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Structural Change Identification at a Wind Turbine Blade using Model Updating

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Abstract. In this paper, a damage and ice accretion localization method based on finite element model updating is tested using the example of a wind turbine blade. Both eigenfrequencies in combination with mode shapes and a new comparison technique based on transmissibility functions are employed in order to define measures for a quantification of the difference between numerical and measured results. Results of these quantifications are used to define an optimization problem, minimizing the deviation between model and measurement by variations of the numerical model using a combination of a global and a local optimization method. A full-scale rotor blade was tested in a rotor blade test facility in order to test those structural health monitoring methods. During the test, additional masses were installed on the structure in order to emulate ice accretion. Afterwards, the blade was driven to damage using an edgewise fatigue test. In this test a crack occurs at the trailing edge of the rotor blade. The model updating algorithm is applied to locate and quantify both structural changes with the two different measures. Though shown to be successful in a numerical study, both measures return incorrect damage locations when applied to real measurement data. On the other hand, ice localization is successful using eigenfrequencies and mode shapes, even quantification is possible. If transmissibility functions are applied, the localization is not possible.

1. Introduction
In cold climates, ice accretion on rotor blades has the potential to endanger the environment of wind turbines. In case the ice mass becomes too big, the danger of throwing ice is growing. Hence, turbines are stopped or operated with reduced speed if ice is on the blade [1]. In addition, unbalanced ice growth at the rotor blades may cause higher fatigue loads in essential structural parts such as the nacelle and the gearbox [2]. Thus, the detection of ice, modifying the structural properties of the blade, at an early stage is of high interest for the operators of wind turbines. Damage is another change of the structural properties. Repair of rotor blades cause the second highest downtime per failure after gearboxes [3]. Hence, structural health monitoring and early damage detection within these assemblies is vital to all wind turbines in operation, especially due to the growing and ageing infrastructure [4]. The exact location of damage is a key component for classification of damages.

Both damage localization and quantification of ice accretion can be regarded as a tracking of structural changes. Finite element model updating [4] is a tool that may be employed to localize these structural changes by updating a numerical model of the investigated structure to the

measured data, provided that the initial model shows a very similar behavior to the measured data. Model updating is applied to localize structural changes in several studies, especially big structural systems such as bridges. Damage localization is successfully applied to a highway bridge in [5]. Corrosion effects in a bridge are investigated in [6], whereas a frame structure is investigated in [7]. In [8], the authors successfully apply model updating for damage localization at a jacket structure of an offshore wind turbine.

In this paper, a finite element model updating approach presented in [9] is applied to a full scale 34 m rotor blade that is tested in a rotor blade test facility. Additional masses are attached to the tip of the blade in order to simulate ice masses on the structure [2]. Afterwards, the same blade is driven to fatigue damage using a load frame exciting the structure in its first edgewise eigenfrequency. Twelve measurement transducers are installed in six positions along the structure in order to observe the vibrations of the blade throughout the tests, four biaxial accelerometers and two biaxial geophones. The signals of the geophones are derived to obtain acceleration signals.

An essential step in finite element model updating is the comparison of measurement data with results from a numerical model [10]. Two different methods are investigated within this paper. The first is the classical approach, using eigenvector and eigenfrequency residuals [4]. The latter makes use of the concept of transmissibility functions. Transmissibility functions are frequency dependent response functions that are evaluated using the ratio of two measured signals [11]. To the best of our knowledge, transmissibility functions have not been used for model updating before. In [12], modal parameters identified from those are used for model updating, but not the functions themselves. Both comparison techniques are used in this paper for the investigation of ice accretion and damage localization.

These quantified discrepancies between numerical model and measurement data are used to define the objective function of an optimization problem which is minimized using variations of the parameterized numerical model. The optimization problem is constrained in order to keep the parameters within a user-defined range. Since it is known that optimization problems arising in model updating are nonlinear and provide several local minima [13], the global optimization procedure 'Simulated Quenching' [14] is used to approximate a local minimum of the problem. Afterwards, the local optimization method 'Sequential Quadratic Programming' [15] is started in order to converge to the exact local minimum. Being a heuristic optimization procedure, the algorithm is started several times in order to ensure finding the global optimum. The final objective function value is used to distinguish local and global optima.

After the mathematical formulation of the model to measurement comparison, measures based on model parameters and transmissibility functions are introduced in the next section, the two-step minimization algorithm is given subsequently. This is followed by a short description of the rotor blade test, the numerical model being formulated based on limited data and a numerical study on damage localization. Finally, the plausibility of the approach is tested via application to real measured data for both damage localization and ice mass quantification followed by a discussion of the results and a conclusion.

