Fault Diagnosis of Wind Turbine Gearboxes through Temperature and Vibration Data

Davide Astolfi*‡, Lorenzo Scappaticci**, Ludovico Terzi***

* University of Perugia - Department of Engineering, Via G. Duranti 93 - 06125 Perugia - Italy

** Guglielmo Marconi University - Department of Sustainability Engineering, via Plinio 44 - 00193 Roma, Italy

*** Renvico srl, Via San Gregorio 34, Milano 20124, Italy

(davide.astolfi@unipg.it, l.scappaticci@unimarconi. it, ludovico.terzi@renvico.it)

‡ Corresponding Author; Davide Astolfi, University of Perugia - Department of Engineering, Via G. Duranti 93 - 06125 Perugia - Italy, Tel: +39 075 585 3709,

Fax: +39 075 585 3703, davide.astolfi@unipg.it

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Abstract- Gearbox faults are one of the most common and severe causes of energy losses in large wind turbine technology. Further, degradation of gearboxes is an elusive phenomenon by the point of view of diagnostics. Yet, nowadays the widespread diffusion of Supervisory Control And Data Acquisition (SCADA) control systems is a keystone for fault prevention. It is desirable to conjugate accuracy of the outputs with intuitiveness and reasonable computational cost. The present work deals with these issues: some methods are proposed for data mining of SCADA gearbox temperature and vibration measurements. In particular, a model based on Artificial Neural Networks (ANN) is proposed and its performances are compared against similar approaches in the literature. It arises that vibration analysis at the time scale of SCADA data is not effective for fault diagnosis, even if powered by the artificial intelligence of the ANN, while the proposed ANN model for gearbox temperatures is useful for early fault diagnosis. The method is tested on the data sets of a wind farm in southern Italy and it is shown that it is useful for the diagnosis of incoming faults to three out of nine wind turbines of the site.

Keywords wind energy, wind turbines, Artificial Neural Network, gearboxes, fault prevention, condition monitoring.

1. Introduction

Large wind turbines are dynamically loaded along all the chain transforming the slow rotation of the main shaft into fast rotation for feeding power output into the electric grid. For this reason, despite the developments in the technology, malfunctioning of gearboxes is one of the most common causes of producible energy loss. In [1, 2] it is estimated that a judicious prevention would cost around the 20% of what a sudden breakdown costs in terms of producible energy loss, and it is shown that the common rate of gearbox breakdowns justifies the need of condition monitoring techniques for fault prevention. This is one of the reasons of the widespread diffusion of control systems in wind turbine technology. As regards gearboxes, Turbine Condition Monitoring (TCM) systems employ accelerometers for recording vibrations at the kHz scale, at meaningful points. Turbine Condition Monitoring (TCM) through vibration analysis has pros and cons: basically high diagnostic power, against high cost and high complexity for elaborating the information [3] from the data stream into knowledge. Due to the scientific challenges of this approach, there is a vast literature about these issues. For some examples, see [4-11]. The point about vibration analysis is dealing with unsteady load conditions due to rapidly changing wind speed: in [12] and [13], for example, an angular resampling algorithm is proposed at this aim. In Figure 1, a practical example is proposed: a sample spectrum of planetary gearbox vibrations is reported. It highlights the features of this kind of data: they are raw and straightforward, but at the same time they are very noisy. In Figure 1, the meshing frequencies are highlighted in red; it arises that the real spectrum has peaks close to this theoretical values, but there is also a spread which is difficult to interpret. It might be due to a fault, but it is very complex to investigate which tooth is damaged without having an historical reference. Or it might be even due to unsteady working operations (i.e. turbulence): for example, in [14], a "wind to gear" approach is adopted to demonstrate that turbines, which are in the lee of the wake of a nearby turbine, are affected by loads manifesting themselves at the level of gearbox vibrations.

