Operational Modal Analysis of a Wind Turbine Mainframe using Crystal Clear SSI

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ABSTRACT

Experimental investigations of the dynamic behavior of wind turbine components as well as of the turbine's overall dynamics are important for the evaluation of applied prediction models. Operational Modal Analysis (OMA) was applied to identify resonant frequencies, corresponding mode shapes and damping values.
Experimental investigations were carried out at the main frame of a Fuhrländer AG 2.5 MW wind turbine with a rotor diameter and a hub height of each ca.100m. Structural responses were recorded at a stopped turbine excited by the stochastic wind only. The complex structure of the mainframe as well as its interaction with the tower and the turbine blades makes it non-trivial to perform the modal analysis.
In the paper the new Crystal Clear Stochastic Subspace Identification (CC-SSI) technique is applied. This technique produces very clear stabilization and easy automatic mode extraction even for complicated systems with a large number of modes as considered here.
At a wind turbine, there is usually a restriction in easily applicable measurement locations. Since time series were recorded only at the main frame of the turbine, overall mode shapes of the entire turbine were identified applying a combined identification using Finite Element Analysis (FEA).

1. INTRODUCTION

In order to avoid resonances in the variable speed range of a wind turbine, resonant frequencies of the entire turbine including substructure resonant frequencies as well as harmonic excitation must be known accurately. Whereas the harmonic excitation frequencies are multiples of the rotational speed and well known, resonant frequencies have to be calculated using a proper model or identified experimentally. A verification of calculated results by a measurement is the preferable approach.
The lowest resonant frequencies of the entire turbine and corresponding mode shapes, affected mainly by tower and blades, have to be considered with respect to the first and third order excitation (rotational frequency and blade passing frequency respectively) in order to avoid severe resonance problems during operation.
Resonant frequencies of the main frame have to be considered with respect to higher excitation orders resulting i.e. from the rotational frequency of the generator. Dynamic deflections of the main frame, potentially inducing undesirable loads of the drive train, have to be minimized.

Two aspects are important in order to obtain experimental data from a wind turbine. Firstly, how the turbine can be excited and, secondly, which measurement locations are accessible?
Easy applicable measurement locations can be found at the tower and at the nacelle, whereas locations at the rotor blades can only be used at a high expense. However, missing experimental rotor blade data are leading to uncertainties in the experimental identification procedure, caused by the fact that mode shapes cannot be identified completely and distinguishable.
In order to excite the entire wind turbine with sufficient frequency content, an artificial excitation using release lines is known but difficult to realize. The application of an excitation mass, as an alternative, is ineffective because of its restricted induced energy content. Therefore, the application of Operational Modal Analysis (OMA) using the stochastic excitation by the wind appeared to be a promising approach.

The experimental investigations described in this paper were carried out at a Fuhrländer AG 2.5 MW wind turbine (rotor diameter and hub height 100m), designed by W2E Wind to Energy GmbH (see Figure 1). Nacelle construction including main frame, gearbox, generator and transformer can be seen in Figure 2.

Figure 2: Nacelle construction with main frame

Figure 1: Fuhrländer 2.5 MW wind turbine, designed by W2E

2. EXPERIMENTAL INVESTIGATION

In using operational modal analysis the structure is excited by ambient vibrations resulting from the wind only. Excitations can be assumed to be random in space and time with small correlation length compared to the size of the wind turbine. Since fluctuations of the wind speed increases by increasing wave length, the white noise excitation level cannot be assumed to be constant over frequency. Accordingly, lower modes should be excited more intensive.

The applied measurement model is shown in Figure 3. In view of an easy sensor installation, only measurement locations at the main frame were used. Degrees of freedom that were not measured at the main frame could be

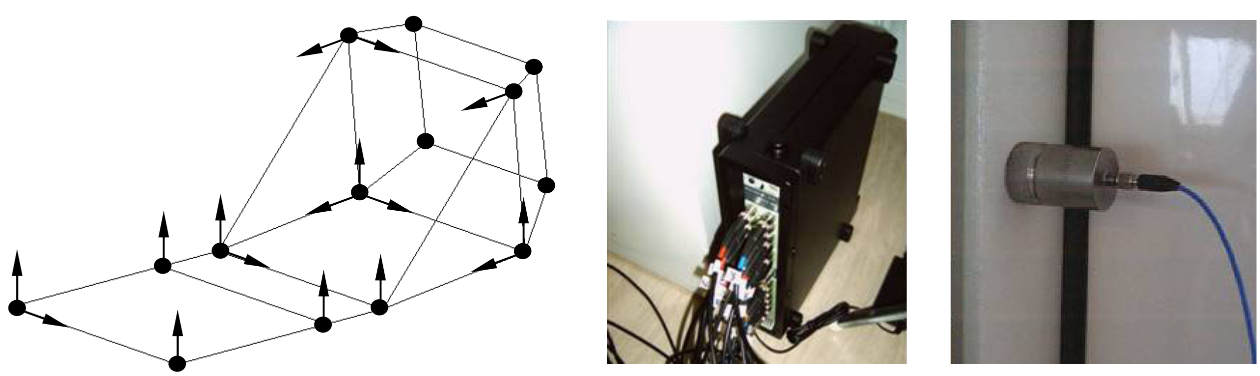

Figure 3: Measurement locations at the main frame, data acquisition system Dyn-X and seismic accelerometer

interpolated within the frequency range considered. To provide an identification of the mode shapes of the entire turbine based on the recorded main frame data, a Finite Element model was additionally generated.
During the measurement campaign the turbine was stopped and the rotor blades were pitched out of the wind (feathered position) The vibration responses were recorded over a period of 60 minutes, sampled with a frequency of 128Hz. For data acquisition a Dyn-X system (BRUEL&KJAER) with 2*24-bit AD-converter (dynamic range 160dB) in combination with seismic accelerometers (piezoelectric, sensitivity: 10V/g, PCB) were applied (see Figure 3).

