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SYSTEM IDENTIFICATION OF A WIND TURBINE USING ROBUST MODEL UPDATING STRATEGY

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Abstract. *This paper presents a robust model updating strategy for system identification of wind turbines. To control the updating parameters and to avoid ill-conditioning, the global sensitivity analysis using the elementary effects method is conducted. The formulation of the objective function is based on Müller-Slany's strategy for multi-criteria functions. As a simulation-based optimization, a simulation adapter is developed to interface the simulation software ANSYS and the locally developed optimization software MOPACK. Model updating is firstly tested on the beam model of the rotor blade. The defect between the numerical model and the reference has been markedly reduced by the process of model updating. The effect of model updating becomes more pronounced in the comparison of the measured and the numerical properties of the wind turbine model. The deviations of the frequencies of the updated model are rather small. The complete comparison including the free vibration modes by the modal assurance criteria shows the excellent coincidence of the modal parameters of the updated model with the ones from the measurements. By successful implementation of the model validation via model updating, the applicability and effectiveness of the solution concept has been demonstrated.*

1 INTRODUCTION

The renewable energy sources have gained high attention due to the current energy crisis and the urge to get clean energy. Wind energy as a strong contender, therefore, is becoming more and more popular. As the wind turbine structure, however, suffers from inevitable ageing and degradation resulting from operational actions, continuous system identification based upon long term monitoring is indispensable. By that, the current state of the structure can be determined and possible failures can be revealed in time. To this end, an adequate numerical model is mandatory to predict the structural behavior. This model needs to be validated by a continuous model updating to ensure a reliable and accurate estimation of the structural behavior.

According to [1], the model updating methods can be broadly classified into direct methods, which are essentially non-iterative ones, and iterative methods. A number of methods that were first to emerge belong to the direct category. These methods update directly the elements of stiffness and mass matrices and are one step procedures. Although the resulting updated matrices reproduce measured modal data exactly, they do not generally maintain structural connectivity and the corrections suggested are not always physically meaningful [2]. The methods in the second category are referred to as iterative methods. Iterative methods use changes in physical parameters to update the finite element models and, thereby, generate models that are physically realistic. From earlier work on finite element model updating it is evident that finite element model updating is essentially an optimization method. Here, the design variables are the uncertain parameters in the model. The objective is to minimize the distance between the predicted data by the model and the measured data. Some applications of the iterative optimization methods are reviewed in [3, 4, 5, 6, 7].

However, some key issues in the iterative optimization method of model updating are not fully matured, especially for continuous system identification, e.g. how to control the updating parameters and to avoid ill-conditioning; how to master the sophisticated simulation-based optimization and solve the non-standard optimization problem. To solve these problems, a robust model updating strategy is proposed in this paper, including four main aspects as described in the next section.

2 PROPOSED MODEL UPDATING STRATEGY

2.1 Updating parameter determination

Specifying the updating parameters is one of the most difficult yet most critical steps in the whole updating process. The number of updating parameters should be large enough to cover all the relevant uncertain parameters, but as low as possible to avoid ill-conditioning. An initial selection of the parameters depends on clearly engineering insight of the model. Such parameters typically are associated to unknown material parameters, approximated geometrical parameters, uncertain boundary conditions, parts with a high level of uncertainty (e.g. joints, localized mass), and etc. They can be described by a vector $\mathbf{x}$ in Equation 1.

$$\mathbf{x} = \left(X_1 \dots X_k\right) = \begin{pmatrix} \text{material parameters} \\ \text{geometrical parameters} \\ \text{boundary conditions} \\ \dots \end{pmatrix} \tag{1}$$

To ensure well-conditioned problem, the number of the updating parameters should not exceed the number of the measured responses. It needs to be limited to the variation of a few key model parameters that account for the observable errors. To identify the impact of different parameters on the model errors, the sensitivity analysis can be conducted. The traditional sensitivity analysis, which is also called local sensitivity analysis, is derivative-based approach and only efficient for linear models. As for nonlinear and non-additive models, the global sensitivity analysis should be used, since this method explores the whole space of the input parameters and includes the interaction effect among parameters as well.

