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Detection of rotor imbalance, including root cause, severity and location

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Abstract. This paper presents a new way of detecting imbalances on wind turbine rotors, by using a harmonic analysis of the rotor response in the fixed frame. The method is capable of distinguishing among different root causes of the imbalance. In addition, the imbalance severity and location, i.e. the affected blade, can be identified. The automatic classification of the imbalance problem is obtained by using a neural network. The performance of the method is illustrated with the help of different fault scenarios, within a high-fidelity simulation environment.

1. Introduction

Rotor imbalance may be due to a number of causes, as for example pitch misalignment, blade damage, poor blade manufacturing tolerances, ice accretion, etc. Pitch misalignment, caused by one blade pitch angle being offset with respect to the others, may be caused by a wrong mounting of the blade on the hub, or could indicate a faulty pitch system. The incorrect alignment of blades is one of the primary wind turbine faults impacting negatively on performance and loads [1]. Ice accretion may cause significant changes in the airfoil shape, in turn causing both aerodynamic and mass imbalances, which again may affect loading and performance.

Irrespective of the cause, rotor imbalances significantly affect wind turbine fatigue, and may result, if protracted in time, in a reduced life. In addition, rotor imbalances may be indicators of faults. As Operation and Maintenance (O&M) costs account for a very significant portion of the Cost of Energy (CoE), methods that are capable of early detection of faults may be used for moving from a classical corrective maintenance approach to a predictive one [2].

Therefore, there is a need to detect rotor imbalances as early and accurately as possible. Ideally, it would be useful to know what is causing a rotor imbalance problem. For example, one would like to distinguish a rotor imbalance caused by a misalignment of the blade pitch from one caused by ice accretion.

In addition, knowing which is (are) the affected blade(s) may be an important piece of information. For example, in the case of pitch misalignment, if one knew only that the rotor is imbalanced, one would still have to devise some way to find out which one of the blades has been mounted incorrectly, maybe by a complicated visual inspection procedure. On the contrary, a technique that is capable of exactly pinpointing the affected blade might result in a significantly less expensive and more rapid corrective action. It would be even better if the technique were also able to say of how much the blade pitch is offset with respect to the others.



To address all these issues, this paper presents a new technique for identifying rotor imbalances, their root causes, severity and location. In particular, four different questions are considered here:

1. Is there a rotor imbalance?
2. Which is the affected blade?
3. What is the severity of the problem?
4. What is causing it?

The paper tries to address these needs by developing a novel method for rotor imbalance detection. The novelty of the approach is in the use of both the phase and the amplitude of measurements performed in the fixed system. In addition, neural networks are used for automating the process of detecting and classifying the problem.

2. Methods

It is well known that a balanced rotor transmits loads to the fixed frame only at the multiple harmonics of the number B of blades ($B \times \text{Rev}$, where “Rev” refers to the rotor frequency). Conversely, an unbalanced rotor transfers loads at all harmonics, the $1 \times \text{Rev}$ being typically the most energetic spurious frequency. Accordingly, a good indicator of rotor imbalances is the appearance of the $1 \times \text{Rev}$ harmonic. The amplitude of this harmonic is related to the severity of the imbalance. In addition, the phase of this harmonic is related to the location of the imbalance, i.e. the affected blade.

These facts are readily verified by considering a signal measured in the fixed reference system, as for example the nodding moment N at the hub. Computing N from the out-of-plane bending moments of the blades, one finds

$$N = \sum_{i=1}^B m_i \cos \psi_i, \quad (1)$$

where ψ_i and m_i are the azimuth angle and bending moment of the i th blade, respectively. For a balanced rotor operating in steady wind conditions, the blade moments are periodic with constant amplitudes and a shift of $1/B$ th of a revolution with respect to each other. Therefore, when summed up in the fixed frame of reference, these loads compensate each other and eventually cancel out. However, a constant bias in one of the blades caused, for example, by a pitch misalignment, will result in a nodding moment $1 \times \text{Rev}$ harmonic with the same phase of the misaligned blade. Similar conclusions hold for other measurements (e.g. accelerations) performed in the fixed frame of reference.

Clearly, when operating in turbulent wind conditions, the response of the wind turbine is not exactly periodic. However, when observed on long enough time windows, the effect of turbulent wind fluctuations tend to compensate and only negligible $1 \times \text{Rev}$ harmonics will appear for a well balanced rotor.

Rotor imbalance is invariably associated with the presence of a significant $1 \times \text{Rev}$ harmonic in the fixed frame response. In addition, the affected blade may be identified by using the phase of this harmonic. Moreover, distinguishing among different root causes of the imbalance may in general require additional information. For example, asymmetric ice accretion on blades will cause the appearance of the $1 \times \text{Rev}$ harmonic in the response, similarly to pitch misalignment, but it will typically create a more significant power loss because of the reduced efficiency of the blade airfoils. Therefore, by looking at both response harmonics and power one may try to distinguish pitch misalignment from ice accretion. Clearly, additional information, if available, may be used to increase the detection reliability.