3. IDENTIFICATION TECHNIQUE

Since the pioneering work of Overschee et al. [1] was presented a decade ago, there is no doubt that the Stochastic Subspace Identification (SSI) techniques are the most well-known and used parametric time domain estimators. Here in this paper a new generation of these techniques is applied. The SSI techniques fit discrete-time stochastic state space realizations with the following underlying model structure:

$$\begin{aligned} x_{k+1} &= Ax_k + v_{k+1} \\ y_k &= Cx_k \end{aligned} \tag{1}$$

where $\boldsymbol{A}$ is the state transition matrix including all the system dynamics. $\boldsymbol{x}_k$ is the internal state vector that holds the current state of the system at time instant k. $\boldsymbol{v}_{k+1}$ is the Gaussian white noise process that is driving the system. The observable output of the system is located in $\boldsymbol{y}_k$ and is obtained by a pre-multiplication of $\boldsymbol{x}_k$ with an observation matrix $\boldsymbol{C}$.

Assuming that the system has been sampled using a sampling interval at T seconds, the continuous-time eigenvalue and mode shape ($\mu;\phi_\mu$) are given by the eigenstructure ($\lambda;\phi_\lambda$) of $\boldsymbol{F}$:

$$\begin{aligned} e^{T\mu} &= \lambda \\ \phi_\mu &= C\phi_\lambda \end{aligned} \tag{2}$$

The natural frequency and damping are the obtained directly from μ .

Only knowing the output data $\boldsymbol{y}_k$ at the time instants $k = 1,\ldots, N$, the aim is to identify the eigenstructure ($\lambda;\phi_\lambda$) of the system (1) with Stochastic Subspace Identification algorithm called the Unweighted Principal Component algorithm, see Overschee et al. [1].

We choose p and q as index variables with $p + 1 \geq q$ that indicate the quality of the estimations, where larger p leads to better estimates, and the maximal system order ($\geq qr$ with the number of measurement channels r). Normally, we choose $p = q - 1$, but in the case of measurement noise $p = q - 1 + l$ should be chosen, where l is the order of the noise. Two data matrices of measured output are constructed:

$$Y_{p+1}^{+} = \begin{bmatrix} y_{q+1} & y_{q+2} & : & y_{N-p} \\ y_{q+2} & y_{q+3} & : & y_{N-p+1} \\ : & : & : & : \\ y_{q+p+1} & y_{q+p+2} & : & y_N \end{bmatrix}, \quad Y_q^{-} = \begin{bmatrix} y_q & y_{q+1} & : & y_{N-p-1} \\ y_{q-1} & y_q & : & y_{N-p-2} \\ : & : & : & : \\ y_1 & y_2 & : & y_{N-p-q} \end{bmatrix} \tag{3}$$

For the Unweighted Principal Component algorithm we build a weighted Hankel matrix from the above data matrices:

$$H_{p+1,q} = Y_{p+1}^{+} Y_q^{-T} (Y_q^{-} Y_q^{-T})^{-1} Y_q^{-} \tag{4}$$

As the computation of (4) usually is a large matrix the calculation is in practice based on QR decomposition of the data matrices, see Overschee et al. [1] for details. The weighted Hankel matrix of (4) can also be expressed in terms of the observability matrix $\boldsymbol{O}_{p+1}$ and a sequence of state vectors $\boldsymbol{X}_q$:

$$H_{p+1,q} = O_{p+1} X_q \quad , \qquad O_{p+1} = \begin{bmatrix} C \\ CA \\ : \\ CA^p \end{bmatrix} \tag{4}$$

The observability matrix $\boldsymbol{O}_{p+1}$ is obtained from an SVD of the matrix $\boldsymbol{H}_{p+1,q}$ and its truncation at the desired model order:

$$\begin{aligned} H_{p+1,q} &= U \Sigma V^T \\ &= \begin{bmatrix} U_1 & U_2 \end{bmatrix} \begin{bmatrix} \Sigma_1 & 0 \\ 0 & \Sigma_2 \end{bmatrix} \begin{bmatrix} V_1^T \\ V_2^T \end{bmatrix}, \\ O_{p+1} &= U_1 \Sigma_1^{1/2} \end{aligned} \tag{5}$$

The observation matrix $\boldsymbol{C}$ is then found in the first block-row of the observability matrix $\boldsymbol{O}_{p+1}$. The state-transition matrix $\boldsymbol{A}$ is obtained from the remaining block rows of $\boldsymbol{O}_{p+1}$, defined as

$$O_p^{\uparrow} = \begin{bmatrix} CA \\ CA^2 \\ : \\ CA^p \end{bmatrix} = O_p A \tag{6}$$

by minimizing the norm of the difference $O_p^{\uparrow} - O_p A$ with respect to $\boldsymbol{A}$. In the ARTeMIS Extractor used for analysis in this paper the minimization is performed conditionally emphasizing a user defined number of most well-excited eigenvalues. The algorithm is called Crystal Clear SSI®, and the details are presented in Goursat et al. [2]. This algorithm results in much more clear stabilization than the usual unconditional minimization schemes by forcing almost all noise modes to have a natural frequency much higher than the Nyquist frequency and thus reducing their disturbing effects on the physical modes.