Therefore, for diagnostic issues it might be as valuable to have data sets which are less "direct", but at the same time naturally denoised: for this reason, the other possible approach for condition monitoring is exploiting Supervisory Control And Data Acquisition (SCADA) control systems. SCADA control systems are more versatile than ad hoc TCM systems, they have lower cost but they have less diagnostic power. For a comprehensive review about the possible approaches to condition monitoring, see [15]. SCADA systems record, usually on 10-minute time basis, the main information about wind conditions, about the response of the turbine (yaw alignment, pitch angle and so on), about power output, about thermal behaviour at meaningful parts of the turbine, possibly about structural vibrations and loads. The versatility of SCADA data results in their use for several intertwined tasks: assessing wind turbine operational behaviour [16-23], understanding wake effects [24-37], possibly in conjunction with complex wind flow induced by the terrain [38-45]. In [46], SCADA data are employed for predicting fatigue life of a main rear bearing in direct drive wind turbines sited in complex terrain. Temperature measurements at the gearbox conjugate simplicity to a reasonable degree of responsiveness to the mechanical status of the wind turbine. For this reason, the analysis of temperatures for fault diagnosis has attracted a considerable amount of attention in the scientific literature and the debate is very fertile. For example, in [47], oil temperature rises as recorded by SCADA control system are used for detection of incoming gearbox failures. In [48], a normal behaviour model of the electrical generator temperature is constructed and incipient failure is detected as anomalous residuals between model and actual temperature. A similar approach was employed for gearbox bearing temperature and cooling oil temperature in the very relevant work of [49], which has been inspiration for this study. In [50], ANN algorithms are employed for processing temperature data from 24 turbines. Bearing faults are predicted 1.5 hours before their occurrence, with 97% of accuracy. The time scale of this advance with respect to the fault onset is not exploitable for intervention: this motivates the need to push further, in order for the diagnosis to be sufficiently early. ANN techniques are employed in [51] for developing optimal maintenance strategies of wind turbines. In [52], a Bayesian network approach is employed for gearbox fault detection. In [53] too, an ANN-based algorithm for condition monitoring is proposed: a self-evolving maintenance scheduler framework for maintenance management of wind turbines is proposed. ANN techniques for anomaly detection are employed also in [54], and in [55] normal behaviour modelling of two wind turbine drive train temperatures has been investigated with several modelling approaches.

One of the shortcomings of SCADA analysis for gearbox maintenance is that, being based on statistical analysis, it commonly requires vast data sets for providing meaningful indications: the most common opinion therefore is that SCADA can detect incipient faults at a late stage. Even if several developments have lately been reached for addressing these shortcomings and detecting faults in manageable advance [56], one of the aims of this work is giving some further response to such challenge. Actually, the objective of this work is employing Artificial Neural Networks, for their capability in reconstructing non-linear dependency between inputs and outputs, and formulating simple models for the diagnosis of occurring faults at the level of gearbox. The data sets employed have the 10-minutes sampling time of the common SCADA control systems; the gearbox vibrations and the gearbox temperatures are selected as target output to model. It will be shown that the time resolution of SCADA is too coarse for reliable vibration analysis, which should be rather observed at its proper time scale (several Hz). The idea is therefore that a phenomenon and its side effects might have very different time scales: this is exactly the case of drivetrain vibrations and bearing heating. Depending on the technology at disposal, whose selection might be a matter of pros and cons basing on cost and complexity, fault diagnosis might be effective by analysing the phenomenon or its side effects. In this case, side effects of vibrations is heating and analysing it at the time scale of SCADA shall be shown to be very effective for fault diagnosis. One of the main novelties of this work is that the ANN model for internal temperatures is formulated in order for it to be as simple as possible. Actually, the minimum possible number of inputs is employed: outdoor temperature and active power. The objective is not only minimizing the computational cost. Comparing against other models in the literature [49], that feed the output at previous time steps as input to the ANN, it is actually shown that the proposed model is superior as regards the diagnostic power. The approach is tested on the data sets of a wind farm sited in southern Italy and it is shown that sharp diagnosis indications are provided for three out of nine wind turbines.