2. Optimization based model updating

Finite element model updating is a technique that uses data acquired from vibration tests to update a numerical model in structural dynamics. Therefore, the difference between the dynamic response of the numerical model and the measured data is evaluated using $f(\boldsymbol{\theta}) \in \mathbb{R}$. The aim is to minimize this measure using an optimization algorithm via modifications of the parameters $\boldsymbol{\theta} \in \mathbb{R}^n$, with n being the number of parameters. The parameters $\boldsymbol{\theta}$ modify predefined quantities within the numerical model such as masses or stiffnesses.

2.1. Quantification of deviations between numerical model and measured data

Two different measures are used within this study. The first employs modal parameters whereas the latter is formulated based on transmissibility functions. The use of modal parameters has the advantage of a fast numerical simulation. Moreover, it is possible to use the average modal parameters of several measurements. Operational modal analysis is a big research field comprising a large variety of methods for identifying modal parameters from measured data. However, the choice of the method influences the results. In addition, many methods provide a certain user dependency by means of parameters needing to be adjusted problem dependent. Employing transmissibility functions for model-to-measurement comparison has the advantage of avoiding the effort needed for operational modal analysis and hence excludes a possible source of errors. Furthermore, in contrast to other frequency or time domain based approaches, it is sufficient to measure the output of the structure solely without exact knowledge of the excitation, since this information can hardly be gathered exactly in many real life applications.

2.1.1. Deviation quantification based on modal parameters. Modal parameters are most commonly used for model-measurement comparison [13]. In this study, a combination of eigenfrequencies $\boldsymbol{\omega}$ and mode shapes $\boldsymbol{\phi}$ using

$$f(\boldsymbol{\theta}) = \|\frac{\omega_m - \omega_s(\boldsymbol{\theta})}{\omega_m}\|_2 + \sum_{i \in \mathcal{Y}} \|\boldsymbol{\phi}_m^i - \boldsymbol{\phi}_s^i(\boldsymbol{\theta})\|_2 \tag{1}$$

is employed for this purpose. The subindices m denote measured quantities and s simulated quantities, respectively. $\mathcal{Y}$ represents the set of considered eigenvectors. For each considered eigenmode the difference between measured and simulated data is determined for eigenfrequencies and eigenvectors using the Euclidean norm.

2.1.2. Deviation quantification based on transmissibility functions. Transmissibility functions (TF) are frequency-dependent response functions, that describe the relationship between two responses from different locations on the structure [11]. Transmissibility functions are defined as

$$\boldsymbol{TF}_{ij,k}(\omega) = \frac{\boldsymbol{X}_i(\omega)}{\boldsymbol{Y}_j(\omega)} = \frac{\boldsymbol{H}_{ik}(\omega) \cdot \boldsymbol{F}_k(\omega)}{\boldsymbol{H}_{jk}(\omega) \cdot \boldsymbol{F}_k(\omega)} = \frac{\boldsymbol{H}_{ik}(\omega)}{\boldsymbol{H}_{jk}(\omega)} \tag{2}$$

with $\boldsymbol{X}(\omega)$ and $\boldsymbol{Y}(\omega)$ denoting the responses at the locations i and j. $\boldsymbol{H}(\omega)$ denotes the frequency response function between the response $\boldsymbol{X}(\omega)$ at the location i and $\boldsymbol{Y}(\omega)$ at the location j and the employed force $\boldsymbol{F}(\omega)$ located in k. Since the force can be cancelled, the transmissibility function solely depends on the location of the force. It is independent from the magnitudes. In this study, transmissibility functions are evaluated using

$$\boldsymbol{TF}_{xy} = \frac{\boldsymbol{P}_{yx}}{\boldsymbol{P}_{xx}}, \tag{3}$$

with $\boldsymbol{P}_{yx}$ denoting the cross power spectral density of the responses $\boldsymbol{X}$ and $\boldsymbol{Y}$ and $\boldsymbol{P}_{xx}$ denoting the power spectral density of the response $\boldsymbol{X}$. For damage and ice localization, the transmissibility function is evaluated with two measured acceleration time series and compared to the transmissibility function determined from the corresponding acceleration time series of the numerical model using the l_2 norm. The objective function used for model updating is defined as

$$f(\boldsymbol{\theta}) = \sum_{i=1}^{n} \frac{\|\boldsymbol{TF}_{xy,i}^m - \boldsymbol{TF}_{xy,i}^s(\boldsymbol{\theta})\|_2}{\|\boldsymbol{TF}_{xy,i}^m\|_2}, \tag{4}$$

where n denotes the number of considered transmissibility functions, $\boldsymbol{TF}_{xy}^{m}$ denotes the transmissibility functions resulting from the measurement and $\boldsymbol{TF}_{xy}^{s}$ denotes the simulated transmissibility functions.

