Dealing with harmonics in continuous modal analysis

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Abstract

Noise, vibration and harshness (NVH) problems are critical issues to be tackled in case of rotating machineries. At this purpose, operational modal analysis (OMA) represents a powerful tool. OMA methods can be applied under the assumption that the excitation acting on the system under analysis is white noise. This requirement is not met in case of rotating machines, due the presence of excitations related to rotating elements. For this reason, harmonics need to be dealt with. This work focuses on two techniques for dealing with harmonics: the use of a cepstrum signal editing procedure and the use of order based modal analysis (OBMA). This paper shows the potential of these two methodologies when processing a continuous stream of real data coming from an offshore wind turbine drive train.

1 Introduction

In the field of mechanics, design values such as the modal parameters are essential: they are governing the system response to vibration sources. To avoid problems such as the transmission of undesired vibrations and the generation of tonalities, the design values must be optimized. Since in non-linear systems working at highly variable loads, modal parameters (and in particular damping values) strongly depend on the operating conditions, the experimental verification of prototypes is necessary for guaranteeing the reliability and the safety of the structure [1]. To this purpose Operational Modal Analysis (OMA) represents a powerful approach: it allows to extract the modal parameters from the dynamic response of the structure to unmeasured operational forces. The industrial design process currently comprises component-level testing and full-scale-machine testing both in laboratory environment and in the field. However, these tests are generally performed over short periods, trying to catch specific operating conditions to be tested. With this work, we want to propose an innovative approach for long-term operational modal analysis (OMA) testing of machines operating in the field or in a laboratory environment. The goal, is to give the designers information that allow to take decisions on how to improve the subsequent design variants based on what can be learnt in real operating conditions, i.e. with the machine running through every possible scenario that it could meet during its operating life. Coupling the modal parameters with the state of the machine allows to analyse how the environmental and operating conditions influence the modal behavior of the structure. The scope of this research is to make OMA suitable for processing a continuous stream of data coming from the operating machines. To do so, state-of-the-art vibration processing techniques are combined with methodologies coming from big data analysis and machine learning disciplines. As already mentioned, OMA is a highly capable methodology to extract modal parameters from operating machines [2]. What is missing to employ OMA as an approach for the proposed design methodology is the availability of reliable modal estimators capable of automatically processing the data received from the sensors, send the needed information to the cloud and provide a continuous view of the design values evolution. OMA is a technique that estimates the modal parameters from the dynamic response of the analysed system by fitting the data with parametric models and solving an optimization problem. The procedure is performed iteratively, using at each iteration a model with increased order (model order). However, the classical algorithms make use of the so-called stabilization diagram: a graph where the poles are plotted for each model order allowing to observe the stabilization of the poles and distinguish the mathematical from the spurious ones. Description of algorithms that automatically select the physical poles from the stabilization diagram can be found in literature [3, 4, 5]. Starting from these ideas we want to move to the next step in order to achieve a methodology that is able to continuously process a stream of data, selecting the parameters needed for the analysis in an automatic way based on the operating conditions and the physical characteristics that can be extracted from the signals. This implies the implementation of automatic procedure also for both the pre- and post-processing steps. In case of rotating systems, a main challenge for the use of classical OMA is the problem of the harmonics. OMA is based on the assumption that the excitation to the system is a white noise signals, indeed, if this assumption is not satisfied, the output of the parameter estimators is a combination of structural modes and components already present into the excitation signal (e.g. harmonics), giving erroneous results [6, 7]. Unfortunately, this problem affects most of the cases in which the use of OMA would be useful for the designing purposes explained above, so finding a solution for dealing with the presence of harmonics is of high interest.

2 State of the Art

2.1 Operational Modal Analysis

OMA techniques aim at obtaining modal parameters characterizing the dynamics of the systems based only on the knowledge of the response (i.e. output) of the structure to various ambient excitations, which are not measured (e.g. wind, rain, traffic..). The greatest advantage of OMA techniques is in providing the dynamic model of the structure under actual operating conditions and real boundary conditions. For this research the poly-reference Least-Square Complex Frequency-Domain (pLSCF) algorithm has been selected as starting point of the work. This method consists in a frequency-domain Modal analysis method that requires as primary data the output spectra of the system under analysis [8]. This method is based on the assumption that the excitation to the system is a white noise spectrum signal. Under this assumption is indeed possible to model the output spectra exactly in the same way used for the frequency response functions (FRFs) H(ω):