The Crystal Clear SSI® algorithm has been successfully applied to applications where conventional SSI algorithms usually have performance problems such as non-stationary short time series, e.g. measurements of launch of aerospace vehicles, see Goursat et al. [3].

4. RESULTS

4.1 PARAMETER IDENTIFICATION

As noted before, the software ARTeMIS Extractor was used for modal parameter identification. To extract resonant frequencies, corresponding mode shapes and damping values, a frequency domain technique (Enhanced Frequency Domain Decomposition, EFDD) was applied for a preliminary analysis as well as a time domain technique (Stochastic Subspace Identification, SSI [1]) for a detailed analysis. In case of the Stochastic Subspace Identification the new feature Crystal Clear SSI® was employed and compared to the standard algorithm.

Using the EFDD, a Singular Value Decomposition (SVD) of the Power Spectral Density (PSD) was carried out in a first step. Since the singular values near the resonant frequency are proportional to the PSD of a SDOF system, it was used as a starting point for modal parameter estimation [4], [5]. To reduce random and leakage errors in PSD estimation, especially for damping identification of the first modes (starting from 0.3Hz), the long recording times (60 minutes) were necessary [6], [7].
Singular values of PSD matrices for the lower frequency range are shown in Figure 4. Because of the spectral characteristic of ambient wind loading, especially low frequency modes of the turbine structure were well excited. Hence, singular values were showing their typical behavior and modal parameters could be identified easily. Problems occurred identifying the damping and separating the mode shapes of repeated modes using first and secondary singular values. Partially this is caused by the incompleteness of the measurement model, especially for the lower frequency range.

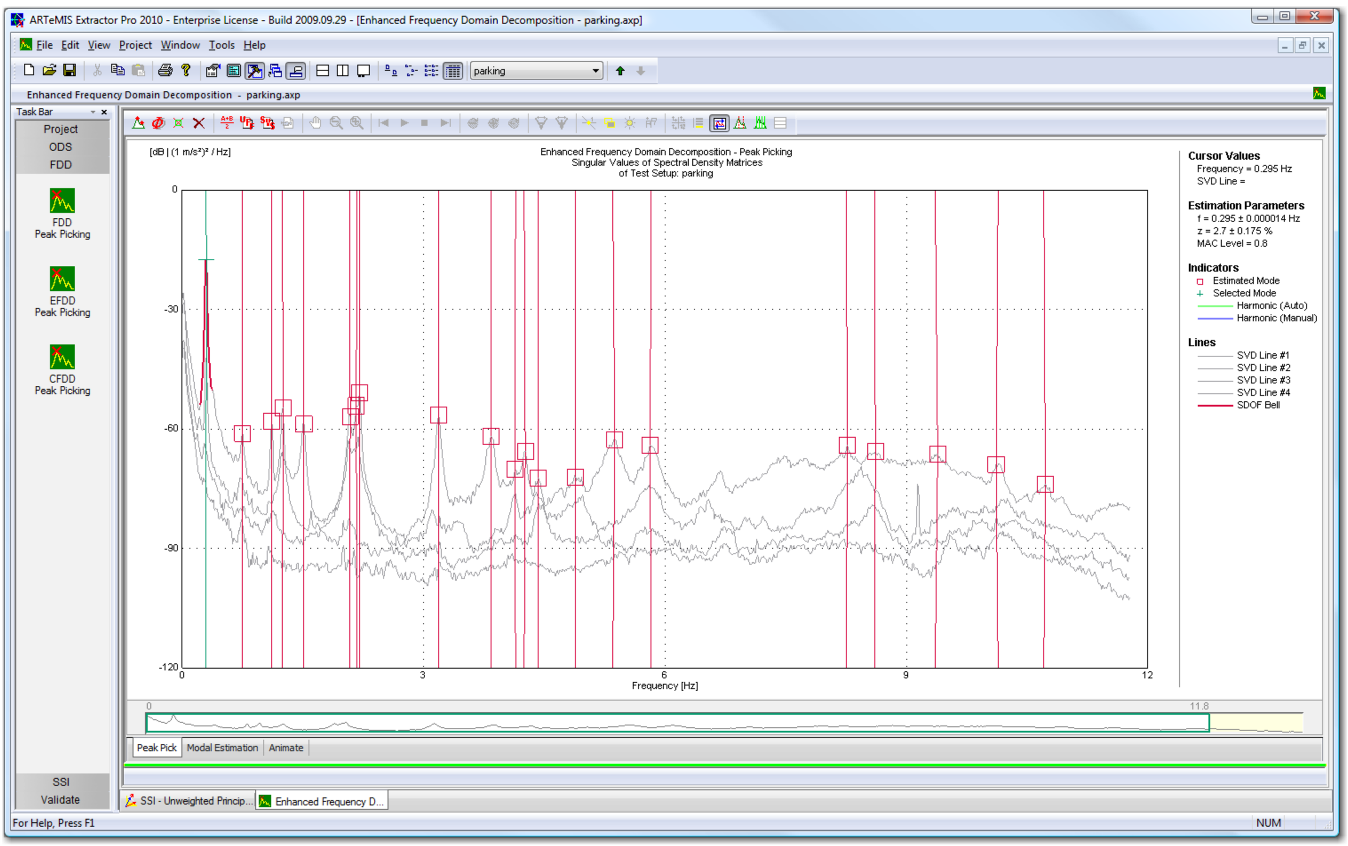

Figure 4: Singular values of spectral density matrices at the lower frequency range with selected spectral bell

Taking the advantage of the more sophisticated Stochastic Subspace Identification (SSI) [1], modal parameters were extracted in a detailed analysis. The SSI techniques rely on linear least squares estimation of the model using the raw measured time series. In the past this estimation was unconditionally. The new Crystal Clear SSI® estimation feature, described in detail above, allowed for a conditional estimation, emphasizing a user defined number of physical modes and suppressing the remaining parts of the information in the data.

