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Parameter identification on wind energy structures using dynamic response surface

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ABSTRACT: This work is directed towards two essential aspects of structural health monitoring. The first one concerns the efficiency improvement by use of the response surface instead of direct structural simulation in the framework of parameter identification. The second one concerns the evaluation of the virgin structural state as a reference state for monitoring. These aspects are examined on problems related to the rotor blades of wind turbines and illustrated by two laboratory tests.

KEY WORDS: Parameter Identification, Wind Turbines, Rotor Blade, Structural Health Monitoring, Response Surface

1 MOTIVATION AND INTRODUCTION

Wind turbines are usually exposed to intensive dynamic loading for 20 to 30 years of the designed lifetime. A rapid development of new machines, carrying structures and foundation types in the offshore area causes diverse scientific and technological challenges with respect to structural health monitoring. There exist almost no commercially available and reliable solutions for offshore structures although the so-called condition monitoring systems (CMS) are requested by permission authorities. Structural health monitoring shall increase the availability and efficiency of wind turbines and minimize the operation breakdowns. The aim of monitoring is the early diagnosis and prevention of severe damages or failures. Various CMS solutions for rotor blades, tower or foundation are currently under development and testing.

A typical challenge for all monitoring systems is not only the measurement technique or the measurement process itself, but mainly the structural assessment and damage or lifetime prediction. In our opinion, this step is almost impossible without a validated structural model that correctly describes structural response and provides a link between measured data and real physical parameters of interest. Usually, such a model takes into account interaction mechanisms and allows for the best utilization of structural bearing capacity.

Model validation as well as damage assessment usually requires identification of essential parameters by use of the measured data in static or dynamic response. Such parameter identification is a typical issue in structural health monitoring. From the mathematical viewpoint, it leads to an optimization problem, which could be computationally very expensive. The efficiency of a costly optimization process can be enhanced in advance by reducing the number of relevant parameters within a sensitivity analysis. Even so, numerous structural simulations have usually to be performed at each step of the optimization process. Reduction of the computational efforts is still a challenge.

The present study is directed towards two essential aspects of structural health monitoring. The first one concerns the efficiency improvement by use of the response surface instead of structural simulation during optimization. The second one is dedicated to the evaluation of the virgin structural state as a reference state for monitoring. The uncertainties of the initial state can strongly handicap damage assessment, thus, shall be reduced. These aspects are examined in the present study on problems related to the rotor blades of wind turbines. They represent space thin-walled carrying structures that are typically subjected to extreme aerodynamic loads, experience severe dynamic deformations (Figure 1) and are damage-sensitive.

Figure 1: Deformation of rotor blade under operation

The present contribution is prepared within the Joint Research Project “BladeTester” financed by the German Federal Ministry for the Environment, Nature Conservation and Nuclear Safety . This project develops an automated approach for cost-effective, serial integrity tests of rotor blades appropriate for production facilities. At that, manufacturing faults shall be automatically detected, localized and assessed with respect to their impact on the integrity of rotor blades in operation. An individual test certificate for each rotor blade after manufacturing shall document the virgin state and serve as initial information for further monitoring and inspection measures. A continuous test data collection and statistical analysis of the faults shall open new possibilities for description of initial imperfections and pre-damages and to introduce modern quality management systems.

2 INITIAL STATE FOR SHM

As stated above, an SHM system demands a reference state to which properties measured during service can be compared to. This raises the question, which point in time of a structures ‘life’ could serve as a suitable reference state: Shall it be one during an early phase or at the very beginning of service time or does it have to be even earlier? Obviously, it is desirable to gather necessary information at the earliest. Up to now, this means the start of operation of the wind turbine. Which imperfections already exist at that moment is unknown, so initial defects coming from production cannot be recognized. This is a considerable aspect as rotor blades manufacturing is dominated by manual labor which makes them prone to imperfections. The approach followed in the project is therefore to check the rotor blades already during production. Information which comes out of this check is natural frequencies, dead weight deflection shape, contour accuracy and quality of bonding and layer composition. As rotor blades are produced in series production, trends in manufacturing quality can be observed at the earliest stage. All work within the project is done on a testing facility with a series of rotor blade specimen of 13.4m length (Figure 2), coming from an industrial small-size blade design.

