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GAINING INSIGHT IN WIND TURBINE DRIVETRAIN DYNAMICS BY MEANS OF AUTOMATIC OPERATIONAL MODAL ANALYSIS COMBINED WITH MACHINE LEARNING ALGORITHMS

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ABSTRACT

Detailed knowledge about the modal model is essential to enhance the NVH behavior of (rotating) machines. To have more realistic insight in the modal behavior of the machines, observation of modal parameters must be extended to a significant amount of time, in which all the significant operating conditions of the turbine can be investigated, together with the transition events from one operating condition to another. To allow the processing of a large amount of data, automated OMA techniques are used: once frequency and damping values can be characterized for the important resonances, it becomes possible to gain insights in their changes. This paper will focus on processing experimental data of an offshore wind turbine gearbox and investigate the changes in resonance frequency and damping over time.

NOMENCLATURE

NVH Noise, Vibration and Harshness
OMA Operational Modal Analysis
SCADA Supervisory Control and Data Acquisition

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INTRODUCTION

The susceptibility of rotating machineries to structural vibrations generating tonalities is a main design issue in this field. Modal parameters (i.e. eigenfrequencies, damping ratios, mode shapes and modal scaling factors) are thus a core design driver in the development of new rotating machines. The wind turbine application is a prime example. New turbines are only allowed on the market if stringent noise emission levels are met. The experimental verification of modal parameters forms as such an essential part of this process, especially for allowing model validation. Adequate dynamic design guarantees the safety and reliability of the wind turbine structure [1]. A prime parameters for tonality design is damping. The boundary conditions realized by the elastomer bushings supporting the gearbox influence the damping values and are amplitude dependent. The modal parameters can change depending on the (rotating) speed of the structure or the parts. As such, it is important to experimentally verify the modal design values during all operating conditions the machine will run at, i.e. around the different operating points.

Operational Modal Analysis (OMA) targets the characterization of structures when exposed to environmental excitations. The environmental loading is used as excitation source, rather than applying known excitation forces. As such OMA is a powerful approach: it allows to extract the modal parameters from the dynamic response of the structure while it is operational and exposed to its normal operational forces. The latter are not measured and assumed to have a white noise character. This method is however based on several assumptions that are typically not fulfilled for rotating machines. One of the key issues that make traditional OMA approaches unsuitable for rotating machines is the presence of strong harmonics masking the modal content. Given that inputs forces are unmeasured and not of white noise nature, the results of the parameters estimation become sensitive to the excitation acting on the structure. Harmonics can be misinterpreted to be resonances with very low damping. Indeed, the non-white noise input signal will result in an output of the parameter estimation that is a combination of structural modes and harmonic components already present into the input signal [2, 3]. This strong influence of the harmonics is particularly important for the wind energy domain. Wind turbines operate in a continuously variable environment that result in highly dependent on the operating conditions at the site. These variable conditions induce important mechanical stresses in the different drivetrain subcomponents. In addition, the current trend towards increased torque density of the drivelines linked to the increase of turbine size to produce more energy has caused a significant increase in the drivetrain loads. These are amongst others playing a role in premature component failures, since not all aspects of the dynamics of the machine are fully understood [4]. For better understanding these dynamics the extraction of the modal parameters while the turbine is in operation becomes more and more important. The current design process in industry comprises testing at component-level and full-scale machine testing. Both of these tests are performed in the laboratory and in the field. In general, the duration of these tests is short. The test tries to catch only the specific operating conditions targeted. What is however not present in the current testing approach is continuous data acquisition and processing in order to gain insights in the behav- ior of the machines during their overall lifetime. This requires insights in their behavior for all important operating conditions [5]. This lack of detailed insights on the importance of certain operating conditions on the behavior of the machines makes the solution of the tonality challenges cumbersome and thus results in a not efficiently optimized machine. By moving towards continuous modal analysis, the industry could target a new kind of design process centered around field data. The decisions on how to improve simulation models and turbine designs could then be taken based on what can be learnt from the information acquired in the field. Rather than looking at a single machine, several machines that are already operating in the field could be used to gain insights in the dynamic response during all important operating conditions. The main requirement to achieve this objective is an automated modal analysis algorithm capable of continuously and autonomously processing the streams of data.

The research discussed in this paper targets this continuous identification of the modal parameters of wind turbine drivetrains. These are one of the main important drivers in tonality issues and critical for the dynamic behavior of the overall machine.

