

Experimental validation of stochastic subspace algorithms for structural health monitoring of offshore wind turbine towers and foundations

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Abstract

The efficiency of wind turbines (WT) is primarily reflected in their ability to generate electricity at any time during their design life. Downtimes of WTs due to “conventional” inspections for damage detection are very costly and undesirable for WT investors, especially offshore. For this reason, the Wölfel Group has developed a wide range of products with vibration-based SHM systems for damage and ice detection. This publication concentrates on application of two vibration-based SHM algorithms for stability and structural change monitoring. Only data driven, output-only algorithms based on stochastic subspace identification (SSI) in time domain are considered. One of the algorithms only considers changes of lower order stochastic subspace models, which can be interpreted in a physical way as changes in the vibration modes. The other algorithm, however, also considers the changes in the higher orders of stochastic models and is known as the stochastic subspace faults detection (SSFD) algorithm. The sensitivity of the methods for monitoring purposes are demonstrated through their application on long time measurements from a 1:10 large scale test rig of an offshore WT under different conditions: undamaged, different levels of loosened bolt connections between tower parts, different levels of fouling, scouring and structure inclination. The limitation and further requirements for the approaches and their applicability on real foundations are discussed along the paper.

1 INTRODUCTION

In the past, different vibration-, guided waves- or acoustic-based SHM methods for offshore WTs were developed. To date no national or international standardizations or requirements for the SHM of WT by means of one method or another exists. In the industrial application, which this publication is focused on, mostly vibration-based, output-only methods are used. Data-driven methods are used for monitoring of damage and change detection and model-based methods for the life cycle estimation monitoring, see [1], [2] and [3]. Different methods for damage localization and damage extension are based on the analysis of local measurements [1], however the model-based (e.g. finite element models) damage localization methods ([4], [3]) are currently not established for continuous monitoring purposes. Today, the localization and/or identification of damage resp. change



type is possible only in a limited way by using different methods and indicators, where each method or indicator is more or less sensitive to one type of structural change or another [1]. An overall available algorithm, method or indicator for all kinds and types of WT structural damages does not exist. The selection of an algorithm resp. method depends on the monitoring purpose, structural hot spots, specifically on the dynamic behavior of the foundation and - not least - on the experience and knowledge of the SHM system designer regarding structural mechanics and dynamics, signal and data processing, statistical pattern recognition, big data handling, sensor selection, etc.

Actually, in offshore environment the sensors used for industrial SHM purposes measure mostly the acceleration, inclination, local strain or displacement of the WT structure in a low frequency domain (the wind and wave excitation occurs considerably below 10 Hz). In most of the cases the sensors are placed over the water level ([1], [4], [3]). There are also a few instrumentations known with sensors under the waterline. However, the service life expectancy of those sensors is very low.

The basic principle of a vibration-based, output-only, data-driven SHM-method is illustrated in Figure 1. The structural response at the sensor positions is measured (see block measurements in Figure 1). The measured time series themselves are rarely directly used, but present meaningful features or feature vectors extracted from the signals that are useful to compare different structural states. The feature extraction is made by means of signal processing methods in time, frequency or time-frequency domain. Examples of features are statistical moments, parameters of statistical distributions, coefficients of time series models, statistical numbers of time series residuals (e.g. from the “family” of autoregressive models), or stochastic model residuals, Fourier coefficients, statistical moments of spectral data, eigenfrequencies, modal damping, mode shapes, modes curvatures, wavelet coefficients, etc. The application of dynamic features in SHM-context is described in a compact form e.g. in [1], [5], [3].

The dynamic response and its features do not only contain the “isolated” system dynamics, but also effects of the environmental and operational conditions (EOCs) on the structure and effects of the dynamic coupling on other parts of the turbine. So it is necessary that in a “learning phase”, the normal conditions of the structure under different EOCs are identified and reference models (acting as observer) for normal conditions are built (see block pattern recognition in Figure 1). In the “detection phase”, the actual dynamic features of the structural parts are compared to the reference models.

