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Experimental application of OMA solutions on the model of industrial structure

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Abstract. It is very important and sometimes even vital to maintain reliability of industrial structures. High quality control during production and structural health monitoring (SHM) in exploitation provides reliable functioning of large, massive and remote structures, like wind generators, pipelines, power line posts, etc. This paper introduces a complex of technological and methodical solutions for SHM and diagnostics of industrial structures, including those that are actuated by periodic forces. Solutions were verified on a wind generator scaled model with integrated system of piezo-film deformation sensors. Simultaneous and multi-patch Operational Modal Analysis (OMA) approaches were implemented as methodical means for structural diagnostics and monitoring. Specially designed data processing algorithms provide objective evaluation of structural state modification.

1. Introduction

There are many challenges in structural health monitoring, few of the mains being resolution of SHM methods, stability of its parameters, and costs. The most accurate existing solutions are very expensive, but cheaper solutions do not allow required resolution. The costs are accumulated from the equipment used (high-precision transducers, data acquisition systems with multiple channels) and from the human factor (high-skilled personnel needs to reach remote structures for inspection using complex equipment and machinery).

This paper introduces an optimal compromise between resolution and cost – multi-patch OMA techniques [1]. This type of OMA does not require a multi-channel data acquisition system, only few channels will be enough. Besides that, also the type of transducers can be altered to fit the budget. As it has been proven on practice [2,3], for SHM even low precision deformation sensors can be applied for the task. This reduces the cost significantly. Lastly, using above mentioned solutions, it is possible to automate the process and receive structural health data from remote objects to perform monitoring and even diagnostics of a structure.

2. Objective and tasks

The main objective of this paper is optimal choice of methodical and technical solutions of Operational Modal Analysis (OMA) and validation of its capability for Structural Health Monitoring (SHM) of typical industrial structures. The resulting system should be versatile and affordable for industrial use. Three basic tasks are considered:

- To create a laboratory model representing typical industrial structures,
- To select technical and methodical solutions acceptable for OMA application in industrial environment,

- To evaluate diagnostic features of chosen technical and methodical solutions using the laboratory model of an industrial object.

In order to accomplish mentioned tasks the following set of actions is taken:

- Choice of an object to represent a typical industrial structure (including structural and operating parts),
- Forming requirements for an objects model,
- Design and production of the model,
- Design of the measurement setup for dynamic data acquisition
- Study of model's dynamic characteristics, including:
  - numerical modelling (FEM analysis)
  - modal testing using dynamic excitation
  - modal parameters estimation
  - development of data processing techniques
- OMA techniques optimization (multi-patching) for application on industrial objects
- Study of damage detection possibility using OMA
- Research of OMA applicability on industrial objects that experience large deterministic excitation.

3. Problem analysis of OMA application for industrial objects

An object may have different states. Some are considered healthy, others are considered to be faulty or defected, and it is important to identify what kind of state the object is in.

There are two health monitoring techniques, presented in this paper. One is based on modal parameters (modal shapes and frequencies) comparison between object's states to detect condition modification. This approach briefly considered in 3.2 is commonly recognized and is applied widely. However, on a way to industrial application appearing technical and methodical problems require appropriate solutions and optimization. One of these solutions is the second health monitoring technique, presented in this paper, which utilizes modal characteristics in the form of singular vectors, without the need for modal parameters estimation.

3.1. Technical solutions

The basic task of OMA is evaluation of object's dynamic features. There are different sensor types for dynamic data acquisition of large scale industrial objects where two main groups could be outlined. Fiber Bragg grating (FBG) using distributed sensors is the most modern, however, its frequency range is too narrow for dynamic data measurements. Typical industrial objects have dominant modes in the range from few Hz to 1 kHz and more, but FBG optics based system can provide frequency range less than few tenth Hz. Other problem is high costs of FBG based systems required for large scale industrial object.

State-of-the-art accelerometers may provide frequency and dynamic range enough for vibration measurements. Special advantage of accelerometers is availability of 3D measurements. The system combined of 3D accelerometers would have high resolution and accuracy but will cost a lot.

Deformation transducers based on piezo-film sensor paired with a pre-amplifier are a good compromise between measurement effectiveness and low budget price. For precision measurements such deformation transducers are not acceptable because of sensitivity scatter from one transducer to another and individual calibration is a problem. However, sensitivity scatter is not subject of time and ambient factors (within operating range) and it has no decisive role for SHM purposes. As separate sensors to be combined in integrated measurement network, the solutions for wiring and connections are also important. High level of electromagnetic noise in industrial circumstances demands noise proof solutions for cables and connectors.

3.2. Methodical solutions

OMA application for monitoring of industrial objects meets different problems that demands new methodical approaches. This section provides short description of OMA and multi-patch OMA, together with its applicability to the tasks presented in section 2. Moreover, structural health monitoring and diagnostic parameters are introduced.

3.2.1. OMA basics. Vibrational data from an object is gathered as time series data $x(t)$. This $x(t)$ is unique for each sensor, i.e. Degree of Freedom (DOF). Say there are $i = 1,2...N$ DOFs in the measurement, so there are N $x(t)$ vectors.

The goal of OMA is to obtain a set of modal parameters (frequency, mode shape and damping), which together fully describe dynamic characteristics of a system. There are several modal parameter estimation techniques and they may process $x(t)$ differently. OMA requirements for measurements are following:

- The excitation has to be random and flat in frequency (white noise).
- Spatial distribution of excitation has to be even across the object.

