System Identification of a Wind Energy Converter using Wavelet-based Damage Detection and Robust Model Updating Strategy

submitted by

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Xiangqin Liu
Due to the worldwide demand for green energy and, therefore, due to the rapidly increasing numbers of modern wind energy converters (WECs), the structural health monitoring (SHM) of wind turbines becomes more and more important, with respect to both economical and ecological aspects. Simultaneously, the apparent benefits of SHM necessitate new solution approaches as well as new numerical methods. This particularly applies for the improvement of system identification methods needed for an accurate estimation of structural behavior and a continuous updating of the related numerical models, predominantly finite element models.

As a consequence, the systematic development of a powerful system identification method, being generally applicable for continuous SHM of wind turbines, is one of the prime objectives of the present dissertation. Starting with an in-situ permanent monitoring of a near-by reference WEC, the subsequent data acquisition and data preprocessing, along with the continuing determination of the modal parameters of the dynamic structural behavior, are prerequisite for the reliable system identification. The techniques proposed for the identification procedure are described in full detail. Specifically, the results obtained from the technique variants investigated, and the outcome of the plenitude of measurement samples are compared to each other to verify the software elaborated, and to validate the reliability of the identification method implemented. To ensure an efficient and a robust non-destructive damage detection method, it could be shown that the wavelet transform possesses numerous advantages and, therefore, is the best choice for damage detection, damage localization and damage severity as well. As a result, an integrated wavelet-based damage detection method has been established which is able to accurately detect and localize incipient damages of a WEC, in particular in operating condition. Hereby, the internal issues of solving customary problems encountered in wavelet analysis are addressed; this e.g. includes how to choose the optimal mother wavelet, how to deal with large sampling
distances and edge effects, and how to reduce the influence of measurement noise.

A further prime objective of the present dissertation is model updating which has to be used for life cycle management of wind turbines, primarily for later life time estimation of a structural system or its parts. The model updating problem, in the context of continuous SHM, represents a simulation-based non-standard optimization problem (defect minimization problem), the solution of which warrants highly qualified finite element models of the structural system monitored. To this end, a unified framework for model updating has been developed in the dissertation which provides both damage integration as well as robust model validation. It is scrutinized how the efficient parameterization, how the definition of the multi-objective or optimization function, how the selection of the suitable optimization algorithm and how the implementation of the simulation-based optimization have been accomplished. By means of representative numerical tests the capabilities and the effectiveness of the proposed solution concept are elucidated. Based on the insights obtained, an accurate structural evaluation and damage assessment as well as prediction of the expectable structural responses can be realized. This, in turn, allows for the subsequent (future) reliable lifetime prediction of damage sensitive structural parts.

**Keywords**: system identification, wind energy converter, modal identification, damage detection, model updating
Nomenclature

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<table>
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<th>Description</th>
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<tr>
<td>BEM</td>
<td>Blade element momentum</td>
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<tr>
<td>CV</td>
<td>Coefficient of variation</td>
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<td>CVA</td>
<td>Canonical variate analysis (algorithm used in SSI)</td>
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<tr>
<td>CWT</td>
<td>Continuous wavelet transform</td>
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<tr>
<td>DE</td>
<td>Differential evolution strategy</td>
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<tr>
<td>DOFs</td>
<td>Degree of freedoms</td>
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<tr>
<td>DWT</td>
<td>Discrete wavelet transform</td>
</tr>
<tr>
<td>EAs</td>
<td>Evolutionary algorithms</td>
</tr>
<tr>
<td>EE</td>
<td>Elementary effects method</td>
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<td>EEMKE</td>
<td>Equivalent element modal kinetic energy</td>
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<tr>
<td>EEMSE</td>
<td>Equivalent element modal strain energy</td>
</tr>
<tr>
<td>EES</td>
<td>Enhanced evolution strategy</td>
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<tr>
<td>EFDD</td>
<td>Enhanced frequency domain decomposition</td>
</tr>
<tr>
<td>Abbreviation</td>
<td>Description</td>
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<tr>
<td>EMKE</td>
<td>Element modal kinetic energy</td>
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<tr>
<td>EMSE</td>
<td>Element modal strain energy</td>
</tr>
<tr>
<td>ES</td>
<td>Evolution strategy</td>
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<tr>
<td>FRFs</td>
<td>Frequency response functions</td>
</tr>
<tr>
<td>IDK</td>
<td>Kinetic energy indicator</td>
</tr>
<tr>
<td>IDS</td>
<td>Strain energy indicator</td>
</tr>
<tr>
<td>MAC</td>
<td>Modal assurance criterion</td>
</tr>
<tr>
<td>MOPACK</td>
<td>Multi-method optimization package</td>
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<tr>
<td>NMD</td>
<td>Normalized modal difference</td>
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<td>OMA</td>
<td>Operational modal analysis</td>
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<tr>
<td>PC</td>
<td>Principal component (algorithm used in SSI)</td>
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<td>SE</td>
<td>Superelement</td>
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<tr>
<td>SHM</td>
<td>Structural health monitoring</td>
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<td>SSI</td>
<td>Stochastic subspace identification</td>
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<tr>
<td>SVD</td>
<td>Singular value decomposition</td>
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<tr>
<td>SWT</td>
<td>Stationary wavelet transform</td>
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<tr>
<td>UPC</td>
<td>Unweighted principal component (algorithm used in SSI)</td>
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<td>WEC</td>
<td>Wind energy converter</td>
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Chapter 1

Introduction

1.1 Motivation

The renewable energy sources have gained much attention due to the current energy crisis and the urge to get clean energy, in particular, the Fukushima disaster in March 2011, has caused an accelerated entrance to green energy. Wind energy as a strong contender, therefore, is becoming more and more popular. According to the report of the Global Wind Energy Council (GWEC), the global annual installed capacity of wind power has been increased from 1.2GW in 1996 to 44.7GW in 2012 (Figure 1.1) and keeps rising with a high rate. Behind this, there is a strong political will to strengthen the research and innovation on renewable energy sources. For example, currently in EU about 65GW installed wind power capacity satisfies 4.2% EU electricity demand, but the European Wind Energy Association (EWEA) increased the target for total installations of the wind power by 2020 from 180 GW to 230 GW, which means 14-18% EU electricity demand (60% EU households) will be fulfilled.

However, the wind energy project also runs into resistance. Many people worry about the landscape will be destroyed and the climate might also be impacted by massive wind energy converters (WECs) installed across vast stretches of the land. Accordingly, more positive aspects of the wind power have to be developed to compensate the negative effects, e. g., by decrease of the wind energy cost and by increase of the reliability. In this context, the long-run operating performance and the lifetime of WECs are exceptionally momentous.

Ciang et al. (2008) summarize the possible types of damage that can occur on a
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WEC during its service life. Although structural damage can happen to any structural component, the most common types of damage is rotor or blade damage as well as different kinds of tower damages. Since steel towers are number one in use of WECs under 85m, in particular, the connections of the steel tower are critical because they are exposed to corrosion and fatigue damage like cracks due to dynamic loading.

Figure 1.1: Global annual installed capacity of wind power from 1996 to 2012 (GWEC)

Since emphasis is placed on the behavior of the structural system (tower, footing), in this thesis, some cases of WEC failures caused by tower damages are to be considered. For example, in France, a turbine tower broke and toppled over during a storm in 2000. However, no detailed information on the actual cause of damage has been given by the operating company. This failure was the first in a series of such incidents that led to a formal investigation (ASHLEY ET AL. 2007). In 2000, in Germany four WECs experienced sudden and total collapse due to “concrete damage” at the base (ASHLEY ET AL. 2007). Furthermore, a WEC on the Klondike III wind farm, east of the town of Wasco in the USA, snapped in half, causing a maintenance worker, on the top of the tower, to fall to his death. The WEC broke at a little more than halfway up the tower, without having ever been in operation (SMITH 2007). Whole towers have also collapsed in Germany and in the United States (e.g., in Oklahoma, 6 May 2005) (ROSENBLOOM 2006) (CWIF 2005), as in that sight can be seen in Figure 1.2.

The reasons for WEC structural damage can be many. Poor quality control, improper installation and component failure are also responsible for structural damage. In this view, the structural health monitoring (SHM) of WECs is of primary importance and of considerable economical relevance, because it offers continuous evaluation of the structure condition, from which early warnings of defects are provided and accurate maintenance decisions can be made before major failure occurs. From the life time evaluation associ-
ated with SHM, the cost of WEC will be affected by each minor extension of the service time.

Figure 1.2: Examples of catastrophic collapse of WECs (Ciang et al. 2008)

1.2 Background

The structural health monitoring (SHM) is the upcoming and well accepted practice of conducting nondestructive tests or inspections of a structure to give a diagnosis of the current state of the structure, and also to provide a prognosis (evolution of damage, residual life, etc.) during its service life. If we consider only the first function “diagnosis”, SHM can be understood as an important application of the structural system identification, which aims at the realization of the system by identifying specified structural parameters through the use of experimental or field testing data. The structural parameters, such as natural frequencies, mode shapes, damping ratios, stiffness matrix, are behavior-relevant quantities in various engineering tasks, e.g. in accurate response predictions for structures subjected to dynamic loads, or in damage assessment and structural evaluation.

In aerospace, mechanical and some parts of civil engineering, system identification in association with SHM has been used for quite a long time. Especially to WECs, system identification has already been used for rotor blades (Larsen et al. 2002, Verijenko and Verijenko 2005), for the tower structure (Gründberg and Göhlmann 2006), and for identification of damages on the main bearings, gearbox and generator (Holzmüller et al. 2006). However, with the demand of extensive use of WECs as well as larger and taller systems, the system identification method for the WEC structure in the past has not been sufficiently consistent and comprehensive, especially with respect to long term monitoring. The promising perspective of the SHM increases new demand for the improvement of the system identification in terms of accurate and continuous estimation of the respective structures.
The most challenging and difficult part of the system identification is the damage identification. Usually four levels of damage identification are discriminated (RYTTER 1993):

- level 1 detection: Is the structure damaged or not?

- level 2 localization: Where is the damaged area located?

- level 3 quantification: What is the extent of damage?

- level 4 prediction: What is the remaining service life of the structure?

This is the practice of conducting nondestructive tests or inspection of a structure to determine the existence, location, extent of damage, and in some cases make a determination as to the remaining life of the system. A profound review of damage identification techniques has been presented in ALVIN ET AL. (2003). Among different techniques, the modal-based or vibration-based damage identification methods are the earliest and most commonly used, although there are still several factors that aggravate the implementation. As one of the modern identification tools, wavelet transform, is becoming promising and powerful in damage detection because of its particular features. Since this method still remains to be heuristic, more efforts are required to fully develop it for successful practical application.

To achieve level 3 damage identification, a structural model is quite often coupled with the vibration-based damage detection methods. However, blind confidence in using finite element models is inopportune because relatively large differences between corresponding experimental and numerically gained modes can exist. These differences come not only from the modeling errors as a result of simplified assumptions in the finite element model but also from parameter errors due to uncertainties in material and geometric properties. A steady adaption and tailor-made updating of an initial finite element model prove themselves the best agreement with the referenced measurements and therefore need be developed for robust and reliable use beyond controlled laboratory test environments.
1.3 Approach and achievement

With the aforementioned background, the main objective of this dissertation is to propose a systematic and comprehensive system identification method for continuous SHM of WEC. It consists of accurate modal identification, finite element model generation and verification, wavelet-based damage detection and a robust model updating strategy. The concept is schematically illustrated by a flow chart in Figure 1.3.

![Flow chart of the proposed system identification approach](image)

Figure 1.3: Outline of the proposed system identification approach

The first issue is the modal identification on the measured vibration response signals. As an essential part of the system identification, the accuracy and reliability of the modal identification plays a vital role. Different techniques in frequency domain as well as in time domain are compared with the purpose of finding the most powerful and reliable method.

Based on the identified modal parameters, a method using modern signal processing
technique is presented to accurately detect and localize incipient damage of WEC under operational condition. This method takes synergistic advantages of the stationary wavelet transform (SWT) and the continuous wavelet transform (CWT). Using SWT instead of the discrete wavelet transform (DWT) in the signal decomposition is to remedy the shift drawback of DWT due to decimation. By generating the line of modulus maxima from the wavelet map of CWT, a distinct and accurate identification of the possible damage position can be conducted. To find an effective criterion to quantify the damage extent, the largest wavelet modulus and the Lipschitz exponent are utilized.

