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WIND TURBINE FAULT DIAGNOSIS THROUGH TEMPERATURE ANALYSIS: AN ARTIFICIAL NEURAL NETWORK APPROACH

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Abstract

Wind turbines undergo dynamic loads along all the phases of transformation of wind kinetic energy into power output to be fed into the grid. Gearbox breakdowns are one of the most common and most severe causes of energy losses and it is therefore crucial to prevent and forecast them. Straightforward vibration analysis is very demanding by the point of view of technology, costs and complexity of signal denoising. A considerable keystone in fault diagnosis is the analysis of Supervisory Control And Data Acquisition (SCADA) systems. In particular, thermal behaviour of wind turbines fits well with the common time scale of SCADA data; heating trends are fairly responsive as a consequence of rotor vibration. Machine learning techniques applied to SCADA data are very powerful in reconstructing inputs – output dependency. On these grounds, in this work an Artificial Neural Network approach is proposed for early diagnosis of gearbox faults. The method is validated on the data of a wind farm operating in Italy. It is shown that the method is capable in recognizing incoming faults with a very manageable advance also with data on short time scales.

Key words: artificial neural networks, wind turbines, fault diagnosis, wind energy, SCADA

INTRODUCTION

Renewable energy sources are becoming more and more widespread everyday and we are looking out at the era in which their use will not be fiscally stimulated. To achieve that goal, the renewable sector must in perspective fight in competitiveness against fossil sources. For this reason, the optimization of source exploitation and technology is crucial. In the renewable sector, wind energy stands apart, due to the nature of the source: it is very variable in space and time and it is even challenging to predict the amount of energy that will be dispatched into the grid on a daily basis [1, 2, 3].

As regards technology, wind turbines are affected by dynamic loads along all the phases of transformation of wind kinetic energy into power output. For this reason, one of the most severe and most common causes of wind turbine breakdowns is gearbox fault. In [4, 5], it is estimated that a judicious prevention (Condition Monitoring through gearbox vibration analysis) would cost around the 20% of what a sudden breakdown costs in terms of energy loss and it is shown that the common rate of gearbox breakdowns justifies the need of condition monitoring techniques for fault prevention.

Condition monitoring of gearbox means collecting at meaningful points and analysing vibrations of the shaft that transforms the slow rotation of the rotor into fast rotation. There is a vast literature on these issues. We refer to [6–10] for an overview. The main point about vibration analysis is that it is demanding, by the point of view of technology, of cost and of complexity of signal, which needs to be denoised for extracting diagnostic information. In [11], for example, it is shown that feature extraction from gearbox vibration signals can be really challenging. The anomalous spectra detected can also be due to unsteady conditions generated by wake interactions [12-20] between nearby turbines and this or similar aspects complicate the scenario.

Supervisory Control And Data Acquisition (SCADA) systems have become ubiquitous in modern wind turbine technology because they have an adequate cost, because they are reasonably simple to be interpreted and because they are versatile. SCADA data are vastly employed for performance monitoring [21-28], and their exploitation for condition monitoring has been expanding recently. SCADA analysis is considered a late stage of fault diagnosis, if compared with spectral vibration analysis. However the boost in machine learning tools and artificial intelligence approach is leading to an improvement in the diagnostic power. Using SCADA data, it is in perspective possible to make gearbox fault diagnosis with manageable advance. One of the main sources of information for SCADA-based condition monitoring are temperatures: actually, the heating behaviour of wind turbines is a "slow" and persisting phenomenon, if compared to vibrations. The time granularity of the data (usually 10 minutes) of SCADA fits well with it and thermal phenomena are fairly responsive to the motion of the shaft. Of course the main issue is being capable of fault diagnosis sufficiently early for intervention. For these reasons, there is a vast literature about the use of SCADA temperature data for fault diagnosis: in [29], oil temperature rises are employed for detection of incoming faults. Processing data from 24 turbines, in [30] bearing faults are predicted, with a 97% accuracy but only 1.5 hours before they occur. This time scale is a typical example of the issue above cited: it does not fit for intervention; for this reason, the objective is pushing forward the techniques. Machine learning techniques are very appropriate for this objective: the capability in recognizing non-trivial dependency between the inputs and the outputs is crucial. Several Artificial Neural Network (ANN) models have been proposed and fault onset is recognized as anomalous mismatch between predicted and actual heating behaviour. This is the case of References [31-34].