The fusion of multiple sensor data in a simple and robust algorithm for fault detection is a non-trivial exercise. To ease this process, the present work uses neural networks because of their flexibility in modeling complex and possibly non-linear processes.

An artificial neural network is a set of interconnected simple computing elements called neurons. A standard neuron consists of a node that computes a single output by processing multiple inputs through a function, most often chosen as a sigmoid [3]. The weights associated with inputs and outputs define the free parameters of the network, which should be identified to obtain a desired behavior. From this point of view, a neural network is simply a parametric function composed of free parameters and assumed modes. The universal approximation property of neural networks ensures that the functional reconstruction error of any given function of sufficient regularity can be bounded as desired, for some appropriately large number of hidden neurons (cf. [4]). This property makes neural networks useful tools for developing black-box models of complex systems, as the case considered in the present work.

Among the many possible network architectures, here we consider a particular type known as multi-layer perceptron (MLP) [3]. As symbolically depicted in Fig. 1, a MLP is fed by a set of measurements (indicated in the figure by grey circles), which are multiplied by specific weights (blue arrows) and are in turn given as inputs to each neuron (green circles) in the hidden layers. The neuron outputs can be either given as input to a next hidden neuron layer, or considered as the final output, shown as yellow circles in the output layer. Finally, each output represents a class to which the set of input parameters belongs.

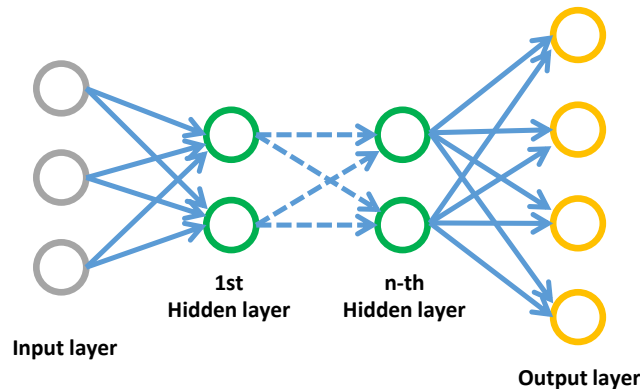


Figure 1. Generic multi-layer perceptron architecture.

At first, the network has to be trained. The training process consists simply in estimating the weights given a known set of measurements and of output classes. Fast and effective algorithms are available to solve such estimation problem, such as the back propagation algorithm used here [3]. Using a heuristic approach, the training process is repeated multiple times by increasing the number of neurons and possibly of hidden layers, until a satisfactory result in terms of classification performance has been obtained.

The total number of available data points are divided into three sets. The first (70%) is the training set, the second (15%) is the validation one, while the third (15%) is the test set. The first two sets are used iteratively for estimating the weights of the network. Finally, the test set, which has not been included in the training data set, is used for assessing the generality of the

trained network and quantifying its performance.

In this work, the network is trained by using load harmonics and other wind turbine response data (i.e. wind speed and torque) depending on the different scenarios of interest. Once trained, the network is fed with data coming from an operating wind turbine, and it automatically classifies the response in terms of the presence or not of rotor imbalance, its location, cause and severity.

Networks with different number of inputs and neurons will be used here for solving different problems of increasing complexity. In the next section, the simple problem of detecting a rotor imbalance will be analyzed first. Afterwards, the problem of detecting which blade is affected by pitch misalignment and with which severity is addressed. Finally, the ability of the proposed approach to distinguish pitch misalignment from iced conditions is demonstrated.

3. Results

The system generating the analysis data is a high-fidelity multibody aeroservoelastic model of a 3 MW wind turbine, developed with the code *Cp-Lambda* [5]. With such a tool, different pitch misalignment and/or different iced conditions can be simulated, yielding synthetic data that approximates what would be typically recorded on board a real wind turbine in the field. The virtual measurements are first post-processed in order to extract the required input variables for the network, and then fed to the training and validation process. It is important to stress that the entire procedure, from measurements to fault classification, will stay the same when using data gathered in the field.

3.1. Detecting rotor imbalances

The problem of detecting whether there is a pitch misalignment in one of the blades is considered next. A total number of 648 10-minute simulations were performed, considering 13 different pitch misalignment angles in each blade, between -2 to 2 deg. Each pitch misalignment was simulated under 18 different wind conditions for different mean wind speeds, turbulence intensity levels and turbulent realizations. Nodding moment measurements were first collected from the simulation and demodulated in order to compute the $1 \times \text{Rev}$ harmonic amplitude A_N . Finally, load harmonics were averaged over 10 minutes in order to remove the fast oscillations induced by turbulence.