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

Where n is the number of complex conjugate mode pairs, $*$ is the complex conjugate operator, ^{T} is the transpose of a matrix, H is the complex conjugate transpose (Hermitian) of a matrix, v_i is the mode shape vector of the mode i, l_i^T the modal participation factors of the mode i and λ_i are the poles of the system (occurring in complex conjugate pairs). The poles are linked to the resonance frequencies and the damping ratios of the system by means of the following relation:

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

The relationship between the input spectra $[S_{UU}(\omega)]$ and the output spectra $[S_{yy}(\omega)]$ of a system represented by the FRF $H(\omega)$ is described by:

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

In case of output-only analysis, the auto-spectra are the only available information. The most important consequence of assuming the input signal as a white noise excitation is that the power spectrum of the input signal is constant; therefore $S_{UU}(\omega) = S_{UU}$ [8]. Considering this assumption and combining equation (1) and (3) it is possible to write the modal decomposition of the output spectrum matrix as following:

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

Where g_i are the operational reference factors, which replace the participation factors in case of output-only analysis. A right matrix model (equation 5) is then used to fit the measured FRFs data. The use of the right matrix model as parametric model has the advantage that the participation factors are available when constructing the stabilization diagram, thus a clearer stabilization diagram is generated, on which closely spaced modes are separated.

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

Where $H(\omega) \in \mathbb{C}^{l \times m}$ is the FRF matrix containing the FRFs between the m inputs and the l outputs, $B(\omega) \in \mathbb{C}^{l \times m}$ is the numerator matrix polynomial and $A(\omega) \in \mathbb{C}^{m \times m}$is the denominator matrix polynomial.

The results of the fitting of the measured FRFs data by means of a parametric model, are represented in the stabilization diagram [9]. The measured FRFs data are fitted with increasing model order models and the poles estimated for a certain model order are compared to the poles estimated for the lower model order. If their differences are within pre-set limits, the pole is labelled as stable one. The spurious numerical modes will not stabilize at all during this iteration procedure and they can be then easily sorted out of the modal parameter estimates. The stabilization diagram shows how the poles stabilize for increasing model orders and it allows the analyst to distinguish the physical modes from the spurious ones.

2.2 Cepstrum editing procedure

As already stated, OMA does not require input force information but it makes assumptions about the nature of the input excitation forces: 1) the excitation must be represented by a flat white noise spectrum in the frequency band of interest and 2) the forces acting on the structure must be uniformly distributed and uncorrelated temporally and spatially [10]. Both these assumptions imply that excitation is considered stochastic in time and space. Unfortunately, most of the time these assumptions are not fulfilled in case of complex rotating mechanical systems due to the presence of discrete components (i.e. harmonics) coming from internal sources (e.g. gear meshing phenomena) and aeroelastic forces. From the vibration analysis point of view, this research focuses mainly on dealing with the problems of harmonics. 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 [11]. 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 [11]. One possibility for dealing with this problem 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 [12]. In this work cepstrum-based time-domain signal editing procedure is adopted to reduce the in 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 6:

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

Where (X(t)) is the original signal in the time domain, A(f) and ϕ(f) are respectively the amplitude and phase of the frequency domain signal. By setting the phase to zero in equation 6, the formulation of the real cepstrum can be obtained (eq. 7):

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

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 called rhamonics, 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 [13]. 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:

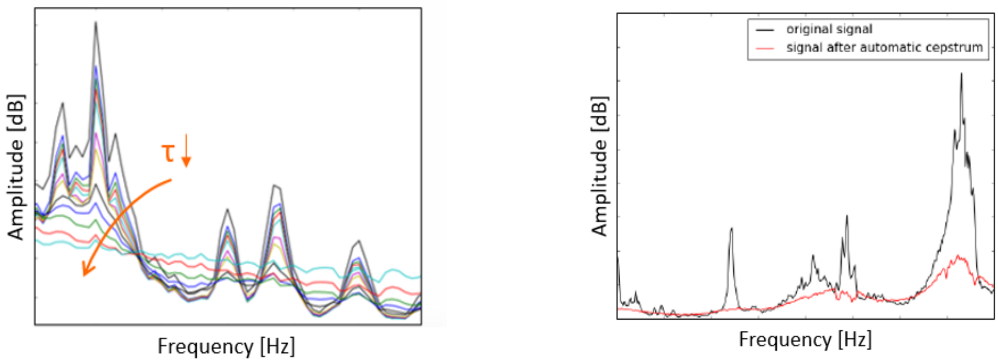
$$\xi_r = \xi_m - \frac{1}{2\pi f_r \tau} \tag{8}$$