The Fast Fourier Transforms (FFT) of the vibrational output $x(t)$ is $X(\omega)$ which can be expressed as

$$X(\omega) = H(\omega)F(\omega), \tag{3.1}$$

where $H(\omega)$ - is frequency response function (FRF) of a system and $F(\omega)$ – is the applied force. In OMA $F(\omega)$ is not measured, so the only way to obtain $X(\omega)$ is to apply above mentioned requirements which indulge that $F(\omega)$ is a white noise. The frequency spectrum of a white noise is flat, so

$$X(\omega) \sim cH(\omega), \tag{3.2}$$

i.e. measured time signals mimic the FRF of the system. Factor c denotes a constant force and is necessary to match physical units. Note, that measured data is not actual FRF, but only an approximation of the latter. Some modal parameter estimation techniques use time domain (Stochastic Subspace Identification (SSI) algorithms [4,5]) or frequency domain (i.e. Extended Frequency Domain Decomposition (EFDD)[5,6,7]).

3.2.2. Multi-patch OMA. OMA technique requires concurrent measurement so, for monitoring of an industrial object with plenty of sensors each of them is to be provided with a measurement channel. Each measurement channel has to ensure signal conditioning, analog-to-digital conversion and data managing. Cost of multiple channels system is essential and this compresses potential area of OMA application. To avoid such obstacle the multi-patch approach could be used. This name means that OMA can be done in patches.

Let N be the amount of DOFs to measure and m – amount of available sensors ($m < N$). Certain sensors called *reference* sensors ($r = 1,2 \dots R$) are placed and not moved. Other available sensors are *roving* sensors and are moved between measurements. Each j patch is formed as

$$\{x_j\} = \begin{Bmatrix} \left[x_{ref_j}\right] \\ \left[x_{rov_j}\right] \end{Bmatrix}, \tag{3.3}$$

and consists of ($i = 1,2 \dots I$) measured DOFs, where

$$\left[x_{ref_j}\right] = x_{1_j}, x_{2_j} \dots x_{REF_j}; \quad \left[x_{rov_j}\right] = x_{1_j}, x_{2_j} \dots x_{ROV_j}, \tag{3.4}$$

where $REF = R$ is the number of reference sensors. Total amount of patches depends on its size and number of DOFs N. The idea is to mimic ordinary OMA setup by measuring all DOFs (not synchronously however). Sensors are not necessary to move around if they are already positioned the right way. In this case sensors are switched between available channels.

The problem of multi-patch OMA is that one system is being measured in different times, thus the applied forces vary for different patches. It is possible, however, to stitch patches together using data from reference sensors. Reference sensors are used to determine the energy of the excitation in each patch. After all DOFs are measured, patches are scaled to a designated patch k. Scaling patches together (or simply patching) can be performed in both time and frequency domains. Here the frequency domain case is shown. Temporal vectors $\{x_j\}$ from patch j are FFT transformed into $X_{ij}(\omega)$ and then formed into a $I \times REF$ matrix of power spectra

$$G_{ir}(\omega)_j = X_{ij}(\omega)\left(X_{rj}(\omega)\right)^*, \tag{3.5}$$

where i is an index number for a DOF in a patch, asterisk * - complex conjugate. Same goes for other patches. Patch j can also be divided into

$$G_{XX}(\omega)_j = \begin{Bmatrix} G_{XX}^{rov}(\omega)_j \\ G_{XX}^{ref}(\omega)_j \end{Bmatrix}. \tag{3.6}$$

There are different patching techniques (Classic approach, Post-Global Parameter Estimation (PoGER) and Pre-Global Parameter Estimation (PreGER)), with their advantages and disadvantages, but the most promising one is PreGER [1]. The rescaled power spectra matrix of patch j is obtained as follows

$$G_{XX}^{rov}(\omega)_{j\to k} = G_{XX}^{rov}(\omega)_j\left(G_{XX}^{ref}(\omega)_j\right)^{-1} G_{XX}^{ref}(\omega)_k. \tag{3.7}$$

After all patches are rescaled to have similar energy, their power spectra matrices are formed into one full power spectra matrix $G_{XX}(\omega)$ representing the whole structure. This matrix is then subject for a desired modal parameter estimation algorithm.

3.2.3. Methodical solutions. Traditionally simultaneous and multi-patch OMA is used to obtain modal parameters of tested object. This is necessary if one needs to diagnose structural health, as changes in modal shapes and frequencies show changes in objects condition. In order to validate OMA applicability for SHM and diagnostics, it is necessary to establish the variance of modal parameters between different measurements of the same state (condition). Obtained variance is then set as a threshold. If future modal parameters exceed the threshold, this would signalize that the objects state has changed. Some study about modal parameter variation for the same state has been done in [8] and here this work is extended with higher number of measurements.

Meanwhile, modal parameters comparison can be cumbersome and is rather subjective, just as the whole process of modal parameter estimation. There is a standard tool to asses condition change in objects – Damage Detection Indicator (DDI) [9], implemented in a well-recognised software product. This tool, however, is only applicable for synchronous OMA, so there is a need for DDI extension or alternative for multi-patch OMA. This paper introduces a method called Singular Vector Change Assessment (SVCA) and validates its effectiveness. As can be deduced from the name, this approach uses Singular Value Decomposition (SVD).

3.2.4. Singular Vector Change Assessment for state monitoring. Singular Value Decomposition is widely used in modal parameter estimation due to its ability to extract modal characteristics from measured vibrational data and it can be used for monitoring of structure's condition. SVD of cross-power spectra matrix of multi-channel output data is done as

$$G_{XX} = USV', \tag{3.8}$$

where U is orthogonal square matrix $N \times N$ of singular vectors, S is a diagonal $N \times R$ matrix of singular values and V' is the conjugate transpose of orthogonal $R \times R$ matrix V (also singular vectors).

Singular vectors U represent information about systems modal shapes, although not being directly modal shapes.