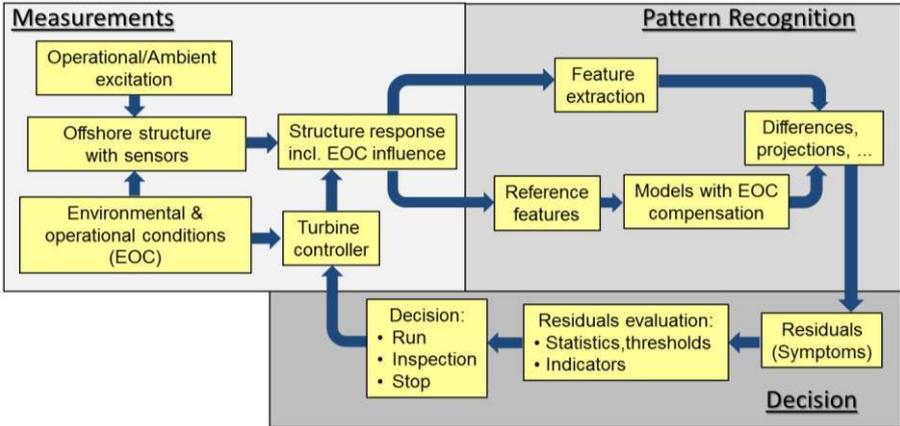


Figure 1: Basic principle of a vibration-based, output-only, data-driven SHM-method

The residuals between the actual data and the reference models are statistically interpreted and “compressed” to one or more indicators (see block decision). In practice, different indicators calculated from signals of different sensors with their features and models are used and sometimes combined for monitoring of different structural parts. In this case each indicator has its sensitivity regarding different damages or changes.

Some rough explanations of the WT dynamic behavior, feature extraction procedure, and reference model building for two stochastic subspace-based algorithms are given in the following section.

2 ROUGH THEORETICAL BACKGROUNDS

The equations of a linear dynamic system already show that changes in stiffness and mass have an effect on the system’s vibration behavior. This is one of the basic principles of the vibration-based damage identification approaches implemented in Wölfel’s WT monitoring systems. The simple application of the linear and time-invariant equation of motion for the examination of a complex dynamic system on site (e.g. a wind turbine) is not sufficient. The system is not stationary and superimposed by transient, stochastic and periodic excitations of the turbine. Due to variable boundary conditions, temperature fluctuations, changes of mass inertia moments, water level, etc., the dynamic system of a wind turbine is highly non-linear and can be well described by the following equations of motion ([6], [7]):

$$\mathbf{M}(\boldsymbol{\theta}_d, \boldsymbol{\theta}_e, \mathbf{x}, t) \ddot{\mathbf{x}} + \mathbf{g}(\boldsymbol{\theta}_d, \boldsymbol{\theta}_e, \mathbf{x}, \dot{\mathbf{x}}, t) = \mathbf{F}(\boldsymbol{\theta}_d, \boldsymbol{\theta}_e, t), \quad (1)$$

$$\dot{\boldsymbol{\theta}}_d = \boldsymbol{\Gamma}(\boldsymbol{\theta}_d, \boldsymbol{\theta}_e, \mathbf{x}, \dot{\mathbf{x}}, t), \quad (2)$$

$$\mathbf{y}(t) = \mathbf{h}(\boldsymbol{\theta}_d, \boldsymbol{\theta}_e, \mathbf{x}, \dot{\mathbf{x}}, t). \quad (3)$$

where \mathbf{M} is the mass matrix, \mathbf{g} the vector of elastic forces, damping forces, etc. and \mathbf{F} the external load vector; $\ddot{\mathbf{x}}$, $\dot{\mathbf{x}}$, \mathbf{x} are acceleration, velocity and displacement vectors. $\boldsymbol{\theta}_d$ is a time (t) dependent vector with damage parameter, and the parameter vector $\boldsymbol{\theta}_e$ indicates the influence of environmental and operational conditions, e.g. temperature, pitch angle, rotational speed, changing boundary conditions, etc. The non-linear function $\boldsymbol{\Gamma}$ describes the evolution of $\boldsymbol{\theta}_d$, e.g. crack length, play, loss of stiffness, change of mass, etc. A temporary decrease of system stiffness, e.g. as a result of damage, is formally assigned to $\boldsymbol{\theta}_d$, given that the damage is not one of the expected (normal) EOC changes. In the measurement Eq. (3), \mathbf{y} is the measured system response, which stays in a non-linear and time-variant relationship \mathbf{h} to $\boldsymbol{\theta}_d, \boldsymbol{\theta}_e, \mathbf{x}, \dot{\mathbf{x}}$ and t, see also [3].