Since most related studies are limited to simple beam or plate structure under laboratory condition, in this thesis, the ability of the wavelet analysis to identify the abnormality of mode shapes is demonstrated on a wind turbine structure under operational condition, which opens promising perspective of the wavelet analysis for practical application. The thesis addresses some common issues encountered in the wavelet analysis, e.g., selection of an effective signal, dealing with large sampling distance, edge effect, and the influence of measurement noise. It also presents a discussion on how to choose an optimal mother wavelet. To select an appropriate wavelet type, many requisites have to be considered, including (bi-)orthogonality, compact support, symmetry, number of vanishing moment. Based on the discussion, the mother wavelets db4, sym4, coif2 and rbio4.4 are selected as optimal wavelets and their effectiveness is verified in the application procedure.

As explained in the last section, to achieve level 3 damage identification (damage quantification), a numerical model is usually coupled with the damage detection methods. In this study, a 3-D FE model based on beam elements is developed and further verified by comparison with more detailed models using solid or shell elements.

The underlying FE model customarily deviates from the real world system by approximation or even errors in the physical parameters or boundary conditions, model validation is compulsory to check the FE model through measurements. To this end, an iterative process of minimizing the defect between the model and the actual system behavior is mandatory, which is known as model updating. In continuous monitoring, the model updating is successively requested to accurately represent the current state of the real world system including damages and deteriorations. With this aim a unifying framework of model updating is developed in this thesis.

In the framework of model updating, an efficient parametrization method plays a vital role in achieving successful and reliable model updating results. An initial selection of the updating parameters consider those model parameters associated to unknown material pa-
rameters, approximated geometrical parameters, uncertain boundary conditions, parts with a high level of uncertainty (e.g. joints, localized mass). To ensure well-conditioned problem, the number of updating parameters needs to be limited to the variation of a few key model parameters that account for the observable errors. Two methods, one is location-based and the other is parameter-based can contribute to efficient parameter selection. In the location-based parameter selection method, the element modal strain energy, which uses the modelled mode shapes and the equivalent element modal strain energy, which uses the measured mode shapes, are compared to indicate the model error areas by large differences. In the parameter-based method, sensitivity analysis is conducted to identify the impact of different parameters on the model errors. Compared to the local sensitivity analysis, which is a derivative-based approach and only efficient for linear models, the global sensitivity analysis has the attraction of being more informative and robust for non-linear and non-additive models. In order to integrate structural damage or deteriorations into the FE model, a prior knowledge of possible damage position can be achieved from the process of wavelet-based damage detection, so that the damage can be parameterized with a limited set of parameters, and the damage extent, in terms of the local change in stiffness, is readily estimated with the aid of model updating.

The updating process is dealt with as a simulation-based multi-criteria optimization problem. Formulation of the objective function involves a priori articulation of preferences and the weighted Chebyshev method. Defects between the model and the real structure are measured by modal-domain data (eigenfrequencies and mode shapes) and space-scale-domain data (wavelet modulus), in which the latter one is more damage-sensitive and specially used in the process of damage integration.

Furthermore, because the model updating constitutes a simulation-based optimization and the existing simulation software offers normally no powerful optimization tools, the Java-based optimization framework, MOPACK (NGUYEN ET AL. 2010), is adopted in this approach and a simulation adapter is developed to integrate different simulation software into MOPACK. Due to the complexity of the optimization problem, the evolutionary algorithms (EAs) instead of the traditional deterministic techniques have to be considered. The enhanced evolution strategy (EES) and the differential evolution strategy (DE), in the class of EAs, are employed in the representative numerical test, with which the effectiveness of the proposed solution concept will be demonstrated.

Based on this system identification strategy, an accurate structural evaluation and damage assessment as well as prediction of the structural responses can all be realized in the
continuous SHM. Reliable lifetime prediction for damage sensitive parts can also be implemented in future work based on the continuously improved numerical model.

1.4 Overview of the dissertation

The organization of this thesis follows closely the procedure described in Figure 1.3.

Chapter 1 introduces the thesis by stating the strong motivation, highlighting the contributions, and clarifying the organization of the text.

As a basis for the study, the state-of-the-art of structural system identification for WEC is reviewed in Chapter 2. It describes different technologies in the frame of operational modal analysis, discusses the research status and common problems of the damage detection methods, and reviews the development as well as challenges of the model updating techniques.

Chapter 3 deals with in-situ monitoring, data acquisition and preprocessing, and modal identification of the investigated wind turbine. The employed identification techniques and proposed identification procedure are elaborated, with which the results from different techniques and from different samples are compared to validate the reliability of the method.

Chapter 4 focuses on the development and analysis of the FE model in ANSYS. 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. However, to verify the validity of the beam models, alternate models using solid or shell elements with fine-grained mesh have also been created. Different analysis types are carried out to determine the vibration characteristics (natural frequencies and mode shapes) for individual structural components and the overall system, or to simulate the structural responses of the whole wind turbine (including rotating blades) under a realistic time variant wind field.

In chapter 5, an integrated wavelet-based damage detection method is established to detect and localize incipient damage of WEC under operational condition. The method includes signal decomposition by multilevel SWT, damage localization from the line of the modulus maxima in the wavelet map, and damage quantification using the largest wavelet modulus. The methodologies of solving common problems encountered in wavelet analysis have also been addressed, e.g., how to select appropriate data as signal, how to choose optimal mother wavelet, how to deal with large sampling distance and edge effect, and how
to reduce the influence of measurement noise. The effectiveness of the proposed method is demonstrated in this chapter in terms of several examples.

Chapter 6 develops a unifying framework of model updating for robust model validation and damage integration in the continuous system identification of WEC. It is discussed in detail in this chapter about the efficient parametrization, formulation of the multi-objective function, selection of the suitable optimization algorithm and implementation of the simulation-based optimization. Representative numerical tests are conducted to demonstrate the effectiveness of the proposed solution concept.

Finally, Chapter 7 summarizes the investigation and includes recommendations for further study.
Chapter 2

State-of-the-art of structural system identification

The term “system identification” has been used in a broad context in the technical literature. In structural dynamics, it refers to the extraction of information about the structural behaviour from measurement data, without necessarily requesting a numerical model (e.g., identification of the number of active modes or the presence of natural frequencies within a certain frequency range). However, with the increasing use of the numerical model in the analysis of the structural dynamic behaviour, the system identification nowadays more often contains the development (or the improvement) of structural models from the measurements performed on the real structure using vibration sensing devices. In this dissertation, there are several important aspects considered in the frame of system identification, including the modal identification technologies, experimentally validated finite element modeling, and its important application in health monitoring, also referred to as damage detection. This chapter gives reviews of the developments in the main aspects of system identification as mentioned above.

2.1 Review of modal identification technologies

In traditional modal analysis, excitations and responses of the structure are measured to extract the modal parameters. However, since many civil engineering structures are measured under operational condition, the measurement of all natural excitations is impossible, but only the responses can be measured. In this context, the modal analysis has to be carried
out based on the responses only. This modal identification method is called output-only modal analysis or operational modal analysis (OMA).

There are two main groups of operational modal analysis: nonparametric methods essentially developed in frequency domain and parametric methods in time domain. The nonparametric methods in frequency domain contain Peak Picking Method (PP) (FELBER 1993), Frequency Domain Decomposition (FDD) (BRINCKER ET AL. 2001), Enhanced Frequency Domain Decomposition (EFDD), etc.. The parametric methods in time domain include Stochastic Subspace Identification (SSI) (BRINCKER AND ANDERSEN 2006), Least Squares Complex Exponential (LSCE) (BROWN ET AL. 1979), Poly Reference Complex Exponential (PRCE) (VOLD ET AL. 1982), etc..

The Frequency Domain Decomposition (FDD) is an extension of the Basic Frequency Domain (BFD) technique, or more often called the Peak-Picking technique. This approach uses the fact that modes can be estimated from the spectral densities calculated in the condition of a white noise input and a lightly damped structure (HERLUFSEN ET AL. 2005). The FDD technique estimates the modes using a Singular Value Decomposition (SVD) of each of the Spectral Density matrices. This decomposition corresponds to a Single Degree of Freedom (SDOF) identification of the system for each singular value. The simple peak picking technique gives frequency and associated mode shape at the selected frequency. BRINCKER ET AL. (2001) gives explanation for understanding the FDD technique.

In the later developed so-called Enhanced Frequency Domain Decomposition (EFDD), a SDOF model is imposed on the singular values in a user-defined frequency band around the peak providing the estimate of frequency and damping. An average of the corresponding singular vectors, weighted by the singular values in the band, provides the estimate of the mode shape. Modal damping is obtained by half power band width method. See GADE ET AL. (2005) for a detailed description of the EFDD methods.

The Stochastic Subspace Identification (SSI) techniques fit parametric models directly to the measured time responses. They are based upon the stochastic state space model described by:

\[
x_{t+1} = [A]x_t + w_t \\
y_t = [C]x_t + v_t
\]  

(2.1)

where \(x_t\) is the state vector at time \(t\), \([A]\) is the system matrix (state matrix), \(y_t\) is the response vector at time \(t\), and \([C]\) is the observation matrix. The response is generated by two stochastic processes \(w_t\) and \(v_t\) called the process noise and the measurement noise respectively (HERLUFSEN ET AL. 2005).
The steps in the SSI techniques from the time responses $y_t$, via optimal predictors of $x_t$, least square error estimates of $[A]$ and $[C]$, to the estimated modal parameters are described in several references, including Møller et al. (2005), Van Overschee and Moor (1996) and Aoki (1987).

Modal models are estimated for the different state space dimensions up to a selected maximum state space dimension. The setting of maximum state space dimension depends upon the number of modes, the excitation, the number of sinusoidal components in the response signals and the number of noise modes needed to fit (predict) the measured response signals. The results are achieved by a singular value decomposition of the full observation matrix, which is a matrix calculated from the measured responses, and extracting a subspace holding the modes in the model.

2.2 Review of structural damage detection methods


Among these, the modal-based or vibration-based damage identification methods are the earliest and most commonly used, principally because they are simple to implement on any size structure. The basic idea behind this technology is that modal parameters (notably frequencies, mode shapes and modal damping) are functions of the physical properties of the structure (mass, damping and stiffness). Therefore, changes in the physical properties, such as stiffness reductions resulting from cracks, corrosion or loosening of a connection, will cause distinguishable changes in the modal properties. A summary review of the numerous vibration-based damage identification methods is presented in Doebling et al. (1998).

By contrast, there are several factors that aggravate the implementation of vibration-based damage identification methods. For example, it is more difficult to excite the higher
frequency modes that are more susceptible to damage than the lower frequency modes. In addition, most vibration-based methods also require knowledge of the undamaged state of the structure that is unavailable especially in the case of existing and aging civil structures. To get insights on the damage events, various numerical methods have been developed. The Fourier transform, although it allows the detection of the characteristic frequencies and provides useful information pertaining to the state of the structure, it can not quantify the defect, neither in magnitude nor in space/time.

Most recently, the wavelet analysis has become one of the most promising techniques for detecting damages. The important property of wavelet analysis is its capability to obtain the location and severity of a damage. In this method, it is no longer necessary to have a non-damaged structure. LIEW AND WANG (1998) firstly applied the wavelet analysis for damage detection. HONG ET AL. (2002) used CWT for the estimation of Lipschitz exponent for damage detection. DOUKA ET AL. (2004), LOUDRIS ET AL. (2004) applied wavelet transform for crack identification in beam and plate structures. CHANG AND SUN (2005) presented spatial wavelet-based technique for damage detection. Further literature on this topic include CAO AND QIAO (2008), CHANG AND SUN (2005), FAN AND QIAO (2009), HONG ET AL. (2002), OKAFOR AND DUTTA (2000), POUDEL ET AL. (2007).

Despite many successful experience, the wavelet method for damage detection is still limited to simple structures and laboratory environment. Further research is needed to get better insight and quantitative understanding for practical application.

2.3 Review of model updating techniques

Since the WEC system suffers from inevitable ageing and degradation resulting from operational actions, a continuous system identification for long term monitoring is required to determine the current state of the structure and reveal possible failures. In this context, a continuously updated finite element model could be quite useful in the prediction of the structural behavior or even in the residual lifetime estimation.