2.2. Minimization of the deviation between numerical model and measured data
The optimization algorithm used is presented in [9]. The measures outlined above are employed for the definition of a minimization problem of the form

$$\min_{\boldsymbol{\theta}} f(\boldsymbol{\theta}) \tag{5a}$$

$$\text{subject to } c_i(\boldsymbol{\theta}) \geq 0 \; \forall \; i \in \mathcal{I} \,. \tag{5b}$$

The objective function f depending on the parameter set $\boldsymbol{\theta}$ is minimized by variations of $\boldsymbol{\theta}$ subject to collection of inequality constraints ($\mathcal{I}$). These constraints ensure that the parameters remain within a defined range. For instance, these constraints may be used to keep physical feasibility of the model, e.g. masses must be positive. A two-step optimization algorithm is used to minimize the objective function. Problems arising in model updating are known to have several local minima [13]. Therefore, a global optimization algorithm is employed to solve problem (5). In this study, Simulated Quenching, an enhancement to the Simulated Annealing algorithm, is used. Simulated Annealing is inspired by the slow annealing of metals [14], where the atoms arrange in a crystal lattice in configuration of minimal energy. At certain temperatures, particles may leave the lattice or arrange in it. Transferred to optimization, this means that random solutions are accepted if they have a lower energy E, and hence a lower objective function value. In addition, it is checked whether the constraints are fulfilled. If constraints are violated, a new solution is created randomly. Worse solutions with bigger values $f(\boldsymbol{\theta})$ are accepted if a random number between zero and one is smaller than $e^{\frac{-\delta E}{T}}$, where δE denotes the difference between the actual and the next objective function value and T denotes the actual 'temperature'. For low temperatures this acceptance probability is decreased. After N repetitions the temperature is lowered repeatedly. Thus, no minimum is left if the algorithm is close to the end and the optimization algorithm converges towards an optimum. The main disadvantage of Simulated Annealing is that it requires a long time to converge towards the exact minimum. Hence, Simulated Quenching is used, which uses an exponential cooling scheme with $T_{k+1} = T_0 \cdot e^{((C-1)k)}$ instead of a linear one in order to accelerate the algorithm [16], with k denoting the iteration counter. T_{k+1} denotes the next temperature and C denotes an appropriately chosen value for the annealing constant. Both Simulated Annealing and Simulated Quenching are based on randomness. Hence, it can not be guaranteed that the algorithm calculates the correct minimum. In this study, the minimum is approximated several times in order to overcome this. After approximating an initial solution using Simulated Quenching, the exact minimum is determined using a local optimization algorithm. In this study, a Sequential Quadratic Programming method is used. Sequential Quadratic Programming methods combine an unconstrained optimization problem employing Newton's method with constrained consideration using Lagrange's method [15]. A quadratic subproblem is constructed at the actual iteration $\boldsymbol{\theta_k}$, approximating the objective function quadratically and the constrains linearly. The subproblem can be written as
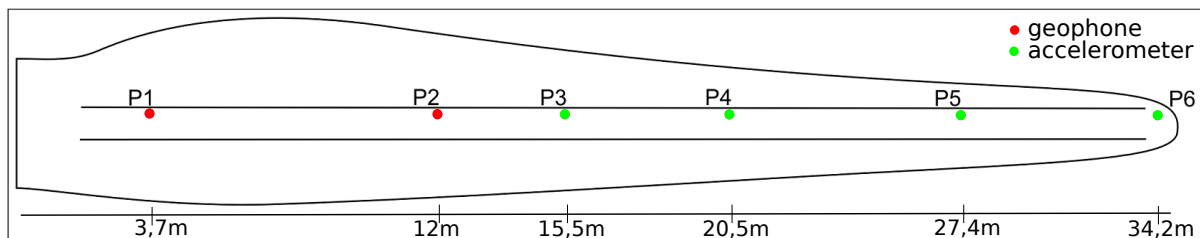
$$\min_{\boldsymbol{p}} \frac{1}{2}\boldsymbol{p^T}\nabla_{\boldsymbol{\theta\theta}}^2 \mathcal{L} \, \boldsymbol{p} + \nabla f_k^T \boldsymbol{p} + f_k \tag{6a}$$

$$\text{subject to } \nabla c_i(\boldsymbol{\theta_k})^T \boldsymbol{p} + c_i(\boldsymbol{\theta_k}) \geq 0 \; \forall \; i \in \mathcal{I}, \tag{6b}$$

with $\nabla_{\boldsymbol{\theta\theta}}^2 \mathcal{L}$ denoting the Hessian of the Lagrangian of problem (5) and $\boldsymbol{p}$ denoting the solution used as an iteration step towards the final solution. f_k is the objective function evaluated at

