Long term operational modal analysis for rotating machines

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Abstract. Wind energy is one of the most promising renewable energy available today. The continuous demand of wind energy production led the interest of the wind industry towards bigger turbines. This upscaling trend has imposed bigger (not quasi-static) loads that are significantly influencing the fatigue life of the wind turbine components and the tonalities generated by the drive train. To tackle noise and vibration problems and validate complex models it is of high interest to continuously track the modal parameters of the machines under different operating conditions. This allows a better design of the new prototypes and the reduction of the risk of premature component failures, followed by a possible decrease of the cost of the energy. To do so Operational Modal Analysis represents a powerful tool. One limitation affecting this methodology when applied to rotating machines comes from the presence of harmonics. Their predominance in the spectrum masks the modal content in the signal, making the extraction of the modal parameters impossible. The objective of this research is then to achieve a combination of automatic methodologies for dealing with the harmonics and automatic OMA techniques in order to be able to autonomously process a continuous stream of data.

1. Introduction

The continuous demand of wind energy production led the interest of the wind industry towards bigger turbines. The up-scaling phenomenon in the wind turbine industry is related to the effort of reducing the cost of the energy by increasing the height of the turbines and by developing higher capacity models [1]. In line with this idea, offshore farms started to be installed: in the sea the wind is generally more stable and stronger and there are less limitations on the size and on the produced noise due to the lack of interaction with the human habitations. The increase of the size of the wind turbines and their installation offshore, cause an increase of the loads acting on the different components, amongst the others on the drivetrain, making the operating conditions of the machines even harder. The main problem is that the loads acting on the different components of the machines strongly depend on the conditions at which the machines operate and they are difficult to be predicted and simulated. This led to a significant problem: a not complete understanding of the dynamics of the components. For this reason, the design of the machines based on the simulated models only cannot be considered enough and additional experimental tests must be implemented to have a better insight of the loads acting on the machines and improve the design of the components. The industrial design process currently comprises component-level-testing and full-scale machine testing both in laboratory environments and in the field. These validation procedures are affected by a limitation: these
tests are generally performed over short periods trying to catch specific operating conditions to be tested. What is missing is a continuous insight into the modal behavior of the machines during their overall lifetime and under each operating condition [3]. The lack of information concerning the behavior of the machines under every possible operating condition has significant consequences on the reliability of the machine and its operating and maintenance. This can cause not efficiently optimized machines and premature components failures. Therefore, a new additional approach must be implemented. With the advent of the era of the industrial internet of things, the wind industry could move towards a new kind of designing process where the decisions on how to improve the subsequent design variants are taken based on what can be learnt from the information acquired on the fleet of machines that are already operating in the field. In this way, it could be possible to catch every possible operating condition. The goal is then to have a turbine park in which a considerable number of turbines are equipped with sensors that allow to have information on the current status of the machine and on the different parameters of interest (vibrations, temperature, pressure, wind speed, pitch and yaw angles...). This requires the building of a scalable database capable of acquire the information, store them and make them available for automated analytic program. Once the database is available and the data are stored on a server, there is the need of tools able to process automatically and continuously the data. What is currently missing to enable this innovative design method is the availability of methodologies that are able to autonomously process the data and send the needed information to the cloud. For this reason, very advanced vibration analysis need to be performed on each machine combining signal processing techniques and machine learning algorithms.

For processing the vibration data, Operational Modal Analysis (OMA) represents a powerful approach; it allows to extract modal parameters from the dynamic response of the structure to unmeasured operational forces providing the experimental values of operational natural frequencies and operational aerodynamic damping. However, in case of wind turbines, the application of OMA is not straightforward, due to the violation of important assumptions that are at the basis of this analysis.

First of all OMA assumes time invariance of the system. Due to the fact that a wind turbine consists in subsystems moving with respect each others, this assumption is violated. A solution to deal with this problem is to separately process group of data in which the machine is running at constant operating conditions and where the subsystems are as stable as possible. This is feasible thanks to the availability of SCADA (Supervisory Control and Data Acquisition) data. Coupling SCADA with vibration data is the key to overcome this problem and to observe how the turbine behaves at different operating point and different subsystems configurations.

Another problem in the application of OMA on wind turbines, is the violation of the assumption concerning the nature of excitation forces. To fulfill the requirements of OMA, the excitation has to be randomly distributed both temporally and spatially. The excitation from wind turbulence is for its nature ideal for this application. However the effects of the rotor rotation dramatically change the characteristics of the aerodynamic force [18]. A deep analysis of the nature of the aeroelastic forces in a wind turbine and its effect on the applicability of OMA is given in [18] together with a possible solution for dealing with this phenomenon.