Finite element model updating emerged in the 1990s as a subject of immense importance to the design, construction and maintenance of mechanical systems and civil engineering structures. Since then, large number of model updating methods have been proposed. A comprehensive survey on model updating has been conducted by FRISWELL AND MOTTERSHEAD (1993) who also published details of model updating methods in their book FRISWELL AND MOTTERSHEAD (1995). According to FRISWELL AND MOTTERSHEAD (1995), model updating techniques can be classified into two main categories: direct and indirect methods.
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 (e.g. Lagrange Multiplier methods and Matrix Mixing methods). 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.

The methods in the second category are referred to as iterative methods, which use changes in physical parameters to update the finite element models and, thereby, generate models that are physically realistic. These methods can be further categorized into sensitivity-based methods and iterative optimization methods.

FRISWELL AND MOTTERSHEAD (1995) discussed sensitivity-based methods in detail (also named as inverse eigensensitivity method). The approach is to minimize the residuals between measured and model-predicted output data, which are typically the modal model (natural frequencies and mode shapes) and the frequency response functions (FRFs). Usually the measured output will be a non-linear function of the parameters. In these cases, minimizing the error between the measured and predicted data will produce a non-linear optimization problem. The sensitivity-based methods use a truncated Taylor series of the output data as a function of the unknown parameters to produce the linear approximation

$$\delta z = S\delta \theta,$$

(2.2)

where $\delta \theta$ is the perturbation in the parameters, $\delta z$ is the perturbation in the measured output and $S$ is the sensitivity matrix. The sensitivity matrix $S$, contains the first derivative of the output with respect to the parameters. The derivative of an eigenvalue can be calculated by taking the derivative of the eigenvector equation. Eigenvector derivatives are more difficult to calculate. Two methods to calculate eigenvector derivatives are given by Fox and Kapoor (FOX AND KAPOOR 1968). The sensitivity of the FRFs to the parameters may be calculated directly from the dynamic matrix or by using the eigenvalue and eigenvector sensitivity (FRISWELL AND MOTTERSHEAD 1993). The linearized residuals are then solved by the least squares method and iterated until a predefined convergence criterion is satisfied. Since the number of degrees of freedom in the numerical model is always much larger than the number of sensors used in measurements, the model reduction or modal
expansion has to be applied. Besides, regularization is often needed, which applies extra constraints to the parameters to ensure a unique solution.

Another category of the iterative methods used for model updating is iterative optimization method based on simulations. With the rapid growth of the optimization and simulation technologies in recent years, the simulation-based optimization method (SO) is becoming an exciting topic in the field of industrial engineering, computer science, applied mathematics and adjacent disciplines. It is the process of finding the best values of some design variables for a system where the system performance is evaluated based on the output of a simulation model of this system. The simulation-based optimization method is in recent years also a dominating solution concept for model updating.

Many exciting research results have been reported, e.g., MÜLLER-SLANY (1993) presents a hierarchical scalarization strategy in multicriteria optimization problem for model updating. Also, a plenty of comprehensive reviews have been written on this topic. In the survey TEKIN AND SABUNCUOGLU (2004), the existing techniques for simulation-based optimization have been classified according to the characteristics of the problems, such as objective functions (single or multiple objectives), parameter spaces (discrete or continuous parameters) as well as shapes of the response surfaces (global as compared to local optimization).

The model updating using simulation-based optimization has also been considered as a promising approach for damage detection, e.g., for geotechnical problems (Y. ZHANG ET AL. 2009); on stay cables (MORDINI ET AL. 2008); on concrete bridge (EL-BORGİ ET AL. 2008); in composite structures (GIORGİO NOSENZO ET AL. 2003). More reviews of applications and researches can be found in MARWALA (2010).

The success of model updating strongly depends on accurate parameterisation, suitable definition of the objective function, and an effective robust optimization algorithm. Some of the main challenges include: typical localized damage of interest in practical SHM applications may not induce significant influence on the dominant lower frequencies and the corresponding mode shapes of the monitored structure, therefore, finding damage-sensitive properties is crucial for the definition of the objective function. On the other hand, physically admissible solutions are not always attainable, because the model updating procedure is an inverse problem that may often be ill-conditioned. One approach to avoid ill-conditioning is to select a sufficiently small number of updating parameters. Although the damage is often local in nature and therefore the effect of the loss of stiffness may require only a small number of parameters, the lack of knowledge of the location means that
a large number of candidate parameters must be included. So the problem is how to select the number of updating parameters which should be large enough to cover all the relevant uncertain parameters, but as low as possible to avoid ill-conditioning. In addition, defining a suitable objective function and choosing an effective robust optimization algorithm are also challenging problems in the process of model updating.
This chapter deals with the application of the modal identification technologies on the monitored wind energy converter (WEC). As an essential part of the system identification, the accuracy and reliability of the modal identification plays a vital role. The techniques used in the present work include the Enhanced Frequency Domain Decomposition (EFDD) technique and the Stochastic Subspace Identification (SSI) technique. Firstly in this chapter an overview of the investigated structure and the monitoring system is given. Then the implementation procedure is illustrated in detail. Results will be generated and compared in two cases to verify the accuracy and reliability of the proposed method.

3.1 Monitoring on WEC

3.1.1 Wind turbine data

The structure under investigation is a 500 KW gearless wind turbine with 63 meter tower height and 40.3 meter rotor diameter. It has a conical steel tower which is anchored on a reinforced concrete mat foundation. The outer diameter of the tower is 2.99 m at the bottom, 2.15 m at elevation 21 m and 1.2 m at the top. The tower consists of three segments of length 21 m each, joined by bolted, prestressed flanged connections. The tower wall thickness starts with 10 mm at the top and increases in increments of 2 mm towards 22 mm at the bottom. With respect to the rotor, it consists of three rotor blades made of fiberglass
reinforced epoxy (GRP). They have a length of 19.13m and a maximum chord length of 1.92m. The rotor runs clockwise on the upwind side of the turbine at a variable rotational speed from 18 to 36 rpm. Table 3.1 lists the basic data of the WEC.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>power</td>
<td>500 kW</td>
</tr>
<tr>
<td>tower height</td>
<td>63 m</td>
</tr>
<tr>
<td>height of the rotor center</td>
<td>65 m</td>
</tr>
<tr>
<td>number of blades</td>
<td>3</td>
</tr>
<tr>
<td>length of blade</td>
<td>19.13 m</td>
</tr>
<tr>
<td>diameter of the rotor</td>
<td>40.66 m</td>
</tr>
<tr>
<td>rotation area</td>
<td>1298 m²</td>
</tr>
<tr>
<td>rotor speed</td>
<td>variable, 18-36 rpm</td>
</tr>
<tr>
<td>blade material</td>
<td>GRP</td>
</tr>
<tr>
<td>tower material</td>
<td>steel</td>
</tr>
<tr>
<td>construction year</td>
<td>1997</td>
</tr>
</tbody>
</table>

Table 3.1: Data of the investigated WEC

### 3.1.2 Monitoring system

To provide comprehensive data for an accurate assessment of the structure, a monitoring system is conducted on the tower of the WEC including 9 three-dimensional accelerometers, 6 deformation transducers, 6 thermometers and one three-dimensional ultrasonic anemometer as listed in Table 3.2. For more details of the monitoring system, LACHMANN ET AL. (2011) can be referred to. To correlate with the nacelle position and the rotor speed, corresponding signals are obtained directly from the nacelle monitoring and incorporated in the measurement system.

Figure 3.1: Photos of the installed sensors
3.1. MONITORING ON WEC

### Table 3.2: Monitoring system on the WEC (LACHMANN ET AL. 2011)

<table>
<thead>
<tr>
<th>Measure</th>
<th>Count</th>
</tr>
</thead>
<tbody>
<tr>
<td>Acceleration</td>
<td>9</td>
</tr>
<tr>
<td>Strain</td>
<td>6</td>
</tr>
<tr>
<td>Temperature</td>
<td>6</td>
</tr>
<tr>
<td>Wind Speed</td>
<td>1</td>
</tr>
<tr>
<td>Available operational data</td>
<td></td>
</tr>
<tr>
<td>Azimuth angle</td>
<td></td>
</tr>
<tr>
<td>Pitch angle</td>
<td></td>
</tr>
<tr>
<td>Rotational speed of the rotor</td>
<td></td>
</tr>
<tr>
<td>Power output</td>
<td></td>
</tr>
</tbody>
</table>

3.1.3 Data acquisition and preprocessing

The measurements are captured by three different data-loggers, which are connected to an on-site computer. After converting the raw data from binary to ASCII type, the on-site computer sends the data via DSL to the server system where software agents synchronize and store the data into the MySQL database system (SMARSLY AND HARTMANN 2009). From the database, the data can be exported into different formats. With the aim of interactive data inspection, a web application is developed by HILFERT (2009), providing a quick and clear way to visualize the data for different time, sensor or data length.
CHAPTER 3. MONITORING SYSTEM AND MODAL IDENTIFICATION

Figure 3.2: MySQL tables

Figure 3.3: Web application
3.2 Implementation of OMA on WEC

3.2.1 Identification techniques

The Enhanced Frequency Domain Decomposition (EFDD) method as an extension of the Frequency Domain Decomposition (FDD) is still popular in use because it retains the properties of being simple and straightforward. However, this frequency selection procedure becomes a subjective task in case of noisy civil-engineering data, weakly-excited modes and relatively close eigenfrequencies.

The Stochastic Subspace Identification (SSI) technique has recently emerged in civil and mechanical engineering field, but it is considered to be the most powerful class of the known identification techniques for natural input modal analysis. This method has many benefits compared to the frequency domain technique, such as no leakage, no problems with deterministic signals (harmonics) and less random errors.

Therefore, the main method used in this work is the SSI technique, although the EFDD method is included for comparison and because of its historical value.

Three different algorithms are often used in the SSI techniques, the Unweighted Principal Component (UPC), the Principal Component (PC) and the Canonical Variate Analysis (CVA) algorithms. The Stochastic Subspace Identification techniques all uses the same estimation engine for estimation of state space realizations (models). In general, the input to this engine is a weighted version of the so-called Common SSI Input matrix that consist of compressed time series data. The difference between the three Stochastic Subspace Identification techniques is how this matrix is weighted. In practical use, the UPC and PC algorithms work best with data having modes with comparable energy level. In such cases it will produce good results using reasonable small state space dimensions. The CVA algorithm has the ability to estimate modes with a large difference in energy level, but it is more time consuming because it forces the use of a larger state space dimension than UPC and PC algorithms. In our case, since the responses are stochastic and the modes have a comparable energy level, UPC and PC algorithms are preferred for the sake of fewer computational efforts.

3.2.2 Identification procedure

Among the measurements, time histories of accelerations are used to identify the modal parameters of the structure. The accelerometers are installed on the inner surface of the
steel tower at 6 different elevations. With a sampling frequency of 100 Hz, the acceleration data in local coordinates of each accelerometer have been recorded. Data processing are mandatory to transform the accelerations from local coordinates to the global coordinates and from the circumference to the centre of the cross section. The origin of the global coordinate system is set at the center of the tower bottom. The +Z axis is set upward and the +Y axis is taken to be opposite to the orientation of the rotor. Since the orientation of the rotor depends on the wind direction and measured by an azimuth angle, the +Y axis of the global coordinate system is continuously adapted according to the measured azimuth angle. After transformation, the accelerations in X direction (parallel to the rotation plane) and Y direction (perpendicular to the rotation plane) are used for the structural modal identification. With the current measurements setup, the first a few bending modes of the tower can be extracted.

The applied OMA software in this project is the ARTeMIS Extractor, which is a powerful and versatile tool for OMA. It works in a user-friendly way and offers many of the modal identification methods, of course including the EFDD and SSI technologies. To use different analysis techniques in ARTeMIS Extractor, an input configuration file is required which defines the model geometry, sensor locations and sensor orientations, file details of measured responses and boundary conditions. Because the measurements are limited to the tower only, a simple line geometry model is created with six nodal points, representing the sensor locations.

The number of samples is chosen by considering the characteristics of the data. The fundamental assumption in OMA is that the inputs causing motion have white noise characteristics in the frequency range of interest. The more random input sources there are, the better the modal results will be obtained.

### 3.2.3 Identification results

To maintain the stochastic characteristics, five random data sets of the accelerations, each containing half hour time histories are used as one measurement sample in the identification procedure. The SSI-UPC method is firstly applied on the data to extract the modes of the tower in X direction.