There are several different methods that belong to the class of global sensitivity analysis, as described in detail by [8]. The choice of the proper sensitivity analysis technique depends on such considerations as: the computational cost of running the model; the number of input factors; features of the model (e.g. linearity, additivity). Considering a modest model computational expense (e.g. up to 10 minutes per run) and dozens of parameters (e.g. 20 to 100), the elementary effects (EE) method is recommended as a simple but effective way to identify the few important factors among the many contained in the model and cope with nonlinearity and interactions. The fundamental idea behind this method is owed to Morris, who introduced the concept of elementary effects in 1991 [9]. While adhering to the concept of local variation around a base point, the EE method makes an effort to overcome the limitations of the derivative-based approach by introducing wider ranges of variations for the inputs and averaging a number of local measures so as to remove the dependence on a single sample points. An elementary effect is defined as [8]:

$$EE_i = \frac{Y(X_1, X_2, \ldots, X_{i-1}, X_i + \Delta, \ldots, X_k) - Y(X_1, X_2, \ldots, X_k)}{\Delta} \tag{2}$$

The sensitivity measures, μ and σ, proposed by Morris, are respectively the mean and the standard deviation of the elementary effects calculated from finite randomly sampled inputs. The mean μ assesses the overall influence of the factor on the output. The standard deviation σ estimates the ensemble of the factor's effects, whether nonlinear and/or due to interactions with other factors. Campolongo et al. [10] proposed replacing the use of the mean μ with μ^*, which is defined as the mean of the absolute values of the elementary effects. The use of μ^* can prevent cancellation effects when the model is nonmonotonic or has interaction effects. μ^* is a practical and concise measure to use, especially when there are several output variables. Campolongo et al. [10] have also shown that μ^* is a good proxy of the total sensitivity index S_T of the variance-based method [8]. With the aid of the global sensitivity analysis, the few decisive key parameters can be selected as updating parameters for the following process.

2.2 Objective function formulation

The objective function used in model updating evaluates the defect between the model predicted and the measured data. Typical measurements include the modal model (natural frequencies and mode shapes) and the frequency response functions (FRF). Based on Müller-Slany's strategy [11], the error expressions $\varepsilon_i(\mathbf{x})$ between the numerical and measured dynamic properties are components of the vector objective function $\mathbf{f}[\varepsilon(\mathbf{x})]$ in Equation 3. To express errors of natural frequencies and mode shapes, the modal frequency shift [12] and the modal assurance criterion (MAC) [13] can be utilized.

$$\mathbf{f}[\varepsilon(\mathbf{x})] = \begin{bmatrix} \varepsilon_1(\mathbf{x}) \\ \varepsilon_2(\mathbf{x}) \\ \varepsilon_3(\mathbf{x}) \\ \varepsilon_4(\mathbf{x}) \\ \cdots \end{bmatrix} = \begin{bmatrix} \text{error expression of total mass} \\ \text{error expression of natural frequencies} \\ \text{error expression of mode shapes} \\ \text{error expression of FRF} \\ \cdots \end{bmatrix} \tag{3}$$

It is worth noting that the measured and analytical natural frequencies and mode shapes must relate to the same mode, that is, they must be paired correctly. Arranging the natural frequencies in ascending order of magnitude is not sufficient, because the mode orders may not be correct when two modes are close together in frequency, and the finite element model normally provides more degrees of freedom than those can be identified from measurements. The approach to pair the modes is by using the modal assurance criterion (MAC). For a reference mode, the corresponding numerical mode should have the largest MAC value.

After formulating the individual objective functions separately, the linear weighting sum method (LWS) [14], which is based on the concept of aggregation functions, is adopted to combine the multi-objective functions into a scalar objective function of Equation 4, using appropriate weighting factors w_i so that the relative importance of the individual objectives can be reflected:

$$f(\mathbf{x}) = \sum_{i=1}^{k} w_i \varepsilon_i(\mathbf{x}) \tag{4}$$

With the objective function having been formulated, the model updating is established by solving the constrained multi-criteria optimization problem of Equation 5, in which $\mathbf{h}(\mathbf{x})$is the constraint function, while $\mathbf{x}_L$ and $\mathbf{x}_U$ are the lower and upper bounds, respectively.

$$\min_{\mathbf{x}\in\Sigma}\{f(\mathbf{x}) \mid \mathbf{h}(\mathbf{x}) = 0\}, \Sigma := \{\mathbf{x} \in R^n \mid \mathbf{x}_L \leq \mathbf{x} \leq \mathbf{x}_U\} \tag{5}$$

2.3 Optimization algorithm selection

It is crucial to choose a suitable algorithm for the optimization involved in the model updating, because the existence and correctness of the solution as well as the convergence speed largely depend on the nature of the optimization problem. The optimization problem in the model updating has a number of properties, which makes it hard to solve:

- The interdependence between residuals and the updating parameters is highly nonlinear; therefore the common derivative-based approaches are not fully applicable.
- Since a multi-criteria objective function has been formulated, a large number of local minima have to be taken into consideration.
- Due to the complexity of the real-world problem, as a rule, the objective function is not continuously differentiable.
- The presence of numerical noise introduces additional difficulties.