As mentioned above, the measured data is not directly used to compare two system states. In fact, so-called features are extracted from the raw data, which are arranged in a vector. The feature vector \mathbf{f}_y extracted by the feature extraction operation (FE) is

$$\mathbf{f}_y(\boldsymbol{\theta}_d, \boldsymbol{\theta}_e) = \text{FE}(\mathbf{y}(\boldsymbol{\theta}_d, \boldsymbol{\theta}_e, t)). \quad (4)$$

The sensitivity of the i-th feature with respect to the j-th structural changes parameter is expressed by the first partial derivative

$$s_j = \frac{\partial \mathbf{f}_y(\boldsymbol{\theta}_d, \boldsymbol{\theta}_e)}{\partial \theta_{dj}} \quad (5)$$

and shows that the dynamic behavior of the structure and its features depend simultaneously on damage state and the EOC. Thus, the compensation of the effect of EOCs on the dynamic

behavior of a wind turbine is of particular importance.

Two vibration-based SHM-algorithms appropriate for stability and structural change monitoring of offshore wind turbines are presented below, both of them belonging to the stochastic subspace identification (SSI).

2.1 SSI-based structural change detection

The first approach considers only changes of lower order stochastic subspace models, which can be interpreted in a physical way as changes in the vibration modes. This is based on the covariance-driven stochastic subspace identification (SSI-COV) algorithm and often is used in context of operational modal analysis [8]. As features of the dynamic system the eigenmodes are calculated and automatically interpreted in the following steps:

First, the non-linear Eq. (1) is fragmented by several linear, time-invariant equations, with unknown stochastic input, each only available for different classes of EOCs. The criteria for choosing class ranges and number of classes are defined by means of Eq. (5). In the second step the eigenmodes are calculated in time domain by means of SSI-Covariance-Driven method.

The third step consists in the automated selection of stable poles from stability plots. Such a stability plot gained from measured data of a wind turbine structure is shown in Figure 2(a). The black circles indicate that the eigenfrequencies, the modal damping and the mode shapes do not change with higher model (state space) order. The continuous gray line represents the mean power spectral density (PSD) of the signals. Only using stability plots is not enough for an automatic feature extraction approach. For this purpose, further classification algorithms are used. These algorithms automatically choose the number of class centers and give the representative stable poles at the class centers (see the blue vertical straight lines in the left part of Figure 2(a)).

After these steps, the sensitivities of the modal parameters due to the changes of EOCs are well known and can be modeled by means of linear or non-linear correlations. Figure 2(b) shows the linear dependency of one eigenfrequency on one measured EOC feature. Of course, depending on the vibration mode, the feature vector (modal data) shows different dependencies to different EOCs. The impact of the EOCs on the modal data is shown by Eq. (5). These dependencies/models are established during the time when there is no structural change of the WT (“learning phase”). These models represent the system references.

If the actual feature vector (during the “detection phase”) shows a significant statistical deviation from the reference in (%), an alarm is triggered. The state condition of the plant is summarized in just one indicator/ residual, which is proportional to the structural changes.