If the drivetrain is considered as scope of the analysis, an additional limit in the applicability of OMA is given by the presence of deterministic forces in the excitation signal, due to the presence of self induced vibration originated by the rotating and reciprocating parts (e.g. gear meshing phenomenon). This work addresses this phenomenon. The presence of harmonics in the spectrum masks the modal content of the signal, and their predominance in the frequency band of interest makes the extraction of the modal parameters impossible. To show this problem, an example from a real case is shown. The expected gear meshing frequencies can be calculated by means of equation 1 and their influence in the spectrum is shown in figure 1.
Frequency [Hz] = Gear Ratio [-] × Shaft Speed [Hz] \hspace{1cm} (1)

Figure 1: Observation of the influence of the gear meshing harmonics in the frequency band of interest (limited to 4 components for each harmonic family).

2. State of the art
In literature there are several examples of extended OMA techniques tailored to deal with harmonics disturbances. These methods either assume that the frequency of the harmonic disturbances is known or identify the harmonics frequency from the data via noise poles on the unitary circles \[3\]. These methods are based on the assumption that the harmonic frequencies are stationary (i.e. they are constant in amplitude, frequency and phase). However this assumption is violated in most of the practical application such as turbines, diesel motors and helicopters. Indeed in these machines the speed can not be assumed constant and therefore the harmonics are smeared in the spectrum of the signals and they influence broader frequency bands. As a consequence the harmonic components in the signal can not be modeled accurately with the methods used in case of stationary harmonics and the extended OMA techniques fail whenever the time varying frequency is close to a resonance frequency of the structure \[3\]. Therefore the research is still going on to find reliable methods to adapt OMA algorithms for applications in which frequency-varying harmonic components are in the signal. One possibility is to use classical OMA algorithms after having filtered the harmonic components from the raw data during a pre-processing step. A list of basic signal processing techniques for removing harmonics from the vibration signals is given in \[4\]. Another possibility is to use the so called order based modal analysis (OBMA), a combination of advanced order tracking techniques and operational modal analysis algorithms that foresees the parameter estimation on tracked orders rather than on the overall spectrum \[5\]. This technique is based on the idea that during run-up or cast-down of the machine, the measured responses are mainly caused by rotational excitations, so it is possible to consider these conditions as multi-sine sweep excitation in the frequency band of interest. Since the goal of this work is to analyze the system in normal operating conditions and not during a run-up or cast-down, filtering the harmonics out of the vibration signal is the most appropriate procedure. For this purpose cepstrum-based time-domain signal editing procedure is adopted to reduce the influence of the harmonics from the raw data.

Cepstrum analysis is a procedure that through the double application of the Fourier algorithm brings the signal from the time domain in the quefrency domain, as shown in equation 2.

\[ C_c(\tau) = \mathcal{F}^{-1}\log(\mathcal{F}(X(t))) = \mathcal{F}^{-1}\ln(A(f)) + j\phi(f) \]  \hspace{1cm} (2)
where $X(t)$ is the original signal in the time domain, $A(f)$ and $\phi(f)$ are respectively the amplitude and the phase of the frequency domain signal. By setting the phase to zero in the equation 2, the formulation of the real cepstrum can be obtained (3):

$$C_r(\tau) = \mathcal{F}^{-1}\ln(A(f)) \quad (3)$$

Ensuring the possibility of going back to the time domain. After that it has been realized that there are many situations in which the editing can be carried out by modifying the amplitude only, the cepstrum started to be considered a powerful signal editing tool: in the quefrency domain, families of harmonics are concentrated in single lines (rhmonics), setting to zero a line in the quefrency domain automatically smooth the corresponding family of harmonics in the time domain.

The success of the use of cepstrum for OMA applications finds its reason in the fact that the information about the modes are concentrated at low quefrency values [6]. The application of a low-pass lifter (an exponential window) on the real cepstrum greatly enhances the modal information with respect to anything else: it allows to remove all the components at higher quefrencies keeping the modal information of the signal. The only distortion introduced at lower quefrency (thus on the interesting part of the signal) is the addition of a known amount of damping, that can be easily removed from the damping value estimated by an OMA procedure by means of the following equation:

$$\xi_r = \xi_m - \frac{1}{2\pi f_r \tau} \quad (4)$$

where, for each estimated mode, $\xi_r$ is the real damping [%], $\xi_m$ is the measured damping [%], $f_r$ is the real frequency [Hz] and $\tau$ is the time constant of the exponential window [s].