For these reasons, the deterministic techniques, which are efficient for smooth problems, turn out not to be applicable here because of their gradient-based characteristic. Instead, the evolutionary algorithms (EAs), known as derivative free methods, can be considered as a reliable alternative in such situations. Bäck and Schwefel [15] and Eiben [16] give overviews on EAs. EAs have several advantages compared to gradient-based methods for complex problems. They require only little knowledge about the problem being solved, and they are easy to implement, robust, and most important, inherently parallel. Since most real-world problems involve simultaneous optimization of several concurrent objectives, parallel approaches are advantageous. EAs are well suited to multi-objective optimization problems as they are fundamentally based on multi-membered biological processes which are inherently parallel.

2.4 Optimization process implementation

The model updating process constitutes a simulation-based optimization. In the simulation-based optimization, all or some of the objective and constraint functions depend on the simulation result. In each optimization iteration, the output from simulation is used to compute the objective and constraint functions. If the objective function does not meet the convergence criteria, new values for updating parameters are created according to the logic of the optimization method and used to reform the FE model. Then, the simulation is invoked again to compute new output. Hence, in simulation-based optimization, optimization and simulation work together as a whole.

The respective simulations are commonly accomplished using commercial finite element software because they are powerful numerical analysis tools providing high reliability and numerous capabilities. In the present work, the applied simulation tool is the commercial finite element software ANSYS 11. Regarding the optimization problem, the complex real world structures often lead to optimization problems difficult to solve. In most of the cases, the existing simulation software offers no direct support for nonlinear optimization or has no powerful optimization tools. For instance, the optimization methods provided by ANSYS are entirely derivative-oriented, making it impossible to solve non-standard optimization problems, like nonlinear or discontinues optimization problems. Therefore, in the present work, the java-based optimization framework, MOPACK, is applied to solve the simulation-based optimization problem. MOPACK is the abbreviation for multi-method optimization package and has been implemented by Nguyen et al. [17]. It contains numerous robust optimization strategies, including deterministic methods and stochastic methods. More details about the available methods in MOPACK can be found in [17]. In particular, the graphical user interface (GUI) of MOPACK provides sophisticated tools for visualization and pre and post-processing. Another important issue is that MOPACK is extensible such it can be enriched with new methods and applications.

To solve the simulation-based optimization problem with the aid of MOPACK, intensive interactions are required between the external simulation software ANSYS and the optimization framework MOPACK. Therefore, a simulation adapter is developed for running the optimization using external solvers in the simulation software and the optimization framework simultaneously [18]. The integration of multiple software in the optimization procedure makes the proposed model updating approach robust for complex structural optimization problems.

3 TEST IMPLEMENTATION

The proposed approach is substantiated on a real world wind turbine located in Dortmund, Germany, which has a gearless system and a 40m-diameter rotor. A complete numerical model of the investigated wind turbine is constructed using ANSYS 11.0. This FE model contains a concrete foundation, a steel tower with flanges, rotor blades and a simplified nacelle. Beam models with coarsely discretized meshes are used for the tower and the blades in order to reduce the development time and to allow parameters to be easily changed and items to be added.

Instead of considering the complete model, it is more reasonable to validate the model components in the first step, in particular the blade model, because several estimations had to be made due to lack of information from the manufacturer.

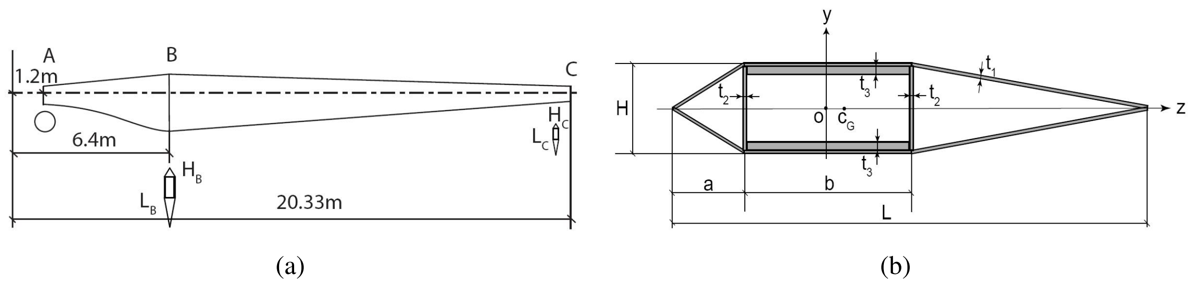

Figure 1: (a) Illustration of the blade geometry (b) Parameters of the cross section

There is no measurement carried out on the blade in the current research project [19], fortunately, a test article of almost the same physical properties has been built and dynamically tested in [20]. Therefore the first five eigenfrequencies provided by [20] are taken as validation criteria for the current blade model.