**Figure 1.** Rotor blade investigated on the test rig [2]

Figure 2. Sensor positions and types at the rotor blade

iteration k. The main advantage of this method is that no evaluation of the objective function is needed to solve the subproblem. The evaluation of the objective function is numerically costly, since every evaluation of the objective function includes a finite element analysis. Central differences are used in order to approximate ∇f_k since no general approach for finding the derivative of the objective function exists. The Hessian $\nabla^2_{\boldsymbol{\theta\theta}}\mathcal{L}$ is approximated using the BFGS-method, making the algorithm a Quasi-Newton procedure [15]. Since the solution is approximated using Simulated Quenching, the parameter set is modified before Sequential Quadratic Programming is started. The parameter with the biggest deviation from the initial value is supposed to be the parameter that needs to be changed. Hence, this parameter and its neighbours are treated variable whereas the remaining parameters are fixed. This procedure significantly reduces the effort needed to solve subproblem (6).

3. Experimental investigations at the rotor blade

In order to validate the model updating algorithm, measurements are performed at a 34 m wind turbine rotor blade made of glass fiber composite material, see Figure 1. Twelve sensors are installed at the rotor blade at six positions in order to measure the structural responses. The sensor position and types are depicted in Figure 2. The rotor blade is tested in six conditions. Firstly, a test is performed at the healthy structure to record the initial configuration. Subsequently additional steel sheets each having a mass of 4.8 kg are fixed at the tip of the blade in four steps in order to simulate ice accretion. The ice accretion steps, including the positions and weights, are given in Figure 3 and Table 1. Finally, the blade is tested in damaged state without ice. This state is achieved by an edgewise fatigue test. Cyclic loading in edgewise direction is applied by a load frame 17.5 m from the blade root. Damage occurs
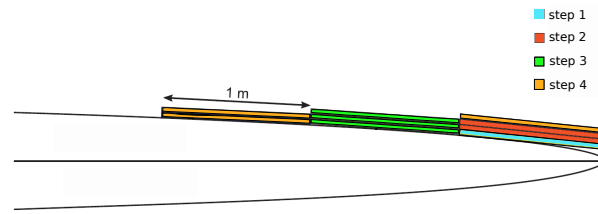
Figure 3. Steps for ice accretion test

Table 1. Steps and added masses for ice accretion localization

Step	Number of steel sheets	Position of steel sheets in m	Added weight of sheets in kg	Added weight in percentage of blade mass in %
1	1	33-34	4.8	0.1
2	3	33-34	14.4	0.3
3	3 3	33-34 32-33	14.4 14.4	0.6
4	4 3 2	33-34 32-33 31-32	19.2 14.4 9.6	0.9

at the trailing edge, 6 m from the root. The structure is excited using hand excitation of the first three eigenmodes and impulse hammer excitations at different locations. The analysis presented here focuses on flapwise hammer excitations 33 m from the blade root. Data driven Stochastic Subspace Identification [17] is used to identify eigenfrequencies and eigenvectors from the measured signals.

4. Model updating at the rotor blade
Only mass and stiffness distributions are known at different spots along the blade. Due to this limited information on the geometry of the blade, it is modelled using a rectangular cross section. Nodes are set at every spot with known properties, resulting in a model with 26 Timoshenko beam elements. Two beam elements are merged in one parameter in order to reduce the number of optimization parameters. Hence, each parameter modifies the initial stiffness of two elements.

