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DIAGNOSIS OF WIND TURBINE MISALIGNMENT THROUGH SCADA DATA

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Abstract

Optimal alignment of wind turbines to the wind direction is a crucial condition for the quality of power output and for the health of the turbines. Actually, bad alignment can cause degraded performances and dangerous loads that can affect, on the long run, the mechanical safety of the wind turbine. Supervisory Control And Data Acquisition (SCADA) systems are becoming widespread in modern wind energy technology because of the appreciable costs – benefits ratio. The common time scale of SCADA, yet, usually is not effective for misalignment diagnosis because the wind varies too rapidly. For this reason, misalignment is often diagnosed using ad hoc techniques as LIDAR-based or spinner anemometers. In the present work, it is shown that very useful indications for the diagnosis of misalignment can be obtained also from the SCADA data, without invoking expensive supplementary control techniques. The method is validated on the data set of a wind farm sited in Italy.

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

INTRODUCTION

Modern wind turbine technology is becoming increasingly widespread and the economic sustainability of wind farms is becoming more and more competitive thanks to the scientific and technological development.

Actually, scientific research has a crucial role as regards the optimization of wind energy conversion for some very basic reason: the nature of the source. Wind is very variable in time: it is very challenging even to forecast expected power production on the day ahead basis [1-4], such that wind can even be modelled using chaos theory framework [5-8]. Wind is very local and it is very difficult to numerically model it, especially in complex terrain [9-13]. When wind turbine technology is addressed too, further challenges arise: how to model the presence of the rotor and how to model the wake effects between nearby turbines. This has a considerable influence on wind farm design [14 - 16] and, due to the economic impact of energy losses caused by wakes, it boosts research and development on wake modelling and experimental wake assessment [17 - 24].

Two objectives, whose line of demarcation is fleeting, motivate research and development: improving the reliability of simulations, in order to optimize the new installations, and improving the energy extraction from existing wind farms, through early fault diagnosis and performance monitoring.

For the former and the latter objectives, data are the keystone and this explains the diffusion of Supervisory Control And Data Acquisition (SCADA) systems. Some examples of performance assessment can be found in [25-29]. SCADA data analysis is very fruitful also for fault diagnosis, even though it is commonly considered, by the point of view of condition monitoring (CM), as a late stage indication. Nevertheless, the improvements in the computational techniques as well as the low cost, with respect to ad hoc CM instruments as accelerometers [30], motivate the research in the field of SCADA analysis for fault diagnosis [31-36].

The present work deals with a very common [37-38] phenomenon: bad alignment of wind turbines to the wind direction. This phenomenon causes producible energy losses and, on the long run, exposes the wind turbine to unexpected loads that might affect its mechanical safety. Diagnosing misalignment is therefore a matter of performances as well as a matter of fault prevention. Although conceptually the problem is very simple, it is commonly believed that diagnosis of misalignment requires external experimental set-ups recording wind direction and wind turbine alignment at the scales of wind variability. For this reason, LIDAR-based [39-41] technology and spinner anemometry [42-44] are developing faster in wind energy industry. This kind of technology, yet, is expensive and adopting it for misalignment detection means a certain cost for an uncertain outcome. It would be desirable to have low, possibly zero, cost misalignment diagnosis methods, which could provide at least a basis for addressing subsequent deeper investigation.

The present work deals exactly with this issue: a method is proposed for the diagnosis of misalignment through SCADA data commonly available from wind turbines. The direction data ("absolute" coming from the nacelle anemometer and "actual", i.e. the nacelle direction) employed for this work are actually those coming from the common SCADA control system: as argued here above, these data are commonly considered too low quality to extract information as regards turbine misalignment, but in the following it will be shown that this is not the case. Actually, the proposed method is validated on the data set from a wind farm sited in southern Italy and it is shown to be effective for underperformance and misalignment diagnosis. One key point of the present work is that the data set is split in two: the second part of it describes the wind farm after the maintenance intervention for correcting the alignment of one turbine. Therefore, the proposed method is validated against a real test case, before and after an intervention, and therefore the reliability of the proposed diagnosis approach is strongly supported. The structure of the Paper is as follows: in Section 2, the wind farm is sketched. The method is discussed in Section 3 and the results are collected in Section 4. Finally, Section 5 is devoted to the conclusions as well as some further direction of the present work.