In the upper part of Figure 3.4 is the stabilization diagram, which presents all estimated eigenvalues as red points and the singular value decomposition of the spectral density matrices as a background wall-paper. This wall-paper has nothing directly to do with the
3.2. IMPLEMENTATION OF OMA ON WEC

Selected Modes

<table>
<thead>
<tr>
<th>Mode</th>
<th>Frequency [Hz]</th>
<th>Std. Frequency [Hz]</th>
<th>Damping Ratio [%]</th>
<th>Std. Damping Ratio [%]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mode 1</td>
<td>0.3753</td>
<td>0.001185</td>
<td>2.322</td>
<td>0.3709</td>
</tr>
<tr>
<td>Mode 2</td>
<td>2.171</td>
<td>0.004739</td>
<td>1.311</td>
<td>0.408</td>
</tr>
<tr>
<td>Mode 3</td>
<td>5.857</td>
<td>0.008932</td>
<td>1.997</td>
<td>0.3345</td>
</tr>
</tbody>
</table>

Figure 3.4: Modes identified with SSI-UPC method in X direction

estimation. However, it is a valuable help in the search of structural modes since these will be located at the spectral density peaks. The analysis is performed with a maximum state space dimension of 200 to include all singular values significantly different from zero. All modes below 10 Hz are identified from a state space dimension of 49, which is the cursor model lined out on the stabilization diagram. To identify the first three bending modes of the tower, reasonable judgement is taken by checking the mode shapes and standard deviations of the frequencies and damping ratios. The information about the first three bending modes of the tower in X direction is listed in the table in Figure 3.4. The corresponding mode shapes are shown in Figure 3.6 in comparison with those identified from the EFDD method.

In the next step, the EFDD method is applied on the same data to provide results for comparison. In this technique, the modes are estimated by picking the peaks in the singular value decomposition (SVD) of the spectral density matrices as shown in Figure 3.5. The automatic search for peaks relies on the estimation of the modal coherence, which identifies the modal domain. The modal coherence at a certain frequency is calculated by taking the
CHAPTER 3. MONITORING SYSTEM AND MODAL IDENTIFICATION

Selected Modes

<table>
<thead>
<tr>
<th>Mode</th>
<th>Mode 1</th>
<th>Mode 2</th>
<th>Mode 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Frequency [Hz]</td>
<td>0.376</td>
<td>2.186</td>
<td>5.819</td>
</tr>
<tr>
<td>Dev. from SSI [%]</td>
<td>0.187</td>
<td>0.691</td>
<td>0.649</td>
</tr>
<tr>
<td>Damping Ratio [%]</td>
<td>1.603</td>
<td>4.465</td>
<td>3.426</td>
</tr>
<tr>
<td>MAC of mode shapes from EFDD and SSI</td>
<td>0.9668</td>
<td>0.9229</td>
<td>0.9847</td>
</tr>
</tbody>
</table>

Dev. = deviation

Figure 3.5: Modes identified with EFDD method in X direction

first singular vector at the position and calculating the averaged dot products with the first singular vectors of the closest neighboring frequencies. The modal coherence is a measure that will be 1 in the region where a specific mode is dominating, which is around the resonance peaks. In between peaks the modes are mixed and the modal coherence will drop significantly. In the SVD diagram of Figure 3.5, the modal coherence is shown with blue color and the modal domain is shown with green color. The top of the diagram indicates a modal coherence of 1 and the bottom is 0. By a specified minimum modal coherence, the individual peaks are framed and the modal domains are identified. Only the largest peak inside the modal domain will be picked.

The table in Figure 3.5 displays the identification results from the EFDD method. By comparing the eigenfrequencies, the SSI and the EFDD methods give almost identical results. The estimates of the damping ratios from two methods, range from 1.3 to 4.4 which are judged as reasonable values for steel structures. The consistency of the mode shapes has been validated by the modal assurance criterion (MAC), which takes values from 0.0
3.2. IMPLEMENTATION OF OMA ON WEC

(a) mode 1  
(b) mode 2  
(c) mode 3  
(d) MAC matrix

Figure 3.6: Comparison of mode shapes in X direction (red line: SSI, green line: EFDD)

(4.09 representing no consistency) to 1.0 (representing a full consistency). High MAC values in the table in Figure 3.5 indicate that the modes detected by the EFDD method agree very well with those detected by the SSI method, although the SSI method gives more real mode shapes as shown in Figure 3.6.

The same procedure has been performed on the data in Y direction and similar results are achieved. Figure 3.7 to Figure 3.9 show the results.

From these analyses, the modal identification technologies have been successfully implemented. The similar results from two independent methods have verified each other. The EFDD technique is more simple and straightforward in the implementation, however, the SSI technique gives more reliable results in the practical use. Therefore, in the following analysis, the SSI method is preferred and the consistency of the results from different data samples is to be examined.
CHAPTER 3. MONITORING SYSTEM AND MODAL IDENTIFICATION

Selected Modes

<table>
<thead>
<tr>
<th></th>
<th>Mode 1</th>
<th>Mode 2</th>
<th>Mode 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Frequency [Hz]</td>
<td>0.3779</td>
<td>2.217</td>
<td>5.837</td>
</tr>
<tr>
<td>Std. Frequency [Hz]</td>
<td>0.0007715</td>
<td>0.01456</td>
<td>0.02695</td>
</tr>
<tr>
<td>Damping Ratio [%]</td>
<td>4.685</td>
<td>3.485</td>
<td>1.904</td>
</tr>
<tr>
<td>Std. Damping Ratio [%]</td>
<td>0.4284</td>
<td>0.2627</td>
<td>0.319</td>
</tr>
</tbody>
</table>

Std. = standard deviation

Figure 3.7: Modes identified with SSI-UPC method in Y direction
3.2. IMPLEMENTATION OF OMA ON WEC

<table>
<thead>
<tr>
<th>Selected Modes</th>
<th>Mode 1</th>
<th>Mode 2</th>
<th>Mode 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Frequency [Hz]</td>
<td>0.3765</td>
<td>2.208</td>
<td>5.73</td>
</tr>
<tr>
<td>Dev. from SSI [%]</td>
<td>0.370</td>
<td>0.406</td>
<td>1.833</td>
</tr>
<tr>
<td>Damping Ratio [%]</td>
<td>2.252</td>
<td>3.245</td>
<td>4.59</td>
</tr>
<tr>
<td>MAC of mode shapes from EFDD and SSI</td>
<td>0.9689</td>
<td>0.9529</td>
<td>0.9903</td>
</tr>
</tbody>
</table>

Dev. = deviation

Figure 3.8: Modes identified with EFDD method in Y direction

Figure 3.9: Comparison of mode shapes in Y direction (red line: SSI, green line: EFDD)
Figure 3.10 displays the eigenfrequencies of the first three bending modes in Y direction detected from 16 different samples. The mean value $\mu$ and mean plus/minus the standard deviation $\sigma$ are plotted as solid and dashed lines, respectively. Considering the inevitable measurement uncertainties, the standard deviations of the eigenfrequencies from different samples are very small, demonstrating quite close results from different samples.

The consistency of the mode shapes are verified by the high MAC values between the mean and the individual mode shapes as shown in Figure 3.11. However, the corresponding modal damping estimates show relatively higher dispersion. This is because it is very difficult to get accurate estimation of modal damping ratios under ambient loads. The modal damping ratios vary with the amplitude of the structural response and are influenced by the wind characteristics, which lead to the existence of aero-dynamic damping. Therefore when the accurate identification of modal damping ratios is required, complementary free vibration tests are recommended.

The above tests prove that a successful OMA can be conducted with the SSI technique, providing consistent and reliable identification results.

Figure 3.10: Frequencies of the first three bending modes in Y direction detected from different samples
3.2. IMPLEMENTATION OF OMA ON WEC

Figure 3.11: MAC between the mean and the individual mode shapes

Figure 3.12: Damping ratios of the first three bending modes in Y direction detected from different samples
Chapter 4

Numerical simulation

4.1 Model generation and verification

In the proposed system identification approach, one important aspect is using the finite element method to generate initial numerical models which will be adjusted later using extensive measured data.

The quality of a model is dictated by the ultimate goal it serves. Model uncertainty is allowed as long as the robustness of the overall system is ensured. Obviously, the more detailed the analysis (i.e., localized stresses) the more complicated the modeling. In this research, beam models with somewhat coarse discretization meshes are used for later analyses because of the following reasons: although the coarse character of the beam model will not be sufficient for certain analysis, it retains the original model’s physical significance; the beam model has similar dynamic behavior as the operational modal analysis results; it takes rapid development time and allows parameters to be easily changed and items added. These characteristics make the beam model convenient in different analyses. To ensure the reliability of the beam model, detailed models have also been developed for comparison of the dynamic characteristics of the tower and the blade. The software used for the FE model generation and analysis is the commercial software ANSYS.

In the detailed tower model, 3-D 8-node solid shell element SOLSH190 is used to model the tower structure including flanges and the door opening, as shown in the middle of Figure 4.1a. By using the local mesh control method, the element number and shape can be controlled in the part that has irregular changes. For example, the door opening is finer meshed by using smaller element size along the geometrical lines of the door. However,
the detailed FE model possess over 4000 elements, which consumes a large amount of time and storage resource during computing, especially for the transient dynamic analysis. To make the model more efficient, a simplified beam model is developed using 3-D elastic tapered beam element BEAM44. This element type is chosen because it allows different geometries at two nodes. It has six degrees of freedom at each node and is designed as a uniaxial element with tension, compression, torsion and bending capabilities in ANSYS (ANSYS Inc 2007). The beam model of the tower, given in the right of Figure 4.1a, has only 23 elements.

![Figure 4.1: Detailed and beam models of the wind turbine components](image)

While the beam model of the blade is constructed using element BEAM44 as that used for the beam model of the tower, the detailed blade model is generated using linear multilayer shell element SHELL99. Figure 4.1b gives a view of the detailed and beam models of the blade. In the middle of the figure is the cross section of the detailed blade model.

The cross-sections of wind turbine blades have the shape of airfoils. Many different standard airfoils developed for aircraft have been used for wind turbine blades, e.g., the NACA 63-4xx series, NACA 63-6xx series and NACA 64-4xx series from the NACA airfoil families. There are also some dedicated airfoils developed from the experience of the traditional airfoils, including S8xx series (NREL, USA), FFA W-xxx (FOI, Sweden),
In the detailed model of the blade, airfoil NACA 63-415 is applied. Figure 4.2a is a section-view illustrating a typical structural architecture for wind turbine blades, which contains the sandwich-type skin, upper and lower spar caps and two shear webs. For the beam model, the cross section properties are calculated using the simplified multi-cell closed cross section as shown in Figure 4.2b.

The terms “flapwise” and “edgewise” are used to denote bending loads that are perpendicular and parallel, respectively, to the airfoil chord line. The spar cap is a relatively thick laminate with primarily unidirectional content, and provides the primary strength to carry the flapwise bending loads. Blade skins are typically double-bias or triaxial fiberglass, with balsa or foam core used as needed for buckling resistance. Most modern rotor blades on large wind turbines are constructed using either all-fiberglass laminate or primarily fiberglass construction with selective use of carbon for local reinforcement. Table 4.1 lists some of the structural properties of common materials for wind turbine blades, from which properties of material type 1 are assigned to the blade model.

Comparing to 420 elements used in the detailed blade model, the beam model of the blade uses only 20 elements. To ensure the reliability of the beam models, vibration characteristics including natural frequencies and mode shapes are compared between the detailed and beam models. To generate the vibration characteristics, modal analysis in ANSYS is performed. In ANSYS modal analysis is a linear analysis and several mode-extraction methods are available: Block Lanczos, subspace, PCG Lanczos, reduced, unsymmetric, damped, and QR damped. The first four methods (Block Lanczos, PCG Lanczos, subspace, and reduced) are the most commonly used. In the presented work, the subspace method is used. This method uses the subspace iteration technique, which internally uses
CHAPTER 4. NUMERICAL SIMULATION

<table>
<thead>
<tr>
<th>Material (UD denotes unidirectional fibers)</th>
<th>Ultimate tensile strength (MPa)</th>
<th>Ultimate compressive strength (MPa)</th>
<th>Specific gravity</th>
<th>Young’s modulus E (GPa)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Glass/polyester ply with 50% fiber volume fraction and UD lay-up</td>
<td>860-900</td>
<td>~ 720</td>
<td>1.85</td>
<td>38</td>
</tr>
<tr>
<td>2 Glass/epoxy ply with 50% fiber volume fraction and UD lay-up</td>
<td>Properties are very close to those for GRP given above</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3 Glass/polyester laminate 50% fiber volume fraction and 80% of fibers running longitudinally</td>
<td>690-720</td>
<td>~ 580</td>
<td>1.85</td>
<td>33.5</td>
</tr>
<tr>
<td>4 Carbon fiber/epoxy ply 60% fiber volume fraction and UD lay-up</td>
<td>1830</td>
<td>1100</td>
<td>1.58</td>
<td>142</td>
</tr>
<tr>
<td>5 High yield steel (Grade Fe 510)</td>
<td>510</td>
<td>510</td>
<td>7.85</td>
<td>210</td>
</tr>
<tr>
<td>6 Weldable aluminium alloy AA6082</td>
<td>295</td>
<td>295</td>
<td>2.71</td>
<td>69</td>
</tr>
</tbody>
</table>

Table 4.1: Structural properties of materials for wind-turbine blades

the generalized Jacobi iteration algorithm (ANSYS INC AND ANSYS EUROPE 2007). It is highly accurate because it uses the full K and M matrices. Although the number of modes found by the subspace method (up to about 40) is fewer than that found by the Block Lanczos method or the PCG Lanczos method, it is far from enough in our case.