Since it has been shown that the cepstrum lifter works better for narrow harmonics [6], before editing the acceleration signals, speed correction has been performed: a virtual resampling of the signal allows the samples to correspond to fixed angular positions rather than being temporally equi-spaced. In this way it is possible to compensate for speed fluctuations narrowing the frequency bands excited by the harmonics. However, resampling the signal, one alters the resonance phenomena, that are not tied to the speed of the shaft [7]. For this reason, after having used the cepstrum lifter to reduce the influence of the harmonics on the raw signal, the latter is brought back to the time domain (i.e. samples every $\Delta t$ seconds).

3. Methodology

In order to be able to process a continuous stream of data coming from a rotating machines, the use of the time-domain cepstrum editing procedure must be combined with an automatic modal parameter estimator and an automatic tracking algorithm. Attention is given to the automation of the procedure and of the algorithms.

3.1. Automatic cepstrum editing procedure

The state-of-the-art cepstrum editing procedure algorithm is implemented and coupled with a procedure that automatically selects a value for the required parameter: the cutoff-quefrency, i.e. the time constant of the exponential window to be applied in the quefrency domain. The key idea is to exploit the knowledge of the frequency bands at which the harmonics are introduced in the signal: the method implemented is based on the reduction of the energy introduced by the harmonics consequent to the use of the cepstrum lifter. The method applies iteratively a cepstrum lifter on the given signal with decreasing values of the cutoff-quefrency.

An example representative of the different iterations is shown in figure 2a. The comparison between the original signal and the one obtained after the automatic procedure is shown in
figure 2b. From the two graphs, it can be seen how the use of the cepstrum lifter smears the energy of the peaks in the frequency band around them, producing a spectrum with a better energy distribution.

3.2. Automatic modal parameter estimation
The automation of the modal parameter estimator can be divided in two steps: the estimation of the modal parameters for each subset and the observation of the evolution of the estimates along different data sets (i.e. over longer periods and different operating conditions). Concerning the modal parameter estimation, the Poly-reference Least-Square Complex Frequency-Domain (p-LSCF) estimator [8] is used. The choice of this method amongst all the possible OMA algorithms [9] is linked to the fact that it estimates the poles with negative damping ratio as non-physical poles and it excludes them from the stabilization diagram [10], generating a clear stabilization diagram. However, the method still requires the manual selection of the physical poles. The extensive algorithm-analyst interaction required by the p-LSCF estimator (and by the OMA algorithms in general) is inappropriate if automatic modal parameters tracking wants to be performed on a continuous stream of data. A valid solution to solve the problem of the distinction between physical and spurious poles, is the use of heuristic rules, fuzzy logics and clustering analysis to group the modes with similar characteristics ([11, 12, 13, 14]). In this work, the method described in [16] is adopted, since it results to be systematic and it doesn’t require the manual definition of any parameter.

Concerning the tracking procedure, the modal parameters estimated for each data set are tracked, following the concept investigated in [15]. The comparison amongst the estimates of each dataset is performed using MAC and poles values, in order to measure in which extend the the estimates are coherent in terms of mode shapes (represented by the MAC value) and frequency/damping values (represented by the poles values). In this work, a completely automatic procedure that does not require the definition of the reference dataset is implemented.

4. Results
In this work, we implemented a complete procedure to automatically track the evolution of the modal parameters. Starting from raw data, the available datasets are classified in function of the operating conditions and according to that, they are pre-processed to generate a suitable input for the modal parameter estimation. Once the modal parameters have been estimated for each dataset, the results have been post-processed in order to track the evolution of the modes along the analyzed period.
In [17], the procedure has been applied on a limited number of datasets (10 datasets acquired with the turbine in stand still condition and 7 acquired while the turbine was producing energy). The choice of analyzing a few number of datasets was linked to the possibility of having full control of the procedure implemented. The main conclusion obtained in [17] is the importance of editing the signal with the cepstrum lifter in order to reduce the influence of the harmonics masking the modal content of the signal. The second important consideration that can be inferred from the results in [17] is the presence of significant error bands when the confidence bounds are calculated for the tracked modes.

This result can be linked to the length of the observation window used to process the data. In [17], 10 minutes long datasets have been processed. Since the scope of the analysis (i.e. an offshore wind turbine drive train) is a complex dynamic system, it is possible that considering such a long observation window averages the dynamic behavior without allowing a correct observation of the variation of the system. For this reason, in this work 1 minutes long observation windows have been adopted, in order to investigate whether this parameter influences the results. 260 datasets acquired with the turbine in stand still condition or running in normal operating condition have been considered. In both the cases, the acquisition period is the same as the one used in [17], in order to have a direct comparison of the results.