THEORETICAL BACKGROUND

Operational Modal Analysis

OMA techniques allow to obtain the modal model of systems without requiring knowledge about the forces (e.g. wind, traffic) exciting it. As no artificial excitation sources need to present, this methodology has as big advantage that it has the potential to continuously characterize the dynamic behavior of structures. Moreover, it allows to perform the modal testing in the real operating and boundary conditions of the structure. OMA algorithms are based on several assumptions, among other that the excitation force has a white noise spectrum. In general, this assumption does however not hold true. Different OMA algorithms have been developed in literature. In this work, a polyreference Least-Square Complex Frequency-Domain (pLSCF) estimator was used. The full theoretical background behind this algorithm can be found in [6]. It is a frequency domain estimator that requires the output spectra of the system as primary data. If it is assumed that the input forces are white noise, it is possible to model these spectra in a similar way as Frequency Response Functions (FRFs) $H(\omega)$ are modeled in Experimental Modal Analysis (EMA). This will be demonstrated in the discussion which follows. For EMA, the FRFs can be written as follows:

$$H(\omega) = \sum_{i=1}^{n} \frac{\{v_i\}\left\langle l_i^T \right\rangle}{j\omega - \lambda_i} + \frac{\{v_i^*\}\left\langle l_i^H \right\rangle}{j\omega - \lambda_i^*} \tag{1}$$

In this equation, n is the number of estimated complex pole pairs (i.e. the model order), v_i is the mode shape vector for mode i, l_i are the modal participation factors and λ_i are the poles of the system. Furthermore, * is denoted for the complex conjugate, ^{H} for the Hermitian transpose of a matrix and ^{T} for the transpose of a matrix. The resonance frequencies (ω_i) and the damping ratios (ξ_i) of the structure can then readily be obtained from the estimated poles:

$$\lambda_i, \lambda_i^* = \xi_i \omega_i \pm j\sqrt{1-\xi_i^2}\,\omega_i \tag{2}$$

To make the transition towards an OMA framework, it is needed to investigate the relation between the input spectra $[S_{uu}(\omega)]$ and the output spectra $[S_{yy}(\omega)]$ for a system with transfer function $H(\omega)$:

$$[S_{YY}] = [H(\omega)][S_{UU}(\omega)][H(\omega)]^H \tag{3}$$

In case of OMA, the input spectra are thefore modeled as a white noise excitation, meaning that $[S_{uu}(\omega)] = [S_{uu}]$. By combining Equations 1 and 3, the following modal decomposition is obtained:

$$S_{YY}(\omega) = \sum_{i=1}^{n} \frac{\{v_i\}\langle g_i\rangle}{j\omega - \lambda_i} + \frac{\{v_i^*\}\langle g_i^*\rangle}{j\omega - \lambda_i^*} + \frac{\{g_i\}\langle v_i\rangle}{-j\omega - \lambda_i} + \frac{\{g_i^*\}\langle v_i^*\rangle}{j\omega - \lambda_i^*} \tag{4}$$

In this Equation, g_i are the operational reference factors. These are the equivalent of modal participation factors in case of OMA. The pLSCF estimator then uses a right matrix formulation as parametric model:

$$[H(\omega)] = [B(\omega)][A(\omega)]^{-1} \tag{5}$$

From Equation 4, it can be seen that the number of estimated pole pairs n needs to be imposed. As this is not known beforehand, it is common practice to use an iterative procedure, where the model order is increased with each iteration. A combination of mathematical and physical poles will then be obtained from a certain point on, as the modal order will be over-specified. A stabilisation diagram that shows the stability of the extracted modal parameters as a function of the model order is then classically used afterwards to help the analyst to distinguish between physical and spurious modes [7].

Cepstrum editing procedure

As already shown, OMA formulations are based on the assumption that the excitation forces have a white noise spectrum in the frequency band of interest. This hypothesis implies that the excitation is stochastic, both in time and space. This assumption will however be violated in several applications, for example when processing vibration data of rotating machines. In this case, the rotating components introduce deterministic harmonic content in the spectra. This paper will focus on how to deal with this content. In literature, several techniques are available [8–10]. The majority of these methods however assume that the harmonics are stationary (i.e. constant in frequency and amplitude). This limits their applicability in the field of rotating machinery, as in this case the harmonics are non-stationar due to speed and load fluctuations. The former moreover results into the fact that the harmonics are smeared in broad frequency bands.