Figure 2: Testing facility with rotor blade

2.1 *Geometry Measurement and Imperfections*

Obviously, contour accuracy directly affects the degree of efficiency, hence the profit of the wind energy plant. Furthermore, internal defects can also lead to faults visible on the outside shape.

Therefore, Blade Tester aims at finding correlations between defects in manufacturing visible internally (i.e. detectable with non destructive testing, see section 2.3) and externally. For the geometry measurement of such large volumes, a unique combination of a laser tracker and a 3D white light scanner has been developed. While the scanner takes shots of patches of a size of approx. 0.5m², the tracker is able to match these patches in a global coordinate system (Figure 3). In this way, a scan of the surface of the rotor blade, partly or completely, can be captured. The so achieved 3D information can be used to find local imperfections as dents or bulges. If it is sufficient just to check the contour accuracy in representative sections, these can be captured by the laser tracker in stand-alone mode (Figure 6).

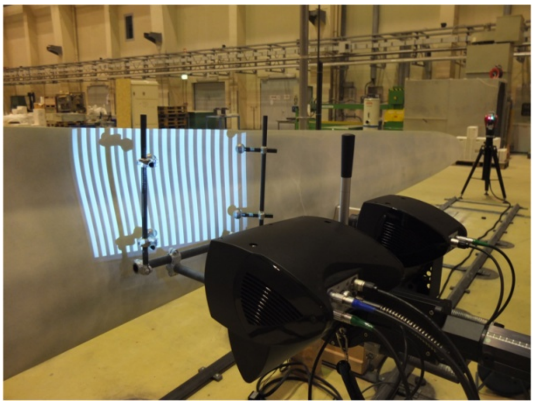

Figure 3: Geometry scanning with a 3D white light scanner (foreground) and a laser tracker (background)

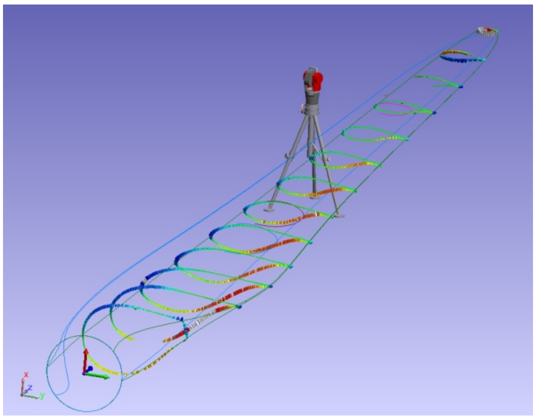

Figure 4: Contour sections measured with laser tracker

2.2 *Finite-Element-Model and Validation*

However, the surface captured as described in the previous section belongs to a deformed state of the part, thus depending on boundary conditions, loads and structural properties. Therefore it will be impossible to adjust to fit a reference surface coming from a CAD-model to it. Thus, the approach followed here is to compare the measured surface to a reference computed in a finite element model or, in other words, to validate a computational model with the measured data. It is evident, that this computational model will not initially fit to the measured one as many structural and material parameters cannot be exactly determined in advance. Additionally, each part presumably contains manufacturing faults (which are to be found). Getting the model coming from simulation in line with the measured one by means of the global deflection and dynamic behavior can only be achieved by a model update process, which basically is a certain application of optimization algorithms.

Though, the finite element model of this small size rotor blade (Figure 5) already consists of more than half a million DOF, not to mention what a model of a current large size blade would have. Obviously this causes problems in terms of computability when multiple simulation runs are necessary each time the fitting process should be done and this is usually the case for an optimization process. So it requires a general approach, in which the ‘structural response’ to a certain set of boundary conditions, loads and structural parameters is stored and which offers interpolation of intermediate values. A methodology which features these requirements is the Response Surface Methodology (RSM) which will be outlined in section 4.3.