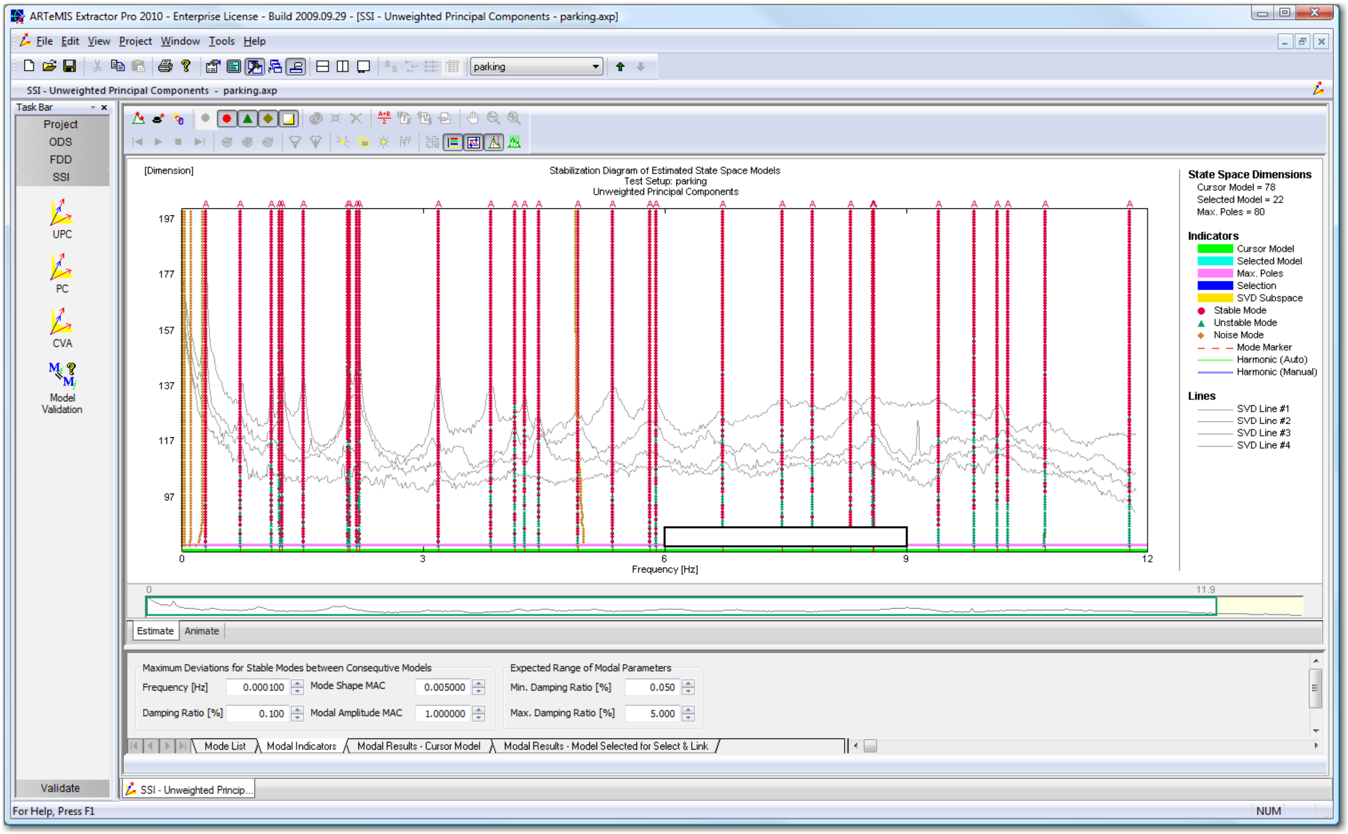

Figure 5: Stability diagram using Crystal Clear SSI® at the lower frequency range

