailed Malfunctioning Index better discriminates between the wind turbines, and it arises that the index peaks more for turbines T42, T53 and T58. In Figure 4, the Mode Index of Equation 3 is shown for the sample month and, in Figure 5, the Error Index is shown.

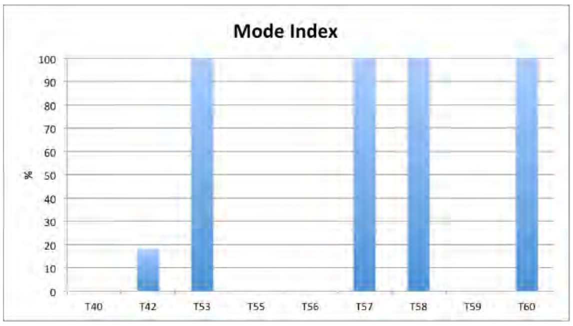

Fig. 4: Mode Index. Sample month.

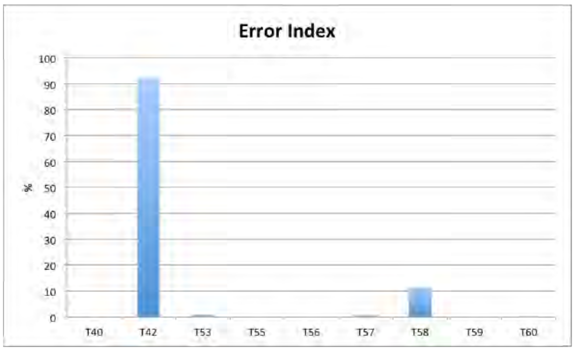

Fig. 5: Error Index. Sample month.

From Figure 5 it arises that turbine T42 has undergone an error for the 92% of the time of the month, T58 for the 11.5% and the rest of the wind farm has undergone a negligible or even zero time of error activation. From Figure 4, it arises that turbines T53, T57, T58, T60 show a Mode Index which is exactly 100%: this means that all the time during which they have undergone an error, they were doing something different from most of the farm. In other words, most likely they weren't producing, while the other turbines were producing. The situation is different for T42: the Mode Index is 18.3%. This means that for the 81.7% of the time of error activation at turbine T42, the wind turbine was doing the same thing as the other turbines: most likely, producing. From the Figures above, therefore, one gets some hints that T42 has undergone a stop due to a problem, and it has restarted producing while still having errors activated for the rest of the month. T58 should instead have undergone a considerable stop, during which it hasn't produced while the rest of the farm was producing. This is confirmed by the following further plot, obtaining crossing our state and error analysis to the SCADA data set. The number of time steps of error activation, during which the wind speed was higher than a threshold, is computed for different values of the threshold and plotted against the value of the threshold itself. The underlying philosophy is that errors and downtimes due to maintenance should be concomitant to low wind periods, in order to minimize energy losses. If there are many errors even at medium or high wind speeds, it is more likely that a wind turbine has undergone an unexpected problem. Figure 6 shows this analysis for the selected sample month, and it arises that T42 and T58 are the only turbines showing errors at medium wind speeds.

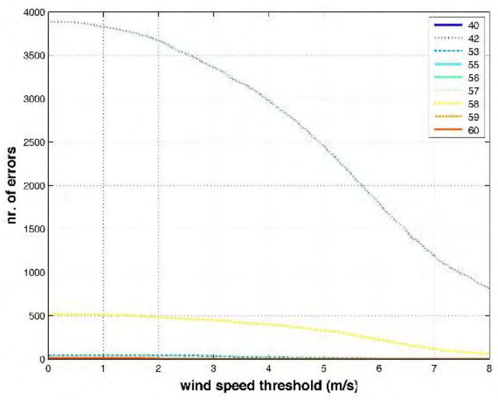

Fig. 6: Number of errors against wind intensity thresholds

Finally, in Figure 7 the classification of the error time steps is reported according to the severity criterion of Table 2. The picture is consistent with what hinted from Figures 4 and 5: T42 shows a non-negligible amount of highest severity time steps and a vast quantity of lowest severity time steps. In other words, it has undergone errors and a stop (affecting potentially productive wind regimes, as shown in Figure 6). Further, for most of the time it has been productive, there were still errors activated. For T58, instead, the errors all fall in the highest severity class: this means that the errors are associated to a fault and a stop of the wind turbine.

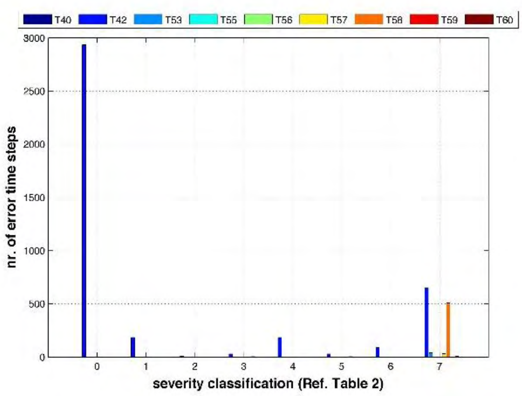

Fig. 7: Severity error analysis according to Table 2.