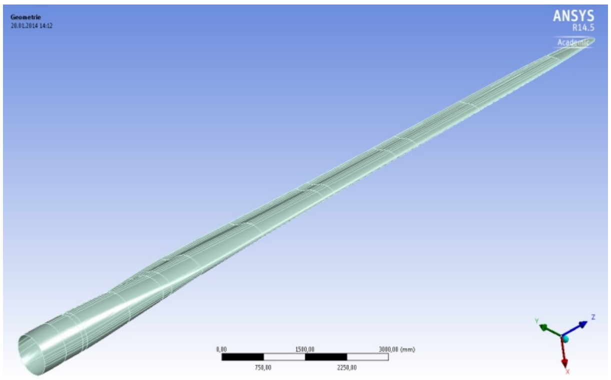

Figure 5: Finite element model of rotor blade

Beyond external sensing such as vibration sensors and the geometry measurement system, each rotor blade specimen is equipped with a fiber-optic sensing system which allows for the capture of distributed strain sensing along the fiber length. It is therefore possible, to validate the computational model in terms of strain data in 4 lines along the blade length.

2.3 Non-Destructive Testing and Fault Detection

Rotor blades can currently get various manufacturing faults due to handwork in the production cycle. Some of manufacturing defects are less critical and relates to the surface quality and repairs. Some of them can cause even structural failure and thus are very critical. In both cases, they cause operational breakdown and reduce the cost efficiency of the wind turbine. Non-destructive testing (NDT) should help to detect relevant manufacturing defects and to identify the virgin state of the rotor blade.

The main goals of the NDT application are detection, localization and identification of manufacturing defects as well as assessment of their effects on the safety and integrity of rotor blades. For that purpose, various techniques are applied in BladeTester. The main problem in detection of local defects or damages is that each of them does not significantly influence the global behavior of the rotor blade and, thus, can hardly be measured in the global structural response, both static and dynamic. We apply various techniques based on wave propagation, since wave of small length interact well with the local damages or defects. The effects of defects can become well measurable.

The applied NDT techniques can generally be subdivided into two groups: those based on electro-magnetic and elastic waves. Without going into details, we prefer elastic or mechanical waves, since they interact with the mechanical properties of the structure that are in focus of the study.

Figure 6 shows a cross-section of a rotor blade with a typical structure consisting of two half-shells, two shear walls and several bond joints. Figure 7 shows a special ultrasonic scan of this blade component with reduced color resolution for better identification of defects. One can recognize numerous air voids in the bond layers or some surface damages due to poor workmanship.

Figure 6: Cross-section of a rotor blade with manufacturing faults

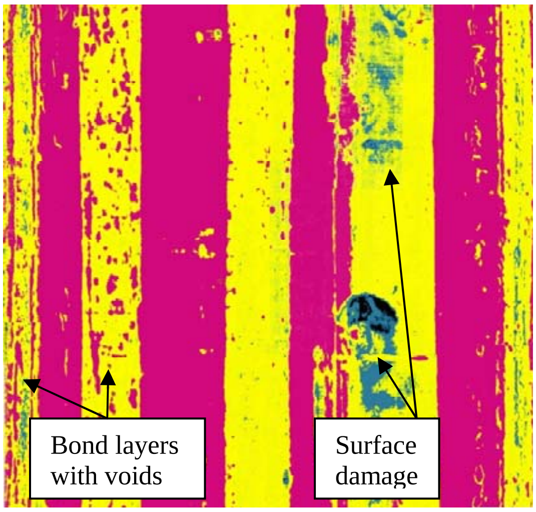

Figure 7: Ultrasonic scan of a rotor blade segment with manufacturing defects

A typical problem arises with respect to manufacturing defects after their detection. In order to evaluate the effects of defects, such defects have to be introduced into the structural model. At that, it is important to determine the order of the model sophistication and the size of defects, which are relevant and shall be taken into account in the structural model. For example, it is practically impossible to account for individual voids of the bond layers in Figure 7. They can be homogenized over a certain section of the bonding and cause some reduction of stiffness or strength of the joint. Other alternative solutions are also possible. Currently, suitable strategies and approaches are under development.