U vectors are directly dependant on the systems state – if the state is modified, then modal characteristics change, thus U changes as well. SVCA utilizes this property of U vectors. First, vibrational data is formed into power spectra matrix G_{XX} with the size of $N \times R \times f_s$ (the latter is the sampling frequency). Then this 3D matrix is SVD decomposed and $N \times N \times f_s$ U matrix is obtained. This version of SVCA takes only the first column vector of U matrix (first singular vector), because it is represented with the most energy on a particular frequency (property of SVD). Matrix of first singular vectors is formed with the size $N \times f_s$. This matrix or singular vector field is then normalized value-by-value with baseline condition singular vector field. The overall mean of the resulting difference matrix is a single SVCA parameter

$$SVCA = \frac{1}{N \cdot 0.5 f_s} \sum \frac{U}{U_{base}}, \tag{3.9}$$

which shows a value of condition change relative to the initial (baseline) condition. The baseline singular vector field U_{base} is obtained from an averaged set of singular vectors obtained from reference condition measurements. There are new methods that allow evaluating condition without baseline data [10], which can be useful for some applications. However, these methods are limited to the complexity of the structure, e.g. are only able to analyse plate structures. That is why, for reliability reasons, baseline data are still required.

In equation (3.9) SVCA parameter is normalized to the number of DOFs times half the sampling frequency. Singular vectors for negative and positive sides of power spectra are copies of each other. This would result in a doubled SVCA parameter, hence the factor 0.5 in the denominator.

Main privilege of SVCA application for SHM is that it does not require preliminary identification of modal properties of the object and it can be easily implemented in automatic data processing applications.

3.2.5. Damage Identification Using Modal Parameters Variation. Above considered SVCA allows monitoring of structure's state but not damage identification. For latter case the estimation of object's modal parameters modification is required. There are examples and some experience in estimation of modal parameters variation in [3]. To estimate modification of k^{th} mode the Modal Parameters Variation (MPV_k) is used as integrated parameter, which considers both modal frequency and shape modification from its initial state (or baseline). The Degrees of Freedom (DOFs) where dynamic data are measured are considered distributed alongside the object by J sections (levels, etc.) and each section (level) has I DOFs. The ensemble of modal parameters experimentally obtained using OMA in the state S could be written as eigenvector matrix

$$[\boldsymbol{M}]_{\mathbf{S}} = [\boldsymbol{m}_{i,j,k}] \tag{3.10}$$

where i – number of DOFs in one section ($i = 1 \ldots I$),
j – number of sections ($j = 1 \ldots J$),
k – mode number ($1 \ldots K$),
$m_{i,j,k}$ – eigenvalue measured at $DOF_{i,j}$ of k^{th} mode.

For difference $\Delta \boldsymbol{M_S}$ estimation between current state $\boldsymbol{S}$ and initial state $\boldsymbol{B}$ (or baseline) the modal parameter $\boldsymbol{M_S}$ to be compared with the modal parameter $\boldsymbol{M_B}$

$$[\Delta \mathbf{M_S}] = [\mathbf{M_S}] - [\mathbf{M_B}] = [\mathbf{m}_{\mathrm{i,j,k}}]_{\mathbf{S}} - [\mathbf{m}_{\mathrm{i,j,k}}]_{\mathbf{B}}. \tag{3.11}$$

Keeping in mind that MPV_k is estimator of $\boldsymbol{k^{th}}$ mode, we can present (3.11) in another way

$$[\Delta\mathbf{M_S}] = \mathrm{MPV}_\mathbf{S} = \frac{1}{k}\sum_{1}^{k} MPV_k. \tag{3.12}$$

$\mathrm{MPV_S}$ parameter measures total difference between two states of an object's in relative scale and depends on DOF number. As a parameter, independent from DOF amount, the Modal Parameters Variation Intensity $MPVI_\mathbf{S}$ is used

$$MPVI_\mathbf{S} = \left[\frac{\sum_i \sum_j \sum_k m_{i,j,k}}{IJK}\right]_S. \tag{3.13}$$

$MPVI_\mathbf{S}$ does not depend on DOF amount and may be applied for consideration of the object states with different measures. This measure is good for SHM purpose to estimate how much the current state has changed compared to the baseline.

3.2.6. Random Component Extraction. OMA technique works well in case of random excitation but there are very few objects with random excitation only. Most industrial objects have external sources of periodic excitation - rotating machines/mechanisms or any other deterministic actuators. In OMA dynamic data of an object is obtained from dynamic signals and if some deterministic components are not negligible, OMA results can be corrupted. To conform to OMA assumptions, only the random component of dynamic data is to be extracted.

The solution for proper data extraction is based on consideration of object's dynamic behavior as superposition of natural modal oscillations (under random excitation) and vibration forced by deterministic actuation. For large structures ambient environment is the main source of wide frequency band random excitation, like wind, waves, passing transport and so on. Also, practically all machinery on industrial objects radiate random component of vibration generated by bearings, gears, blades, etc. So, the essential part of vibration energy that actuates an object's structure is random and is distributed in wide frequency range.

Thus, to apply OMA for SHM of industrial object one needs to separate vibrational signal into random and deterministic. Random component extraction or "refinement" could be arranged by deducting periodic component from a raw signal. Typically, vibration of an object contains periodic components of different origins that is why periodic components are consequently deducted in data processing stage. The "refined" wideband random component may be used for modal properties identification using OMA techniques. Then periodic components can be used for vibration diagnostics of actuating part of objects, like rotor and bladed machines, gearboxes, generators etc. Random signal refinement is not studied in this paper leaving it as a topic for detailed analysis in future series of papers.