In this work, a methodology based on cepstrum editing is adopted [10]. In this case, the vibration data is pre-processed by filtering the deterministic harmonic contents from the measured data, significantly reducing their influence. Cepstrum editing consists of first transforming the time domain signal into the quefrency domain by means of a double Fourier transform:

$$C_c(\tau) = \mathscr{F}^{-1} log(\mathscr{F}(X(t))) = \mathscr{F}^{-1} ln(A(f)) + j\phi(f) \tag{6}$$

In this Equation, X(t) is the time domain signal, A(f) and $\phi(f)$ are respectively the amplitude and the phase of the signal in the frequency domain. A common practice is to do the filtering procedure by only editing the amplitude. To this end, the phase is set to zero and the following formulation is obtained:

$$C_r(\tau) = \mathscr{F}^{-1} ln(A(f)) \tag{7}$$

This ensures that is possible to go back to the time domain. The strength of the cepstrum for signal editing is based on the observation that the relevant modal content is based at low quefrencies, whereas the harmonic content is concentrated at higher quefrency values. Moreover, it was observed that setting the amplitude of a family of rhamonics to zero, automatically smooths the corresponding family of harmonics in the time domain. These observations justify applying a short-pass lifter in the quefrency domain, as this allows to obtain a time domain signal in which the influence of the harmonics is greatly reduced.

It has however been shown that the cepstral lifter works best for discrete peaks in the quefrency domain. For rotating systems, these peaks will however smear due to speed fluctuations. To this end, the cepstral editing procedure does not directly take place on the measured vibration signals. The raw data is rather first resampled in the angular domain [11], allowing to obtain discrete peaks of rhamonics in the cepstrum of the resampled time signal. A short-pass lifter is then used. This resampling procedure however alters the resonance phenomena of the structure, meaning that it is essential to bring the data back from the angular domain to the time domain before performing the modal parameter estimation.

In this work, there is opted to not do the angular resampling in case of standstill data, as in this case the harmonics are much more narrow by nature. In the discussion that follows, the different implement methodologies will now be validated by processing vibration data of an offshore wind turbine.

METHODOLOGY

Automation of the procedure

To achieve a methodology allowing to perform OMA on continuous time series the two previously discussed methods are combined. The automation of the modal parameter estimator can be divided in two sub-steps. As a first step, the p-LSCF algorithm is automated. This allows to eliminate the necessity for manual interaction by the analyst. A clustering method is used to autonomously interpret the stabilization diagram resulting from the modal estimation procedure. The automated approach groups poles that show stable characteristics to allow the extraction of physical poles based on the statistical properties of each cluster. In a second step the modal model estimation algorithm is combined with an automatic tracking algorithm. This tracking step allows to unveil the evolution of the modal parameters within multiple datasets over a long period of time [12]. To allow tracking the modes of each dataset need to be compared. This is done by means of the MAC and poles values to indicate to which extent the estimates show coherence with regard to mode shape (represented by the MAC value) and resonance frequency and damping values. This paper uses a fully automatic procedure that does not require the definition of the reference dataset. The cut-off quefrency of the cepstrum editing procedure is selected using an automatic selection algorithm. This cutoff-quefrency is a crucial parameter for the cepstrum analysis, since it determines the time constant of the exponential window applied to the signal in the quefrency domain. To choose this quefrency the locations and strength of the harmonics present in the signal are used. The selection is based on achieving a maximum reduction of the energy present in the harmonics. Modal analysis can use different input signal types. Where order-based modal analysis needs run-up data, the OMA methods prefer steady state measurements. Thus, an automated method is necessary to distinguish between on the one hand steady state operating conditions (turbine in idling conditions or when it is running at stable speed) and on the other hand run-up/coast-down events. The introduction of an algorithm able to automatically detect these events in the signal allows to complete the block scheme represented in the diagram in Figure 1. To guarantee that only qualitative data is used an additional step is done: data validation. Such validation is necessary as it allows to assess the quality of the input signals and allows to avoid corrupted results from processing bad-quality signals, such as for example caused by the detachment of the sensor from the measured structure.