Following the results of the tracking procedure are shown for both the data acquired with the turbine in stand still conditions (3) and running in normal operating conditions (4). In figure 3a and 4a, the rotor speed is also shown, this value has been extracted from the signal coming from the tachometer installed on the low speed shaft. The visualization of the speed together with the evolution of the modal parameters, is important to understand how the turbine behavior is influenced by the operating conditions of the turbine.

![Figure 3](image)

(a) Evolution of the modes along different datasets.
(b) Average value and confidence bounds of the estimated modes.

Figure 3: Use of the automatic tracking for datasets acquired with the turbine in stand still conditions. (Normalized axes for confidentiality reasons).
Evolution of the modes along different datasets.

Average value and confidence bounds of the estimated modes.

Figure 4: Use of the automatic tracking for datasets acquired with the turbine in normal operating conditions.
(Normalized axes for confidentiality reasons).

In figure 3a it is possible to notice a lack of modes estimation for a significant amount of datasets (from 69 to 85). Looking at the speed profile, it is possible to notice that in correspondence of these datasets the turbine is in idling conditions, with a rotational speed that is approaching zero. This lack of modes detection can be due to the fact that there is not enough energy in the system to excite the modes. What is interesting to observe in figure 4a is a correlation between the peaks in the speed and the value of the damping of few modes. This results shows that a slight change in the operating conditions of the turbine has a significant impact in the damping of the system, confirming the strong dependence of the modal damping on the operating conditions, as already stated in [14].

In figures 3b and 4b the results of the tracking procedure have been processed in order to obtain punctual values and confidence bounds of the estimates. The uncertainty levels linked to each of the modal estimates is an important parameter to assess in order to increase the confidence a designer can have in the results obtained from the use of autonomous OMA. A comparison between the results obtained and the ones in [17], shows a significant reduction of the error bands of the tracked modes and the increase of the number of estimates. This is a demonstration that using shorter observation windows allows to better appreciate the modal content of the system and how the modes are excited in different operating conditions.

Figure 5: Comparison of the results of the tracking in different types of datasets. (Normalized axes for confidentiality reasons).
In figure 5 the results obtained from the two tracking processes (on stand still data and normal operating data) are compared. The comparison shows coherent results between the two cases, showing that the use of the cepstrum lifter does not affect the modal content of the system. A difference that can be notice is the estimation of three modes in stand still conditions only (0.135, 0.495 and 0.95 normalized frequencies). The 0.135 and 0.95 normalized frequency values are at the lower and upper extremes of the frequency bands of interest, showing that in the stand still case the energy is spread in a more uniform way. The 0.495 normalized frequency values is in correspondence of a known harmonics coming from a source that is outside from the analyzed component. Since in the case of stand still data no cepstrum lifter is adopted, the presence of the harmonics is justified.

5. Conclusions
During this research the focus has been on the implementation of an algorithm that autonomously tracks the evolution of the modal parameters analyzing a continuous stream of data coming from a machine in real operating conditions. The main challenge posed by this analysis is the presence of harmonics masking the modal content of the signals.

Since no reference modal parameters were available for the investigated machine, the procedure has been validated considering results obtained from a stream of data acquired while the turbine was in stand still conditions (i.e.: while it was not producing energy). In this condition the main issue affecting the use of OMA on rotating machines (the problem of harmonics) can be considered negligible, since it affects a limited portion of the frequency band of interest. Future research associated to this work is the collaboration with manufacturers, in order to compare the experimental results obtained with OMA with the results obtained from simulated aeroelastic and stability analyses. The latter could represent a solid basis for evaluating the accuracy and robustness of the proposed methods.

By means of a comparison with previous work the influence of an important parameter of the analysis (i.e. the length of the observation window) has been investigated, showing an increase in the accuracy of the estimates. However in this work, still an arbitrary value has been selected. For this reason future researches will focus on the definition of an optimum value of this parameter.

Another issue that has been confirmed by this work, is the dependence of the modal parameters on the operating conditions, a topic already highlighted by other authors. For this purpose, this work poses a fundamental basis to move a step forward in the generation of an approach valuable from an academic and industrial point of view. What is interesting is to use this algorithm in parallel with an algorithm able to track the operating and environmental conditions (available from the SCADA data) and analyze how the latter influence the modal behavior of a machine.

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