4. The laboratory model of industrial objects

There are many types of industrial objects like energy towers, bridge supports, dams, etc., which functionality requires its health monitoring. Its structural damage or loosing of load carrying features may cause dramatic consequences. The most damageable group includes those industrial objects, which on top of ambient excitation may suffer additional dynamic loads from its own functioning. For instance, wind generators, going ships or flying aircrafts, operating pipeline parts next to pump station etc.

The laboratory model supposed for validation of SHM techniques must have typical features of industrial structures:

- a massive foundation capable to simulate grounding of the model,
- a structure similar to industrial,
- functional unit generating both periodical and random excitation.

The measurement system of the model must provide:

- collection of dynamic signals from whole structure,

- signals commutation to multichannel measurement system

This section reveals in details what is the wind generator model, how the measurement network is designed and is functioning along with some measurement setup.

4.1. Model construction

The laboratory scaled model of wind generator (figure 1) that is high as an adult human was built up to conform above requirements. The model includes three structural parts: the base (1), the tower (3) and the rotor head (4). The base (1 on figure 1b) is the massive 1 by 1 m concrete slab weighting approximately 70 kg. It rests on the floor via rubber pads. This base acts as an immovable mass that separates the rest of the model from the floor and vibrational noise.

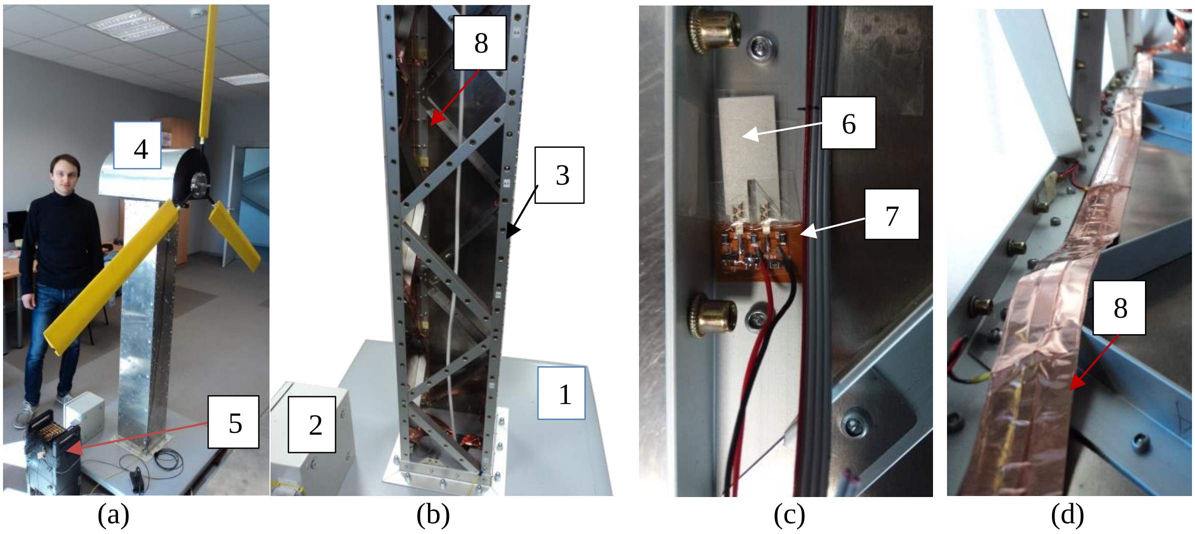


Figure 1. Wind generator model: (a) common view, (b) view on the tower structure without front panel, (c) measurement unit (film sensor with preamplifier), (d) harness cable. 1 – base; 2 – commutation box; 3 – tower; 4 – head; 5 – DAQ; 6 – piezo-film; 7 – preamplifier; 8 – cable.

The base bears the tower (3 on figure 1b) and the commutation box (2 on figure 1b). The tower is a frame made out of 20 by 20 mm aluminium angle beams. The tower has outer walls, riveted to the frame from three sides and a removable panel is screwed on the fourth side. The rotor unit (4 on figure 1a) is equipped with three rotating blades driven by electric motor and transmission inside a housing part. The electric control unit is mounted on the back of the housing to turn power on/off and adjust rotation speed. When operated, the motor, the transmission and the rotor provide periodic excitation to the tower, but blades also generate air turbulent excitation of the tower structure. Electric noise shielding is provided for the cables in such way that could be used as prototype in industrial conditions on the next study stage. Figure 1d illustrates the shielded ribbon cable connecting deformation transducers to commutation unit.

4.2. The measurement and data processing system

The model is equipped with 32 deformation transducers allocated around the models structure. Each transducer includes piezo-film sensor (6 on figure 1c) and preamplifier (7). Such sensor type was successfully used for OMA application for pipeline condition monitoring in [2] and rotating blade models [3]. Each sensor is attached to the surface of the frame beams using adhesive tape. Transducer leads are soldered to the flat ribbon cable 8 (figure 1d), stretching along the tower, curving around obstacles. There are four cables, one cable for each tower edge. Cables are terminated in the commutation box allowing signals grouping by patches.

All sensors are allocated vertically along each beam axis. There are seven vertical levels and one diagonal group with four sensors in each. Each set of four sensors is grouped into single connector in the commutation box and can be freely connected to any set of 4 input channels on the data acquisition system (DAQ). Sensors are numerated from 1.1 to 8.4. First digit stands for the group position (1-7 are horizontal, 8 is diagonal), with 1 being the lowest to the ground and 7 is the highest, just under the rotor unit. Second digit denotes one of four edges where sensor is located on. In this study diagonal group of sensors (8.1 – 8.4) was not used.

Data processing system includes DAQ that is Brüel & Kjær PULSE 48 channel frame (5 on figure 1a) and processing unit that is PC with Artemis software platform.