3 FINITE ELEMENT SIMULATION

For the purpose stated in the precedent sections, a finite element model was developed that offers options to simulate manufacturing faults (i.e. inclusions in bonding) and delaminations. It consists of approx. 120,000 shell elements which are modeled with the layered laminate composition of the rotor blade design and exceeds by far the complexity of the models commonly used in structural design.

Simulations include computation of static deflections in each test position (Figure 8) and corresponding modal parameters (Figure 9), in both figures shown for 2-point support on suction side.

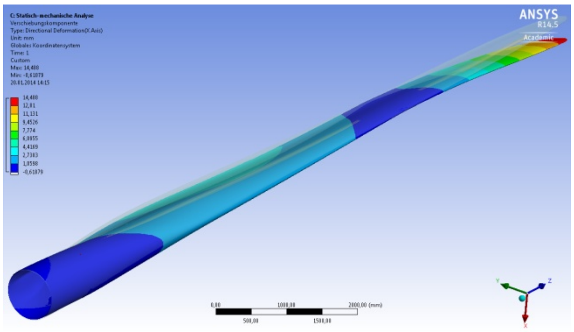

Figure 8: Deflection due to deadweight

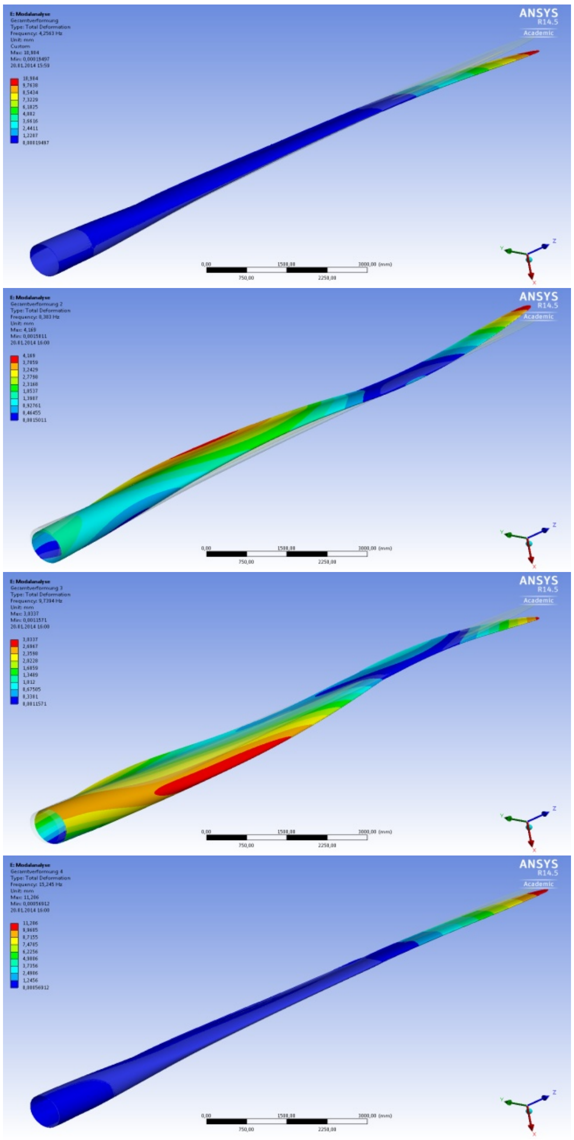

Figure 9: First 4 mode shapes of the rotor blade

4 PARAMETER IDENTIFICATION

Basically, the process of parameter identification is an optimization process with the aim of reducing a previously defined objective function to a minimum. Although simple at a first glance, the procedure can become very costly in terms of computational time when the set of variables increases, which is likely to be the case in real-world applications. Obviously, a first step is to reduce the set of input and output parameters by checking them for interaction, e.g. to eliminate dependent variables. This reduction of the problem's dimension is done with a sensitivity analysis. The efficiency of the main procedure can be increased by capturing the results for a given set of input values from a response surface instead of performing a simulation run in each step. A properly defined response surface hereby allows for interpolation of intermediate values instead of a full simulation.