Where for each estimated mode, ξ_r is the real damping [%], ξ_m is the measured damping [%], f_r is the real frequency [Hz] and τ is the time constant of the exponential window [s]. Since it has been shown that the cepstrum lifter works better for narrow harmonics [13], speed correction has been performed before editing the acceleration signals: 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 [14]. 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 Δt seconds). This step is not necessary fr stand still data, since in this case harmonics present in the signal are narrow for nature (small speed variation in case of harmonics due to the gear meshing and differentf origin of the harmonics).

3 Methodology

3.1 Automation of the procedure

The two procedures described in the previous section must be combined and improved in order to achieve a valuable methodology for performing OMA on a continuous stream of data acquired on rotating machines. The automation of the modal parameter estimator can be divided in two sub-steps. First the p-LSCF algorithm is made automatic eliminating the analyst-algorithm interaction by introducing a clustering method that autonomously interprets the information collected in the stabilization diagram. Clustering analysis is used to group poles that show stable characteristics. The physical poles are then selected automatically by considering statistical features for each cluster. The algorithm used to estimate the modal model of the analysed system is then coupled with an automatic tracking algorithm that shows how the modal parameters evolve along different datasets (i.e. for longer periods) [15]. The comparison amongst the estimates of each dataset is performed using MAC and poles values, in order to measure in which extend 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. Concerning the cepstrum editing procedure, an algorithm that automatically select the parameter required by the analysis is implemented. The mentioned parameter is the cutoff-quefrency, i.e. the time constant of the exponential window applied to the signal in the quefrency domain. The idea is to exploit the mechanical characteristic of the system to have knowledge of the frequency bands at which the harmonics are introduced in the signal: the method is based on the reduction of the energy introduced by harmonics consequent to the use of the cepstrum procedure. The method is iterative and a representative example of it is shown in figure 1. The iterative application of a cepstrum lifter with decreasing cutoff quefrency is stopped when the desired energy reduction is achieved. In figure 1a it is possible to observe the effect of the subsequent iterations, while in figure 1b it is possible to see 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.



(a) Effects of a decreasing cutoff quefrency

(b) Signal before and after the use of cepstral editing procedure

Figure 1: Use of the automatic cesptrum procedure.

To apply automatic OMA on a continuous stream of data, it is also needed an automatic distinction between steady state data conditions (data acquired with the turbine in idling conditions or running at almost constant speed) and run-up/coast-down events. This is necessary due to the different pre-processing procedure that has to be used depending on the type of data analyzed. The implementation of an algorithm able to automatically detects event in the signal is implemented, allowing to complete the scheme represented in the block diagram in figure 2. In figure 2 it is also possible to notice that an additional step is introduced: data validation. This allows to assess the validity of the signal and avoid processing corrupted signals (for example erroneous acquisition due to the detachment of the sensor from the structure to be analyzed).

Since the automatic modal parameter estimation has already been showed and validated in previous works [16], the missing step to make this analysis running continuously over a significant amount of time is the introduction of the automatic classification of 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 subsequent 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 removed from the set of data that will be analyzed. However, as it can be seen in figure 2, 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.