5. Study of the models dynamic characteristics

5.1. FEM analysis

To support modal identification of experimentally obtained results, Finite Element Analysis using NeiNastran was performed on the 3D solid model of the wind generator tower. However, even after careful modelling FEM results had large discrepancy with experimental data. Still, FEM analysis of an approximate wind generator model allowed evaluating principal mode shapes that are expected in the experimental results.

5.2. Physical experiments

Principal tasks of experimental stage are:

- Adaptation of the modal testing technique for the given object,
- Experimental study of natural modes of the object, towers modes identification and comparison with modelled ones;
- Evaluation of estimated modal parameters uncertainty in simultaneous tests,
- Experimental study of natural modes of the object using multi-patch approach,
- Evaluation of estimated modal parameters scatter (uncertainty) in multi-patch tests.

Section 6 will also include study of damage detection approaches for the tower.

5.2.1. Excitation

The scaled model is designed to provide periodic excitation to the studied structure, as it is often a case in real life scenarios. In section 3 it has already been mentioned that OMA requires excitation close to white noise (flat in frequency domain). Obviously periodic excitation contradicts this requirement and poses a problem for OMA. It is assumed, however, that one can overcome this problem and even use periodic excitation for SHM. This assumption is not dealt with in this paper and is left for study for the next research stage.

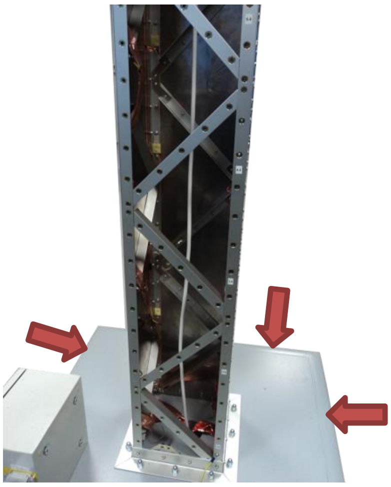


Figure 2. Illustration of sledge hammer impacts on the base of wind generator model.

On the study described in this paper only random impacts were used to generate excitation of the model. Impacts by the plastic head hammer on to different points of the model excited the structure. To optimize excitation technique three types of actuation, including points, impacts force and frequency have been tested. Number of discovered modes and its repeatability were the criteria of excitation technique suitability.

Impacts with a sledgehammer on the base, powerful enough to excite certain modes. Impacts fall normally on four sides of the base (red arrows in figure 2) in horizontal plane, simulating earthquake effect of the structure. Occasional impacts are variated around the base to fulfil OMA requirement about random spatial distribution of excitation.

Impacts with sticks on the walls. The hammer impacts in this case overload the sensors so researcher hits the walls of the tower with wooden stick. Hits are made in random locations.

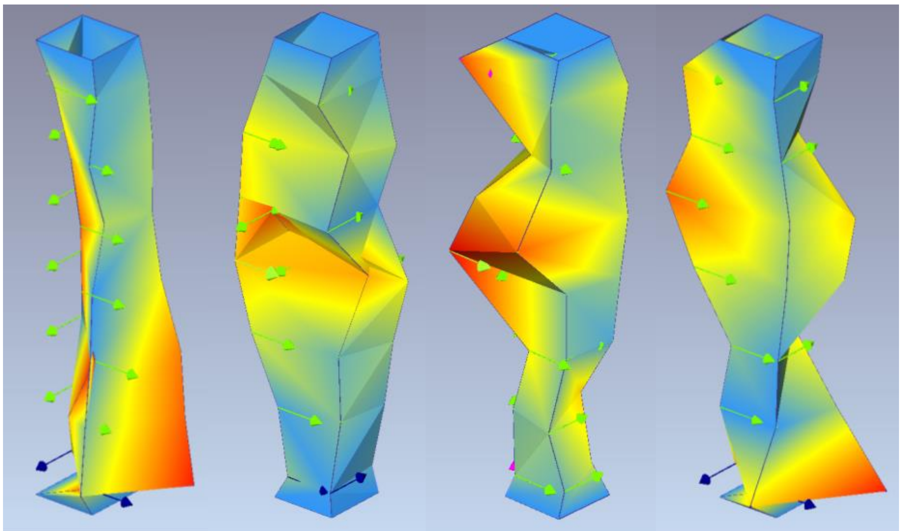
Impacts on the top of the model with a sledgehammer. The hits were made across the perimeter of the rotor unit (header), frequently, in the same manner as with the first excitation case.

As it turned out, impacts on the walls and on the top did not provide satisfactory excitation because of weak modes emanation and repeatability. With the second case (hits on the walls) it appeared that the walls reacted to the excitation more than the frame. As can be seen on figure 1c, the sensors are placed on the frame and walls vibration does not excite the structure well enough. Energy from impacts on the top did not distribute around the structure well, and hits overloaded the sensors (measurement channels).

After examination of excitation types it was decided to go with impacts on the base for the study. By this way of actuation the base acts as a buffer and impacts provide sufficient energy to the structure to excite natural modes. Single hit energy is being provided to a point on the base, which dissipates this energy and provides spatially even distributed energy to the frame as opposed to the hits on the frame itself, where all energy of the hit is dissipated closely around the impact point.

5.2.2. Simultaneous measurements

Each modal test of the model is a 120 seconds simultaneous measurement of 28 sensors (only horizontal sections are used; 4 diagonal sensors are excluded). Test output is deformation data collected from 28 sensors.



Nr. 1 Nr. 2 Nr. 3 Nr. 4

Figure 3. Experimentally obtained mode shapes. Left – 66.1 Hz (1st bending mode); center left – 206.1 Hz (1st axial mode); center right – 323.7 Hz (1st torsional bending mode), right (combined mode) – 534.6 Hz.