Before formulating the optimization problem, sensitivity analysis is conducted on the following six geometrical parameters of the blade cross section:

- X_1: thickness t_1 of the skin;
- X_2: thickness t_2 of the two shear webs;
- X_3: thickness t_3 of the top and bottom spar caps.
- X_4: ratio r_1 between the height H and the chord length L at position B;
- X_5: ratio r_2 between the distance of the two shear webs b and the chord length L;
- X_6: ratio r_3 between the height H and the chord length L at position C;

Some assumptions have been made to reasonably simplify the problem: The parameters t_1, t_2, t_3 and r_2 are considered as constants along the blade. A cosine shape function is used between position A and B to transform the shape smoothly, while a linear shape function is used between position B and C. All parts of the cross section are assumed to consist of GRP (Glass fibre Reinforced Plastic) material having the same modulus of elasticity and shear and the same material density.

By implementing the elementary effects method, three sensitivity measures μ^*, μ and σ are calculated to reveal the influences of the six parameters on the output, which is multiple output including the first five eigenfrequencies. The barplots of μ^*, μ and σ for the multiple output are shown in Figure 2 to Figure 4. As above mentioned, the value of μ^* indicates the total sensitivity, therefore it can be concluded that the flapwise modes are sensitive to parameters X_4

and X_5, while the edgewise modes are sensitive to parameters X_1 and X_6. The influences of the parameters on the output is monotonic because the distributions of μ^* and μ are the same. According to the values of σ, parameters X_1, X_5 and X_6 have large interactions with other parameters.