Table 4.2 compares the first 6 bending modes of the two tower models. It can be found that the simplified beam model behaves just as well as the detailed solid model. The first 5 modes of the two blade models have also been compared, as shown in Table 4.3. Although the beam model is highly simplified, it possesses similar vibration characteristics to the shell model, demonstrating that it can be used as a substitute for the detailed shell model.

Finally the beam models of the tower and the blade are used to construct the complete WEC model. An extra mass is placed on top of the tower to capture the weight of the nacelle. In order to include the influence of the foundation and the soil, a component of elastic foundation is added to the wind turbine model. The complete WEC model can be seen in Figure 4.3
### 4.1. MODEL GENERATION AND VERIFICATION

#### Table 4.2: Comparison of the solid tower model and the beam tower model

| mode | mode shape                 | solid model $f_s$ [Hz] | beam model $f_b$ [Hz] | $|f_s - f_b|/f_s$ |
|------|----------------------------|------------------------|-----------------------|-----------------|
| 1    | 1st bending mode in X dir. | 0.8660                 | 0.8762                | 1.18%           |
| 2    | 1st bending mode in Y dir. | 0.8687                 | 0.8762                | 0.86%           |
| 3    | 2nd bending mode in X dir. | 3.499                  | 3.560                 | 1.75%           |
| 4    | 2nd bending mode in Y dir. | 3.508                  | 3.560                 | 1.48%           |
| 5    | 3rd bending mode in X dir. | 8.197                  | 8.425                 | 2.78%           |
| 6    | 3rd bending mode in Y dir. | 8.205                  | 8.425                 | 2.68%           |

#### Table 4.3: Comparison of the shell blade model and the beam blade model

| mode | mode shape         | shell model $f_s$ [Hz] | beam model $f_b$ [Hz] | $|f_s - f_b|/f_s$ |
|------|--------------------|------------------------|-----------------------|-----------------|
| 1    | 1st flapwise mode  | 1.409                  | 1.403                 | 0.43%           |
| 2    | 1st edgewise mode  | 3.524                  | 3.578                 | 1.53%           |
| 3    | 2nd flapwise mode  | 4.982                  | 4.913                 | 1.39%           |
| 4    | 3rd flapwise mode  | 10.951                 | 11.030                | 0.72%           |
| 5    | 2nd edgewise mode  | 16.475                 | 16.150                | 1.97%           |

Figure 4.3: Complete model of the WEC
When the complete model of the wind energy converter is constructed, it is compulsory to compare its vibration characteristics with those detected from measurements. The measured degrees-of-freedom are in the best case only a subset of the degrees-of-freedom of the finite element model. That means more modes will be provided by the FE model than those from measurements. Hence, the selection of correlated mode pairs between experimentally and numerically obtained modes has to be based on limited spatial information. The mode selection strategy is based on the Modal Assurance Criterion (MAC) (Allemand 2003). The numerical mode with the highest correlation with respect to a certain measured mode will be assigned. According to the modal parameters identified from measurements, the numerical modes corresponding to the tower bending have been selected. Table 4.4 gives the comparison of numerical modes with those identified modes in Figure 3.4 and Figure 3.7. By comparing the first 6 bending modes, the small deviations of frequencies and high MAC values demonstrate very good consistency between the numerical and measured modes. The numerical model has been proved to be a good simulation for representing the dynamical behavior of the real WEC structure.

| mode | mode shape          | from OMA $f_m$ [Hz] | from FE model $f_n$ [Hz] | $|f_m-f_n|/f_m$ | MAC     |
|------|---------------------|---------------------|------------------------|----------------|---------|
| 1    | 1st bending mode in X dir. | 0.3753              | 0.3599                 | 4.34%          | 0.9993  |
| 2    | 1st bending mode in Y dir. | 0.3779              | 0.3612                 | 4.42%          | 0.9994  |
| 3    | 2nd bending mode in Y dir. | 2.217               | 2.250                  | 1.49%          | 0.9951  |
| 4    | 2nd bending mode in X dir. | 2.171               | 2.437                  | 12.25%         | 0.9981  |
| 5    | 3rd bending mode in Y dir. | 5.837               | 5.713                  | 2.12%          | 0.9724  |
| 6    | 3rd bending mode in X dir. | 5.857               | 6.258                  | 6.85%          | 0.9944  |

Table 4.4: Comparison of the modes generated from measurements and from FE model

### 4.2 Structural response simulation

The generated FE model is used for the simulation of the structural responses of the whole wind turbine (including rotating blades) under the influence of a realistic time variant wind field in a nonlinear transient dynamic analysis. Transient dynamic analysis is a technique used to determine the dynamic response of a structure under the action of any general time-dependent loads. The inertia or damping effects are included in the transient dynamic
analysis. With this type of analysis, the time-varying displacements, strains, stresses, and forces in a structure can be determined. The basic equation of motion solved by a transient dynamic analysis is

\[ M \ddot{u} + C \dot{u} + K u = F(t) \] (4.1)

- **M**: structural mass matrix
- **C**: structural damping matrix
- **K**: structural stiffness matrix
- **\ddot{u}**: nodal acceleration vector
- **\dot{u}**: nodal velocity vector
- **u**: nodal displacement vector
- **F(t)**: applied load vector

For the solution of Equation 4.1, the Newmark time integration method (including an improved algorithm called Hilber-Hughes-Taylor (HHT) method) can be applied in the ANSYS program. Furthermore, there are three methods of solution for the Newmark method: the full method, the reduced method and the mode superposition method. In our problem, the full transient method is used, which solves the Newmark method equation directly and makes no additional assumptions. With the rotation of the rotor considered, the structure is fully geometrically nonlinear. The transient dynamical response of the WEC is simulated by a nonlinear analysis using the Newton-Raphson method along with the Newmark assumptions.

![Figure 4.4](image-url)  
(a) Homogeneous steady wind  
(b) Wind shear model  
(c) Stochastic wind model  

Figure 4.4: Representation of wind characteristics (EGGLESTON AND STODDARD 1987)
Since the main dynamic load on the WEC structure is wind load, it is important to characterize the wind in which the structure will operate and to describe how the wind acts on it. There are several models of aerodynamic forces which can be used for analysis. A constant, homogeneous velocity field of fixed direction as shown in Figure 4.4a is the simplest model and offers a feasible starting point. Figure 4.4b is a steady wind with vertical shear. However, the actual wind field experienced by a WEC is a non-deterministic (stochastic) process, which looks like that of Figure 4.4c and changes continually with time.

The time histories of stochastic wind velocities, which are required for the load calculation on the WEC, are generated by the numerical code ANSYS-CFX 11.0. The simulation result contains 5 min fluid flow (3000 time steps, 0.1 second for each step-size). To get the time histories, 25 monitoring points in the rotation plane (in distances of 10 m) and 10 monitoring points along the tower (in distances of 5 m) are defined in the fluid flow domain. More details on the wind field generation can be found in LACHMANN ET AL. (2009).

Then the values of the wind velocities are scaled down by a factor of 0.75 to ensure the WEC is working within the range of full power output below storm protection shutdown. Under such condition the maximum rotational speed of the rotor is reached and assumed to be constant for the analysis. The wind velocities can be accessed by linear interpolation in both spatial and time domain between discrete points. For wind velocity \( v(z, t) \) at height \( z \) and time \( t \), the wind load on the tower is calculated as line pressure \( p_l(z, t) \):

\[
p_l(z, t) = p(z, t) \cdot b(z) \cdot c_f = \frac{1}{2} \rho_{\text{air}} \cdot v^2(z, t) \cdot b(z) \cdot c_f, \tag{4.2}
\]

where \( b(z) \) is the diameter of the tower at height \( z \) and \( c_f \) is the force coefficient. According to DIN1055-4:2005-03, \( c_f \) for a cylinder with finite length is:

\[
c_f = c_{f,0} \cdot \psi_\lambda, \tag{4.3}
\]

where \( c_{f,0} \) is the force coefficient of cylinders (see Figure 4.5) and \( \psi_\lambda \) is the end-effect factor (see Figure 4.6).
4.2. STRUCTURAL RESPONSE SIMULATION

Figure 4.5: Force coefficient $c_{f,0}$ for circular cylinders without free-end flow and for different equivalent roughness $k/b$

Figure 4.6: Indicative values of the end-effect factor $\psi/\lambda$ as a function of solidity ratio $\varphi$ versus slenderness $\lambda$
The wind load acting on the blades is determined by the blade element momentum (BEM) theory. Consider a blade divided up into a number of elements, each of the blade elements will experience a different aerodynamic load as they have a different rotational speed \( u_r = \omega r \), a different chord length \( c \) and a different twist angle. Overall performance characteristics are determined by numerical integration along the blade span.

![Figure 4.7: Forces on the blade element](image)

- \( v_w \): wind velocity
- \( v_a \): reduced wind velocity
- \( v_r \): relative wind velocity
- \( u_r \): peripheral velocity
- \( \theta \): pitch angle
- \( \alpha \): aerodynamic angle of attack

The forces on the blade element are shown in Figure 4.7. A convention in airfoil theory is that the total aerodynamic force on the blade element \( dF \) is decomposed into two components, the lift force \( dL \) and the drag force \( dD \), which are perpendicular and parallel to the incoming flow. \( dF \) can also be decomposed into the tangential force \( dF_T \).
4.2. STRUCTURAL RESPONSE SIMULATION

and the thrust force \( dF_S \), which generates useful torque and exerts a thrust load on the rotor respectively. \( dL \) and \( dD \) can be expressed from the definition of the lift and drag coefficients as follows:

\[
dL = C_L \frac{1}{2} \rho_{air} v_r^2 c_r d_r
\]

\[
dD = C_D \frac{1}{2} \rho_{air} v_r^2 c_r d_r
\]

\( \rho_{air} \) air density

\( v_r \) relative wind velocity at radius \( r \)

\( c_r \) chord length at radius \( r \)

\( d_r \) length of the segment

\( C_D \) drag coefficient

\( C_L \) lift coefficient

Lift and drag coefficient data are available for a variety of aerofoils from wind tunnel data. They vary with the angle of attack \( \alpha \), which is the angle between the resulting flow \( v_r \) and the profile chord. The angle of attack will grow as the wind speed increases. Changes of lift and drag coefficients with the angle of attack are illustrated in Figure 4.8. Good airfoil produces large amount of lift with little drag before stall occurs, which in this graph is at around \( \alpha = 14^\circ \) where there is a massive increase in drag and a sharp reduction in lift.