The first test session of five repeated tests is made (*Base 1*) with the same duration and similar impact parameters using simultaneous measurements. Measured data is processed in frequency range up to 1600 Hz using Enhanced Frequency Domain Decomposition (EFDD) and Stochastic Subspace Identification Unweighted Principal Components (SSI-UPC) techniques in Artemis platform. Resulting modal parameters (frequency and shape) were compared to FEM computed parameters.

After investigation of estimated modes using EFDD and SSI-UPC technique it was found that EFDD provides sufficient and stable estimation of modes, especially those of higher interest. It is decided to further use only EFDD for the sake of consistency.

Figure 3 shows those shapes of the modes, which demonstrated the best shape and frequency stability and repeatability. These modes were estimated consistently for all 5 tests. There were other modes estimated as well, but they were not consistent from test to test, so it is decided to select only the presented ones. As was mentioned earlier, FEM analysis helped in identifying several mode shapes and labeling them accordingly, as written in the caption of the figure 3.

Uncertainty of estimated modal parameters in simultaneous tests was evaluated using scatter of MPVI parameters (considered in section 3.2.4). Repeated set of 5 OMA tests (*Base 2*) was done with the same conditions as for *Base 1*. Scatter estimates of two test series are presented in table 1 in columns titled *Base 1* and *Base 2*.

5.2.3. Multi-patch measurements

There were 5 multi-patch OMA measurement sessions performed executing the approach discussed in 3.2.2. Each session consisted of 6 consecutive tests-measurements. Each test was done by measuring two groups of channels, where one is the 1st sensor group (next to base) and the 2nd is one of the other channel groups. These two groups of 8 sensors form a patch, which gives possibility to measure the structure with 28 sensors using only 8 channels. The group pairing consequence was: {1-2}, {1-3}, {1-4}, {1-5}, {1-6} and {1-7}. Remember, that each group has 4 sensors on the same vertical level. Each measurement was 120 s long. 1st level group sensors are taken as reference sensors. Careful reader might question this choice of reference sensors, as they are not evenly distributed across the structure. This choice is dictated by 1st group being positioned on an actuation path and technical limitations of the measurement setup. As practice showed, modal parameter estimation did not suffer from this. It also is assumed that this choice will not influence the quality of damage identification. Figure 4 shows comparison of SVD plots of the power spectra matrices (regarded here as output spectra) between simultaneous measurement and multi-patch approach.

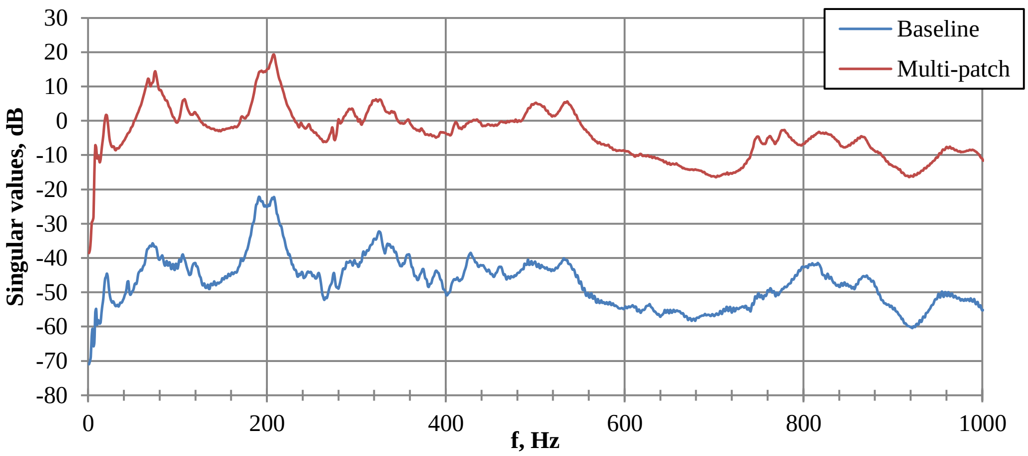


Figure 4. SVD plots of output spectra: a) – simultaneous measurement, b) – multi-patch measurement.

The scatter (uncertainty) of modal parameter estimates between 5 multi-patch sessions is given in table 1 (columns titled as *Multi-patch*).

5.3. Modal parameters variation for a single condition

Variation of modal parameters in all tests was estimated using MPVI. Table 1 and figure 5 illustrate separate (frequency and shape) MPVI values as well as combined ones.

Combined MPVI values were calculated as an average value between frequency and shape scatter. In table 1 scatter of combined parameter for *Base 1* and *Base 2* for different modes vary within 2.6%, however common (average) scatter does not exceed 1.2%. Table 1 also allows comparison of the scatter between modal parameters of repeated tests performed with simultaneous OMA and for multi-patch OMA. It is evident that multi-patch cases have scatter 1.5-2 times less than for simultaneous cases.

Table 1. Modal parameter scatter obtained with MPVI.

mode	f, Hz	Base 1			Base 2			Multi-patch		
		freq.	*shape*	*comb*	*freq.*	*shape*	*comb*	*freq.*	*shape*	*comb*
1	66.6	0.8%	1.37%	1.06%	0.2%	1.66%	0.92%	0.5%	0.51%	0.50%
2	205.8	0.4%	1.26%	0.85%	0.2%	1.43%	0.83%	0.1%	1.06%	0.58%
3	323.4	0.3%	2.95%	1.61%	0.0%	5.24%	2.63%	0.4%	2.38%	1.39%
4	533.4	0.7%	0.72%	0.68%	0.2%	0.61%	0.40%	0.4%	0.52%	0.44%
Average		0.52%	1.58%	1.05%	0.16%	2.23%	1.20%	0.34%	1.12%	0.73%

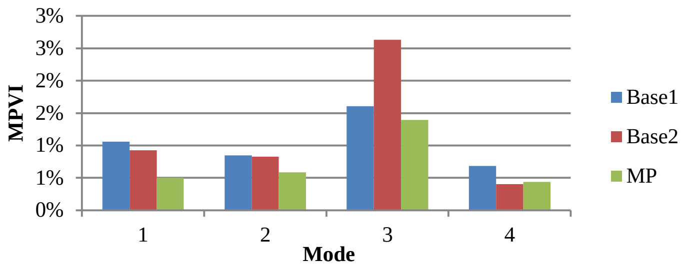


Figure 5. Modal Parameter Variation Intensity (MPVI) in three test series.