1. THE WIND FARM

The validation case of the present work is a wind farm sited in southern Italy, whose layout is sketched in Figure 1. The main features of the wind turbines are presented in Table 1. This peculiar wind farm has been selected for the present work for two reasons: the inter-turbine distance is at least of the order of 8 rotor diameters and this implies that wakes between nearby turbines should not affect significantly the capability of optimal alignment to the wind. Further, turbine T5, as shall be discussed in the following sections, shows a slightly degraded power curve. This was inspiration for inquiring a possible misalignment to wind direction.

Table 1: Main turbine characteristics

Number of turbines	6
Rotor diameter	82 meters
Hub Height	80 meters
Rated Power	2 MW
Terrain	Flat

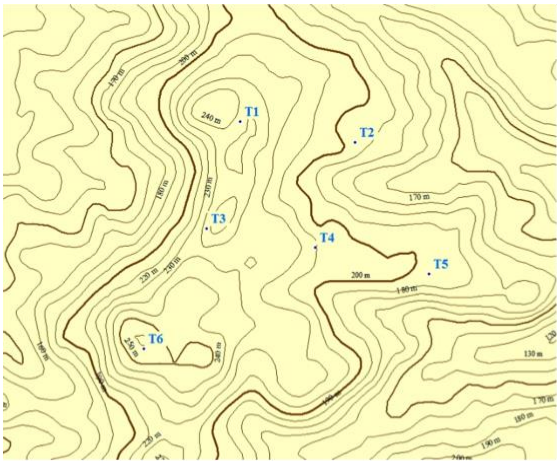

Fig. 1. The layout of the wind farm

2. THE DATA SET AND THE METHOD

In the present work, the SCADA data from the test case wind farm have been appropriately post processed for detecting possible non-optimal alignment of the wind turbines to the wind direction. As a general very brief recap about SCADA data, we recall that their usual form is time average, minimum, maximum and standard deviation: the averaging time scale is commonly 10 minutes and the sampling ratio of the control system is usually of the order of one or few seconds. SCADA control systems record the atmospheric conditions at the nacelle (wind intensity and direction), the response of the wind turbine (yaw position, pitch angle and so on), the main information about the conversion of wind kinetic energy into exploitable form (active and reactive power and so on), possibly temperatures and pressure at relevant points of the wind turbine. The rationale on which the theoretical picture of wind turbines is translated into prescriptions for analysing operating parameters is IEC 61400 [45], provided by the International Electrotechnical commission. Actually, the first tool, used in this work for detecting an underperformance of a wind turbine that might be caused by misalignment, is the power curve analysis as IEC suggests.

The data set employed for the present work has been collected during the year 2016 and it has been filtered on the regime of simultaneous power output production from each turbine of the wind farm. This data set therefore describes the wind farm producing output in unison and this is a crucial point for the formulation of the proposed method. The SCADA channels employed for the present work are nacelle wind speed, power output, wind direction as recorded at the nacelle, nacelle position. Another key point, as anticipated in the Introduction section, is that the data set is split in two: before and after an intervention to one wind turbine, for correcting its alignment to the wind. The dimensions of the two data sets are respectively 19000 and 8616 measurements.

As regards performance analysis, the power curve is plotted, as shown in the next section, by averaging on turbine nacelle wind speed intervals having 0.5 m/s amplitude.

Once a slight underperformance of turbine T5 is highlighted, at the same wind conditions of the other turbines, the analysis is focused on the misalignment. Having at disposal two direction measurements at the nacelle from the SCADA control system, one can compute the relative wind direction for each time step, i.e. the discrepancy between the wind direction at the nacelle and the nacelle position. At this point, comparing one turbine against the other is fundamental and that is why the data set has been synchronized on the request that each turbine was in productive phase. For each time step, the relative wind directions of the turbines are averaged, providing a reference for the farm of the amount of mean misalignment. Subsequently, for each time step the discrepancy between the relative wind direction of each turbine and the farm average is computed. One ends up with a data set of discrepancies. Here statistics comes at hand: the simplest, yet powerful, thing that one can do is observing the distributions of the discrepancies for each turbine and comparing them. Since everything starts with relative measurements and the turbines are the same identical model, it is expected that they respond similarly to the wind. If it is very evidently not, this is a signal that the vane of a wind turbine could be damaged and measures not optimally the wind, forcing the wind turbine to align according to biased measurements. In the following Section 3, it will be shown that this is exactly what happens to turbine T5 and it will be shown that, after the intervention to this turbine, the proposed methods don't highlight it as anomalous anymore. This is a powerful validation of the approach, against a real test case.