The network has two output classes: balanced and unbalanced rotor. By a trial and error approach, it was found that a very simple network with a single output layer and three neurons is capable of distinguishing between the balanced and unbalanced cases. In particular, Fig. 2 shows on the left the architecture of the neural network and on the right the confusion matrix of the test data set.

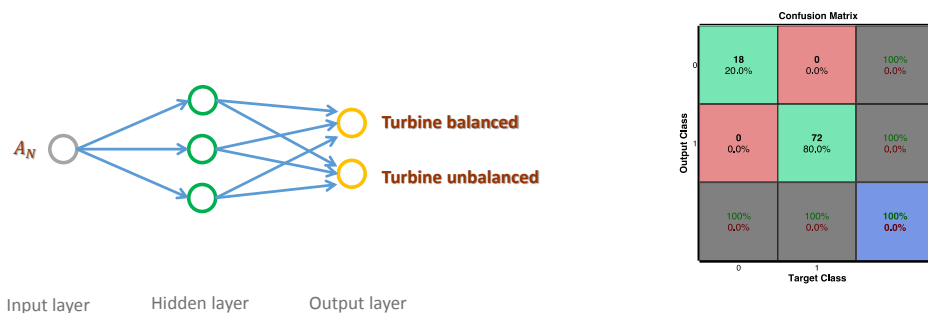


Figure 2. Classification results for imbalance detection at a wind speed of 7 m/s.

In the confusion matrix, rows refer to predictions, while columns to the true state of the system. The generic cell (m, n) indicates the number of instances and percentage in which the n th output is classified as a state m . Accordingly, diagonal cells show where true and predicted classes match, whereas off-diagonal cells indicate erroneous classifications. For example, an element in cell $(1, 2)$ refers to a case belonging to the second class (unbalanced turbine) identified erroneously as belonging to the first (balanced turbine). Hence, it can be viewed as a false positive indication. Viceversa, an element in cell $(2,1)$ refers to a false negative, for the wind turbine is classified as unbalanced and a false alarm is generated. The rightmost column and bottom row show, respectively, the accuracy of each predicted class, and each true class. Finally, the very last cell indicates the global accuracy of the method, reporting the percentage of correct classifications (upper green number) and percentage of errors (lower red number).

Since there is no false indication in the present case, a perfect classification is obtained for this problem.

3.2. Identifying the misaligned blade

As stated earlier, while the amplitude of the $1 \times \text{Rev}$ fixed frame signal is associated to the presence of a pitch misalignment, the related phase can indicate which blade is affected. Hence, it is expected that feeding the neural network with the $1 \times \text{Rev}$ sine N_s and cosine N_c components of the signal could identify the location of the pitch misalignment. To this end, 10-minute averaged components N_s and N_c were given as inputs to a simple classifier with four possible outputs: pitch misalignment in the first, second or third blade, and no misalignment.

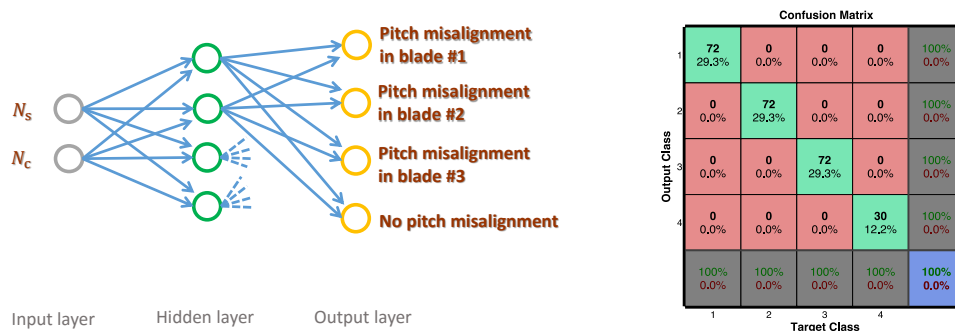


Figure 3. Classification results for pitch misalignment location detection at a wind speed of 7 m/s.

Figure 3 shows on the left the architecture of the neural network, with the input layer consisting of the two measurements N_s and N_c , the hidden layer consisting of four neurons and the output layer with the four output classes. On the right, the confusion matrix shows that the method is capable in all cases of exactly distinguishing a faulty from a non-faulty condition. In addition, in the faulty case the method is always able to detect the affected blade.

3.3. Estimating the severity of pitch misalignment

Maintaining the same input parameters used earlier, it is possible to further refine the classification with the intention of quantifying the fault. Indeed, an exact estimation of the pitch misalignment angle is not necessary, while it can be useful to know an approximate range in order to assess the urgency of repair. For that reason, 13 output categories were defined according to different pitch angle intervals of 0.5 deg amplitude.