It is important to note that the scatter of estimated modal parameters in multi-patch testing appears to be smaller than in simultaneous measurements. Multi-patch reduces uncertainty of modal parameters estimation thanks to more averaging (more measurement time) used from reference sensors perspective. More measurement time results in a higher energy transmitted to the system which can be observed in figure 4.

MPVI here was used to estimate uncertainty in modal parameters estimation for two types of OMA, but this parameter can also be used to determine condition change, hence indicate possible damage.

6. Damage detection

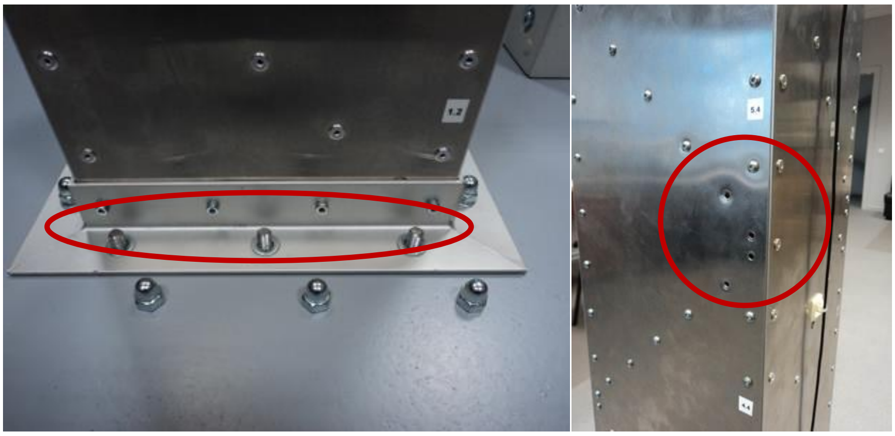
The main goal of discussed study is damage indication and identification in structures. For monitoring purposes any damage indication is enough, but for diagnostic purposes damage identification and localization is necessary. Both above mentioned are considered briefly in this paper: first – using SVCA as the tool for monitoring of structure's health, second – applying MPVI as the parameter for damage identification and localization.

Experimental validation of above techniques includes consequent implementation of two defects into the structure (defects are not mixed). First – unscrewed nuts on the base fixation on one side of the tower (Figure 6a), referred here as Defect 1. This can be classified as a global defect, because it alternates the boundary conditions of the system. Another defect is of a local nature – four unscrewed screws in one joint in the middle of the tower (Figure 6b). These screws serve as connection between the frame and the panel, which means that local stiffness becomes alternated. This defect is referred as Defect 2. Tests aimed for damage identification were done using simultaneous OMA measurements only.

6.1. SVCA as monitoring tool

The data obtained in five OMA tests, shown previously in section 5.2.2 as *Base 1*, were taken as 5 reference measurements. The singular vector fields (section 3.2.4) of *Base 1* were averaged into one single field called *Baseline*. Each of the 5 reference singular vector fields are then related to the

Baseline, together with singular vector fields obtained from 2 defected measurements. The resulting SVCA values were transformed into percentage, where 0% is the baseline value. The higher the value, the more is the difference between singular vector fields, thus the difference between modal characteristics. This difference can signalize how much the condition of the object modified, compared to the baseline (Figure 7).



(a) (b)

Figure 6. Artificial defects. (a) – defect 1; (b) – defect 2.

SVCA shows good sensitivity to a common type of defects, both global and local. Unscrewed base nuts (Def1) lead to 43.9 % difference with baseline that is a good indication of condition modification. Essentially smaller example of structure's modification as lack of 4 screws in joint area between panel and frame gives 27.4 % difference. Taking into account that the uncertainty of the parameter can be subjectively set to less than 2%, SVCA shows good capability for monitoring structural health.

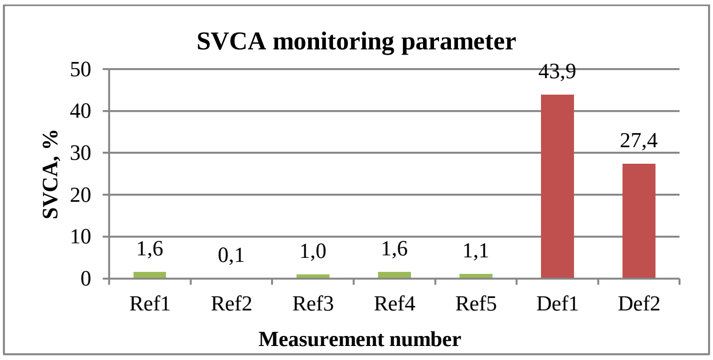


Figure 7. SVCA for 5 primary measurements and 2 defected measurements.

6.2. MPVI application for structural diagnostics

Both defected test data were processed through Artemis software and modal parameters variation were estimated. Table 2 shows MPVI parameters comparison between baseline measurements (also shown in table 1 as *Base 1*) and faulted states of the structure. Defects caused different changes in modal parameters. Figure 8 displays combined MPVI values for all three states.