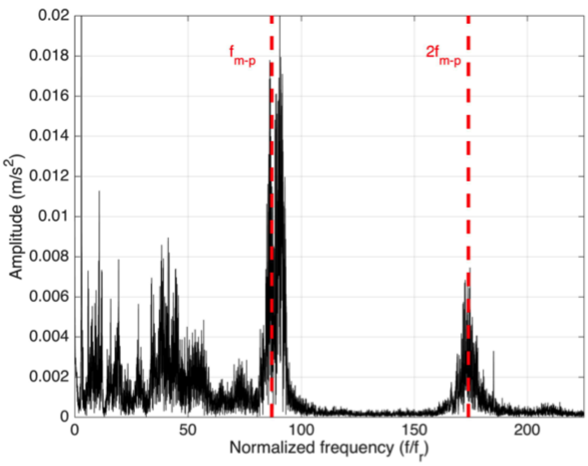

Fig. 1. Sample planetary gearbox vibrations: in red, the meshing frequencies are highlighted. The frequency scale is normalized to the frequency of the rotation of the rotor.

2. Materials and Methods

The testing ground of the proposed methods is an onshore wind farm, sited in southern Italy and featuring 9 turbines with 2 MW of rated power each. This test case has been selected because of the vastness of the data sets at disposal and in particular because three turbines have undergone problems at the gearbox. The main features of the test case are summarized in Table 1.

As regards temperature analysis, two methods are employed and the former, introduced in [56] is a support to the latter. The former method is a plot of the measurements of the rotor bearing temperature against the percentage of power with respect to the rated. This is done by averaging on intervals having as amplitude the 10% of the rated power. Comparing the behaviour of one turbine against the other on a reasonably vast statistical basis allows to identify mechanical problems with a manageable advance, as discussed in [56]. The drawback of this method is that it is demanding by the point of view of the size of the data set, in order to give reliable responses, and it can be prohibitive to reduce the size of the data set for early fault diagnosis.

The philosophy of this work is employing the above approach as a support to another, more responsive, method. The idea is that a considerable statistical basis, describing each turbine producing output under expected thermal behaviour, can be fed to a model: once this is consistently trained, it can be capable of identifying anomalies on time scales shorter than required by the method of [56]. The vastness of the debate in the scientific literature clearly identifies the candidate approach as ANN-based. A similar problem has been addressed in [49], and the starting point for this work has therefore been selected as the same model: rotor bearing temperature as output; as inputs the outdoor temperature, the power output, the rotor bearing temperature one and two time steps earlier. In Section 2, it is shown that this model (named as M_2) is not effective on the selected test case for detecting gearbox problems: in other words, when some wind turbine show anomalous behaviour (identified through the power - temperature plot), anomalous residuals between simulation and actual measurements don't manifest. For this reason, another model is proposed, named as M_1. The idea is therefore that one could possibly select as inputs only "external" variables. Further, the internal temperature signal, selected as target, should be as responsive as possible to the input variables: in this case, external temperature and collective motion of the shaft. Therefore, rotor bearing temperature is selected as output; outdoor temperature and power output are selected as inputs. Due to its relevance for fault diagnosis, which shall be shown later on, the structure of this model is sketched in Figure 2. The ANNs are feed-forward with ten neurons and the number of neurons is set through a sensitivity analysis.

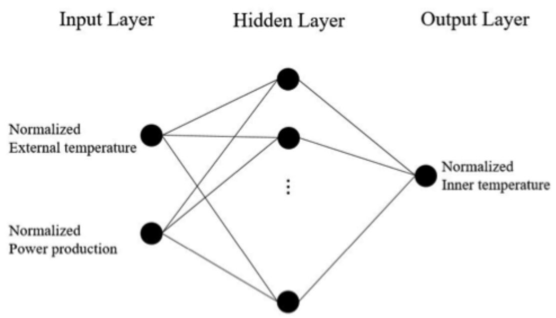

Fig. 2. The structure of the M_2 ANN model.

The test case wind farm has been selected because three turbines (T1, T2 and T6) have undergone gearbox malfunctioning: actually, this malfunctioning has been correctly diagnosed using the approach of this work and that of [56], in support, and it has been possible to service the wind turbines before a traumatic breakdown. The effectiveness of the proposed model is validated on multiple time scales: three months, one month, one week, one day (that is, even just few dozens of points). Actually, one key point of this approach is the fact that the proposed model can be responsive also with few dozens of points as validation data set. This marks a concrete improvement with respect to the method of [56]. In that case, for each diagnosis attempt a considerable data set was required. Instead, with an appropriate model one can train on a historical basis (with a vast data set) once and for all, and validate on very short time scales. This is less time consuming by a computational point of view and the shortness of the data sets required for responsiveness points at a concrete (because validated against a real case) improvement in early fault detection. The training data set is made of 13128 10-minute based measurements, collected over six months, during which the wind farm was producing output in unison.