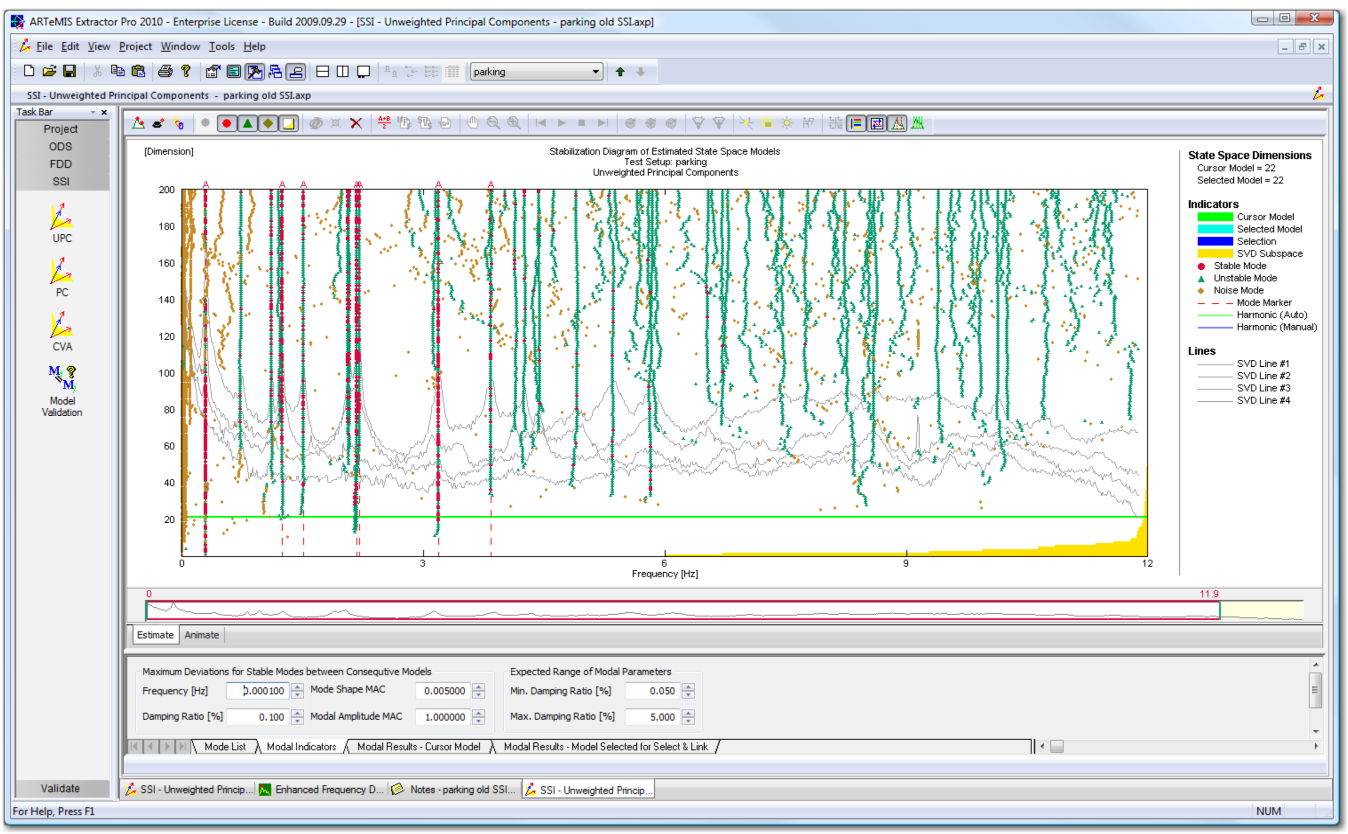

Figure 6: Stability diagram using standard SSI at the lower frequency range

Using this technique it is necessary to specify the maximum number of significant poles (eigenvalues) present in the measurements that should be estimated. The estimation algorithm focuses on the modes by having these poles, and any less significant noise poles are returned with a natural frequency estimate much higher than the Nyquist frequency, and a damping ratio of 100 %. This approach results in extremely clear stabilization of the number of modes specified and nearly no noise modes inside the visible frequency range. Due to the highly consistent estimation of the poles, the search for the optimal model order is less critical when using this new feature. By applying the Crystal Clear SSI® algorithm to the wind turbine data very stable poles occur and the modes could be identified easily with a high accuracy. The corresponding stabilization diagram is shown in Figure 5. Compared to the EFDD a higher number of modes could be identified.

Applying the standard SSI technique to the same dataset, differences in the stabilization diagram could be indicated very clearly as shown in Figure 6. In particular, less exited modes at higher frequencies and high number of modes in a narrow frequency range could be identified much better using the Crystal Clear SSI® algorithm compared to the standard procedure. Also the identification of repeated modes was excellent regardless of the spatial resolution of the measurement model (compared to EFDD). The separation of repeated modes can be seen in Figure 7.