In Figure 8 one can notice that first defect causes MPVI increase for all modes, which shows global nature of the defect. Further analysis shows that first mode frequency has changed by 4.4% and the shape differs by 2.49% (MPVI parameter), which is higher than natural scatter of 0.8% and 1.37% correspondingly. Second mode also has significant frequency shift – 2.3% whereas the scatter is only 0.4%. Similar discussion is right for other modes that have highly pronounced global behaviour, so one can deduce that boundary conditions or other global properties have changed. Taking into account that the first mode shape resembles 1st bending mode, it can be also supposed that the defect is in the lowest area of the tower or on the base. In practice it means that structure's modification could be identified automatically close to the base and an inspection is needed for that part of the structure.

Table 2. Modal parameter scatter obtained with MPVI for baseline and defected conditions.

mode	f, Hz	Base 1			Defect 1			Defect 2		
		freq.	*shape*	*comb*	*freq.*	*shape*	*comb*	*freq.*	*shape*	*comb*
1	67.0	0.8%	1.37%	1.06%	4.4%	2.49%	3.44%	0.6%	1.66%	1.11%
2	205.7	0.4%	1.26%	0.85%	2.3%	2.03%	2.18%	0.1%	1.73%	0.93%
3	324.1	0.3%	2.95%	1.61%	0.4%	5.16%	2.76%	0.2%	6.50%	3.32%
4	532.1	0.7%	0.72%	0.68%	1.3%	2.78%	2.04%	0.5%	1.51%	1.01%
Average		0.52%	1.58%	1.05%	2.10%	3.11%	2.61%	0.33%	2.85%	1.59%

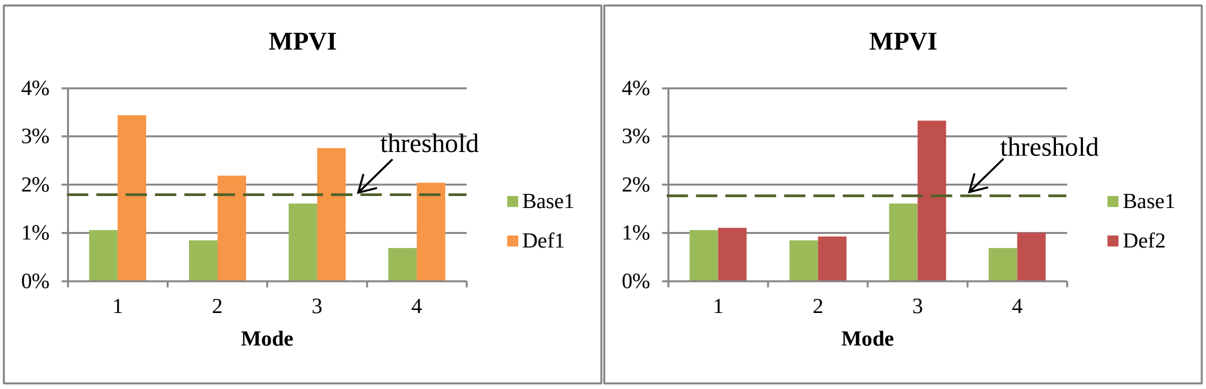


Figure 8. MPVI parameters estimated for baseline and defected measurements.

It is necessary to note that analysis of mode shapes modification also includes mode shape comparison. This means that the mode estimated from the first state is verified (e.g. Modal Assurance Criterion) to be a modified version of the first state estimated mode. Otherwise there is a risk of comparing two different modes, which obviously will give incorrect result.

Defect 2 was applied in the middle of the structure, only on one of four edges. That is why frequency MPVI (0.33%) as global parameter does not signalize any change in the structure and remains within reference scatter (0.52%). However, the shape MPVI of the 3rd mode (6.5%) clearly indicates there is a problem with the structure. As MPVI value exceeds threshold only for the 3rd mode, it means most probable damage location is tower's central section, where maximal deformations were found (figure 3). Obviously, higher spatial resolution and more modes will bring up accuracy of this approach.

These examples clearly show that MPVI is a handy tool for diagnostics of structural condition. With some adjustments and more estimated modes it is even possible to accurately locate the defect using MPVI.

7. Conclusion

The laboratory scaled prototype of operating industrial structure was developed for study of structural health monitoring and diagnostics techniques. Optimization of technological and methodical aspects was addressed, i.e. selection of an object for modelling, measurement network and system, type of transducers, signal processing technique, etc. Selected solutions were evaluated, analysed and validated both computationally and experimentally. As the outcome, wind generator scaled operating model was designed with integrated network of deformation sensors. Experimental testing with OMA application was performed on the model in different states, establishing confidence in possibility to perform damage detection for industrial structures using OMA approaches.

It is necessary to stress the fact, that not only multi-patch OMA modal parameter scatter is lower than for simultaneous OMA, but also modal parameter estimation is more stable, thanks to higher integrated energy provided to the system in multi-patch OMA.

Singular Vector Change Assessment parameter proved to be valuable for monitoring structural condition, as it showed dramatic change of modal characteristics of the modified object. Modal Parameter Variation Intensity together with mode shape visualisation is very handy for diagnostic purposes. An engineer with adequate understanding and experience can identify and localize defects by analysing MPVI and mode shapes or additionally use more advanced algorithms as in [11].

Due to time limitations damage detection using multi-patch OMA was not performed. However, it is of strong confidence that multi-patch OMA results will not differ significantly from simultaneous OMA results, based on the scatter estimates comparison in section 5.3. Future research will feature multi-patch OMA damage detection.

It is also planned to extend OMA possibilities for structures with deterministic excitation, as mentioned in section 3.2.5.

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