Further, it has been investigated if it is effective for fault diagnosis to approach directly vibration amplitudes as collected by the SCADA control system. In particular, drive-train vibration amplitudes are analysed. An approach is adopted, similar to the case of bearing temperatures. Two models are considered: in both of them, drive-train oscillation amplitude is selected as output. In the former, inputs are external temperature and power output. In the latter, inputs are wind speed and power output. In Section 2, it is shown that these models don't provide meaningful indications of incoming problems at the gearbox. In some sense, the philosophy is that vibrations are responsive in a very straightforward way to mechanical faults, when analysed on the proper time scale (several Hz, at least) and with appropriate techniques. If one instead wants to adopt the 10-minute time basis of SCADA data, because it is less demanding by the point of view of the techniques, one can detect mechanical problems through by observing slower and more persisting phenomena, as thermal effects are. In Table 2, a summary of all the models employed in this work is proposed.

Table 1. Features of the test case

Number of turbines	9
Rotor diameter	82 meters
Hub Height	80 meters
Rated Power	2 MW
Terrain	Flat
Rated speed	13 m/s
Cut-in speed	4 m/s
Cut-out speed	25 m/s

Table 2. The structure of the ANN models.

Model	Output	Inputs
M_1	Rotor bearing temperature	Power Output External Temperature
M_2	Rotor bearing temperature	Power Output External Temperature Rotor bearing temperature one and two time steps earlier
M_3	Drive-train vibration amplitude	Power Output External Temperature
M_4	Drive-train vibration amplitude	Power Output External Temperature Drive-train vibration amplitude one and two time steps earlier

M_5	Drive-train vibration amplitude	Power Output Nacelle wind speed
M_6	Drive-train vibration amplitude	Power Output Nacelle wind speed Drive-train vibration amplitude one and two time steps earlier

3. Results

In Figure 3, a rotor bearing temperature vs. power plot is shown. The data set is the one employed for the training of the ANN models. From this Figure, it arises that one should expect the training data sets to have a good quality, in the sense that every wind turbine of the farm has a regular behaviour as regards rotor bearing temperature: the trends are very compact and from the status codes data sets it arises that there are no alarms regarding temperatures

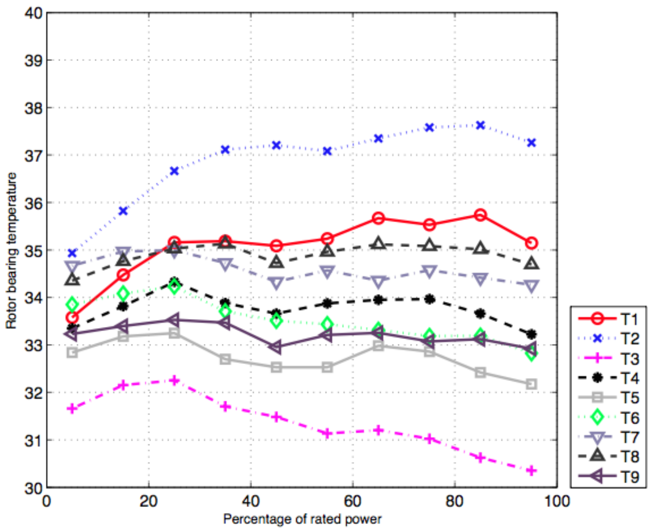

Fig. 3. Rotor bearing vs Power, during the training period. Bins have amplitude of the 10% of the rated power.

For brevity, the model proposed in this work is named M_1 and the model of [49] is named M_2 (see Table 2), and they are going to be validated against several data sets having very different lengths. They are summarized in Table 3. The metrics for evaluating the quality of the validation are the R^2 and the Mean Absolute Error (MAE).