4.1 Sensitivity analysis

Two groups of variables are generally defined for sensitivity analysis: a set of input variables $\boldsymbol{X} = \{X_1, X_2, \dots, X_n\}$, which represent material, geometry and stiffness properties, and a set of state variables $\boldsymbol{Y} = \{Y_1, Y_2, \dots, Y_m\}$, which are physical values of structural response, for example, displacements, strains, stresses or vibration properties.

First, sensitivity analysis should help to discover and eliminate dependent variables within each set $\boldsymbol{X}$ and $\boldsymbol{Y}$. The second goal of sensitivity analysis is to determine, what input variables in $\boldsymbol{X}$ exhibit the largest influence on the response variables of interest $\boldsymbol{Y}$.

A usual procedure for sensitivity analysis involves a total vector of parameters $\boldsymbol{Z} = \{\boldsymbol{X}, \boldsymbol{Y}\}$. By variation of individual input parameters $\overline{\boldsymbol{X}} = \boldsymbol{X} + \Delta\boldsymbol{X}$ and by means of structural simulation, it is possible to calculate several new state variables resulting in $\overline{\boldsymbol{Z}} = \{\overline{\boldsymbol{X}}, \overline{\boldsymbol{Y}}\}$. The dependence of all parameters, both input and state ones, can be estimated by various correlation measures ranging between -1 and 1. At that, the correlation coefficient of -1 or 1 means full correlation, negative and positive, respectively. The value 0 indicates no correlation.

Such a sensitivity analysis is carried out in the present study within the OptiSlang software [6], which is coupled with ANSYS [7] for structural simulations. The results of sensitivity analysis are visualized by the so-called sensitivity matrix, which contains the correlation coefficients, like the one shown in Figure 15.

Since a sensitivity matrix of dimension $(n + m)$ is based on $(n + m)^2$ individual contributions, its calculation can be very expensive for increasing number of variables. It seems to be rational using the response surface methodology in combination of some efficient approaches for statistical simulation, like the Latin Hypercube Sampling [4]. In the present study, we apply a traditional way, since the number of variables is quite limited.

4.2 Optimization approaches

Various optimization approaches can be generally applied within the procedure of parameter identification. The goal is to minimize the difference between the measured and simulated response variables $\boldsymbol{Y}$ by variation of the input $\boldsymbol{X}$. The efficiency of parameter identification can be significantly increased by preliminary sensitivity analysis, as described above.

The optimization problem under consideration can generally be described through the goal function

$$\min J(\boldsymbol{X}) \tag{1}$$

with several problem-specific restrictions, which are not discussed here. In the framework of the least squares approach, we define a residual vector as a difference of the simulated and measured response variables

$$\boldsymbol{R}(\boldsymbol{X}) = \boldsymbol{Y}_{sim}(\boldsymbol{X}) - \boldsymbol{Y}_{measured} \quad (2)$$

and the goal function as a scalar residual product:

$$J(\boldsymbol{X}) = \boldsymbol{R}^{\boldsymbol{T}}\boldsymbol{R}. \quad (3)$$

A typical problem arises from the fact that the properties of the goal function are generally unknown in advance. They can be quite complicated and possess several local minima, as exemplarily shown in Figure 10 for two parameters p_1 and p_2. Thus, a suitable selection of start points and appropriate optimization approaches is required.

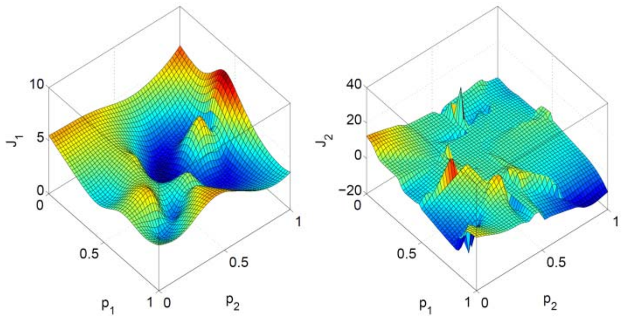

Figure 10: Objective functions

In the present study, we apply several approaches for optimization, among others, the trust region approach, the pattern search approach, the evolutionary algorithms and the simulated cooling approach. Details of these approaches can be found, for example, in [Schumacher].
Due to numerous local minima of the goal function, it is important to find parameter ranges, where minima exist, at least approximately. This preliminary analysis can be efficiently done by use of the response surface as a meta-model instead of the structural simulation at each step of the optimization process.