Extensive prior research showed the validity of our automatic modal parameter estimation [13]. This paper focusses on the missing step to make this analysis run continuously on long-term data is the introduction of this automated event classification algorithm before processing the data. The methodology investigated in this work makes use of a machine learning approach that is based on the fact that turbine run-up and coast-down events are controlled events. It is thus expected that a similar pattern in speed and power can be seen across several of these events. Based on this observation, machine learning algorithms can be used in the following way: standard run-up and coast-down events are learned such that sub- sequent similar repetitions can be detected automatically. Since in this work the focus is on the use of cepstrum-based preprocessing of the data to reduce the influence of the harmonics from steady state data, at this stage the detected events are simply re- moved from the set of data that will be analyzed. However, as it can be seen in figure 1, within the steady state data a further distinction must be made between stand still data (rotating speed approaching zero value) and rotating data. A threshold value on the average speed is then introduced in order to distinguish these two cases.

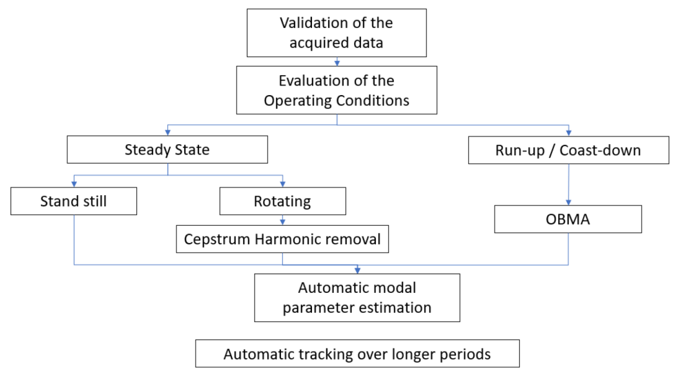

FIGURE 1: BLOCK DIAGRAM FOR THE PROCEDURE IMPLEMENTED TO CONTINUOUSLY TRACK THE MODAL PARAMETERS.

Use of big data analysis and tailored database

Wind turbines are subjected to continuous changes in wind, meaning that they do not always operate at nominal conditions. Furthermore, several transient effects can occur during the lifetime of the turbine (e.g. run-up, coast-down, emergency stop due to grid loss, ...). These transient effects can have a major impact on the lifetime of the turbine due to unfavourable loading, which is why these load cases often govern the design of the machine. During the design of machines, it is important to observe how they globally respond to different load cases. This will allow to validate (and if needed update) simulation models and to overall obtain more insights in the machine dynamics. For wind turbines, the great variability in the operating conditions is however a major challenge. In order to get representative modal behavior in all different operating conditions, it is therefore needed to move towards big data methodologies. This transition however requires to have automatic approaches available. In addition, this huge amount of data results in long computational times, meaning that it is also crucial to have a system available to deal with this big amount of data. Our integrated approach comprises three main steps [14]. 1) Data-acquisition system which allows to capture all the data within one consistent dataset. 2) Scalable data-warehouse in order to deal with a big amount of non-equally sampled data : a no-SQL database is therefore used to tackle problems of scalability and to increase the reliability of the overall system. 3) Parallel computing in order to reduce the computational time. No-SQL architectures distribute the data across the cluster; it is possible to couple it with parallelized querying and data analysis. This architecture permits to combine machine learning algorithms and advanced signal processing techniques. This allows to obtain new insights in the modal behavior of the machine in all operating conditions. Moreover, it opens the door to use data-driven prognostic techniques to predict the way it will respond in the future or in other operating conditions. These data-driven models have the potential to significantly improve new prototypes based on combining physical system knowledge and long-term experimental information.

Results

In order to validate the implemented procedure, a period of time in which several run-up and coast-down events are present has been selected. This allows to test the automatic event detection and to have a sufficient amount of data at different operating conditions to compare. By means of the event detection algorithm used to identify presence of run-up or coast-down in the signal, the events have been eliminated from the set of data analyzed. The remaining datasets have been divided in sub-signals and automatically clustered based on the operating condition of the machine, using as discriminant the average value of the speed. The variation of the speed is also considered in a next step for the post processing of the data.

The output of the tracking procedure is shown in Figure 2. The top graph of Figure 2 represent the evolution of the resonance frequency as a function of time, whereas the bottom graph represents the average speed of the machine over time. It should be noted that all values are normalized for confidentiality reasons. Based on these tracking results, a further processing of the results (hyper-modeling) can show correlations between the available operational parameters in order to get a better idea of which parameters play a role in the operational modal behavior of the machine. In case of wind turbines, these variables are represented by SCADA (Supervisory control and data acquisition) data: rotor speed, pitch and yaw angle, temperature, wind speed.. These data are considered to be representative for the operating condition of the machine. In this work, the hyper-modeling approach has been used only with respect to the rotor speed, obtaining the results shown in Figure 3 and 4.