Table 3. Summary of the validation periods

Period	Duration
P_1	3 months
P_2	1 month
P_3	1 week
P_4	1 day

In Table 4, the results are collected for the P_1 validation data set: it arises that, using the M_1 model, the couple of metrics R^2 and MAE indicates an anomalous mismatch between simulation and real data for turbines T1, T2 and T6. Three months of data are surely enough for investigating the thermal behaviour of the turbines using the same kind of plot of Figure 3: this can be considered a crosscheck of the proposed ANN approach. The results are shown in Figure 4: actually, a severely anomalous behaviour of turbines T1, T2 and T6 is highlighted.

Table 4. Validation metrics: P_1 data set

Turbine	$R^2 - M_1$	MAE – M_1	$R^2 - M_2$	MAE – M_2
T1	0.538	0.043	0.999	0.002

T2	0.534	0.083	0.999	0.002
T3	0.834	0.024	0.999	0.002
T4	0.851	0.030	0.999	0.002
T5	0.819	0.029	0.999	0.002
T6	0.398	0.093	0.999	0.002
T7	0.823	0.028	0.999	0.002
T8	0.820	0.029	0.999	0.002
T9	0.858	0.027	0.999	0.002

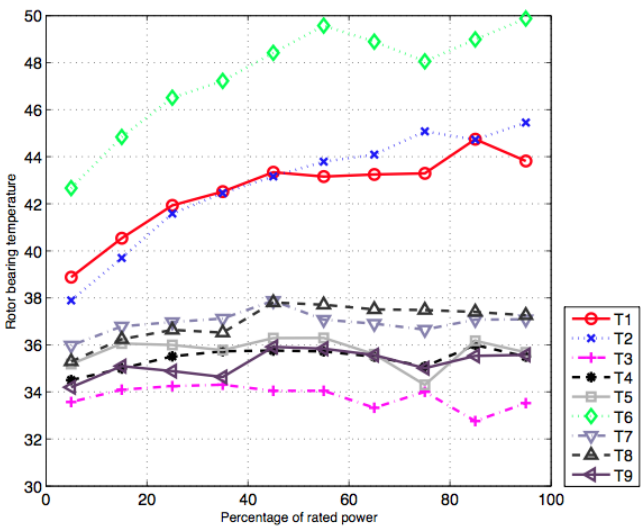

Fig. 4. Rotor bearing vs Power, during the P_1 validation period. Bins have amplitude of the 10% of the rated power.

In Table 5, the results are shown for the validation data set P_2: it arises that, using the M_2 model, the turbines T1, T2, T6 are indicated as anomalous. In particular, the R^2 considerably falls with respect to the other turbines. The M_2 model looks indecisive as regards anomaly detection, on the P_2 data set. On a monthly time scale, it is still reasonable to adopt the approach of Figures 3 and 4, and for this reason the same kind of plot is shown in Figure 5. It arises that turbines T1, T2 and T6 show indeed a very anomalous behaviour, and the suggestion coming from model M_1, in the form of mismatch between simulation and reality, is correct.

Table 5. Validation metrics: P_2 data set

Turbine	$R^2 - M_1$	MAE – M_1	$R^2 - M_2$	MAE – M_2
T1	0.362	0.045	0.998	0.003
T2	0.269	0.078	0.999	0.002
T3	0.697	0.049	0.997	0.003
T4	0.681	0.044	0.997	0.002
T5	0.640	0.036	0.998	0.002
T6	0.189	0.074	0.999	0.002
T7	0.664	0.047	0.998	0.002
T8	0.671	0.036	0.999	0.002
T9	0.762	0.029	0.999	0.002

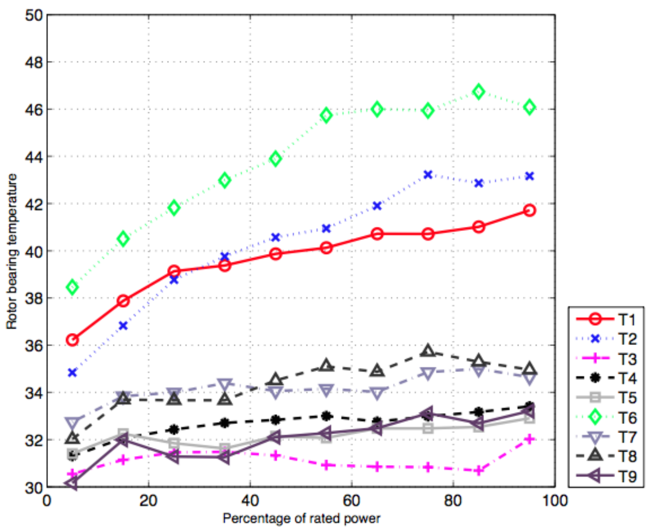

Fig. 5. Rotor bearing vs Power, during the P_2 validation period. Bins have amplitude of the 10% of the rated power.