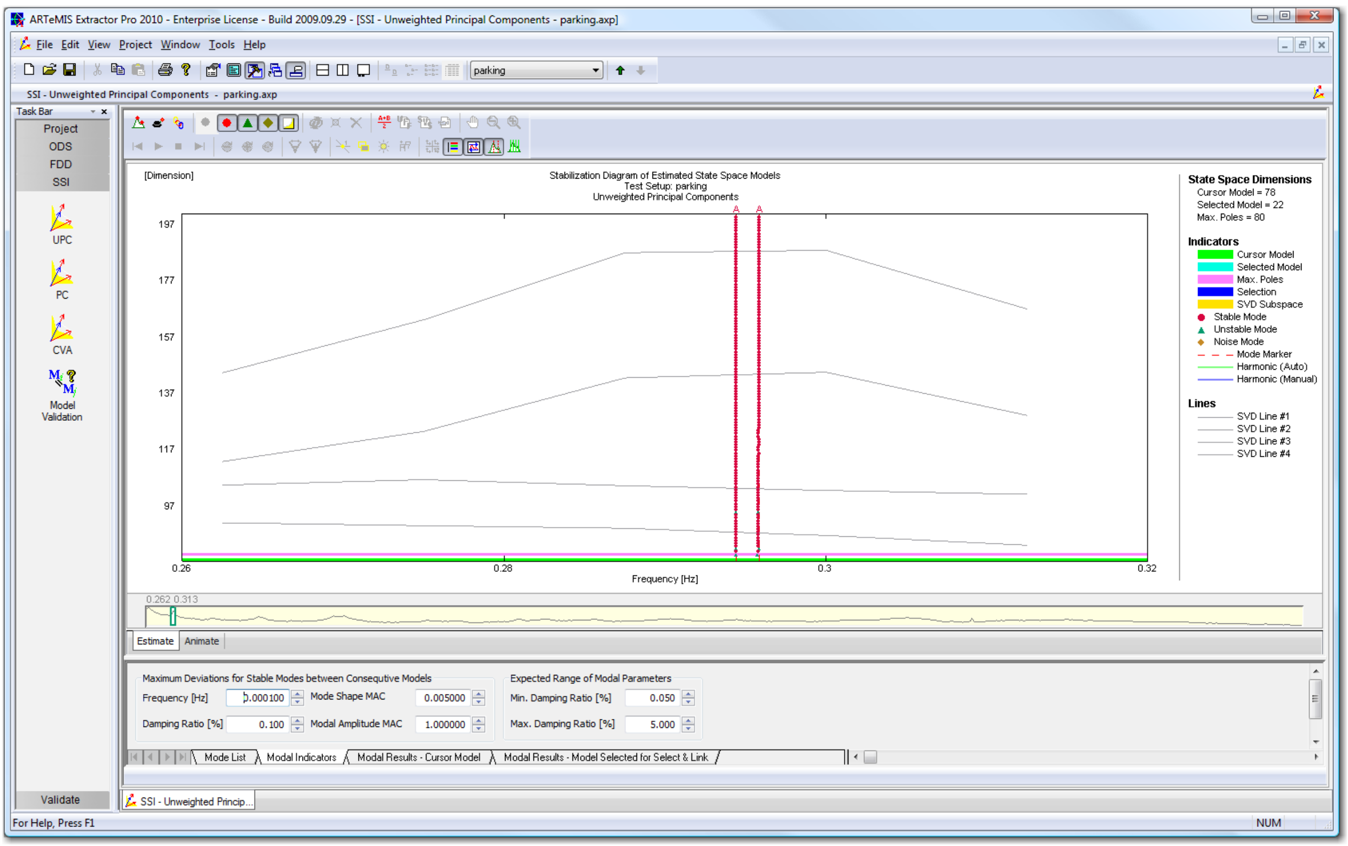

Figure 7: Separation and identification of repeated modes (first tower bending, perpendicular mode shapes)

As already mentioned, the fundamental resonant frequencies and corresponding mode shapes of the entire turbine are affected mainly by tower and blades and can be found in the lower frequency range. Because of the mass and stiffness properties, main frame resonant frequencies are located at higher frequencies. Unfortunately, the intensity of the natural excitation decreases with increasing frequency which results in less excited or weak modes with respect to the main frame. Using the new SSI algorithm a very clear stabilization diagram occurred, even for these modes as shown in Figure 8. The optimal model order could be selected and the model parameters were identified very easily.

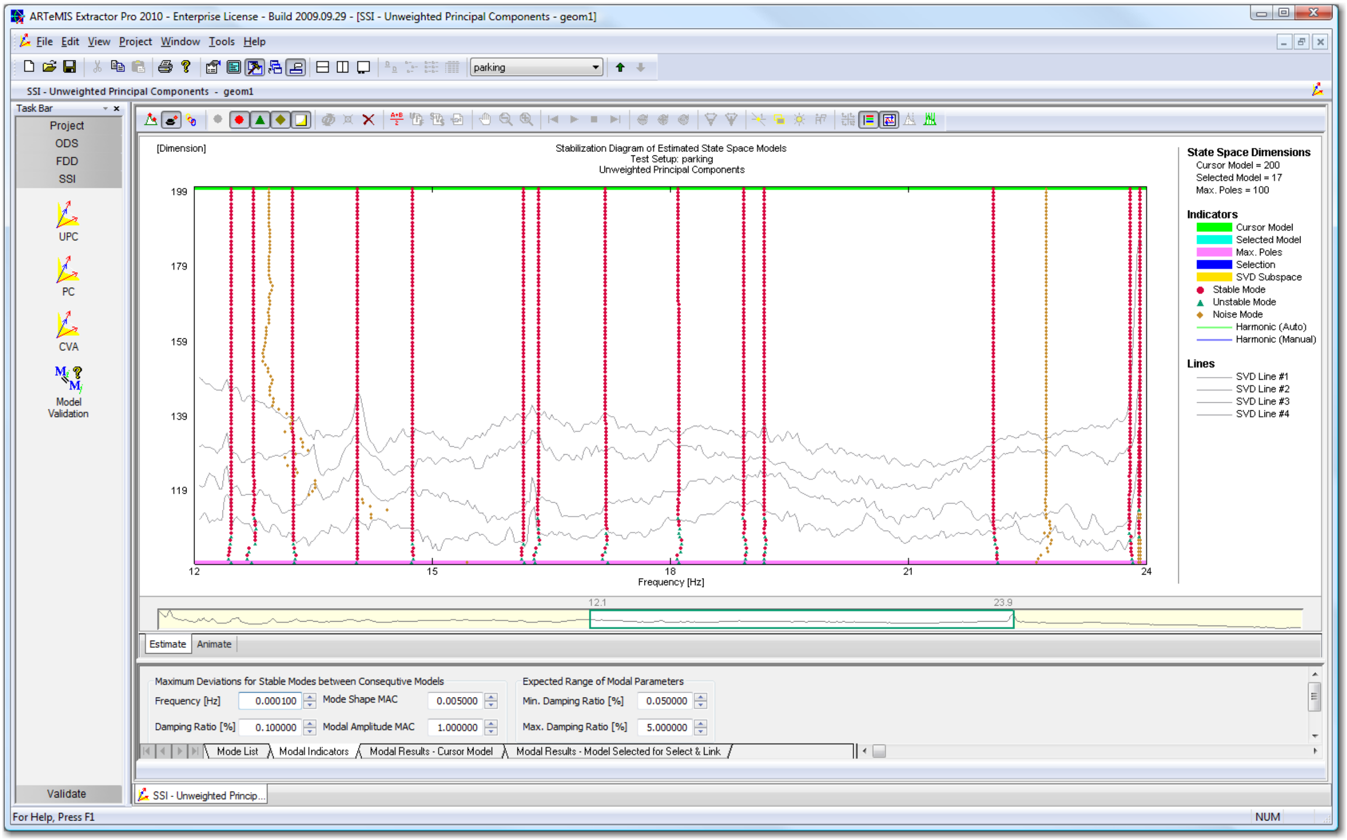

Figure 8: Stability diagram using Crystal Clear SSI® at the higher frequency range