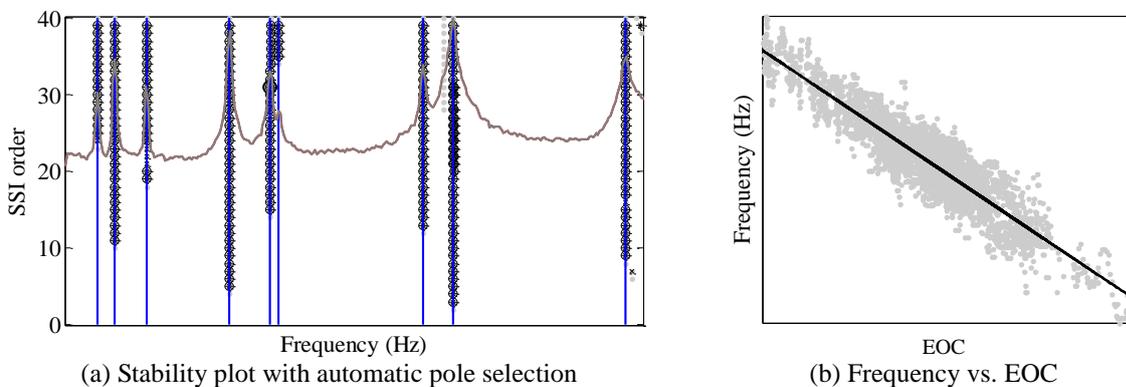


Figure 2: Features and EOC-compensation within SSI-COV-based method

The second method, however, also considers the changes in the higher orders of stochastic models and is known ([9]) as the stochastic subspace fault detection (SSFD) algorithm or null space-based fault detection algorithm (NSFD). The NSFD based indicator use the residuals generated by means of the Hankel-matrices left kernel space. The indicator was firstly proposed in ([9]). This residual turned out to be very sensitive to small structural changes. Details of the algorithm can be found in [3].

Since the purpose of this publication is to show the sensitivity of the approaches due to structural changes of offshore WT, the aspects of EOC compensation on the extracted features are only briefly sketched (specific information about EOC compensation can be found e.g. in [3], [6] and [10]).

3. EXPERIMENTAL VALIDATION

As already mentioned, it is not possible to analyze different isolated structural damages or changes in a systematic manner directly by means of in-situ measurements on existing WTs. For this reason, the sensitivity of the methods for monitoring purposes are demonstrated through their application on a long time measurement campaign at a 1:10 large scale test rig of an offshore WT.

3.1 Test rig, test facilities and experiment purposes

The test rig consisted of a model of the WT structure with monopile foundation placed in the test hall and the sand basin of Test Center for Support Structures of Leibniz Universität Hannover, see Figure 3(a). The measurements were done together with Fraunhofer IWES. The dimensions of the test pit were 10x14x10 m. The pit was filled with sand and water. The water level was controlled.

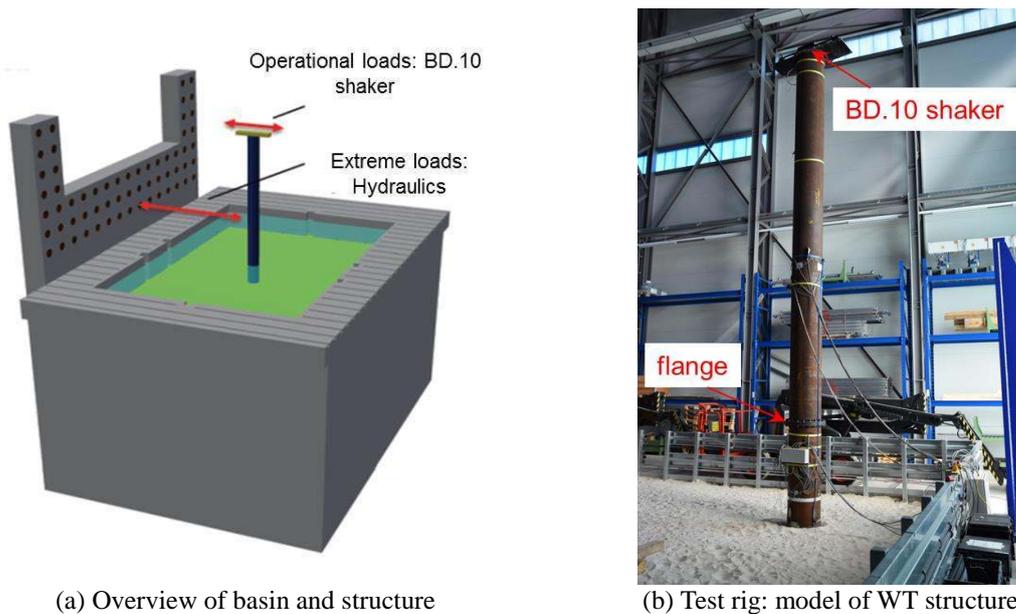
The monopile structure, see Figure 3(b), consisted of two pipes of approx. 0.5 m of diameter and approx. 6 mm of wall thickness. The length of the first pipe (pile model) was 7.5 m. This was vibrated into the sand for a depth of 6 m. The second pipe (tower model) was flanged by means of 20 screws to the first one and had a length of 6.5 m. At the top of the “tower” an electro-magnetic shaker was mounted. The shaker represented the turbine and excited the structure by means of stochastic forces.