Table 5 indicates that the diagnostic power of model M_1 is considerably higher than model M_1. This is reasonable, because if one feeds an ANN with the output at previous steps as input, it is likely that the cross-correlation between subsequent time steps dominates over the dependency on real inputs and is independent on the functioning (anomalous or not) of the wind turbine. Further zoom is actually provided by Figures 6 and 7: they are time series of simulated and real data during validation period P_1, for turbine T6, using respectively model M_1 and M_2. The results are in units of the maximum rotor bearing temperature measured during the training period. From Figures 6 and 7, it arises that the M_2 model reproduces almost exactly the temperature fluctuations, while model M_1 doesn't. Even if it doesn't come as a surprise, on the grounds above, that models M_1 and M_2 have different precision in general, model M_1 reasonably catches the trend of temperature fluctuations on a local scale, but only when the turbine is operating properly: as a crosscheck, this is shown in Figure 8 for turbine T4.

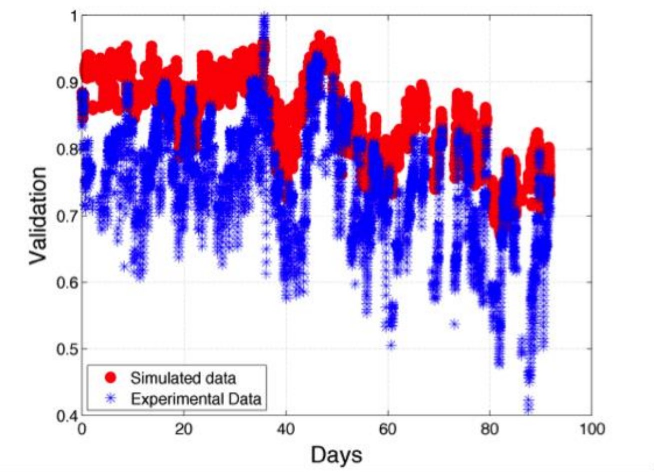

Fig. 6. Time series of simulated vs. measured data, using model M_1: validation period P_1, turbine T6

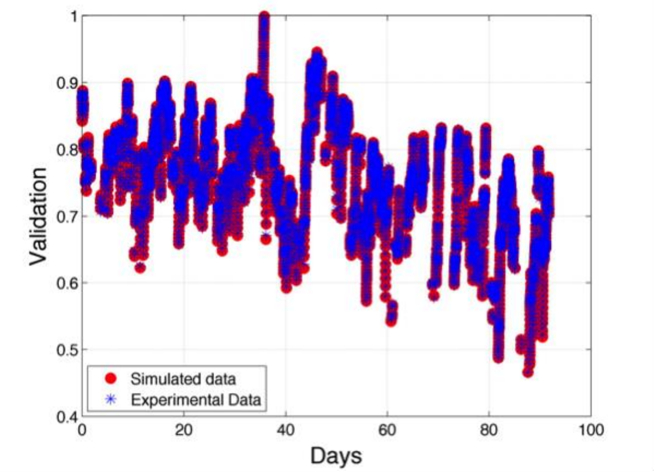

Fig. 7. Time series of simulated vs. measured data, using model M_2: validation period P_1, turbine T6