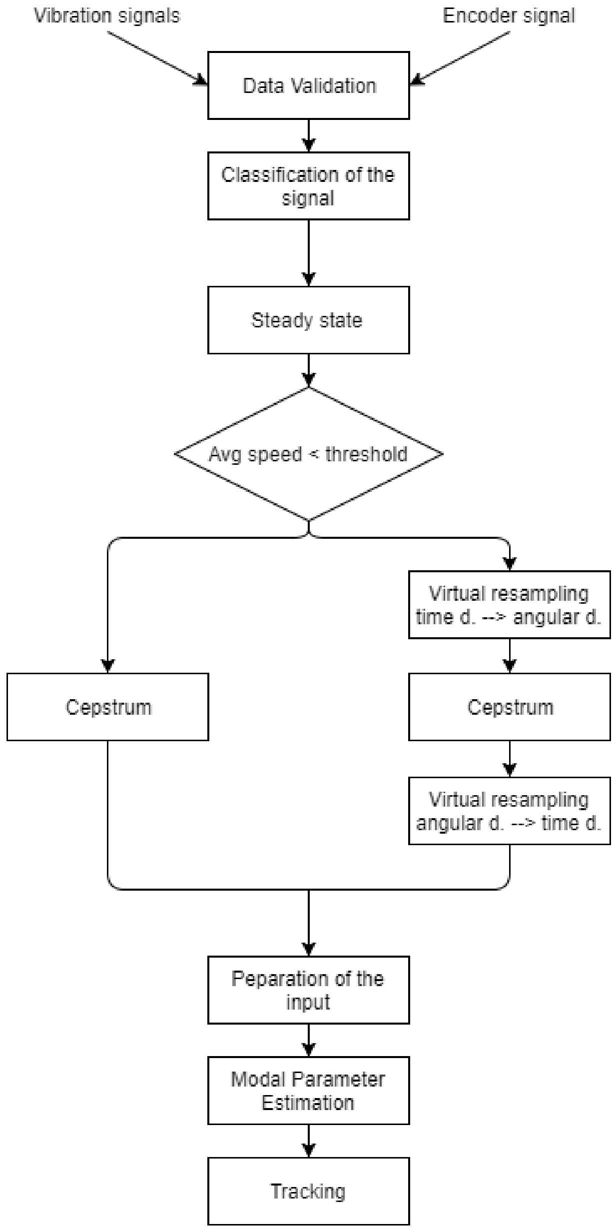


Figure 2: Block diagram of the automatic procedure implemented to autonomously and continuously track the modal parameters.

3.2 Use of big data analysis and tailored database

Due to the variability of the wind, the turbine is not always operating at nominal conditions. Several transient events occur during the control action, and several important loading cases act on the wind turbine (start-up, shut down, emergency stop and grid loss related events). The load cases cover different operating conditions, and the most unfavourable load effects govern the design of the machine. However, during the design process, it is important to observe how the machines globally respond to the different loading conditions. In this way it is possible to optimize the design of future prototypes and predict which is the modal behaviour of the machine in case of critical loads. Long-term analysis and monitoring of the turbines, leads to the need of dealing with a huge amount of data. It requires then an automatic approach able to tackle the described challenges. In addition to the implementation of autonomous algorithms for advanced signal processing, the key is having a system able to deal with such a big amount of data. Our integrated approach comprises three main steps [17]. 1) Data-acquisition system that allows to capture all the data within one consistent dataset:

each machine has its own sensor and data acquisition network consisting of machine embedded sensors and custom monitoring system. 2) Scalable data-warehouse in order to be able to deal with large amount of data non-equally sampled and heterogeneous for nature: a no-SQL database is used to tackle problems of scalability and to increase the reliability in case of node failure. 3) Distributed computing since the analysis of large amount of data is computationally intensive. No-SQL architectures distribute the data across the cluster; it is possible to couple it with parallelized querying and data analysis using Apache Spark (Spark). Our algorithms are written using Python as coding language. This architecture allows to combine machine learning algorithms with advanced vibration signal processing techniques. This allows to gather new insights in the modal behavior of the machine in different operating conditions and make prevision on how it will respond in the future using data-driven prognostic techniques. This allows the designers constructing data-driven models and improving the new prototypes based on physical system knowledge and experimental information.

4 Results

In order to validate the implemented procedure, a period of time in which several events are present has been selected. This allows to test the automatic event detection and to have a sufficient amount of rotating a standstill datasets to compare. In figure 3 it is possible to observe the speed variation of the turbine in the selected period.

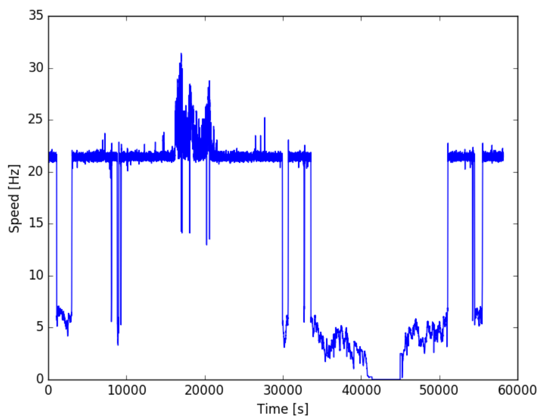


Figure 3: Profile of the speed of the machine in the period selected for the analysis.

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 as rotating data or stand still data, 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, it is shown in figure 4 concerning rotating data and in figure 5 concerning the stand still data.