Different sensors for different purposes were installed on the structure; some of the sensors were applied on the first pipe (in the sand), the other sensors on the second pipe. The sensor types and positions can be seen in Figure 4. For the validation of SSI-COV- and NSFD-based methods only the acceleration signals (the sensors are placed over the “water level”) were used. The used frequency range from the acceleration signals was 0-125 Hz. The frequency range of the stochastic excitation by the shaker was between 2-50 Hz, the forces were assumed to be unknown. The measurement time for each data set displayed in the following graphics was 10 minutes.

The experiment aimed at the validation and development of different approaches for WT monitoring. In this publication, the testing and validation of the sensitivity of two stochastic subspace-based change-detection approaches regarding:

- soil degradation,
- loosened bolts at the flange (represents a loss of stiffness),
- fouling (additional masses),
- scouring (changing of boundary conditions) and structure inclination.

is described.



(a) Overview of basin and structure

(b) Test rig: model of WT structure

Figure 3: Test rig in the sand basin of Test Center Support Structures

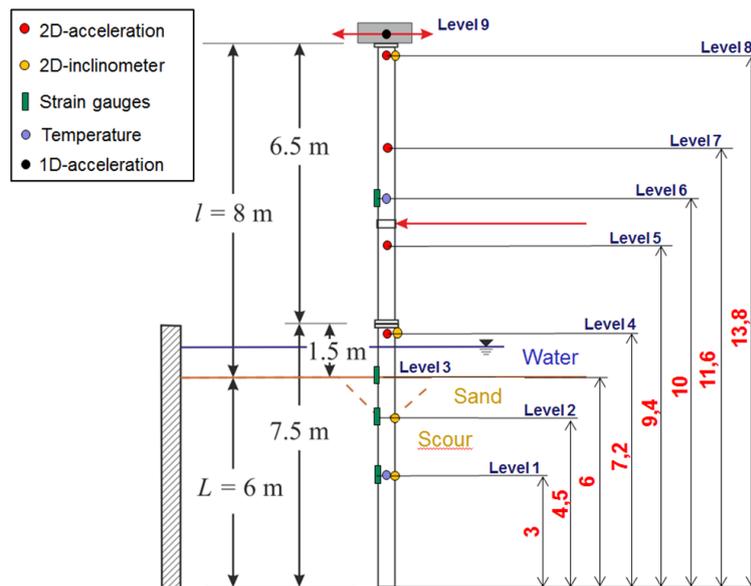


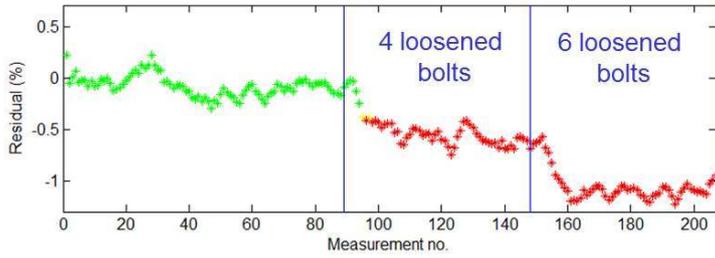
Figure 4: Dimensions and instrumentation of the structure

The time-history of all the measurements during different structural changes and their effect on the first eigenfrequency are shown in [11]. The measurements are taken during a period of 5 months.

3.2 Loosened bolts at the flange

Different damage levels were created by the loosening of 2, 4 or 6 of the flange connection bolts between pile and tower (the flange connection consists of 20 bolts). For security reasons the bolts were not completely loosened, a rest tension remained in the bolts, these were additionally secured by means of counter nuts, as seen in Figure 5(b) and Figure 6(b). The method based on the eigenfrequencies change (four simultaneous

eigenfrequencies), showed that 4 and 6 loosened bolts could be well detected, see Figure 5(a), also the detection of 2 loosened bolts was possible in a limited way.