4.1. Damage localization using simulated data
A numerical example is presented to demonstrate the theoretical functionality of the algorithm. Damage is simulated by different reductions of the stiffness in parameter four, representing damage at 6m. The optimization problem used for damage localization is

$$\min_{\boldsymbol{\theta}} f(\boldsymbol{\theta}) \tag{7a}$$

$$\text{subject to } \theta_i \geq 0.5 \ \forall \ i \ \in \boldsymbol{\theta} \tag{7b}$$

$$\theta_i \leq 1.01 \ \forall \ i \ \in \boldsymbol{\theta} \tag{7c}$$

$$\sum_i (1 - \theta_i) \leq 0.5 \,. \tag{7d}$$

The maximum decrease is constrained to 50% (eq. 7b), a small increase of 1% is allowed (eq. 7c) for numerical reasons. In addition, a constraint is defined ensuring that only one parameter can

Table 2. Results of eight Simulated Quenching and adaptive Sequential Quadratic Programming runs, using modal parameters to localize a stiffness decrease of 3%

SQP run number	Objective funtion value	Parameter number												
		1	2	3	4	5	6	7	8	9	10	11	12	13
1	$3.975 \cdot 10^{-06}$	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.999	1.000	1.000	1.00	1.00
2	$5.032 \cdot 10^{-08}$	1.00	1.00	0.992	0.985	1.001	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
3	$3.494 \cdot 10^{-06}$	1.00	1.00	1.00	1.00	1.00	1.00	0.998	0.996	0.998	1.00	1.00	1.00	1.00
4	$4.007 \cdot 10^{-06}$	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.000	0.998	0.999	1.00	1.00
5	$1.510 \cdot 10^{-08}$	1.00	1.00	1.00	0.978	1.001	0.999	1.00	1.00	1.00	1.00	1.00	1.00	1.00
6	$5.032 \cdot 10^{-08}$	1.00	1.00	0.992	0.985	1.001	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
7	$3.272 \cdot 10^{-06}$	1.00	1.00	1.00	1.00	1.00	0.997	0.994	1.002	1.00	1.00	1.00	1.00	1.00
8	$1.496 \cdot 10^{-08}$	1.00	1.00	1.00	0.978	1.001	0.999	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Table 3. Results of ten Simulated Quenching and adaptive Sequential Quadratic Programming runs, using transmissibility functions to localize a stiffness decrease of 3%

SQP run number	Objective funtion value	Parameter number												
		1	2	3	4	5	6	7	8	9	10	11	12	13
1	0.0537	1.00	1.00	0.996	0.982	1.001	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
2	0.0869	1.00	1.004	0.994	0.982	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
3	2.3264	1.00	1.00	1.00	1.00	1.010	1.010	0.952	1.00	1.00	1.00	1.00	1.00	1.00
4	0.4932	1.010	0.983	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
5	0.0540	1.00	1.00	0.996	0.982	1.001	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
6	0.0538	1.00	1.00	0.996	0.982	1.001	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
7	0.5321	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.997	1.002	0.996
8	2.2413	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.974	1.010	1.010	1.00
9	0.2233	1.00	1.010	0.987	0.978	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
10	2.0297	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.010	1.010	0.966

be close to the maximum estimated stiffness decrease (eq. 7d) [18]. The parameters in $\boldsymbol{\theta}$ modifiy the stiffnesses of two elements. The resulting parameter vectors with the lowest corresponding objective function value of several Simulated Quenching runs for a stiffness decrease of 3% are given in Tables 2 and 3. Since an adaptive reduction of the parameter set is applied after running Simulated Quenching, many parameters are set to 1.0 in the results. It is shown that the runs that localize simulated damage correctly in parameter four lead to much smaller objective function values. Thus, this quantity is used to distinguished between wrong and correct solutions. Therefore, damage localization is possible for the numerical example using both metrics. The parameter vector entries are examined in order to quantify the simulated damage. The parameter vector entries for all correct Sequential Quadratic Programming runs are depicted in Figure 4. It is shown that both metrics lead to similar results. A smaller stiffness decrease leads to a bigger parameter vector entry. Both comparison metrics based on modal parameters and transmissibility functions seem to perform equally good on this theoretical example. The outlier at 2 percent stiffness reduction can be detected by the objective function value, which is 10% bigger than those of the other solutions in this solution class.