3. THE RESULTS

Each turbine has been compared against the others. In the following Figure 2, the power curves of turbines T5 and T1 are compared before the intervention at turbine T5. From here on, this data set shall be labelled as D1, and the one after the intervention as D2. It arises that, at the same conditions of nacelle wind speed, turbine T5 considerably underperforms with respect to turbines T1.

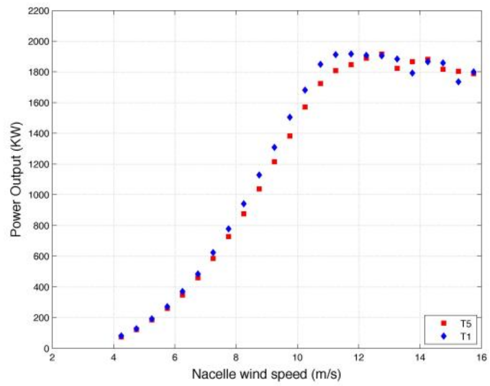

Fig. 2. Power curves of turbines T5 and T1. D1 data set, 0.5 m/s nacelle wind speed interval.

To go beyond the qualitative picture of Figure 2 which takes into account only two turbines for the sake of plot readability, the following procedure has been adopted: the power curve, averaged on nacelle wind speed intervals of 0.5 m/s, has been computed for all the wind turbines of the wind farm. These six curves have been averaged for each wind speed interval, in order to provide an average reference; subsequently, for each nacelle wind speed interval, the percentage variation of each wind turbine against the average has been computed. Further, in order to obtain a unique indicator, the percentage displacements for each turbine have been averaged. In Figure 3, the results are shown for the D1 data set, i.e. before the intervention. Using this indicator, it arises that turbine T5 negatively deviates from the wind farm average for approximately 1.5 standard deviations. Sideways, this so considerable amount of underperformance of turbine T5 supports the suspicion that misalignment is a possible cause.

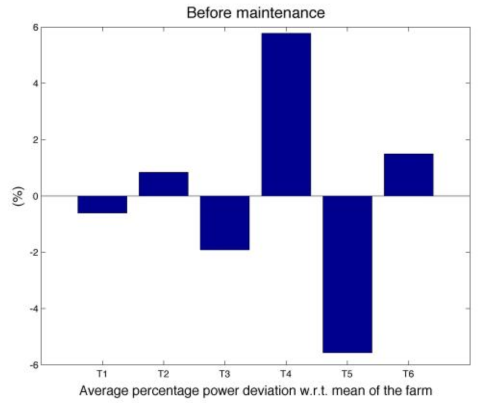

Fig. 3. Average percentage power deviations with respect to the wind farm average. D1 data set.

In the following Figures 4 and 5, for respectively turbines T5 and T1 and data set D1, the difference in population, with respect to farm average, is plotted against intervals of relative wind direction. In other words, the plots show if the relative wind direction distributes for each turbine similarly with respect to the average behaviour of the wind farm. Since the wind turbines are the same model and sufficiently far the one from the other so that wakes are not expected to alter the alignment behaviour, the distribution should to be similar for the various turbines. Figures 4 and 5 show that this is not the case. It shows that exactly the opposite happens: the relative wind direction for turbine T5 is far more frequently very low, with respect to the other turbines. But this, as said before, is not realistic: there is no reason why it should be like that. This phenomenon should instead be interpreted as a problem to the vane of turbine T5. It is as if the vane, being damaged, registers an anomalously good alignment of the wind turbine to the wind direction and therefore sends to the control system wrong inputs. And then the wind turbine obeys these wrong inputs and underperforms. Further, this behaviour is dangerous by the point of view of mechanical loads, affecting the turbine, if it regulates according to wrong inputs. The histograms in Figures 4 and 5 are expected to reasonably oscillate around the 0, while instead they are sharply peaked positively and negatively. For this reason, in order to quantify the anomaly, the size of the longest interval of the histogram having the same sign is computed for all the wind turbines. For the D1 data set, it is reported in Figure 6. It arises that, due to the bias of turbine T5, all the wind turbines show very high values. But further, by comparing them, it arises that in any case turbine T5 is the only turbine deviating from the farm average more than 1.5 standard deviations. This is a further argument supporting the identification of turbine T5 as anomalous.