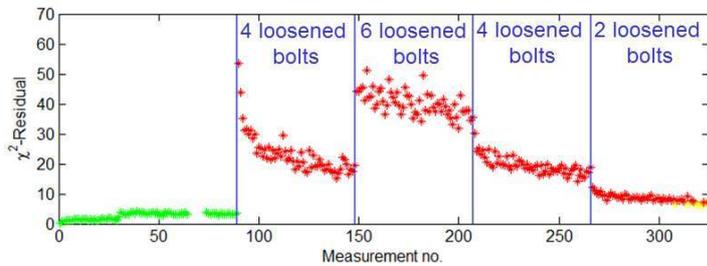
(a) Evolution of the SSI-COV-based indicator



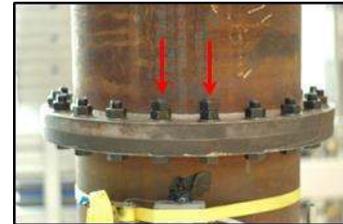
(b) Flange with 4 loosened bolts

Figure 5: Effects of loosened bolts at the flange

The NSFD-based method clearly shows that all levels of loosened bolts can be well identified, see Figure 6(a).



(a) Evolution of the NSFD-based indicator



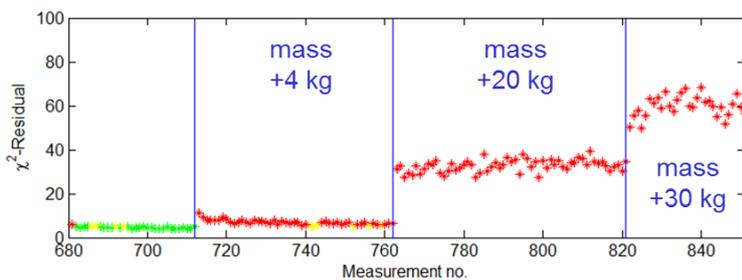
(b) Flange with 2 loosened bolts

Figure 6: Effects of loosened bolts at the flange

3.3 Fouling simulation by means of additional masses

The fouling could be only simulated in a very simplified way by placing additional masses close to the flange. Three different additional masses were mounted to the tower: 4, 20 and 30 kg, as displayed in Figure 7(b). The mass of the tower and shaker was approx. one ton.

The NSFD-based method was able to detect the changes due to additional masses, see Figure 7(a), the SSI-COV-based method was not suitable for clear detection of those masses.



(a) Evolution of the NSFD-based indicator



(b) 4/20/30 Kg additional mass

Figure 7: Effects of additional masses positioned over the flange

Since fouling belongs to the “normal” states of the structure, if its effect on the NSFD-indicators is not compensated, this can cover up the effects of small damages e.g. as the loosening of 2 bolts (the NSFD-indicator is in both cases: 2 loosened bolts and 4 kg additional mass relative similar, approx. 10, compare Figure 7(a) to Figure 6(a)).

3.4 Scouring

Scouring are changes between the structure and the surrounding soil, affecting the structural stability. Also different scouring levels were simulated by grubbing out 30, 60 and 80 cm of sand around the structure.

The effects of scouring on the indicators of both methods are huge, see Figure 8(a) and Figure 9. So it can be supposed, that if scouring is treated simultaneously to other effects e.g. coming from loose of stiffness (damages) the effect of scouring will be dominant and possibly cover up all other effects. In this case it is important for the mentioned change resp. damage detection procedures either to build the references after the scour depth is no longer growing (some months after WT installation) or to compensate the scour effects on the indicators. The first option is dangerous, since during strong storms the scour can change again. The last option is possible if the occurrence of scour or even the scour depth is evaluated by means of other sensors.