4.2. Damage localization using measured data
After validating the model updating algorithm using a numerical example, the algorithm is applied to real measured data of the rotor blade. The minimization problem for damage
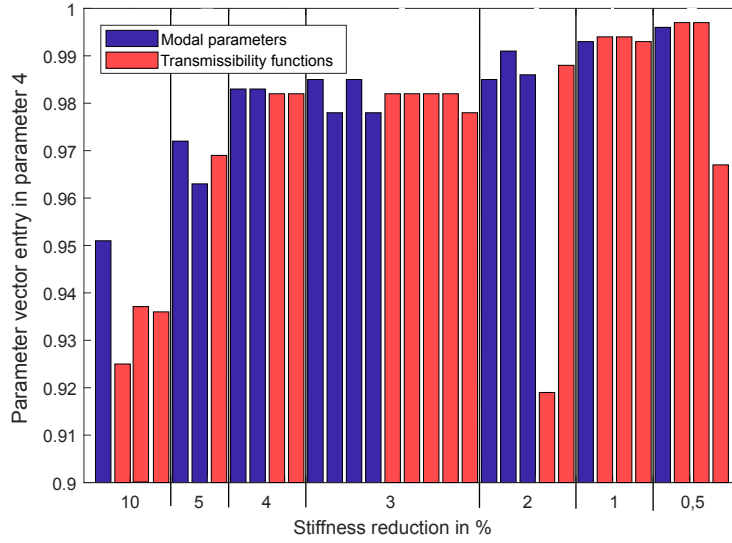
Figure 4. Parameter vector entries for all correct SQP runs for the numerical example

localization using measured data is defined as

$$\min_{\boldsymbol{\theta}} \; f(\boldsymbol{\theta}) \tag{8a}$$

$$\text{subject to } \theta_i \; \geq 0.25 \; \forall \; i \; \in \boldsymbol{\theta} \tag{8b}$$

$$\theta_i \; \leq 1.01 \; \forall \; i \; \in \boldsymbol{\theta} \tag{8c}$$

$$\sum_i \left(1 - \theta_i\right) \leq 0.75 \,, \tag{8d}$$

where a stiffness decrease of 75% is allowed. This stiffness decrease is too high and aims to demonstrate the robustness of the approach. The measure ψ is introduced in order to illustrate results in a comprehensive manner. ψ is evaluated averaging the mean deviation of the parameters from the initial value 1.0 for all optimization runs.

$$\psi_i = \frac{\left| \mathcal{M}_{\boldsymbol{p}_i} - 1 \right|}{max(\boldsymbol{\psi})}, \tag{9}$$

where $\boldsymbol{p}_i$ denotes the vector of parameter i in all optimum solutions and $\mathcal{M}_{\boldsymbol{p}_i}$ denotes the expected value of a vector $\boldsymbol{p}$. The measure ψ resulting from damage localization using modal parameters and transmissibility functions is depicted in Figure 5. Damage occurred in the area covered by parameter three. The model updating algorithm localizes it in parameter five using modal parameters and in parameter one and six using transmissibility functions. Hence, both metrics localize the damage in wrong areas.

4.3. Ice detection and quantification
It is known that ice accretion initiates at the blade tip [2]. Therefore, the parameterization is refined in the area close to the tip. The density is varied in order to modify the mass of the