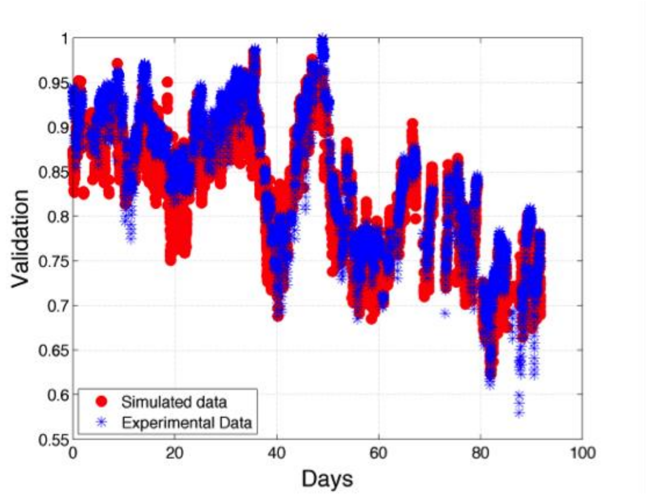

Fig. 8. Time series of simulated vs. measured data, using model M_1: validation period P_1, turbine T4

In Tables 6 and 7, the validation metrics are reported for the P_3 and P_4 data sets. From the Tables, it arises that model M_1 indicates anomalous mismatch and scarce correlation between simulated and real data for turbines T1, T2 and T6. Instead, model M_2 doesn't provide clear diagnostic indications. It is particularly valuable that the approach of Figures 4 and 5 wouldn't be applicable for the P_3 and P_4 data sets, because they are too short. In particular, the M_1 model gives consistent indications also for the P_4 data set, which is composed by just few dozens of measurements.

Table 6. Validation metrics: P_3 data set

Turbine	$R^2 - M_1$	MAE – M_1	$R^2 - M_2$	MAE – M_2
T1	0.482	0.033	0.996	0.003
T2	0.235	0.064	0.997	0.002
T3	0.693	0.023	0.993	0.002
T4	0.485	0.030	0.997	0.002
T5	0.544	0.037	0.996	0.002
T6	0.429	0.050	0.996	0.003
T7	0.539	0.030	0.996	0.002

T8	0.696	0.029	0.997	0.002
T9	0.550	0.036	0.997	0.003

Table 7. Validation metrics: P_4 data set

Turbine	$R^2 - M_1$	MAE – M_1	$R^2 - M_2$	MAE – M_2
T1	0.227	0.043	0.993	0.003
T2	0.021	0.037	0.997	0.002
T3	0.406	0.031	0.981	0.002
T4	0.372	0.026	0.983	0.002
T5	0.113	0.032	0.987	0.003
T6	0.049	0.051	0.997	0.001
T7	0.379	0.031	0.995	0.001
T8	0.358	0.031	0.995	0.002
T9	0.456	0.031	0.990	0.002

As regards ANN models for drive-train vibrations, the model having external temperature and active power as input and vibrations as output is labeled as M_3. M_4 is the model built parallel to the one in [49], having external temperature, active power and vibrations one and two time steps earlier as inputs. M_5 and M_6 are the same as, respectively, M_3 and M_4, but with nacelle wind speed instead of external temperature. See Table 2 for a recap. The selected validation period is P_2, because one month of data has been considered a reasonable halfway and especially because it is already known from Figure 5 and Table 5 that turbines T1, T2 and T6 are undergoing anomalous functioning. The validation metrics are collected in Tables 8 and 9.

Table 8 Validation metrics: P_2 data set

Turbine	$R^2 - M_3$	MAE – M_3	$R^2 - M_4$	MAE – M_4
T1	0.551	0.082	0.874	0.040
T2	0.779	0.058	0.903	0.038
T3	0.776	0.070	0.934	0.030
T4	0.425	0.084	0.899	0.034
T5	0.425	0.100	0.867	0.039
T6	0.450	0.085	0.891	0.036
T7	0.422	0.093	0.906	0.035
T8	0.431	0.076	0.902	0.031
T9	0.497	0.073	0.908	0.033

Table 9 Validation metrics: P_2 data set

Turbine	$R^2 - M_5$	MAE – M_5	$R^2 - M_6$	MAE – M_6
T1	0.600	0.096	0.873	0.043
T2	0.763	0.067	0.907	0.038
T3	0.805	0.064	0.936	0.033
T4	0.446	0.115	0.886	0.038
T5	0.407	0.137	0.860	0.044
T6	0.475	0.113	0.886	0.039
T7	0.502	0.088	0.905	0.036
T8	0.415	0.097	0.901	0.032