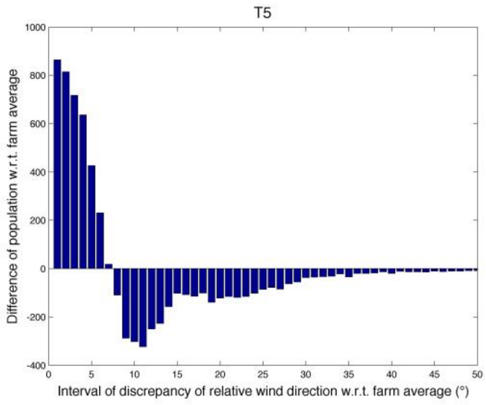

Fig. 4. Difference in distribution of relative wind direction with respect to the farm average, T5. D1 data set.

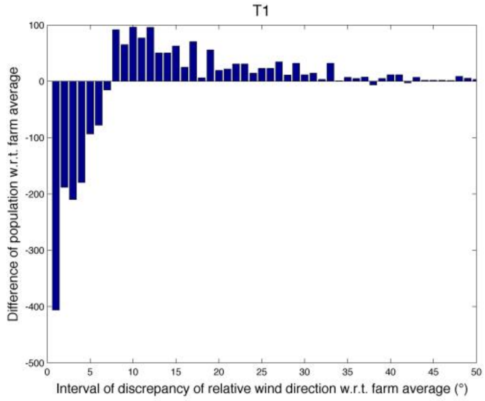

Fig. 5. Difference in distribution of relative wind direction with respect to the farm average, T1. D1 data set.

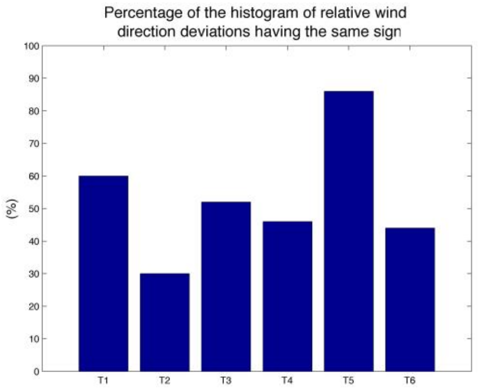

Fig. 6. Size of the longest interval of the histogram of relative wind direction (w.r.t. to farm average) having the same sign. D1 data set.

Summarizing, the method proposed in Section 2 has proven to be very effective in highlighting misalignment of turbine T5 and this has been particularly precious not only for remedying underproductions, but also in perspective of the long term health of the wind turbine. The method has actually provided non-ambiguous guidelines for intervention on T5 wind turbine and this can be crosschecked by analysing the D2 data set describing the wind farm after the maintenance intervention at turbine T5. In Figure 7, the power curves of turbines T5 and T1 are shown. Comparing against Figure 2, it arises that the performances of turbine T5 and T1 are much more similar than before the intervention. The underperformance of turbine T5 is gradually disappearing, as it should. This is supported by computing also the corresponding of Figure 3, which is reported in Figure 8. It arises that now turbine T5 deviates less than one standard deviation with respect to the average of the wind farm.

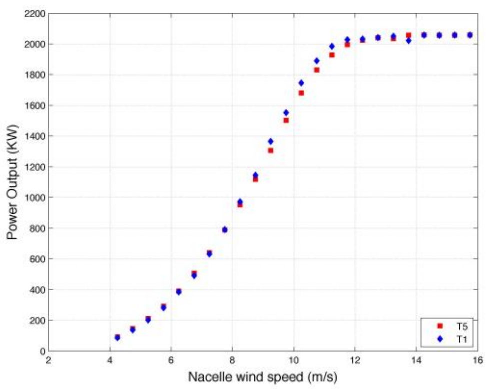

Fig. 7. Power curves of turbines T5 and T1. D2 data set

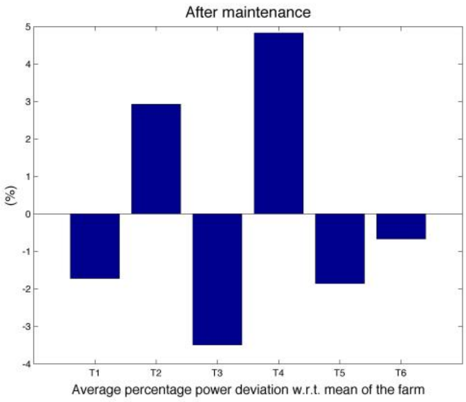

Fig. 8. Average percentage power deviations with respect to the wind farm average. D2 data set.