At a first sight to figure 4 and 5, it can be noticed how, in both the cases, the damping presents a much higher variation, indication of the fat that the damping ratio is a modal parameter highly dependent on the operating conditions of the machine. On the opposite, frequency values present more consistent values along all the datasets.

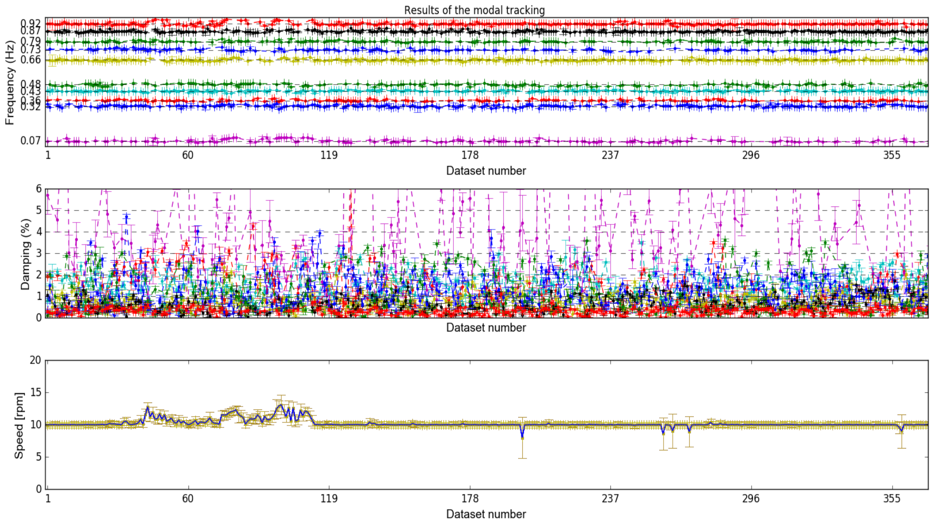


Figure 4: Results on the tracking on rotating data.

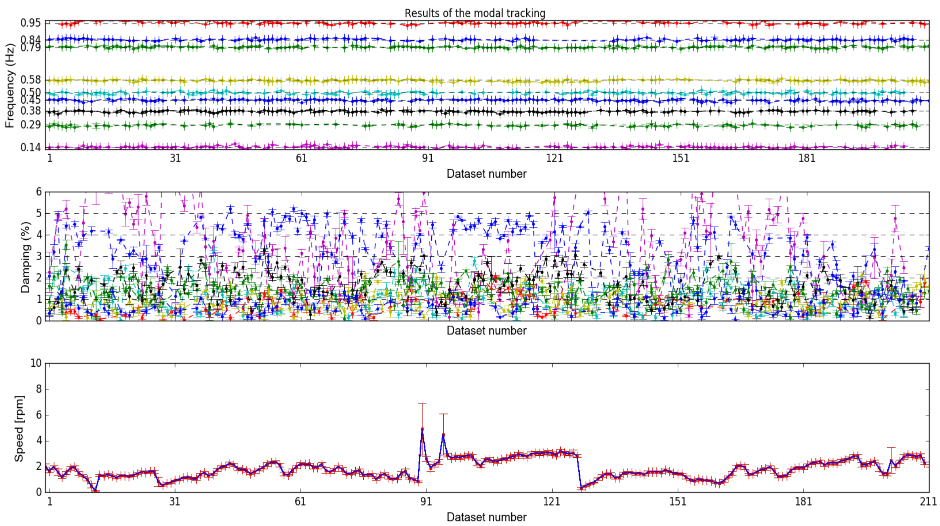


Figure 5: Results of the tracking on stand still data.

5 Conclusions

This paper has investigated a completely automated operational modal parameter estimation scheme, tackling the main challenges in applying OMA on complex systems like wind turbine gearboxes. The approach has been verified by processing real data coming from the drive train of an off-shore wind turbine.

The main challenges posed by the methodology used for the parameter estimation have been already investigated in previous works. With this research emphasis has been given to the automation of the procedure and the implementation of it in an ambient that allows to parallelize the needed steps and save computational power and analysis time. It has been shown that the automatic procedure gives promising results, consistent with the ones obtained with a manual procedure and shown in previous works. This will ensure the results to be objective and less dependent on the analyst decisions, opening the doors to further investigations.

The results obtained, confirm the variation of the modal behavior of a machine with the speed. What it is interesting to investigate, is then the presence of possible correlations between the evolution of the modal parameters and other operating and environmental conditions than using the speed only. Parameters that are generally available through SCADA data.

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