(a) Using modal parameters   (b) Using transmissibility functions
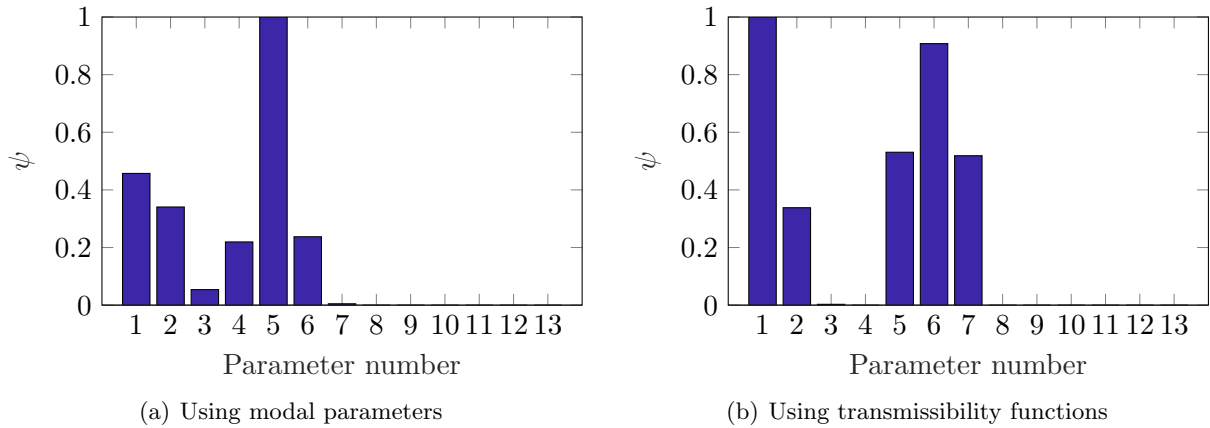
Figure 5. Vector parameter ψ for damage localization
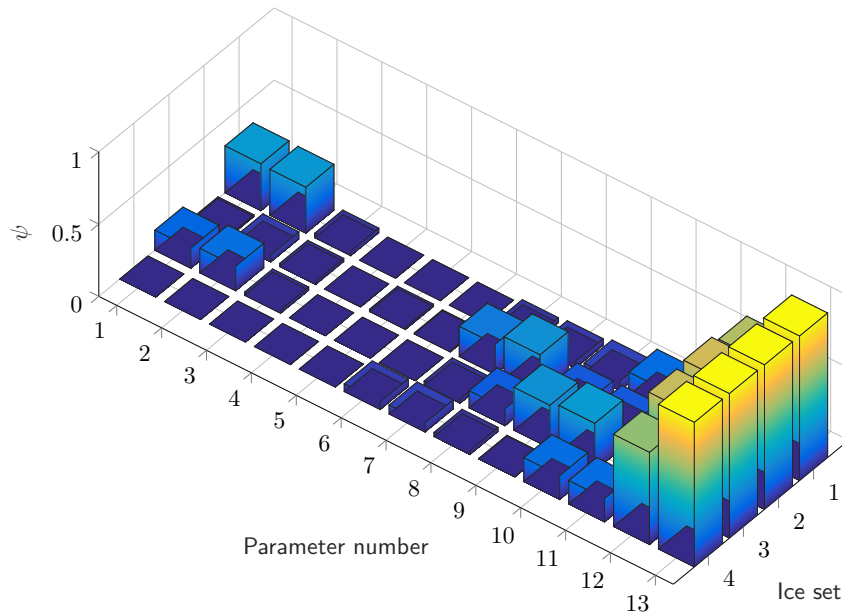
Figure 6. Overview on vector parameter ψ for all four ice steps using modal quantities
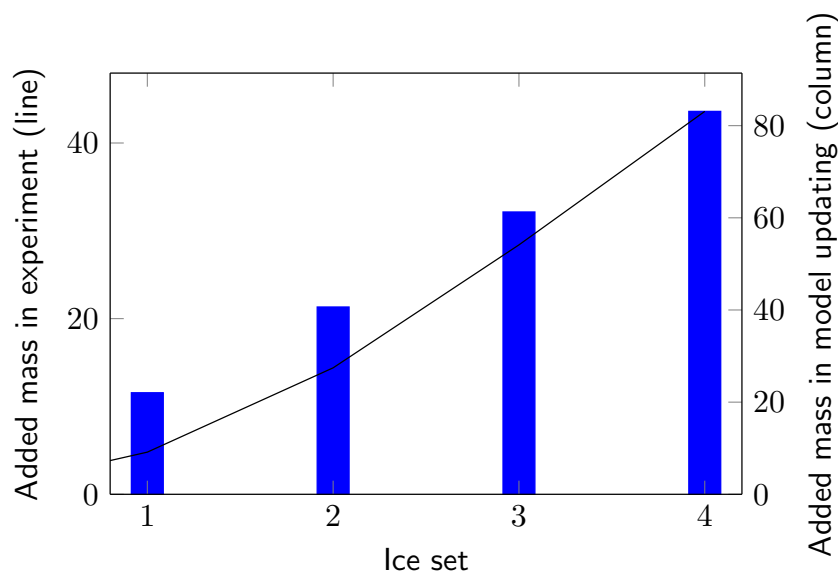
elements. The optimization problem used for ice localization is defined as

$$\min_{\boldsymbol{\theta}} \ f(\boldsymbol{\theta}) \tag{10a}$$

$$\text{subject to } \theta_i \ge 0.99 \ \forall \ i \ \in \boldsymbol{\theta} \tag{10b}$$

$$\theta_i \le 1.75 \ \forall \ i \ \in \boldsymbol{\theta} \,, \tag{10c}$$

where a small decrease of 1% and a increase of 75% of the density is allowed. The measure ψ for ice localization using modal parameters for all ice steps is illustrated in Figure 6. It reveals a clear location of added masses in parameters 12 and 13, which represents the blade tip. Hence, ice localization using modal parameters is possible. The parameter vector entries are used to calculate the extra masses. Masses added in the experiment are compared with the averaged masses determined using model updating in Figure 7. The identified masses overestimate masses added during the experiment by the factor two to three. Both the added masses of experiment

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Figure 7. Comparison of added masses during experiment and average additional mass determined using model updating

and identified using model updating reveal a behaviour close to linearity within the range considered here. This linear relationship may be used to determine the real mass growth on the structure. In contrast to modal parameters, ice detection using transmissibility functions is unsuccessful. The added mass is located in different parameters in the four steps. In the first step, the added mass is located in parameter 2, in step 2 it is located in parameter 12, in step 3 in 11 and in the last step in parameter 10.