This work moves from the grounds of [35]: in [35], it was shown that an intuitive method for temperature data analysis is powerful in diagnosing faults. The main shortcoming about it is that it requires a considerable statistical basis. In this work, inspired by the debate in the literature, we propose an ANN model for processing temperature data and identifying fault onsets. The added value, as will be discussed later on, is that, once the model is trained, the validation can successfully be conducted also on time scales much shorter than the ones in [35]. This improves the advance of fault detection. It is important to highlight that the training has to be performed on an appropriate data set by the point of view of both quantity and quality. Another key point of this work is that the validation is conducted on a real test case, a wind farm sited in Italy. The structure of the work is therefore as follows: in Section 1, the wind farm, the data set and the methods are described. Section 2 is devoted to the results and finally in Section 3 some conclusions are provided, as well as some further directions.

1. THE METHOD AND THE VALIDATION CASE

The validation case of this work is a wind farm sited in southern Italy. It is composed of 7 turbines having 2 MW of rated power each. This validation case has been selected because it provides several added values for the scientific purposes of this work. Vast SCADA data sets are at disposal of the authors and, most of all, 3 turbines have undergone gearbox problems which have actually been prevented in time using the combination of the approach of [35] and of the method of this work. The turbines undergoing gearbox problems are named as T1, T2 and T6.

The method of [35] is used in this work as support to the reliability of the approach proposed here, and therefore it is briefly recalled: in [35], it is proposed to monitor wind turbine temperatures through a plot against the percentage of power with respect to the rated. In [35], the data are averaged on percentage power intervals having as amplitude the 10%. This method is mainly qualitative because it is not automatic, nevertheless it provides some useful indication for diagnosing faults by comparing the behaviour of the turbines the one against the others. This is the conclusion of [35].

In this work, as hinted in the Introduction, an ANN-based approach is proposed. In the latest years, impressive achievements have been reached about the use of data-driven Artificial Intelligence approaches for wind turbine fault diagnosis. In [36, 37], for example, Adaptive Neuro-Fuzzy Interference Systems (ANFIS) are employed. In [38], Self Organizing Map (SOM) method is adopted. In [34], an up to date review of the several possible methods for normal behaviour modelling and anomaly detection is provided. This work moves from the grounds of [31] and [39]. For example in [39], an Intelligent System for Predictive Maintenance (SIMAP), designed for real time monitoring, is described. The approaches of [31] and [39] are ANN-based and one of the inspiring ideas of this work is addressing if the models of [31] and [39] can be simplified even further but keeping a good diagnostic power, in order to reduce the computational time. As shall be shown later on, this is indeed the case. This also motivates why the authors reduced to a two-dimensional problem: the selection of the very minimum number of inputs is inspired by the discussion in [31].

Therefore, the set up of the ANN is the following: the output is an internal temperature signal of the wind turbine, the inputs are turbine active power and external temperature. The main difference with respect to the models in [31] and [39] is that the model is not trained with the output itself at previous time steps. This constitutes a remarkable difference, because training the ANN with the output can dope the method and dilute the diagnostic power.

A feed-forward ANN with 10 neurons is trained for each turbine, using this model, feeding with data sets describing each turbine under correct behaviour (this is further crosschecked using the plot of [35]). A sketch of the model is proposed in Figure 1. The feed-forward architecture is employed because it is very common for facing the problem of reconstructing the dependency between inputs and output [34].

The dimension of the ANN's inner layer was chosen after some tests between 5 to 30: the best setup for the solution of the problem presented to the ANN has been selected. It was decided not to test more complex setup with more inner layers or more neurons in the inner layer to avoid overfitting and to keep the approach as simple as possible.