T9	0.566	0.091	0.913	0.032

From Tables 8 and 9 it arises that the models are not capable of highlighting the anomalies of turbines T1, T2 and T6: the metrics don't distinguish them with respect to the rest of the wind farm. The key point is the sampling time: for vibrations it is several Hz, for SCADA it is 10 minutes. The general lesson is that a straightforward analysis of vibration signals should be addressed on its proper time scale, as for example in [57], where 32 Hz data are analysed with ANN techniques for early fault diagnosis. Consequences of mechanical phenomena might have different characteristic time and therefore be slower and more persistent: this is the case of thermal effects, and that is why ANNs are capable of reconstructing the behaviour of drive-train temperatures using data with 10 minutes sampling time. Comparing models M_1 and M_2, a further lesson arises: precisely because thermal effects are "slow", if one trains a model using as input the output at previous steps, one loses the diagnostic power, because the cross correlation between what happens now and what will happen soon dominates over the dependency on "external" variables.

4. Conclusion and Future Work

This work was devoted to the issue of early detecting of mechanical damages to large wind turbine gearboxes. SCADA data have been selected as source of information to process: actually, as discussed in the Introduction, despite SCADA are considered late stage indication of incoming faults by the point of view of condition monitoring, impressive developments are being achieved. Therefore, as regards fault diagnosis, SCADA analysis (also because of its simplicity, intuitiveness and low cost) is struggling in competitiveness against vibration analysis.

In this work, an onshore wind farm sited in southern Italy has been studied as test case. Rotor bearing temperatures and drive-train vibrations have been elaborated through ANN techniques. The lesson is that, employing 10-minute based SCADA data, the proposed model for gearbox vibrations is not responsive for fault diagnosis. Actually, averaging on 10-minutes basis a phenomenon having typical time scale of several Hz drowns the information. In other words, a phenomenon should be analysed on its proper scale, while consequences of it might have different scales. Anomalous mechanical functioning of gearboxes can have persistent consequences as regards heating and this has indeed proven to be the case for the selected test wind farm. A model has therefore been proposed, targeting rotor bearing temperature as output in function of outdoor temperature and active power, and it has been shown that it is responsive in diagnosing incoming faults, through the anomalous mismatch between actual measurements and simulated ones. Three out of the nine turbines of the test case wind farms are actually highlighted as subject to incoming gearbox faults and the validation has been conducted on several test periods having different lengths (from few months to just one day).

A vast debate in the scientific literature is devoted to optimization of data mining algorithms for wind turbine fault diagnosis. A lesson coming from the test case of the present work is that machine learning algorithms should not be doped with the history of the output to study, because diagnostic power is lost. In other words, if one wants to model rotor bearing temperature, it is better to employ only "external" variables as inputs. If input to the model is also added in the form of the output itself at previous steps, for thermal phenomena the cross correlation between what happens and what will happen dominates over the dependency on variables external to the gearbox and the model reproduces faithfully also anomalous behaviour: no room is left for identifying faults as mismatch between simulation and actual measurements. This lesson is resembled in the fact that the diagnostic power of the proposed model has proven to be superior with respect to the one of [49], on the test case of this work (see Figures 6 and 7).

The results are interesting not only in the context of machine learning techniques. Actually, the method proposed in [56] is used as a support to the one proposed in this work and as a milestone to compare with. The two methods have two main differences: the method of [56] requires a considerably vast data set each time it is applied (a reasonable rule of thumb is one month of data), while the method of this work requires a statistical basis once and for all and can subsequently be validated with success even on very short time scales (P_4 is only one day of data). Further, the method proposed in this work can easily be automated also as regards the phase of fault identification through the analysis of MAE and R^2 metrics.

A challenging further direction of this work is connecting microscopic and macroscopic wind turbine underworlds, i.e. gearbox vibrations to SCADA data. Some first developments are collected, for example, in [14], where a "wind to gear" approach has been proposed for connecting a flow phenomenon to a mechanical phenomenon and understanding the mechanics of the gearbox under complex flow. A "temperature to gear" approach would be very valuable and it would constitute an impressive upgrade of this work.

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