5. Discussion and limitations

The model updating algorithm delivers good results in the numerical analysis. If the damage is located at the right location, the objective function value is about a decimal power smaller. Both considered metrics yield similar results. The entry in the parameter vector gets bigger for smaller stiffness reductions. The identified stiffness reduction underestimates the reference stiffness reduction by a factor of about 0.5.

Using the measured data taken from the rotor blade for damage localization the algorithm yields wrong results. The ice accretion localization using transmissibility functions supplies invalid results. This can be attributed to the sensor positions. Damage localization using modal parameters located the damage in the range of the second sensor. It is possible that the damage effects to the modal parameters are not manifested on vibration signals of the first sensor. Furthermore, the wrong localization may be caused by the impreciseness of the numerical model. Due to limited information on the geometry of the blade, it is modelled using a rectangular cross section, focusing on the webs and girders that carry the loads arising in a rotor blade. During the experiment, damage occurs only at the airfoil. Since the load carrying structure remains undamaged, the influence on the global dynamic behavior is weak. This can be shown by observing the small change of eigenfrequencies and mode shapes after damage. In addition, damping which is influencing results of transient analyses is strongly simplified using a material damping formulation. This approach is probably too simple to capture the real damping behaviour. In the use of transmissibility functions presented here, only ten out of thirty functions are affected by the damage, the remaining contain relationships between sensors

that do not cover the damaged area. Hence, the algorithm may fail because the effect of damage may be obliterated between all functions used.

The metric employing modal parameters locates the added masses correctly at the tip of the blade. The quantification of the identified masses using the parameter vector overestimate the mass added in the experiment by the factor two to three. The nearly linear behaviour of both masses may be used to estimate the real mass growth. Due to the fact that the added masses are localized correctly using modal parameters, it is possible that effect of damage on the modal parameters is too small to localize it correctly.

6. Conclusion and outlook

In this paper, a plausibility test of damage and ice accretion localization using model updating, employing the example of a wind turbine rotor blade is presented. Two different metrics, based on eigenfrequencies and mode shapes and another based on transmissibility functions, are considered to quantify the deviation between numerical model and measured data. The results of both metrics are compared. Furthermore, it is investigated whether it is possible to quantify damage and ice accretion.

The structure used to validate the model updating algorithm is a 34 m long wind turbine rotor blade, which is tested in six conditions. The numerical model is created using 26 Timoshenko beam elements with a rectangular cross section, meaning that one element has a length of $1.3m$. The localization problem is solved using a minimization problem. An objective function is defined to compare measured data with simulated data and build a residuum between them. In this study, the objective function is formulated using modal parameters and transmissibility functions.

The residuum is reduced using a two-step optimization algorithm. This algorithm combines Simulated Quenching, a global optimization technique, with the local Sequential Quadratic Programming. The result of the optimization process is a parameter vector representing the calculated modifications of the parameters of the numerical model. The parameter with the biggest deviation is considered as potentially damaged or as potential location of ice accretion. The objective function value is used to distinguish correct from wrong solutions.

A numerical analysis is performed in order to validate the model updating algorithm. It is shown that a small stiffness reduction of 0.5% can be localized correctly. The damage at the trailing edge of the rotor blade during the experiment can not be located correctly, neither with modal parameters nor with transmissibility functions. Localization of ice accretion using modal parameters yields correct results. A quantification of the identified masses using the parameter vector overestimates the masses added in the experiment by the factor two to three. Both masses reveal a nearly linear behaviour. This may be used to estimate the real mass growth. The ice localization using transmissibility functions yields wrong results.

The influence of sensor positions on localization results should be investigated further. The results of ice quantification presented here are valid only for one blade investigated with small masses. The linearity assumption made for the scaling of the mass within this paper should be validated for bigger masses being attached to the blade. Due to the fact that transmissibility functions are depending on the position of load application it has to be considered whether localization is possible under changing loading conditions.

Within the analysis presented, loads are known and environmental and operational conditions are not included. These should be investigated for applications in real turbines, since these factors heavily affect the structural properties of the turbines. A workaround for this could be to create individual numerical models for similar environmental and operational conditions. Unknown loads may be approximated by the use of Kalman filters.

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