The structure is chosen to have tangent transfer function in the inner layer and linear in the output layer. The feed forward-back propagation training is run with Levenberg-Marquardt algorithm, as is well suited for small and medium scale problems, with weight decay constant set at 0.001.

The stopping criterion is defined as negligible change in the performance, that is set as the lowest mean squared error on part of the data provided.

At this purpose, a random division of the data provided is done, in order to split between those employed for training and for performance calculation.

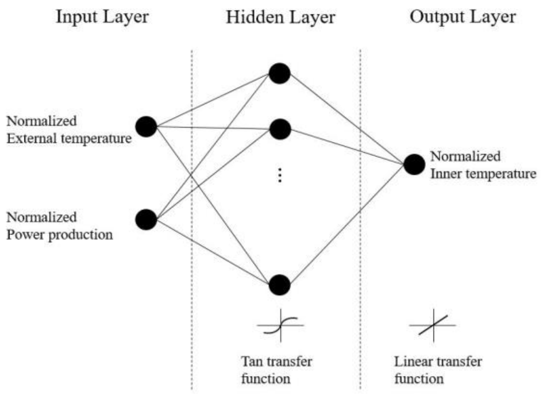

Fig. 1. The structure of the ANN model.

The internal temperature signal, selected as output, should be as responsive as possible to the selected inputs, in particular to the collective motion of the shaft resembling in the amount of power output produced: this is the reason why the main bearing temperature has been selected as output to study. Further, a key point of the approach is that inputs are only external variables. In the literature about internal temperature analysis for fault diagnosis, it is common to train models using the history of the temperature itself. Doing this, the cross correlation between what happens now and what will happen soon might dominate and the method might lose the capability of recognizing incoming faults as displacement between synthetized and observed values.

The training data set is composed by 15866 records, collected over 7 months, filtered on the regime of the whole wind farm being in productive phase and no anomalous events. In Figure 2, the training data set is plotted for the sample turbine T4, the colours refer to inner temperature values. The power output is normalized with respect to the rated. After the training, the ANN for turbine T4 is employed for simulating data on a regular grid having the same intervals as the training data set. This is done in order to compare the "real" surface of Figure 2 against a recognized surface which is learnt in the training from the real data. The surface is plotted in Figure 3 and it arises that the ANN indeed captures very well the dependency of the internal temperature on external temperature and active power.

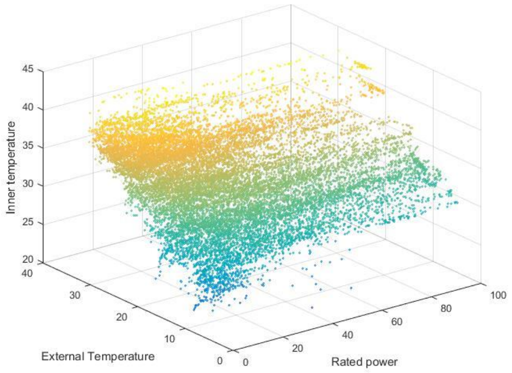

Fig. 2. The training data set for turbine T4.

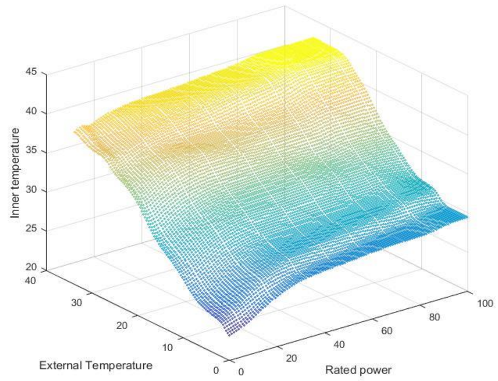

Fig. 3. The simulated data set for turbine T4, after the training of the ANN.

Therefore, as Figures 2 and 3 support, one important point of the method is that the ANN stores the standard wind turbine functioning as regards the relationship between the inputs and output defined, learning from the provided data set.

The validation highlights malfunctioning behaviour of some turbines when the ANN output is far from the observed internal temperature.