4.2 MODE SHAPE IDENTIFICATION

The identification of the mode shapes of the entire wind turbine using the experimental data from the main frame only was realized by combining it with a Finite Element Analysis. Therefore, the contributions of the measurement locations to the different mode shapes were extracted from the calculated results and measured as well as calculated mode shapes were compared using the Modal Assurance Criterion (MAC).

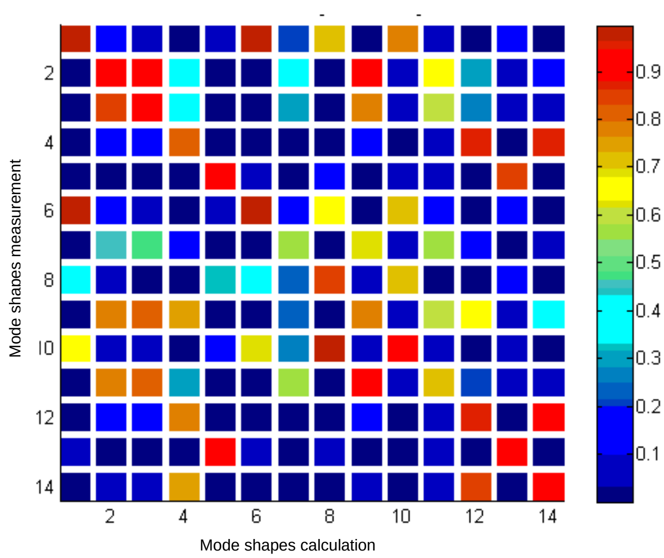

Figure 9: Application of Modal Assurance Criterion (MAC) to experimentally identified and calculated mode shapes

Calculated MAC values are shown in Figure 9 (remark: MAC value of two identical or corresponding mode shapes is equal 1). Using these mode correlation with reference to the expected frequency band (and additionally a “technical viewing”) all resonant frequencies and corresponding mode shapes of the entire turbine in the lower frequency range could be identified. Exemplarily the correlation and mode shape identification for a flap wise blade bending mode is shown in Figure 10.

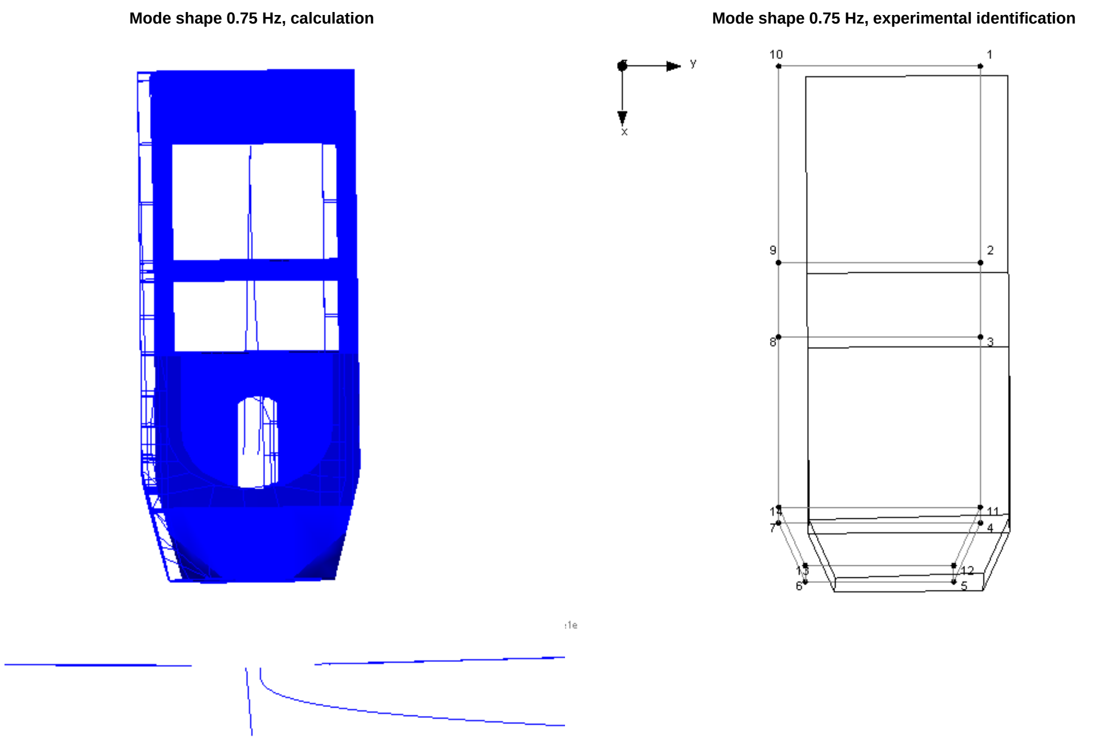

Figure 10: Mode shape identification using correlated modes: calculated flap wise (blades are pitched in feathered position) bending mode (left) and corresponding experimentally identified mode shape (right)