Then the tangential force and thrust force can be derived from drag and lift forces using Equation 4.6 and 4.7.

\[
dF_T = dL \cos \beta - dD \sin \beta
\]

\[
dF_S = dL \sin \beta + dD \cos \beta
\]

The relative wind velocity \( v_r \) varies with the blade radius \( r \) and consists of the reduced wind velocity \( v_\alpha \) and the peripheral velocity \( u_r \),

\[
v_r^2 = v_\alpha^2 + u_r^2 = \left( \frac{2}{3} v_\alpha \right)^2 + (\omega r)^2
\]
where \( \omega \) is the angular velocity of the rotor blades. The tangent of \( \beta \) is

\[
\tan \beta = \frac{u_r}{v_a} = \frac{3\omega r}{2v_w}
\]

(4.9)

Here the tip speed ratio \( \lambda_A \) is introduced, which is the ratio of tip speed to the free-stream wind speed (GASCH 1996).

\[
\lambda_A = \frac{u_R}{v_w} = \frac{\omega R}{v_w} \quad \text{(with } R \text{ being the rotor radius)}
\]

(4.10)

Therefore, the tangent of \( \beta \) is further expressed by a formula including \( \lambda_A \).

\[
\tan \beta = \frac{3}{2} \lambda_A \frac{r}{R}
\]

(4.11)

Since at the tip of the blade losses are introduced, a correction factor needs be added to characterise the reduction in forces along the blade. An approximate method of estimating the effect of tip losses has been given by L. Prandtl (GLAUERT 1935) as expressed in Equation 4.12,

\[
f = \frac{2}{\pi} \cos^{-1}\left\{ \exp\left(\frac{-(B/2)(1 - (r/R))}{(r/R)\cos \beta}\right) \right\}
\]

(4.12)
where $B$ is the number of blades, $R$ is the outer radius and $r$ is the local radius, $\beta$ is the angle between the wind direction and the relative flow as shown in Figure 4.7.

4.3 Gyroscopic effect analysis

In order to analyze the response of the wind turbine tower under operating conditions, various kinds of loads should be considered, like the fluctuating wind loads, self weight, and the forces and moments transferred from the nacelle and the rotor. Normally a wind turbine tower is analyzed with the rotor in the parked condition and the nacelle simplified as a static concentrated mass. However, as an eccentric mass with rotary inertia, the rotating rotor brings extra internal forces and moments to the tower, for example, from the gyroscopic effect.

The gyroscope theory was born in the second half of the 19th century and rapidly developed in the 20th century. It can be best explained by the principle of behaviour of a gyroscope, which is used to construct gyrocompasses in ships, aircraft, spacecraft and vehicles. A gyroscope has a high rate of spin about an axis of symmetry and is so mounted that this spin axis has freedom of angular rotation. It can be defined as two-degree-of-freedom gyro or single-degree-of-freedom gyro by the degrees of rotational freedom of the spin axis. For a single-degree-of-freedom gyro, as the example in Figure 4.9, the spin axis initially assumed parallel to x axis can rotate about y axis but is constrained from the rotation about z axis. When the gyro spins about its spin axis and a rotation about y axis is input, a torque about z axis will be induced. When the rotation about z axis is set free and a torque about z axis is applied, the result will be the rotation about y axis, which is called precession.

Equation 4.13 is the generally useful expression for single-degree-of-freedom gyro analysis (ZIEGLER 1962).

$$ T = I \omega_p \times \omega_s $$

where $T$ is the applied torque, $I$ is the spin angular momentum of the gyro, $\omega_p$ is the angular velocity of precession and $\omega_s$ is the angular velocity of spin. According to the
definition of cross product, the magnitude of the torque is

\[ T = I \omega_p \omega_s \sin \theta \] (4.14)

where \( \omega_p \) and \( \omega_s \) are the magnitudes of vectors \( \omega_p \) and \( \omega_s \), respectively, and \( \theta \) is the smaller angle between \( \omega_p \) and \( \omega_s \), which is 90° in this case. The direction of the torque is decided by the right-hand rule.

The gyroscopic effect may occur in any machine with rotating parts if the direction of the spinning axis changes. For a rotating wind turbine, this phenomenon occurs under yaw controls. Currently, most wind turbines use active yaw control system to turn the rotor against wind. During the yawing process, the rotating axis of the rotor changes its direction in the horizontal plane, inducing a gyroscopic torque perpendicular to the spinning axis and yawing axis. In order to prevent large gyroscopic loads generated by the rotating rotor, the yaw rate is usually kept very low. Also the nacelle is often parked and the yaw drive is not operated unless the wind direction change reaches some pre-defined minimum. On the other hand, when the tower sustains vibration out of the rotation plane under external wind load, the rotating axis of the rotor tilts forward or backward periodically with the motion of the tower. This will also induce gyroscopic load to the structure, as illustrated in Figure 4.10. Some efforts are given in this section with the aim of revealing the exact influence of the gyroscopic effect on an operating wind turbine.

![Figure 4.10: Gyroscopic effect on a wind turbine](image-url)
4.3. **GYROSCOPIC EFFECT ANALYSIS**

In the first step, a simple rotor model is used to validate the ANSYS result. While Equation 4.13 gives the analytical solution of the gyroscopic torque, in ANSYS the transient dynamical structural response (gyroscopic torque) is simulated by a fully nonlinear analysis using an implicit Newmark-type time integration scheme and by incorporating the gyroscopic matrix $G$ into the basic dynamic equilibrium equation.

$$
\mathbf{M}\ddot{\mathbf{u}} + (\mathbf{C} + \mathbf{G})\dot{\mathbf{u}} + \mathbf{K}\mathbf{u} = \mathbf{F}(t).
$$

By comparing the analytical and numerical results, ANSYS is verified to perform the gyroscopic effect very well for beam elements and even better for mass elements (due to less numerical damping).

Based on this, in the next step, the complete wind turbine model is used to simulate the gyroscopic effect on the responses of the wind turbine tower. The rotor blades are represented by an eccentric mass with rotary inertia to avoid convergence problems. Three different models are considered in the analysis. In the first model the total mass of the nacelle and the rotor is positioned directly on top of the tower, while in the second one the eccentricity is included. Then in the third model the rotor rotates with a constant speed. The structural responses and reactions of the wind turbine tower are observed in both spatial distribution and time histories for different models. The tower stress state is examined using the Von Mises criteria. From a comparison of the results, it can be found that the eccentricity of the rotor and the nacelle should be paid attention to, because the stress state on the tower top changes considerably due to the moment caused by the eccentric mass. With the rotation of the rotor included, the gyroscopic torque is generated, inducing a small torsion of the tower, which influences the vibration of the structure as well. From an increase of 5% of the maximum equivalent stress during the rotating state, the gyroscopic torque is considered to be quite small compared to the bending moment caused by the wind load. However, the gyroscopic force induces cyclic stresses to the blade, hub and axle of the turbine. As the rotating axis of the rotor tilts forward or backward, the gyroscopic force tries to twist the turbine into a left or right swing. For each blade, the gyroscopic force is at a maximum when the blade is horizontal and at a minimum when it is vertical. This cyclic twisting can quickly fatigue and crack the blade roots, hub and axle of the turbine. For more details of the aforementioned analysis, Liu et al. (2010) can be referred to.
Chapter 5

Damage detection by wavelet analysis

The ability to damage detection and localization at the earliest possible stage becomes an important issue throughout the aerospace, mechanical or civil engineering communities. The existence of damage in a structure results in changes of global dynamic characteristics. Damage which cannot be identified directly from mode shapes, may be observed on wavelet transforms since local abnormalities in a signal lead to substantial variations of wavelet coefficients in the neighborhood of damage.

Based on the demand of an efficient and robust non-destructive damage detection method for WECs as well as the distinct advantages of the wavelet transform, an integrated wavelet-based damage detection method is presented in this chapter. It consists of the following consecutive steps: in-situ monitoring, data acquisition and preprocessing; mode extraction; signal decomposition; damage localization; and damage quantification. The chapter also elaborates methodologies of solving common problems encountered in the use of the wavelet analysis, e.g., how to select appropriate data as signal, how to choose optimal mother wavelet, how to deal with large sampling distance and edge effect, and how to reduce the influence of measurement noise. The effectiveness of the proposed method is demonstrated in this chapter in terms of several examples.
CHAPTER 5. DAMAGE DETECTION BY WAVELET ANALYSIS

5.1 Theories of wavelet analysis for damage detection

Since the continuous wavelet transform (CWT), the discrete stationary wavelet transform (SWT) and the Lipschitz exponent are combined in the proposed damage detection method, it will be helpful to explain the items mentioned above for a better understanding of the method.

5.1.1 Continuous wavelet transform (CWT)

Continuous wavelet transform (CWT) analyse a signal using a small wavelike function known as a wavelet. It compares the similarity of the signal and the wavelet and can indicate the singularities in a signal. Local failure in a structure like fatigue crack will cause changes in the dynamic response of the structure, because the stiffness in the crack region is changed. By using wavelet transform, the local changes in the response signal can be detected. The signal in consideration can be classified in two domains: time-domain data (time histories of displacement, acceleration or strain) and spatial-domain data (deflection or mode shapes of the structure).

In mathematical terms, the CWT is a convolution of the wavelet function with the signal. It is defined as (Daubechies 1992):

$$W_f(a, b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} f(t) \psi^* \left( \frac{t - b}{a} \right) dt, \quad a > 0.$$  \hfill (5.1)

where $f(t)$ (or $f(x)$ for spatial data) is the input signal, $a$ is a real number called scale or dilation, and $b$ is a real number called position. $W_f(a, b)$ are wavelet coefficients of the function $f$, $\psi \left( \frac{t - b}{a} \right)$ is the wavelet function, and $*$ denotes complex conjugation.

Let $\psi_{a, b}(t) = \frac{1}{\sqrt{|a|}} \psi^* \left( \frac{t - b}{a} \right)$, Equation 5.1 can be written in a more compact form as

$$W_f(a, b) = \int_{-\infty}^{\infty} f(t) \psi_{a, b}(t) dt.$$  \hfill (5.2)

For a given one-dimensional signal $f(x)$ (here in the form of a beam mode shape, as it is shown in Figure 5.1), singularities can be detected by finding the abscissa where the maxima of the wavelet transform modulus $|W_f(a, b)|$ converge at fine scales. The sketch presented in Figure 5.1 illustrates the scheme of operation of the wavelet-based damage detection technique.
5.1. THEORIES OF WAVELET ANALYSIS FOR DAMAGE DETECTION

5.1.2 Discrete wavelet transform (DWT)

Normally, it is difficult to analyze the information content of a signal directly. The local features are not clear in original signal. Therefore multi-resolution is involved. For this purpose, the discrete wavelet transform (DWT) decomposes a signal into a set of details appearing at different resolutions.

In DWT, the signal is decomposed by low pass and high pass filters to get approximation and detail information. The low pass is called the scaling function $\phi$ and the high pass is the wavelet function $\psi$. The signal can be recursively decomposed to get finer detail and more general approximation. Each DWT brings out a higher resolution of the data (details) while at the same time smoothing the remaining data (approximations). DWT using successive low pass and high pass filters is called the Mallat algorithm or Mallat-tree decomposition (MALLAT 2009), as shown in Figure 5.2.

In the figure, the signal is denoted by $f(t)$. The low pass filter is denoted by $H$, while the high pass filter is denoted by $G$. At each level, the high pass filter produces detail information $d[t]$ spanning the upper half of the frequency band, while the low pass filter produces approximate information $a[t]$ spanning the lower half of the frequency band. $\downarrow 2$ is the operation of keeping the even indexed samples, which is called down-sampling. While the half band filters remove half of the frequencies, down-sampling discards half of the samples to avoid redundant information. The process of splitting the signal by multi-level wavelet decomposition is graphically displaced in Figure 5.3.

Figure 5.1: (a) Geometry of the analyzed beam; (b) sketch showing the wavelet-based damage detection technique (RUCKA 2011)

The selection of an appropriate type of the wavelet function is crucial for the effective use of the wavelet analysis and more discussions will be given later.
5.1.3 Stationary wavelet transform (SWT)

The stationary wavelet transform (SWT) is similar to the DWT, except that the decimation is entirely omitted and instead the filters are upsampled at each level of decomposition. The decimation operation from down-sampling removes every other coefficient at the current decomposition level to avoid redundant information, however, the peaks detected in each details will be shifted, as shown in Figure 5.4a. The shift inevitably brings adverse effect on accurate damage localization.

Such a shift drawback in the DWT can be remedied using the SWT as demonstrated in Figure 5.4b, because the number of wavelet coefficients at each level in the SWT is exactly the same as that of sampling points of the analyzed signal, while only the $N/2^L$ (where $N$ is the number of sampling points of the analyzed signal) wavelet coefficients are available at the $L$th level in the DWT.
5.1. THEORIES OF WAVELET ANALYSIS FOR DAMAGE DETECTION

5.1.4 Lipschitz exponent

As aforementioned, a remarkable property of the wavelet transform is its ability to characterize the local regularity of a signal. In mathematics, the local regularity is often measured with the Lipschitz exponent, also known as the Holder exponent.