The left part of Fig. 4 depicts the network employed for this problem, characterized by 13 output categories and only two neurons. In this case, data coming from different wind speeds

were used to train the network. Since wind speed affects load amplitudes to a significant extent, the wind speed itself was given as input to the network to ease detection. The confusion matrix, on the right part of the same figure, shows again that the algorithm assigned all analyzed conditions to the correct category.

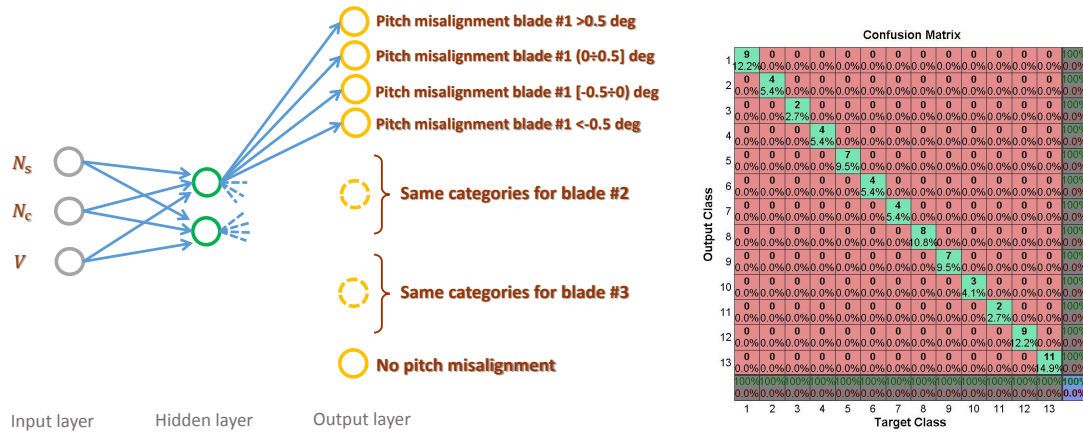


Figure 4. Classification network for pitch misalignment severity estimation.

3.4. Detection of root causes

As already mentioned, asymmetric ice accretion is a common source of rotor imbalances. However, ice accretion differs from pitch misalignment for it will typically generate a more pronounced performance loss than a pure pitch misalignment case. Accordingly, torque (or power) is considered as an additional input to the classification element. In the partial load region II, the machine operates at a constant aerodynamic torque (or power) coefficient C_T (C_P). Therefore, a suitable input to the network is the difference between the actual C_T (C_P) and a reference one, $C_{T_{ref}}$ ($C_{P_{ref}}$). A similar approach can be followed in the full power region III, using this time torque T (or power P) instead of the non-dimensional coefficient, as these quantities remain constant as wind speed changes.

The network architecture employed here, not shown for the sake of brevity, is similar to the one displayed in Fig. 4, with the addition of a new input, i.e. $C_T - C_{T_{ref}}$ in region II and $T - T_{ref}$ in region III, and of a new output class representing the ice accretion case. The aerodynamic torque is obtained from the torque balance equation (cf. Ref. [7]), in order to consider the rotor dynamic response.

A total number of 189 symmetric and asymmetric iced conditions, for different wind speeds and turbulence intensity levels, were considered. The simulations included 21 different combinations of three types of ice accretion, from very light to moderate. The mass distribution and the aerodynamic lift, drag and moment coefficients of the blades were changed according to the specific ice accretion, using data taken from Ref. [6].

The confusion plot of the obtained results, not shown here, demonstrates again the ability of the algorithm to distinguish between pitch misalignment and iced conditions. Moreover, for the pitch misalignment cases, the algorithm is able to detect the location and the severity of the problem as well.

In addition, in order to clarify whether the additional input parameter represented by torque is necessary or not for an effective classification, the very same problem was solved eliminating the torque entry from the neural network. Training was repeated, resulting in a more complicated

architecture. Despite the additional complexity of the network, the algorithm was not able to correctly classify the different scenarios, demonstrating that it is indeed necessary to include the aerodynamic performance of the rotor to discriminate the various cases.

4. Conclusions and outlook

A novel method was developed to automatically detect imbalances on a wind turbine rotor. The method uses a harmonic analysis in the fixed frame to detect if imbalance is present, to what extent and in which blade. Additional rotor response data may be used to classify the root cause of the imbalance. Differently from other approaches, information on blade airfoil aerodynamic performance, which is typically difficult to obtain, is not necessary for the proposed method.

With the help of a high-fidelity aeroservoelastic simulation model, the method has been tested in a wide range of scenarios, of which only a limited subset was shown here. In general, it was found that the use of a properly designed and trained neural network can greatly ease the problem of imbalance detection and classification.

In a continuation of this research, the method should be validated by trying to detect imbalances in the field for wind turbines on which known pitch misalignments have been set. Additional, we are considering the use of the proposed method to detect possible mass imbalances, as discussed in Ref. [8].

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