So, the validation can reliably be conducted also on reasonably short time scales. In the following Section 2, the results are collected.

2. RESULTS

In Figure 4, the main bearing vs active power average plot is shown, according to the method of [35]. The data set is the one used for training. A very limited spread arises between the behaviours of the wind turbines (less than 10 °C, over all the power spectrum): for this reason, the qualitative method of [35] supports the confidence that training data sets has a good quality, in the sense that it describes all the wind farm under not anomalous functioning. A peculiarity of the plot in Figure 4 is that the plot shows a plateau, if not even a descent, approaching rated power. This is reasonable by a mechanical point of view because heating is expected to be more evident with variation of rotational speed and at rated power rotational speed is kept constant. Further, rated power is associated to a vast interval of wind intensities and one can have the same power but very different flow, and therefore air transfer and therefore lower temperature. Further, the behaviour of those lines and of the surface as in Figure 2 is turbine-dependent and, as one ANN is trained per each turbine, this behaviour is part of the information stored in the training.

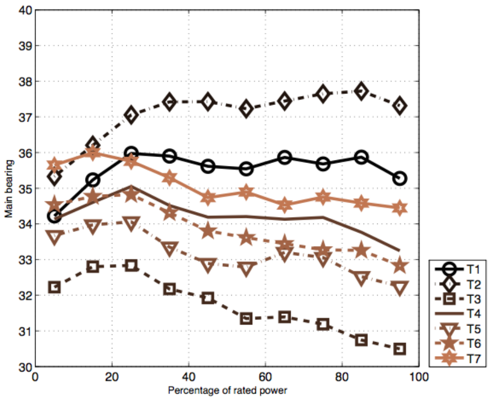

Fig. 4. Main bearing temperature vs Power, during the training period. Bins have amplitude of the 10% of the rated power

Three validation periods are selected, which are not part of the training period: three months made of 7958 records (P_1), one month made of 2804 record (P_2) and few days made of 534 records (P_3). The metrics for evaluating the degree of agreement between simulations and actual measurements are the R^2 and the mean absolute error (MAE). Due to the non-deterministic nature of ANNs, several runs have been launched for each validation period. The result is that the variation of the validation metrics, from one trial to the other, is negligible. The values reported in the bar plot of Figures 5, 6, 9, 10, 11 and 12 are the averages on the set of launches for each period and, for brevity, the standard deviation is not reported explicitly because it is negligible. In Figures 5 and 6, the metrics for the validation period P_1 are reported.

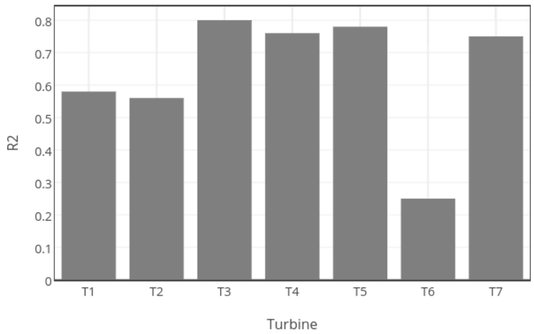

Fig. 5. Validation metric for P_1 data set. R^2.

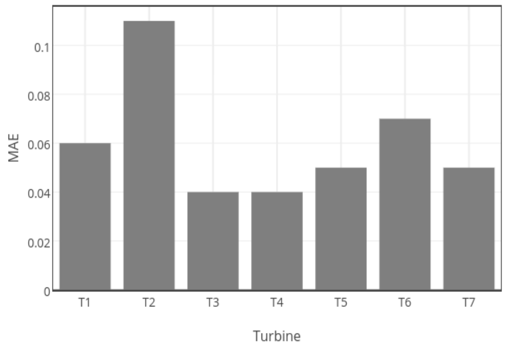

Fig. 6. Validation metric for P_1 data set. MAE.