Figures 3 and 4 show the dependence of the frequency and the damping of each resonance on the speed. Looking at the blue lines in the first subplot (frequency/damping) and in the second one (measured speed), it can be notice that a correlation may exist between the estimates and the rotor speed: for both the frequency and the damping, the estimates show higher variability at lower rotor speed values. To investigate whether an explicit correlation exist within the two parameters (frequency as a function of rotor speed and damping as a function of rotor speed), a hyper-model is used to predict the rotor speed (yellow line in the middle subplot) based on frequency/damping estimates. It can however been seen from the red line in the last subplot that the error between the measured and modeled speed is substantial. This validates the correct working of the cepstral lifter, as there would be direct correlations between the speed and the extracted poles in case harmonics were fitted during the modal parameter estimation.

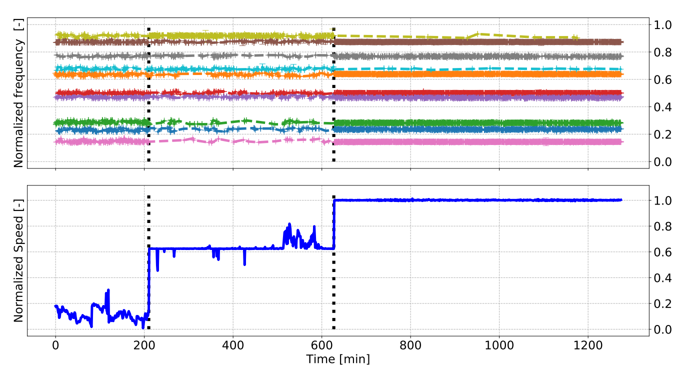

FIGURE 2: RESULTS OF THE TRACKING PROCEDURE OVER THREE DIFFERENT OPERATING CONDITIONS.

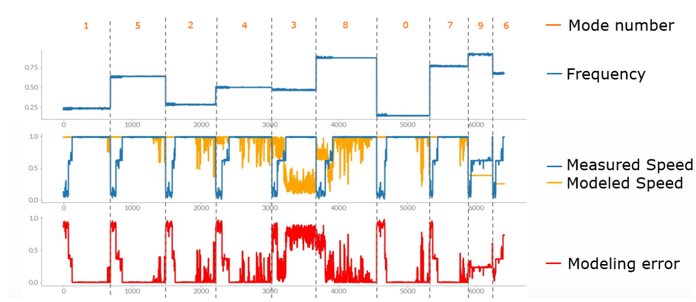

FIGURE 3: MODEL OF THE ROTOR SPEED BASED ON THE FREQUENCY OF EACH RESONANCE.

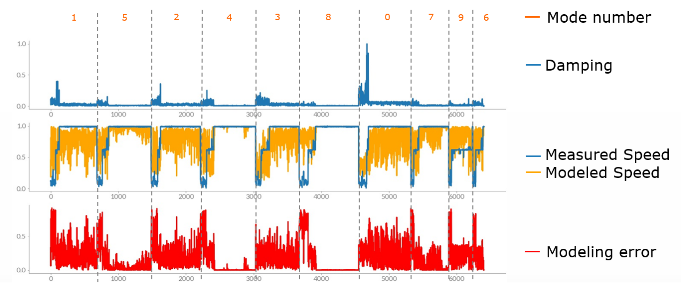

FIGURE 4: MODEL OF THE ROTOR SPEED BASED ON THE DAMPING OF EACH RESONANCE.

This analysis furthermore shows that hyper-modeling is essential to avoid misinterpretation of the results and that rotor speed alone is not sufficient to gain insight in the influence of the operating conditions on the modal behavior of a complex system such a wind turbine drivetrain. Future work will be to further perform automatic OMA to have longer tracking results and to include more SCADA data in the hyper-modeling process in order to further investigate the link between the operating conditions and the modal behavior of the machine.

CONCLUSION

This paper investigated the use of Operational Modal Analysis (OMA) on long-term data of rotating machines. Special focus was given on how to deal with the harmonic content present in the signal by using cepstral editing and on how to integrate the different methodologies within a big data context. Afterwards, the methodology was demonstrated by processing several hours of vibration data of an offshore wind turbine autonomously. Data-driven modeling was then finally used to find correlations between the estimated modal parameters and the operational settings of the turbine, although this showed that further coupling with SCADA of the machine is still needed to draw more meaningful conclusions.

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