4.3 *Response Surface Methodology*

Response surface is a relationship between input variables $\boldsymbol{X}$ and state variables $\boldsymbol{Y}$ represented explicitly in a *(n+m)*-dimensional space:

$$\boldsymbol{Y} = f(\boldsymbol{X}). \quad (4)$$

In this sense, it can be considered as a meta-model or alternative to the structural model.

Relations between $\boldsymbol{X}$ and $\boldsymbol{Y}$ are usually implicit, but can be calculated using a suitable structural model, at least for some discrete values of input variables $\boldsymbol{X}$. Using a certain number of such response states $\boldsymbol{Y}_i(\boldsymbol{X}_k)$, the so-called response surface points, it is generally possible to approximate this surface by an analytical function. Due to diverse reasons, it is usual to apply second-order polynomials of the form:

$$\boldsymbol{Y_i} = a_0 + \sum_{k=1}^{n} a_k X_k + \sum_{j=1}^{n} \sum_{k=1}^{n} b_{jk} X_j X_k\,, i = 1, \dots, m, \quad (5)$$

where *n* denotes the number of input variables and *m* the number of state variables. The coefficients of the polynomial (5) can be calculated by regression analysis, if a sufficient number of real structural states are at disposal as a result of structural simulation or measurements.

A special issue concerns a suitable selection of parameter combinations $\boldsymbol{X}$ that equally cover the full range of input parameters.

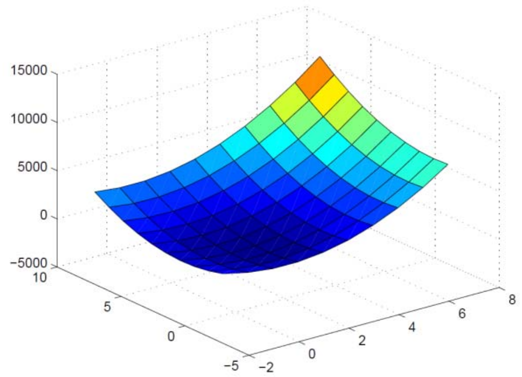

Figure 11: Response surface with two inputs and one output

4.4 *Software framework and test environment*

The procedure stated above is implemented in a Matlab based software (program flow see Figure 12). Given an input file, an initial parameter set and size and type of sampling (Design Of Experiments, abbr. DOE), it starts a solver (e.g. analytical solver or FEM) for all support points.

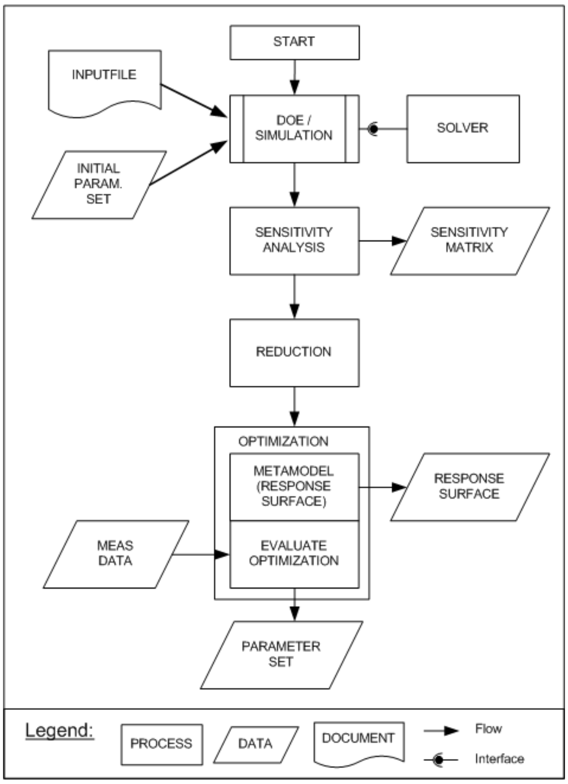

Figure 12: Program flow

When finished this task, a sensitivity analysis is performed and the sensitivity matrix is evaluated with the aim of reducing the set of input and output parameters. Eventually, inside the optimization module, a metamodel is built (which is the response surface) and the core optimization in terms of minimizing the objective function is done by use of the metamodel. Finally, the appropriate set of input parameter leading to the measured structural response is stored.