Figures 9 and 10 show the same histograms as Figures 4 and 5, but on the D2 data set. It arises that, after the intervention at turbine T5, the distributions of relative wind direction (with respect to farm average) for turbines T5 and T1 are much more similar in shape. They oscillate around the 0, as they should, and they are not left (or right, respectively) peaked as Figures 4 and 5 are. This strongly supports the reliability of the proposed method for misalignment diagnosis: in other words, when one or more turbines are misaligned (against a wind farm reasonably aligned in average), the misaligned turbines are highlighted as anomalous. When the anomaly is recovered, the output of the method registers a homogeneous behaviour along the wind farm. This can be seen also computing the corresponding of Figure 6, which is reported in the following Figure 11. The average size of intervals having the same sign is of the order of one third with respect to the case of D1 data set. Further, T5 no longer peaks for deviation with respect to the rest of the wind farm. This supports the picture that, after the maintenance, the alignment behaviour and the performances of turbine T5 are returning back to be consistent with the average of the wind farm.

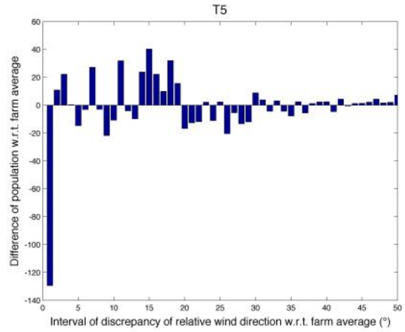

Fig. 9. Difference in distribution of relative wind direction with respect to the farm average, T5. D2 data set.

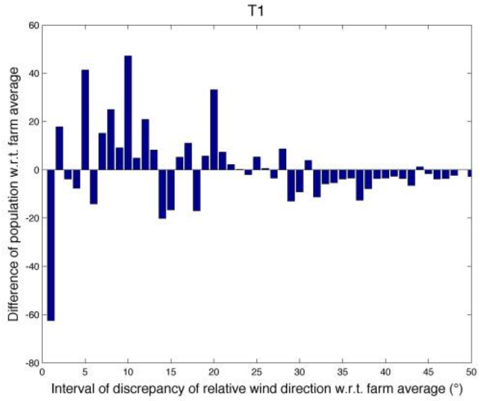

Fig. 10. Difference in distribution of relative wind direction with respect to the farm average, T1. D2 data set.

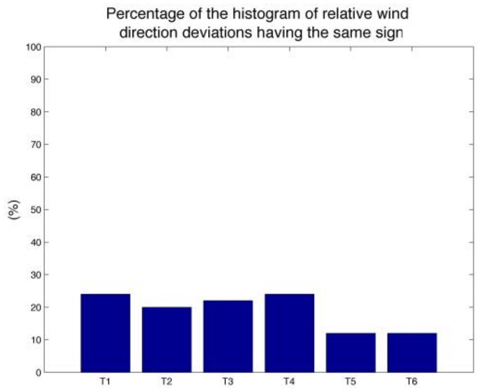

Fig. 11. Size of the longest interval of the histogram of relative wind direction (w.r.t. to farm average) having the same sign. D2 data set.