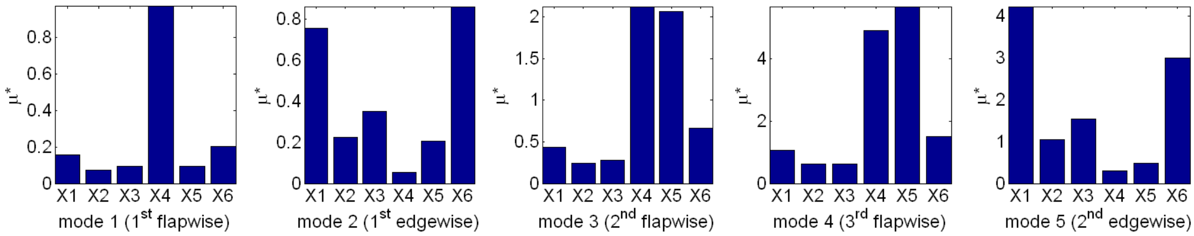

Figure 2: Barplot of μ^* for the first five eigenfrequencies

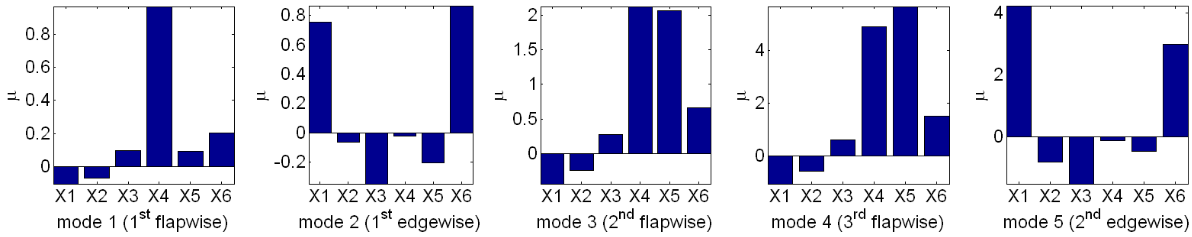

Figure 3: Barplot of μ for the first five eigenfrequencies

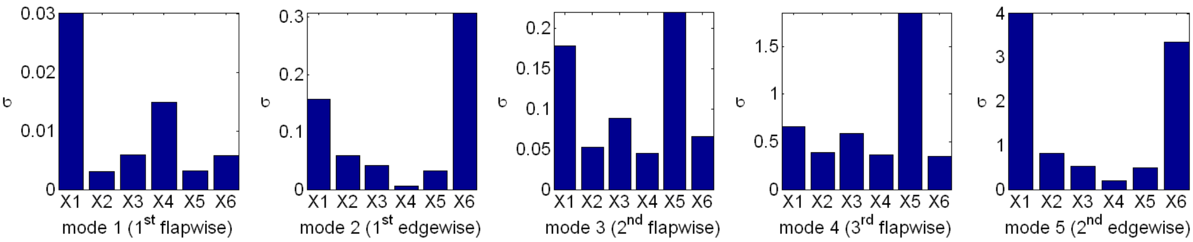

Figure 4: Barplot of σ for the first five eigenfrequencies

Since the number of the initially selected parameters is not large in this case, all of the six parameters are considered in the optimization process. The total weight of the blade serves as a constraint, and the first five eigenfrequencies are computed to compose the objective function. In addition, the modal assurance criterion (MAC) is applied to pair the modes correctly.

Referring to the optimization algorithm, the differential evolution (DE) method, which belongs to the class of EAs, is employed in the present test. The DE is a fairly fast and reasonably robust method with the capability of handling nondifferentiable, nonlinear and multimodal objective functions. It is originally described in [21]. Books [22, 23, 24] have been published on theoretical and practical aspects of using DE in parallel computing, multi-objective optimization and constrained optimizations. The crucial idea behind the DE is using vector differences for perturbing the vector population.

The simulation-based optimization of the blade model has been successfully implemented. Table 1 lists the natural frequencies of the blade model and the deviations (in the parentheses) from the reference before and after model updating. It can be noticed that the defect between the FE model and the reference model has been significantly reduced within the process of model updating.

	blade mode shape	reference frequency f [Hz]	FE model before updating	FE model after updating
1	1st flapwise mode	1.64 Hz	1.503 Hz (8.35%)	1.617 Hz (1.41%)
2	1st edgewise mode	2.94 Hz	3.313 Hz (12.68%)	2.648 Hz (9.94%)
3	2nd flapwise mode	4.91 Hz	5.158 Hz (5.05%)	4.790 Hz (2.45%)
4	3rd flapwise mode	9.73 Hz	12.054 Hz (23.88%)	10.428 Hz (7.18%)
5	2nd edgewise mode	10.62 Hz	15.708 Hz (47.91%)	12.607 Hz (18.71%)

Table 1: Model updating results of the blade model

To validate the complete wind turbine model, an agent-based monitoring system has been established on the tower of the investigated wind turbine for continuous measurement and automated signal processing [25]. By virtue of operational modal analysis (OMA), the modal properties of the wind turbine have been identified from the measured acceleration time histories using the commercial OMA software ARTeMIS Extractor [26]. As listed in Table 2, the first 6 mode shapes are configured in the global coordinate system, whose origin is at the bottom of the tower, X axis is parallel to the rotation plane, Y axis is perpendicular to the rotation plane and Z axis is up. In association with the updated blade model, the complete FE model of the wind turbine provides modal properties quite close to those identified from on-site measurement. Small deviations of frequencies and high MAC values demonstrate very good consistency between the numerical and measured modes. Considering a certain extent of deviation like 5% (normally not avoidable in OMA result due to measurement errors), the FE model can be taken as a very good approximation for representing the dynamic behavior of the real world wind turbine structure.

	mode shape	measured f [Hz]	FE model f [Hz]	deviation	MAC
1	1st bending in X-Z plane	0.3753	0.3595	4.22%	0.9993
2	1st bending in Y-Z plane	0.3779	0.3611	4.44%	0.9994
3	2nd bending in Y-Z plane	2.217	2.242	1.11%	0.9951
4	2nd bending in X-Z plane	2.171	2.380	9.63%	0.9981
5	3rd bending in Y-Z plane	5.837	5.598	4.09%	0.9724
6	3rd bending in X-Z plane	5.857	6.223	6.25%	0.9944

Table 2: Comparison of the measured and numerical modal properties

4 CONCLUSION

The model updating problem serving as a pivot for system identification has been solved by a novel procedure using simulation-based multi-criteria optimization. The crucial aspects of the solution concept include: updating parameter determination by global sensitivity analysis; objective function formulation using multi-criteria; optimization process implementation on the basis of an interface between the MOPACK package and the simulation software; and employment of the evolutionary algorithms for complicated optimization problems. The proposed solution concept has been successfully implemented on a real world wind turbine. The numerical models have been validated by measuring the dynamic response of the rotor blade test article, and of the wind turbine in operation.

In continuous system identification, the numerical model could be successively updated if the system has been subjected to structural modification (damage), which opens new opportunities for modern residual lifetime estimation.

5 ACKNOWLEDGEMENT

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