With all the explanatory information provided by the proposed methods, one can go back to the states and errors data set and inquire if the method has provided consistent interpretation. This is indeed the case: it arises that T58 has undergone a stop for a problem at the gearbox. T42 has undergone a stop due to a problem at the pitch system. But, once the turbine had returned to the productive phase for most of the month, there were still errors activated, still at the pitch system. This could be due to problems in switching back to the expected control system settings, but it is somehow a false flag because the problem was already solved and the turbine was producing again normally. In conclusion, the proposed methods have provided a correct interpretation key for understanding the behavior of the wind farm during a very diversified sample month, for which the straightforward analysis of state and error data sets would result to be indecisive.

4. CONCLUSION AND FURTHER DIRECTIONS

The objective of this study was inquiring if, for the sake of wind turbine fault diagnosis and performance evaluation, there is an added value in discretizing a continuous data set: the dynamics of wind turbine states and status codes. The motivation lies in the fact that often the straightforward analysis of such dynamics proves to be indecisive for analyzing wind farm behavior. Actually, the state and error data sets often at the practical level are ambiguous and superabundant, and they must therefore somehow be elaborated to extract knowledge from information. In Section 2, the method has been presented in detail: it is based first of all on the hierarchization of the information. An algorithm is proposed for constructing two number maps, employing the most urgent (and then hierarchically important) information: the states (what the turbine is doing) and the errors (why the turbine is doing what it is doing). These two maps are crossed the one against the other and exploited for formulating some statistical indices. The application to a real test case, owned by Renvico s.r.l. and sited in southern Italy, showed that the method and the final output (the indices) have a remarkable explanatory power. For the analysis, a sample month was selected during which the wind farm showed a very diversified and complex behavior: there was one turbine undergoing a sudden error and a consequent stop, one turbine undergoing errors for almost all the time but producing output for the greatest part of this error time, some turbines undergoing optimal maintenance (when there is low wind). The results in Section 3 demonstrate that the proposed approach allows to interpret correctly this complex behavior. The valuable selection of the test case supports also one key feature of the method: its versatility. It can be used for understanding the nature of error onsets, and therefore for fault diagnosis. It can be used for evaluating the quality of wind turbine maintenance. It can be used for assessing performances. Further, the proposed indices are all non-dimensional and don't depend on the particular codifying of the dynamics of states and errors: they can be therefore used for managing a vast portfolio of wind turbines. Several are the further directions of the present work. One important feature of the selected test case is that it has a compact design and, despite some variability in the behavior at low wind because of wakes, the wind farm basically moves at the unison. Since the indices of Equation 1 to 4 employ a relative classification of time steps, compactness is a key feature. It would be interesting to test the method on complex wind farms, having large layouts [32], and understand if they can still be treated as a whole, or rather if they must be split in compact subclusters. Further, it would be valuable to extend the hierarchy chain and include in the analysis the low-severity information provided by warning and info logs and, in perspective, also include vibration analysis [33] in order to have a holistic picture of the wind turbine.

REFERENCES

[1] Rifkin J. The zero marginal cost society: the internet of things, the collaborative commons and the eclipse of capitalism. Macmillan 2014.

[2] Castellani F, Garinei A, Terzi L, Astolfi D. Applied statistics for extreme wind estimate. Wind Energy 2015; 18 (4): 613-624.

[3] Castellani F, Gravdahl A, Crasto G, Piccioni E, Vignaroli A. A practical approach in the CFD simulation of off-shore wind farms through the actuator disc technique. Energy Procedia 2013; 35: 274-284.

[4] Castellani F, Astolfi D, Terzi L, Hansen KS, Rodrigo JS. Analysing wind farm efficiency on complex terrains. Journal of Physics: Conference Series 524, 1.

[5] Rodrigo JS, Gancarski P, Arroyo RC, Moriarty P, Chuchfield M, Naughton JW, Hansen KS, Machefaux E, Koblitz T, Maguire E, et al. Iea-task 31 wakebench: Towards a protocol for wind farm flow model evaluation. part 1: Flow- over-terrain models. Journal of Physics: Conference Series 2014.

[6] Moriarty P, Rodrigo JS, Gancarski P, Chuchfield M, Naughton JW, Hansen KS, Machefaux E, Maguire E, Castellani F, Terzi L, et al. Iea-task 31 wakebench: Towards a protocol for wind farm flow model evaluation. part 2: Wind farm wake models. Journal of Physics: Conference Series 2014; 524.

[7] Castellani F, Burlando M., Taghizaded S., Astolfi D:, Piccioni E. Wind energy forecast in complex sites with a hybrid neural network and CFD based method. Energy Procedia 2014; 45: 188-197.