4. CONCLUSION AND FURTHER DIRECTIONS

In the present work, a method, based on SCADA data analysis, has been proposed for the diagnosis of misalignment of wind turbines to the wind direction. As discussed in the Introduction, this work is motivated by the fact that misalignment is a very common cause of energy losses, possibly also affecting the long term health of wind turbines, but its diagnosis is somehow demanding. Actually, due to the typical time scale of variability of the wind and of the response of wind turbines, misalignment is often diagnosed using LIDAR or spinner anemometry. These techniques have a high certain cost, against an uncertain outcome. For these reasons, employing SCADA for misalignment diagnosis, or for at least some instructive guidelines for further intervention, would be very precious and money saving. In this work, it has been shown that this is indeed possible on the test case of a wind farm sited in Italy. Using standard power curve techniques, an underperforming turbine has been identified. Subsequently, the statistical distribution of the relative wind direction (i.e. the difference between the wind direction measured at the nacelle and the nacelle position) for each turbine has been analysed and compared for the various turbines. It is shown that the underperforming turbine displays an anomalous distribution of relative wind direction, with respect to the rest of the farm. This is not realistic, because the wind turbines are identical and the way the nacelle follows the wind direction should be similar, especially on the vast statistical basis employed for the present work. Therefore, one argues that the underperforming turbine has a problem at the vane, that registers an anomalously good alignment to the wind direction and therefore sends wrong inputs to the central control system. This explains the underperformance of the wind turbine. This intuition, arising from the proposed diagnosis method, has been crosschecked against the reality because the data set at disposal is split in two: before and after the maintenance intervention at the underperforming turbine. After the maintenance intervention, the anomalies highlighted by the proposed method are shown to be negligible. This is indeed a key point because the approach is therefore supported as being reliable and responsive and this is exactly what one would expect from a diagnosis procedure.

In conclusion, the proposed method allows the diagnosis of possible misalignments of wind turbines to the wind direction by employing at zero cost (that is, without invoking further ad hoc measurements campaigns) the source of information available from the usual SCADA control systems. This is very useful for preventing considerable energy losses, but also for safeguarding the long term health of the wind turbines.

A very interesting further direction of this work would be pairing the proposed method to the information coming from Condition Monitoring systems, where available. Actually, having at hand signals from accelerometers at meaningful points of the wind turbines would allow to understand the mechanical consequences, in terms of loads [46], of the misalignment. Further, it would be in perspective very challenging to upgrade from a statistical treatment of misalignment to a local analysis, by the point of view of time and space. This requires the understanding of the chaotic fluctuations of wind speed on a local scale [1-9], but also of the response of the technology (i.e. the wind turbines), taking into account that clusters might matter more than individual turbines [20, 21].

REFERENCES

1 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, 2014, 753(8): 082002.

2 Jónsson T, Pinson P, Madsen H. On the market impact of wind energy forecasts. Energy Economics, 2010; 32(2): 313-320.

3 Cassola F, Burlando M. Wind speed and wind energy forecast through Kalman filtering of Numerical Weather Prediction model output. Applied Energy, 2012; 99;154-166.

4 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.

5 Luo HY, Liu TQ, Li XY. Chaotic forecasting method of short-term wind speed in wind farm [J]. Power System Technology, 2009; 9:19.

6 Chen P, Chen H, Ye R. Chaotic wind speed series forecasting based on wavelet packet decomposition and support vector regression. In IPEC, 2010 Conference Proceedings., 2010: 256-261.

7 Tao D, Hongfei X. Wind speed chaotic prediction model based on optimal neighborhood. Acta Energiae Solaris Sinica, 2011; 4:21.

8 Xu X, Niu D, Fu M, Xia H, Wu H. A Multi Time Scale Wind Power Forecasting Model of a Chaotic Echo State Network Based on a Hybrid Algorithm of Particle Swarm Optimization and Tabu Search. Energies, 2015; 8(11):12388-12408.

9 Rodrigo JS, Gancarski P, Arroyo RC, Moriarty P, Chuchfield M, Naughton JW, Hansen KS, Machefaux E, Koblitz T, Maguire E. 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; 524.

10 Moriarty P, Rodrigo JS, Gancarski P, Chuchfield M, Naughton JW, Hansen KS, Machefaux E, Maguire E, Castellani F, Terzi L. 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.

11 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.

12 Moreno P, Gravdahl AR, Romero M. Wind flow over complex terrain: application of linear and CFD models. European wind energy conference and exhibition, 2003: 16–19.

13 Lee M. Lee SH, Hur N, Choi CK. A numerical simulation of flow field in a wind farm on complex terrain. Wind and Structures, 2010: 13(4), 375.