In Figures 7 and 8, the time series of simulated and actual measurements on the P_1 data series are plotted. The data are normalized to the maximum value during the training phase. Figure 7 refers to turbine T2, the one showing highest mismatch between simulation and reality. Figure 8 refers to turbine T4 and highlights that the model is capable in locally reproducing temperature fluctuations on their proper time scale, when a turbine is functioning normally. Instead, when the turbine undergoes gearbox anomalous functioning, this agreement breaks down (Figure 7).

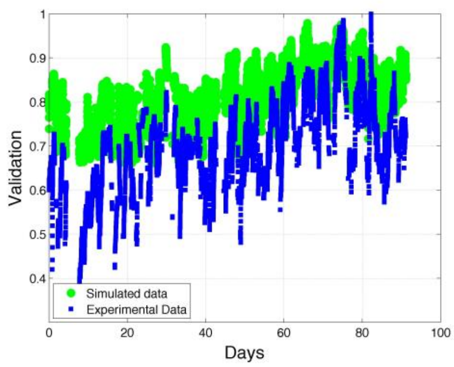

Fig. 7. Time series of simulated and measured data. Turbine T2, P_1 validation data set.

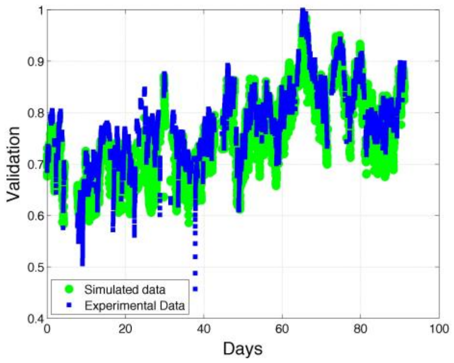

Fig. 8. Time series of simulated and measured data. Turbine T4, P_1 validation data set.

In Figures 9 and 10, the validation metrics for the P_2 data set are shown, and in Figures 11 and 12 for the P_3 data set. From Figures 5, 6, 9, 10, 11 and 12 it arises that, as expected, R^2 is a more accurate indicator for highlighting anomalies and it shows better the anomalous events if calculated on a shorter period. If one wants to automate the detection, a possible route is the following: compute the average and standard deviation of the indicators for all the wind turbines except the suspect of anomalies (which are T1, T2 and T6) and then compute how many standard deviations separate the indicators for the suspects from the above computed average, suspects excluded. A reasonable threshold for highlighting an anomaly is 5 standard deviations: applying this method, T1, T2 and T6 are isolated as anomalous by using the R^2, but not using MAE. Nevertheless, the MAE is also useful for a bird's eye view and that is why it is reported also.

Notice that the results are very clear and valuable also in the case of the P_3 data set, for which (due to its size) the method of [35] would not give reliable responses.

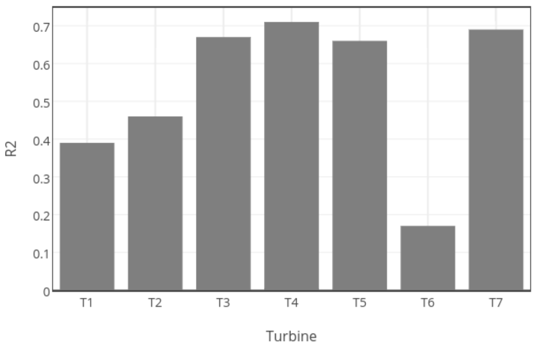

Fig. 9. Validation metric for P_2 data set. R^2.

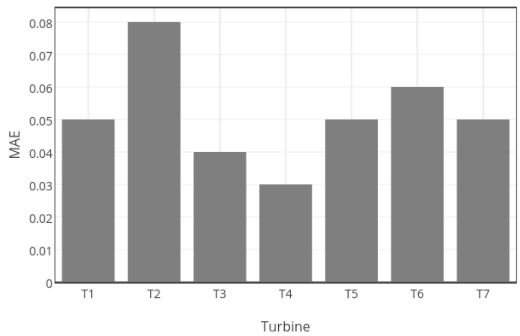

Fig. 10. Validation metric for P_2 data set. MAE.