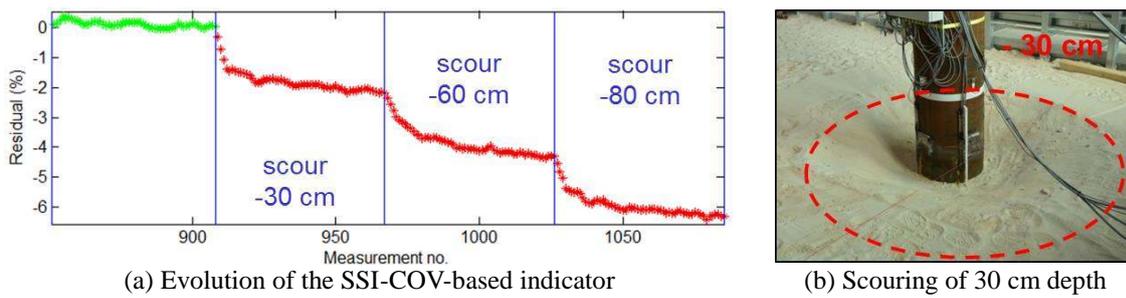


Figure 8: Effects of scouring

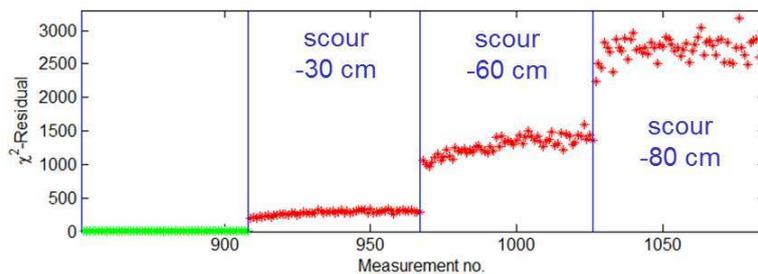


Figure 9: Evolution of the NSFD-based indicator

3.5 Structure inclination

The structure inclination was reached by means of periodic eccentric loads from a hydraulic cylinder. Depending on the eccentric loads, different levels of structure inclination at tower top were reached; the remaining inclination after each loading period is smaller than 0.05° . After each loading period the hydraulic system was decoupled and the structural response during the shaker excitation was measured.

The lower part of Figure 10 shows that after each hydraulic loading the remaining inclination was higher than at the previous hydraulic loading. During the shaker excitation the structure was gradually straightened. Both, the hydraulic loading and the excitation by the

shaker led to the structure soil connection changes. The simultaneous effects of the soil structure connection changes and structure inclination can be seen in the changes of the first eigenfrequency of the structure (upper part of Figure 10). In the case of structure inclination monitoring it is more useful to use directly the information from the inclination measurements.

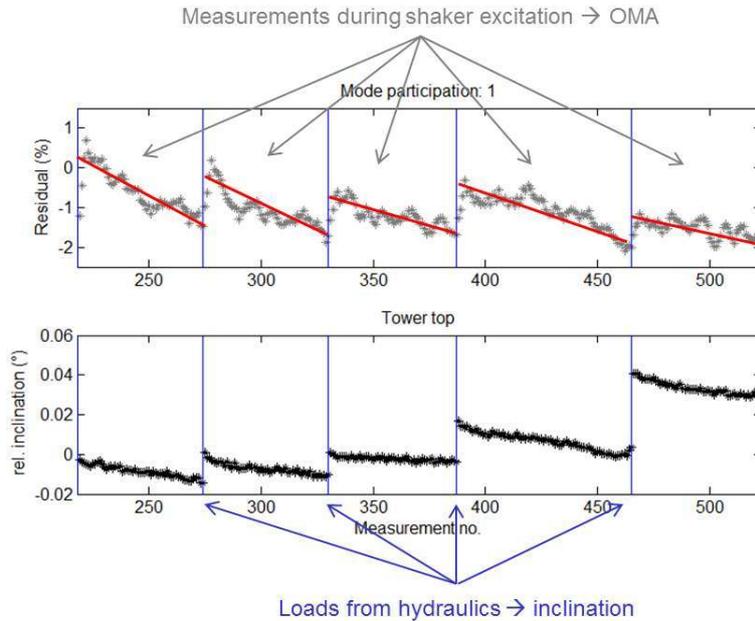


Figure 10: Structure inclination after hydraulic loading and during shaker excitation

4. CONCLUSIONS

The sensitivity and limitation of two stochastic subspace identification methods for SHM of foundations of WT were investigated by means of a long-time measurement campaign. The measurement was performed at a 1:10 large-scale test rig of an offshore WT under different conditions: no damage, structural changes, different levels of loosened bolt connections between pile and tower, different levels of fouling, scouring and structure inclination.

The results show that both methods are sensitive to small damages as loosened bolts in the flange connections and also to changes in the system stability induced by scouring. The NSFD-based method is sensitive to mass changes too. The essential knowledge or lesson learned from the application of the methods on the measured data at the test rig is: In general, the approaches are more sensitive to soil changes than to structural changes. Based on this knowledge, if the structural change detection of a WT has to be monitored in presence of strong soil changes, the effects of soil changes have to be compensated, e.g. by means of separate scour depth measurements (options for compensation of measured parameters on stochastic subspace indicators are already available and can be found in [3] and [10]).

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