Based on Mallat (2009), the Lipschitz exponent is briefly explained as follows. A function $f(x)$ is said to be Lipschitz $\alpha \geq 0$ at $x = v$ if there exists $K > 0$ and a polynomial $P_v(x)$ of degree $n$ ($n$ is the largest integer satisfying $n \leq \alpha$) such that

$$f(x) = P_v(x) + \epsilon_v(x),$$

where

$$|\epsilon_v(x)| \leq K| x - v |^\alpha.$$  \hspace{1cm} (5.4)

The error term $\epsilon_v(x)$ can be thought of as the residual that remains after fitting a polynomial of order $n$ to the function, or as the part of the signal that does not fit into an $n + 1$ term approximation. In order to detect singularities, a transform is needed that ignores the polynomial part of the signal. A wavelet transform that has $n + 1$ vanishing moments is able to ignore polynomials up to order $n$:

$$\int_{-\infty}^{\infty} t^n \psi(t) dt = 0$$

\hspace{1cm} (5.5)
CHAPTER 5. DAMAGE DETECTION BY WAVELET ANALYSIS

If the CWT with \( n + 1 \) vanishing moments is applied to the function of 5.3, the result becomes

\[
W_f(u, s) = W_{\epsilon_v}(u, s), \tag{5.6}
\]

since \( W_{p_v}(u, s) = 0 \). So that the Lipschitz \( \alpha \) at \( x = v \) can be derived from \( W_f(u, s) \) when \( u \) is in the neighborhood of \( v \).

JAFFARD (1991) shows that if a square-integrable function \( f(x) \) is Lipschitz \( \alpha \) at \( x = v \), then the asymptotic behavior of the CWT \( W_f(u, s) \) near \( x = v \) becomes

\[
|W_f(u, s)| \leq A s^{\alpha+(1/2)} \left( 1 + \left| \frac{u - v}{s} \right|^{\alpha} \right) (A > 0). \tag{5.7}
\]

Near the cone of influence of \( x = v \) (see Mallat 2009 for the definition of cone of influence), Equation 5.7 reduces to

\[
|W_f(u, s)| \leq A' s^{\alpha+(1/2)} (A' > 0), \tag{5.8}
\]

which is equivalent to

\[
\log_2 |W_f(u, s)| \leq \log_2 A' + \left( \alpha + \frac{1}{2} \right) \log_2 s. \tag{5.9}
\]

Ignoring the offset due to the coefficient \( \log_2 A' \), the slope \( m = \alpha + \frac{1}{2} \) is then the decay of the wavelet modulus maxima across its scales. The wavelet modulus is the absolute value of the wavelet transform and its maxima are ridges of high-valued coefficients that progress through the space-scale plane.

\[
m = \alpha + \frac{1}{2} = \frac{\log_2 |W_f(u, s)|_{\text{maxima}}}{\log_2 s} \tag{5.10}
\]

The reason for considering the Lipschitz exponent in damage detection is to characterize the singularity type. For example, a function that is bounded but discontinuous at \( v \) is Lipschitz 0 at \( v \). If \( 0 < \alpha < 1 \) at \( v \), then \( f \) is continuous at \( v \) but its derivative is not continuous at \( v \). If \( 1 < \alpha < 2 \) at \( v \), then one can conclude that only the original function \( f \) and its first derivative are continuous at \( v \). A higher value of \( \alpha \) indicates a better regularity or a smoother function.

5.2 Procedure and methodology

Based on the properties of different wavelet transforms discussed in the last section, an integrated damage detection method is hereby proposed to locate and quantify incipient
damage of the wind turbine structure under operational condition. The common problems like sampling distance, edge effect and measurement noise have also been considered.

5.2.1 Consideration of common problems

Choose appropriate data as the analysis signal

Although many researchers applied wavelet analysis directly on time histories of measurements, using time-domain data needs certain excitation type and prior knowledge of the damage position. On the other hand, since the local damage also changes the structural global properties, the spatial-domain data (mode shapes) can also be considered in the wavelet-based damage detection. Since this method still remains to be heuristic in terms of small damage quantification, further study is hence needed to get better insight. In the present method, only the first few mode shapes are considered due to their stability and easy extraction from measurement.

As aforementioned, the wavelet analysis identifies local damage by detecting singularities or discontinuities in the mode shapes. From the preliminary study of the author (Liu et al. 2012), using mode shapes directly failed in damage detection because the discontinuities in mode shapes caused by the damage is veiled by the structural inherent discontinuities, e.g., the flange connection and the abrupt change of the wall thicknesses. To eliminate the influence of the structural inherent disturbance, the mode shape differences of the damaged and intact structures are considered as the signal instead.

Deal with large sampling distance and edge effect

In wavelet analysis, a relatively high density of samplings is required due to their natural difficulty to process a low number sampling points. However, the density of sensors in practice can not be too high because of the technical and financial limitations and the disturbances on mode shapes by too many sensors. To overcome this conflict, a piecewise cubic spline data interpolation is proposed in the sparse samplings. The cubic spline interpolation increases the resolution of the signal and assures the conservation of signal data between sampled points without large oscillations.

Another problem in wavelet analysis is the edge effect. There are peaks near the boundaries in the wavelet transform because of the finite length sequence. Therefore the crack cannot be detected when it is near the boundaries. In the present method, extrapolation is
applied by adding extra data points using a fit polynomial in the vicinity of the boundaries to eliminate the edge effect for finite length sequence.

**Investigate the influence of measurement noise**

Measurement noise is inevitable in the measured structural dynamic responses, which further contaminates the mode shapes. In this work, the statistical methods are applied to reduce the influence of the measurement noise, and the robustness of the damage detection method will be verified by the consideration of the measurement noise.

### 5.2.2 Damage detection procedure

The procedure to implement the wavelet-based damage detection for wind turbine structure consists of the following consecutive steps.

1. In-situ monitoring, data acquisition and preprocessing.

2. Mode extraction. From acquired dynamic responses, mode shapes are extracted by the technique of operational modal analysis. The mode shape differences between the intact and damaged structure are used as analysis signals.

3. Signal decomposition. Multilevel wavelet decomposition by SWT is performed on the signal to extract details which keep track of the fluctuations in the signal.

4. Damage localization. By performing CWT on selected details and plotting the wavelet map, discontinuities on the signal can be indicated by peaks in the wavelet modulus. The possible damage position is identified by the abscissa where the line of modulus maxima progresses to fine scales.

5. Damage quantification. To find an effective criterion to quantify the damage extent, the largest wavelet modulus and the Lipschitz exponent will be considered in the following work. The analyses from signal decomposition to damage quantification are carried out in Matlab 7 using the wavelet toolbox.

### 5.2.3 Choose optimal mother wavelet

To select an appropriate wavelet type, the following requisites have to be considered.
1. (Bi-)orthogonality. The SWT requires that the mother wavelet should have orthogonality or biorthogonality (Daubechies 1992), since it implements decomposition using filter-bank, while the CWT aims to provide a spatial-scale representation of the decomposed signal, so that the orthogonality or biorthogonality of the mother wavelet is not required for the CWT.

2. Compactly supported. wavelet has nonzero coefficients with only indexes from \( n \) to \( n+m \) with the wavelet function support is \([n, n+m]\).

3. Symmetry. The property of symmetry is preferred, because it can avoid the phase distortion in localization of the local damage.

However, one cannot have compact support with symmetric and orthogonal wavelet, except for Haar wavelet. Table 5.1 lists the properties of some common used wavelets. To select optimal wavelet for damage detection, compromise has to be made among the three properties.

<table>
<thead>
<tr>
<th>wavelet family</th>
<th>(bi-)orthogonality</th>
<th>symmetry</th>
<th>compact support</th>
<th>DWT</th>
</tr>
</thead>
<tbody>
<tr>
<td>Haar (db1)</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Daubechies</td>
<td>yes</td>
<td>no</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Symlets</td>
<td>yes</td>
<td>no (~yes)</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Coiflets</td>
<td>yes</td>
<td>no (~yes)</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Biorthogonal</td>
<td>no (bi- yes)</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Reverse biorthogonal</td>
<td>no (bi- yes)</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Meyer†</td>
<td>yes</td>
<td>yes</td>
<td>no</td>
<td>yes*</td>
</tr>
<tr>
<td>Morlet‡</td>
<td>no</td>
<td>yes</td>
<td>no</td>
<td>no</td>
</tr>
<tr>
<td>Mexican_hat†</td>
<td>no</td>
<td>yes</td>
<td>no</td>
<td>no</td>
</tr>
<tr>
<td>Gaussian</td>
<td>no</td>
<td>yes</td>
<td>no</td>
<td>no</td>
</tr>
</tbody>
</table>

†: This wavelet family has only a single wavelet.
‡: This wavelet family has no scaling function.
*: DWT is possible but without fast wavelet transform (FWT).

Table 5.1: Properties of different wavelet families

In the first selection, the Daubechies (db), Symlets (sym), Coiflets (coif), Biorthogonal (bior) and Reverse biorthogonal (rbio) wavelets are selected. These wavelets have different order \( N \). Table 5.2 lists the order, the number of vanishing moments and the size of support of these wavelets.

4. Number of vanishing moments. To measure the local regularity of a signal, selecting a appropriate number of vanishing moments is crucial. The vanishing moment is a crite-
CHAPTER 5. DAMAGE DETECTION BY WAVELET ANALYSIS

<table>
<thead>
<tr>
<th>wavelet</th>
<th>order N</th>
<th>number of vanishing moment</th>
<th>size of support</th>
</tr>
</thead>
<tbody>
<tr>
<td>db</td>
<td>$N=1,2,\ldots$</td>
<td>$N$</td>
<td>$2N-1$</td>
</tr>
<tr>
<td>sym</td>
<td>$N=2,3,\ldots$</td>
<td>$N$</td>
<td>$2N-1$</td>
</tr>
<tr>
<td>coif</td>
<td>$N=1,2,\ldots,5$</td>
<td>$2N$ (for wavelet function $\psi$)</td>
<td>$6N-1$</td>
</tr>
<tr>
<td></td>
<td>$N=1,2,\ldots,5$</td>
<td>$2N-1$ (for scale function $\phi$)</td>
<td></td>
</tr>
<tr>
<td>bior</td>
<td>$N=1,2,\ldots,5$</td>
<td>$N_r$ for dec.</td>
<td>$2N_r+1$ for rec.</td>
</tr>
<tr>
<td></td>
<td>$N=2,3,4,5,6,7,8$</td>
<td>$N_d=1,N_r=1,3,5$</td>
<td>$2N_d+1$ for dec.</td>
</tr>
<tr>
<td></td>
<td>$N=4,5,6,7,8$</td>
<td>$N_d=2,N_r=2,4,6,8$</td>
<td></td>
</tr>
<tr>
<td>rbio</td>
<td>the same as bior</td>
<td>$N_d$ for dec.</td>
<td>$2N_d+1$ for rec.</td>
</tr>
</tbody>
</table>

Nd: order for decomposition  
Nr: order for reconstruction

Table 5.2: Order, number of vanishing moments and size of support of different wavelet families

Prior about how a function decays toward infinity. The larger, the faster. If a wavelet has $n$ vanishing moments then the wavelet transform can be interpreted as a multiscale differential operator of order $n$. In the proposed damage detection of the WEC, the first four mode shapes are used, which can be approximately modeled using polynomials up to the degree of four. In order to make polynomial components in mode shapes vanishing, the number of vanishing moments of an optimal mother wavelet should be not less than four.

5. Size of support. The size of support indicates the filter length. The accurate localization of a crack prefers that mother wavelet has short-size effective support. However, this property is not as important as the number of vanishing moments.

6. Regularity. The wavelet regularity represents the smoothness of the wavelet. Smoother wavelets provide sharper frequency resolution of the function. After the number of vanishing moments is determined, the regularity is less important, because it is intimately related to the number of vanishing moments.

Since requisite 2 to 6 are applicable for both SWT and CWT, the same mother wavelet will be used in both phases. On the basis of the above discussion, the following wavelets will be considered in the damage detection process: db4, sym4, coif2, and rbio4.4. The reason for discarding the bior4.4 is the consideration of the smoothness and regularity of the decomposition wavelet. Figure 5.5 displays the scaling and wavelet functions of the
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selected wavelets.