14 Kusiak A, Song Z. Design of wind farm layout for maximum wind energy capture. Renewable Energy, 2010; 35(3): 685-694.

15 Wang L, Tan A, Gu Y. A novel control strategy approach to optimally design a wind farm layout. Renewable Energy, 2016; 95:10-21

16 Shakoor R, Hassan MY, Raheem A, Wu YK. Wake effect modeling: A review of wind farm layout

optimization using Jensen′ s model. Renewable and Sustainable Energy Reviews, 2016; 58: 1048-1059.
17 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.
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, 20100; 27(8):1302-1317.
19 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.
20 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.
21 Castellani F, Astolfi D, Sdringola P, Proietti S, Terzi L. Analyzing wind turbine directional behavior: SCADA data mining techniques for efficiency and power assessment. Volume 185, Part 2, 1 January 2017, Pages 1076–1086
22 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.
23 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.
24 Castellani F, Astolfi D, Piccioni E, Terzi L. Numerical and experimental methods for wake flow analysis in complex terrain. In Journal of Physics: Conference Series, 2105; 625(1): 012042.
25 Astolfi D, Castellani F, Garinei A, Terzi L. Data mining techniques for performance analysis of onshore wind farms. Applied Energy, 2015; 148: 220–233.
27 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
28 Herp J, Pedersen NL, Nadimi ES. Wind turbine performance analysis based on multivariate higher order moments and bayesian classifiers. Control Engineering Practice, 2016; 49:204-211.
29 Chang TP, Liu FJ, Ko HH, Cheng SP, Sun LC, Kuo SC. Comparative analysis on power curve models of wind turbine generator in estimating capacity factor. Energy, 2014; 73: 88-95.
30 Castellani F, Astolfi D, Terzi L, Hansen KS, Rodrigo JS. Analysing wind farm efficiency on complex terrains. Journal of Physics: Conference Series, Vol. 524, No. 1, pp. 012142.
31 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. Vol. 753, No. 11, pp. 112008
32 Zaher ASAE, McArthur SDJ, Infield DG, Patel Y. Online wind turbine fault detection through automated SCADA data analysis. Wind Energy,2009; 12(6), 574-593.
33 Schlechtingen M, Santos IF, Achiche S. Wind turbine condition monitoring based on SCADA data using normal behavior models. Part 1: System description. Applied Soft Computing, 2013; 13(1):259-270.
34 Schlechtingen M, Santos IF. Wind turbine condition monitoring based on SCADA data using normal behavior models. Part 2: Application examples. Applied Soft Computing, 2014; 14, 447-460.
35 Kim K, Parthasarathy G, Uluyol O, Foslien W, Sheng S, Fleming P. Use of SCADA data for failure detection in wind turbines. In ASME 2011 5th International Conference on Energy Sustainability, 2011: 2071-2079).
36 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.
37 Condition Monitoring. Exploring the innovations, challenges and potential of the products and services that keep wind turbines operating. Windpower Monthly, Haymarket Media Group, July 2013.
38 Wind Turbine Control Systems. Exploring the capabilities of the latest systems, and the drivers and challenges for further development. Windpower Monthly, Haymarket Media Group, March 2014.
39 Smith DA, Harris M, Coffey AS, Mikkelsen T, Jørgensen HE, Mann J, Danielian R. Wind lidar evaluation at the Danish wind test site in Høvsøre. Wind Energy, 2006; 9(1-2): 87-93.
40 Schlipf D, Schlipf DJ, Kühn M. Nonlinear model predictive control of wind turbines using LIDAR. Wind Energy, 2013; 16(7):1107-1129.
41 Lang S, McKeogh E. LIDAR and SODAR measurements of wind speed and direction in upland terrain for wind energy purposes. Remote Sensing, 2011; 3(9):1871-1901.
42 Mikkelsen T, Angelou N, Hansen K, Sjöholm M., Harris M, Slinger C, Vives G. A spinner integrated wind lidar for enhanced wind turbine control. Wind Energy, 2013; 16(4): 625-643.
43 Zahle F, Sørensen NN. Characterization of the unsteady flow in the nacelle region of a modern wind turbine. Wind Energy, 2011: 14(2):271-283.
44 Demurtas G, Pedersen TF, Zahle F.Calibration of a spinner anemometer for wind speed measurements. Wind Energy. 2016; 19:2003–2021
45 Emanuel H, Schellschmidt M, Wachtel S, Adloff S. Power quality measurements of wind energy converters with full-scale converter according to IEC 61400-21. In Electrical Power Quality and Utilisation, 2009. EPQU 2009. 10th International Conference on (pp. 1-7). IEEE.
46 Braccesi C, Cianetti F, Tomassini L. An innovative modal approach for frequency domain stress recovery and fatigue damage evaluation. International Journal of Fatigue. 2016: 91, 382-396.

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