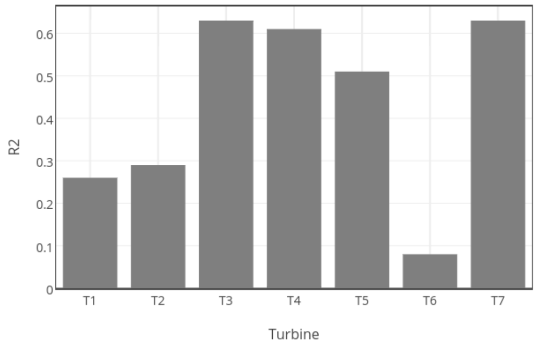

Fig. 11. Validation metric for P_3 data set. R^2.

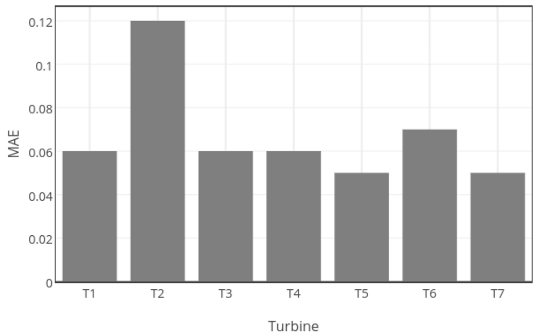

Fig. 12. Validation metric for P_3 data set. MAE.

3. CONCLUSION AND FURTHER DIRECTIONS

This work has been devoted to a very fertile field in wind energy technology: early diagnosis of gearbox faults. This work moves from a very stimulating debate in the scientific literature, about the use of SCADA data for condition monitoring of wind turbines. The direct source of information about the motion of the main shaft is vibration of the main shaft itself. The vibration high quality data are very demanding by the point of view of cost, technology and complexity of denoising and interpretation. SCADA data are therefore widely employed for condition monitoring, although they are not direct data sets. In some cases, as for example temperatures, the much coarser time grain of SCADA naturally "denoises" and fits well for describing the heating consequences of the motion of the main shaft. This work moves from [35], where a versatile and intuitive SCADA-based approach for fault diagnosis was proposed. The shortcoming of that method was that it required considerably vast data sets for statistical treatment: actually, a reasonable rule of thumb is employing the method of [35] on a monthly basis, but this can be too demanding for the purpose of early fault detection. And, further, using Artificial Intelligence techniques, one can aim at automating the detection of anomalies (as is suggested in the Results section above) and this is difficult to achieve using the method of [35]. The idea of this work, therefore, was exploiting machine learning for establishing a reasonable model of shaft temperatures. Subsequently, if the model works well, it can be used also on very short time scales and incoming faults should be highlighted as anomalous mismatches between simulation and reality. This has proven to be the case. The selected temperature signal was main bearing temperature, because it is responsive on the selected input variables: active power and external temperature. The validation has been conducted on the test case of a wind farm sited in Italy, featuring 7 turbines with 2MW of rated power each. It has been shown, on multiple time scales (down to the order of few days, which means in our peculiar case 534 measurements), that the proposed method highlights fault onsets in reasonable advance for 3 (T1, T2 and T6) out of the 7 turbines. A lesson coming from our validation case is that the simple model proposed is indeed very responsive. This inspires the idea that only external variables should be fed as inputs and it should be avoided to feed the model with the history of the output itself, because it would “dope” the model. Since this operation is very common in ANN-based anomaly detection and it is performed also in [31] and [39], one of the further directions could be comparing the performances of the model of this work against the models of [31] and [39]. Preliminary results about this point indeed support the plausibility of the above assertion about the effect of using the output at previous time steps as inputs.

Several are the possible further directions of the present work: as regards SCADA-based condition monitoring, it would be interesting to analyze pressures at relevant points of the wind turbine, as for example gear pump or inlets. By the point of view of temperatures, an interesting scientific development would be a “temperature to gear” approach. Moving from the spectral analysis of [11], it would be preciously insightful to try to connect unsteady load and fatigue conditions [40, 41] under complex flow to vibrations and to heating behavior.

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