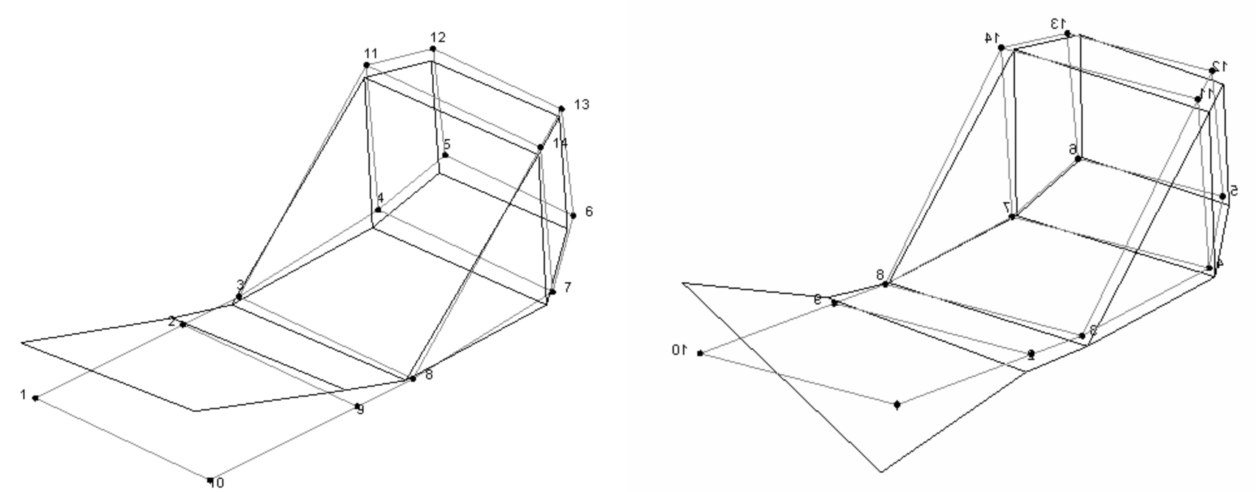

Figure 11: Experimentally identified mode shapes of the main frame, based on measurement data only

Unlike the mode shape identification of the entire turbine (using FEA) mode shapes of the main frame (or more precisely: mode shapes with a dominant main frame contribution) were extracted from the measured dataset only. Exemplarily, two fundamental mode shapes of the main frame are shown in Figure 11.

5. FURTHER INVESTIGATIONS

Based on the modal data obtained experimentally the generated prediction model could be evaluated with respect to the resonant frequencies. Particular attention was directed to the dynamic behaviour of the main frame. It is the intention to use the main frame model as a flexible body within a Flexible Multi-body Analysis for a load prediction of wind turbine components.

Structural as well as parametric uncertainties, leading to variations in the structural behaviour, have to be considered whenever a Finite Element prediction model is used. These variations were identified and minimized by a subsequent Computational Model Updating (CMU) procedure. Calculated mode shapes of the main frame, extracted from a comprehensive wind turbine model, including tower, blades, mass points for gearbox, generator, transformer etc., are shown in Figure 12.

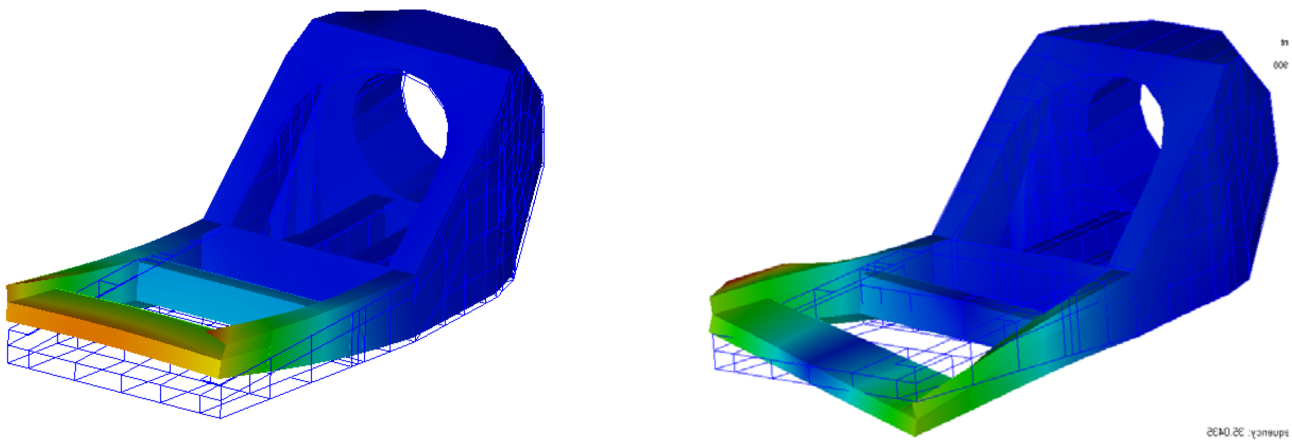

Figure 12: Calculated mode shapes based on the comprehensive wind turbine model

The application of Operational Model Analysis was proven as an easily applicable tool for modal parameter estimation of wind turbines. The experimental data acquisition using the stochastic excitation from the wind as well as the very user friendly Crystal Clear SSI® parameter estimation technique are making this approach useful not only for scientific institutions but also for practical applications in the industry.

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