[8] Kusiak A, Zhang Z, Verma A. Prediction, operations and condition monitoring in wind energy. Energy 2013; 60: 1-12.

[9] 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.

[10] Tchakoua P, Wamkeue R, Ouhrouche M, Slaoui-Hasnaoui F, Tameghe TA, Ekemb G. Wind turbine condition monitoring: State-of-the-art review, new trends, and future challenges. Energies 2014; 7(4): 2595-2630.

[11] Astolfi D, Castellani F, Terzi L. Fault prevention and diagnosis through SCADA temperature data analysis of an onshore wind farm. Diagnostyka 2014; 15(2): 71:78.

[12] Feng Y, Qiu Y, Crabtree CJ, Long H, Tavner PJ. Monitoring wind turbine gearboxes. Wind Energy 2013; 16(5): 728–740

[13] Kusiak A, Verma A. Analyzing bearing faults in wind turbines: A data-mining approach. Renewable Energy 2012; 48: 110-116.

[14] Wilkinson M, Darnell B. van Delft T, Harman K. Comparison of methods for wind turbine condition monitoring with SCADA data. Renewable Power Generation 2014; 8(4): 390–397.

[15] Zhang ZY, Wang KS. Wind turbine fault detection based on scada data analysis using ann. Advances in Manufacturing 2014; 2(1):70–78.

[16] Mc Kay P, Carriveau R, Ting DSK.:Wake impacts on downstream wind turbine performance and yaw alignment. Wind Energy 2013; 16: 221-223

[17] 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 2012; 15(1): 183-196.

[18] 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 2010; 27(8): 1302-1317.

[19] Barthelmie R, Hansen K, Pryor S. Meteorological controls on wind turbine wakes. Proceeding of the IEEE 2013; 10(4): 1010-1019.

[20] Porté - Agel F, Wu YT, Chen CH. A numerical study of the effects of wind direction on turbine wakes and power losses in a large wind farm. Energies 2013; 6(10): 5297–5313.

[21] Castellani F, Astolfi D, Garinei A, Proietti S, Sdringola P, Terzi L, Desideri U. How wind turbines alignment to wind direction affects efficiency? A case study through SCADA data mining. Energy Procedia 2015; 75: 697-703.

[22] Castellani F, Astolfi D, Sdringola P, Proietti S, Terzi L. Analyzing wind turbine directional behavior: SCADA data mining techniques for efficiency and power assessment. Applied Energy 2015.

[23] Castellani F, Astolfi D, Burlando M, Terzi L. Numerical modelling for wind farm operational assessment in complex terrain. Journal of Wind Engineering and Industrial Aerodynamics 2015; 147: 320-329.

[24] Castellani F, Astolfi D, Piccioni E, Terzi L. Numerical and experimental methods for wake flow analysis in complex terrain. Journal of Physics: Conference Series, 625. IOP Publishing (2015)

[25] 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 2014; 8 (4): 367-379.

[26] Gaumond M, Réthoré PE, Ott S, Pena A, Bechmann A, Hansen KS. Evaluation of the wind direction

uncertainty and its impact on wake modeling at the horns rev offshore wind farm. Wind Energy 2014; 17(8): 1169–1178.

[27] Bastankah M, Porté - Agel F. A new analytical model for wind-turbine wakes. Renewable Energy 2014; 70: 116-123.

[28] Wu YT, Porté - Agel F. Modeling turbine wakes and power losses within a wind farm using LES: An application to the Horns Rev offshore wind farm. Renewable Energy 2015; 75: 945-955.

[29] 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, 2013; 14(4): 35-42.

[30] Astolfi D, Castellani F, Garinei A, Terzi L. Data mining techniques for performance analysis of onshore wind farms. Applied Energy 2015; 148: 220–233.

[31] Astolfi D, Castellani F, Terzi L. Mathematical methods for SCADA data mining of onshore wind farms: Performance evaluation and wake analysis. Wind Engineering 2016; 40(1): 69-85.

[32] Castellani F, Astolfi D, Mana M, Burlando M, Meißner C, Piccioni E. Wind power forecasting techniques in complex terrain: ANN vs. ANN-CFD hybrid approach. Journal of Physics: Conference Series 2016; 753(8): 082002.

[33] Castellani F, D'Elia G, Astolfi D, Mucchi E, Dalpiaz G, Terzi L. Analyzing wind turbine flow interaction through vibration data. Journal of Physics: Conference Series 2016; 753(11): 112008.

Received 2016-08-07
Accepted 2016-09-30
Available online 2016-11-21

Nicola BARTOLINI is a Phd student in applied mechanics at the University of Perugia (ITALY). He is a member of the Wind Tunnel “Raffaele Balli” Test Team, involved in activities concerning the aerodynamic optimization of motorbikes and the develop of small wind turbines both horizontal and vertical axis.
Another research topic includes experimental and numerical analysis on shock absorbers, regarding in particular innovative detection methods about the evolution of internal phenomena such as cavitation and knocking noise.