5 EXAMPLES

The framework introduced above was tested up to the current stage of work with a variety of smaller (lab-size) structures: Amongst others dynamically with a laboratory beam structure and statically with a sandwich panel consisting of the same material composition as current technology rotor blades. The latter was equipped with fiber optic sensors which allow for the static and dynamic measurement of strain data continuously along the length of the fiber. As stated above, the rotor blade specimens are equipped with this system as well.

5.1 Laboratory beam structure

A simple beam is loaded with a shaker (m1) and two additional masses (m2 and m3). The general setup is shown in Figure 13, the measurement setup in Figure 14 where A1 to A8 are the locations of the sensors. The structure is excited initially by impact with a hammer to get the natural frequencies which are in a subsequent step excited with a shaker to capture the corresponding mode shapes. The values at start of the parameter update are shown in Table 1.

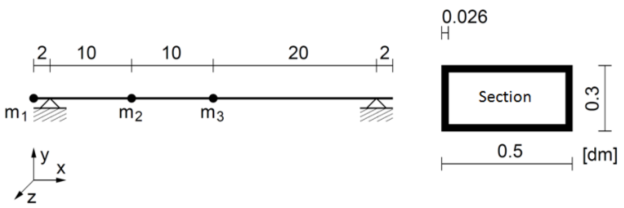

Figure 13: Lab structure – general setup

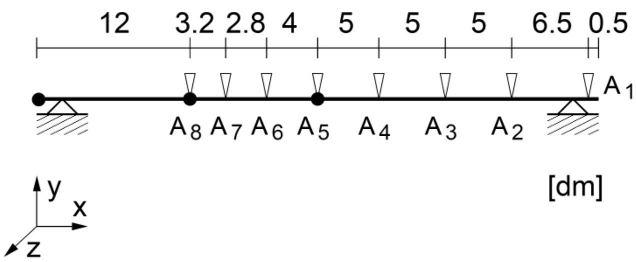

Figure 14: Lab structure – measurement setup

Table 1: Initial parameter set

Parameter	Initial Value	Lower Bound	Upper Bound
Young's Modulus [GPa]	190	180	220
Shaker Mass (m1) [kg]	2.5	2	4
Distance m3 to Origin [m]	2.2	2.18	2.22

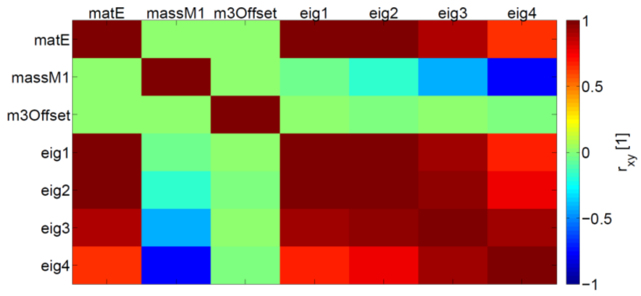

Figure 15: Sensitivity matrix

The sensitivity matrix (Figure 15) shows linear correlation between the output parameters (the natural frequencies eig1 to eig4) with the global stiffness (represented by the young's modulus) as well as the mass of the shaker, although the latter affects the results less. An offset of the mass m3 within the given bounds does not show any significant influence on the natural frequencies and can therefore be eliminated from the core optimization process. After 3 iteration steps the values as shown in Table 2 were computed.

Table 2: Updated parameter set

Parameter	Measured Value	Updated Value
Young's Modulus [GPa]	-	198
Shaker Mass (m1) [kg]	3.2	3.15
First Mode [Hz]	5.4	5.47

5.2 Sandwich plate

A sandwich plate consisting of a laminate shell on each side of the cross section and a foam core is tested in a four-point bending test. This causes a curve of the bending moment which is linear between the supports and the load application and constant between the load applications. The panel is equipped with fiber optic strain sensors on the bottom side which leads to positive strain values generally proportional to the bending moment.

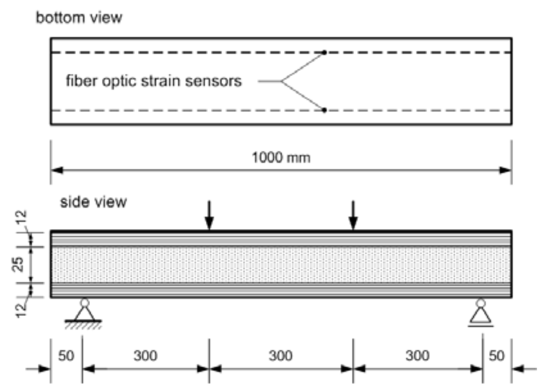

Figure 16: General test setup – top view and side view

The panel was tested under compression load in a test stand at MFPA (Institute for Materials Research and Testing) Weimar. Several test iterations at lower loads showed a linear behavior of the structure. The computational model was able to simulate frictional behavior at the supports as well as at the load punches.

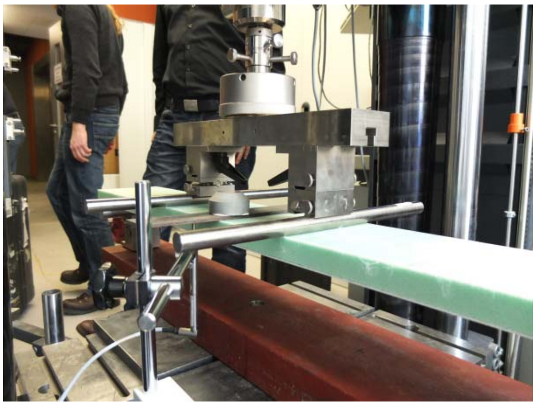

Figure 17: Testing the sandwich plate

Although dominated by local effects at the supports and the load punches, the optimization procedure was able to fit the set of parameters quite well to the measured strain data (Figure 18). Input parameters were mesh density, distance of supports, young’s modulus of the foam core and laminate shells, thickness of the foam core and frictional coefficients at supports and load punches.

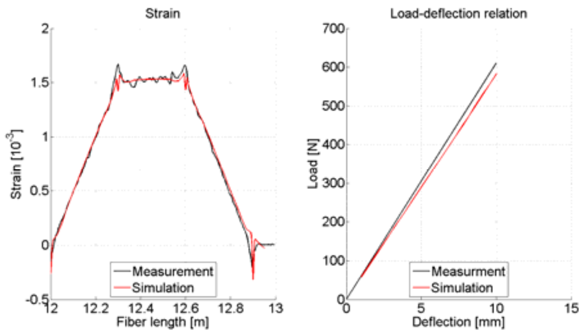

Figure 18: Comparison of computational and experimental results

Dynamic and static parameter identification using response surface as shown in both examples above will be combined and applied to the work on the rotor blade specimen introduced in section 2.

6 CONCLUSION AND OUTLOOK

The present study shows that response surface can help to increase efficiency of the sensitivity analysis and parameter identification, especially in the phase of preliminary analysis. Response surface reflects the main relationships between the input and state variables and, thus, helps to eliminate superfluous parameters. The accuracy of the response surface as alternative for structural simulation depends on the approximation quality of the second order polynomials for the actual parameter relationship.

The present study also shows typical challenges in the assessment of the virgin structural state on example of rotor blades. This task usually includes geometry measurement and identification of imperfections as well as nondestructive material testing with damage detection and identification. All this information is necessary as reference for the initial state within structural health monitoring procedures. However, even if such information is available, it is still a challenge, how it can be introduced into the structural model in a rational way. It is evident that only a validated model can serve as a basis for structural monitoring.

ACKNOWLEDGMENTS

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