Figure 5.5: Scaling and wavelet functions of db4, sym4, coif2 and rbio4.4

5.3 Application on wind turbine structure

This section is devoted to the application of the damage detection method on the wind turbine prototype as described in Chapter 3. Due to limited financial means, however, the existing monitoring system can measure accelerations at only 6 levels, which restricts the information for detecting potential local damage. To overcome this problem, the measurements are simulated using the FE model at 19 equally distributed points along the tower, i.e. at each 3.5 m. Meanwhile, synthetic damage is appropriate and mandatory. As a wind turbine undergoes complicated and dynamic wind load, fatigue failure in terms of crack initiation or failed welds may occur on the tower structure. To simulate such real world damage, an open crack is introduced to the structure as described in the following.
5.3.1 Crack modeling

The wind turbine tower can be considered as a beam structure. The common approaches to model a crack in a beam structure fall into three categories: local stiffness reduction, discrete spring models, and complex models in two or three dimensions, as shown in Figure 5.6.

![Figure 5.6: Different approaches to crack modeling (a) local stiffness reduction (b) discrete spring model (c) complex model](image)

Friswell and Penny (2002) gave comprehensive surveys of these three approaches. The simplest method is to reduce the stiffness locally, for example by reducing a complete element stiffness to simulate a small crack. This approach suffers from problems in matching damage severity to crack depth, and is affected by the mesh density. An improved method introduces local flexibility based on physically-based stiffness reductions. The second class of methods divides a beam type structure into two parts that are pinned at the crack location and the crack is simulated by the addition of a rotational spring. This approach is a gross simplification of the crack dynamics and does not involve the crack size and location directly. Using the third approach produces detailed and accurate models, but costs intensive computational efforts. In addition, many researches have shown that the very detailed models do not substantially improve the results from crack detection and location. In this context, the simple stiffness reduction method is applied in the present work by considering physically-based stiffness reduction.

Figure 5.7a shows the variation in beam stiffness according to Christides and Barr (1984) (solid line) and Sinha et al. (2002) (dashed line). To simplify the problem, the dashed line will be used. The damage may occur at different locations, e.g., near the connection to the foundation, to the nacelle, or in the vicinity of the welds between the flange and the tower wall, etc. The extent of the crack can be characterized by two factors:
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5.3.1 Design Variables

(a) Design Variables

k4k1 k2 k3
(bending stiffness of connection between tower and nacelle)
(bending stiffness of connection at flanges)

Figure 5.7: Crack modeling on the wind turbine tower

the width \( w \) and the depth \( d \). To interpret the depth, or namely, the stiffness reduction \( d \), the damage is considered as partial deterioration of the circumference at the damage position, as shown in Figure 5.7b. Severity of the damage is represented by the damage angle \( \theta \). It is assumed that the tower mass remains constant and only its bending stiffnesses change due to the damage. Such a damage leads to different values of the moment of inertia \( I_y \) and \( I_z \) in the element coordinates, however, due to the uncertainty of the damage position along the circumference, the average of the two moments of inertia is assigned to both of \( I_y \) and \( I_z \). Taking \( \theta = 30^\circ \) as an example, the stiffness reduction \( d \approx 8.3\% \).

5.3.2 Mode extraction and decomposition

To present the result of mode extraction and mode decomposition, a single local damage occurring at the lower connection of the tower (see Figure 5.7) is used. For clarity, the damage is referred to as S1D1 and described in Table 5.3. The intact state D0 is taken as a reference.

<table>
<thead>
<tr>
<th>Scenario 1</th>
<th>location</th>
<th>extent</th>
</tr>
</thead>
<tbody>
<tr>
<td>S1D1</td>
<td>( x = 21.17m )</td>
<td>( \theta = 30^\circ, w = 0.03m )</td>
</tr>
<tr>
<td>D0</td>
<td>intact</td>
<td></td>
</tr>
</tbody>
</table>

Table 5.3: Damage scenario 1
The structure responses under operational condition are simulated by the consideration of stochastic wind load as well as the rotor rotation. More details about the numerical simulation have been presented in Chapter 4. The acceleration time histories are recorded at 19 positions with a sampling rate of 0.02s. From the simulated measurements, the modal parameters of the intact and damaged structures are extracted by the techniques of Stochastic Subspace Identification (SSI) as introduced in Chapter 3. Figure 5.8 shows the first four mode shapes of the wind turbine tower for D0 and S1D1. To eliminate the influence of the structural inherent disturbance, the mode shape differences of the damaged and intact structures shown in Figure 5.9 are used as signals. Signal 1 to signal 4 denote the mode shape differences of S1D1 and D0 from mode 1 to mode 4. Interpolation and extrapolation are performed to deal with the large sampling distance and to avoid edge effect.

Following the mode extraction is the mode decomposition by the stationary wavelet transform (SWT). The mother wavelet in use is the Symlets wavelet sym4. Comparison of different mother wavelets will be discussed in the following section. With 3-level decompositions of signal 3 and signal 4, the smoothed data containing lower frequency component are stored in the approximations (Figure 5.10) and the finer resolutions of the signals containing higher frequency component (local features) are stored in the details (Figure 5.11).
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Figure 5.8: mode shapes of D0 and S1D1

Figure 5.9: mode shape difference of D0 and S1D1
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Figure 5.10: 3-level approximations for S1D1

Figure 5.11: 3-level details for S1D1
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5.3.3 Damage localization

After performing the mode extraction and mode decomposition, details of the signals are further transformed to wavelet coefficients by the continuous wavelet transform (CWT). The wavelet modulus $|Wf(u,s)|$ is the absolute value of the wavelet coefficients and the modulus maximum describes any point $(u_0,s_0)$, such that $|Wf(u_0,s_0)|$ is locally maximum at $u = u_0$. The line of wavelet modulus maxima is used to describe a connected curve $s(u)$ in the scale-space plane $(u,s)$ along which every point is modulus maximum. A possible damage can be indicated by the largest wavelet modulus $|Wf(u,s)|_{max}$ and the damage position can be detected by finding the line of the modulus maxima across $|Wf(u,s)|_{max}$.

In this stage, different damage positions listed in Table 5.4 will be considered to test the effectiveness of the presented method.

<table>
<thead>
<tr>
<th>Scenario 2</th>
<th>Location</th>
<th>Extent</th>
</tr>
</thead>
<tbody>
<tr>
<td>single damage</td>
<td>S2D1 (=S1D1)</td>
<td>$x = 21.17m$, $\theta = 30^\circ$, $w = 0.03m$</td>
</tr>
<tr>
<td>S2D2</td>
<td>$x = 42.17m$, $\theta = 30^\circ$, $w = 0.03m$</td>
<td></td>
</tr>
<tr>
<td>multi-damage</td>
<td>S2D3</td>
<td>$x_1 = 31.32m$, $\theta_1 = 90^\circ$, $w = 0.03m$</td>
</tr>
<tr>
<td>S2D4</td>
<td>$x = 48.82m$, $\theta_2 = 30^\circ$, $w = 0.03m$</td>
<td></td>
</tr>
<tr>
<td>near boundary</td>
<td>S2D5</td>
<td>$x = 59.32m$, $\theta = 30^\circ$, $w = 0.03m$</td>
</tr>
</tbody>
</table>

Table 5.4: Damage scenario 2

Figure 5.12 displays the contour plot of the wavelet modulus for S2D1, in which the colors red and blue correspond to the maximum and minimum values, respectively. By extracting the line of the modulus maxima across the largest modulus, the possible damage position is indicated by the abscissa where the line progresses to fine scales as shown in Figure 5.13. The result is quite satisfactory. By analyzing different damage scenarios listed in Table 5.4, it has been proved that, the proposed method can accurately localize a single damage as well as multi-damage when the damage occurs in the middle part of the wind turbine tower. Edge effect has been eliminated, so that the damage near boundaries can also be detected, however, deviations in the position identification have to be taken into account. Besides, by viewing the damage angle used in scenario S2D3 to S2D5, it can be found that a damage near the free end ($x = 60m$) is easier to be detected than that near the fixed end ($x = 0$).
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Figure 5.12: Contour plot of the wavelet modulus for S2D1

Figure 5.13: The line of wavelet modulus maxima for S2D1
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Figure 5.14: Contour plot of the wavelet modulus for S2D2

Figure 5.15: Contour plot of the wavelet modulus for S2D3
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Figure 5.16: Contour plot of the wavelet modulus for S2D4

Figure 5.17: Contour plot of the wavelet modulus for S2D5
5.3.4 Damage quantification

To find an effective criterion to quantify the damage extent, the largest wavelet modulus in logarithm scale \( \log_2(\|Wf(u,s)\|_{max}) \) and the Lipschitz exponent \( \alpha \) have been considered on the following damage scenarios.

<table>
<thead>
<tr>
<th>Scenario 3</th>
<th>Location</th>
<th>Extent</th>
</tr>
</thead>
<tbody>
<tr>
<td>S3D1 (=S1D1)</td>
<td>( x = 21.17 \text{m} ) ( \theta = 30^\circ ), ( w = 0.03 \text{m} )</td>
<td></td>
</tr>
<tr>
<td>S3D2</td>
<td>--- &quot; &quot;</td>
<td>( \theta = 60^\circ ), --- &quot; ---</td>
</tr>
<tr>
<td>S3D3</td>
<td>--- &quot; &quot;</td>
<td>( \theta = 90^\circ ), --- &quot; ---</td>
</tr>
<tr>
<td>S3D4</td>
<td>--- &quot; &quot;</td>
<td>( \theta = 120^\circ ), --- &quot; ---</td>
</tr>
</tbody>
</table>

Table 5.5: Damage scenario 3

Taking the detail \( d_2 \) of signal 4 for S3D1 as an example, the wavelet modulus of the maxima line across \( \|Wf(u,s)\|_{max} \) is plotted in Figure 5.18 in logarithm scale. \( \log_2(\|Wf(u,s)\|_{max}) \) is used as one damage quantification criterion, while the other one, the Lipschitz exponent \( \alpha \) depends on the decay of the maxima values at fine scales. By applying the linear regression technique, the Lipschitz exponent \( \alpha \) can be estimated as:

\[
\alpha = m - \frac{1}{2},
\]

where \( m \) is the slope of the regression line.

The largest wavelet modulus \( \log_2(\|Wf(u,s)\|_{max}) \) for different damage extent are plotted in Figure 5.19 using all 3-level details. Since the magnitude of the details gets larger from \( d_1 \) to \( d_3 \), the wavelet modulus increases from \( d_1 \) to \( d_3 \) as a result. It is clearly and consistently shown that, as the damage extent becomes severer (damage angle \( \theta \) becomes larger), the value of \( \log_2(\|Wf(u,s)\|_{max}) \) gets larger. This suggests a possibility to correlate the damage extent to the largest wavelet modulus.

Figure 5.20 displays the relationship between the damage extent and the Lipschitz exponent \( \alpha \). \( \alpha(d3) > \alpha(d2) > \alpha(d1) \) is consistent with the fact that the regularity increases from \( d_1 \) to \( d_3 \). However, for the small local damage presented in this case, \( \alpha \) is not sensitive enough to reveal the different damage severities.

After comparing these two criteria, the largest wavelet modulus is preferred for quantification of the small damage.
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Figure 5.18: The decay behavior along the modulus maxima line for S3D1

Figure 5.19: Largest wavelet modulus $\log_2(\|Wf(u,s)\|)_{max}$ for different damage extent
Figure 5.20: Lipschitz exponent $\alpha$ for different damage extent
5.3.5 Consideration of different mother wavelets

Based on the discussion in Section 5.2.3, the wavelet type sym4, db4, coif2 and rbio4.4 have been suggested for damage detection and their effectiveness will be verified in the current section. Considering the signal 4 of damage scenario S1D1 again, all of the wavelets provide good results in damage localization, as shown in Figure 5.21 and 5.22, except db4 giving some distortion, which is due to its unsymmetry as discussed in Section 5.2.3.

The largest wavelet modulus $\log_2(|Wf(u, s)|)_{max}$ using different mother wavelets are listed in Table 5.6. The values from different wavelets are quite close, which demonstrates the consistency of these wavelets in damage quantification.

As a result, the wavelet type sym4, coif2 and rbio4.4 have been proved to be optimal for damage identification.

<table>
<thead>
<tr>
<th></th>
<th>sym4</th>
<th>db4</th>
<th>coif2</th>
<th>rbio4.4</th>
</tr>
</thead>
<tbody>
<tr>
<td>d1</td>
<td>-22.7678</td>
<td>-22.8272</td>
<td>-22.7596</td>
<td>-22.7269</td>
</tr>
<tr>
<td>d2</td>
<td>-18.4894</td>
<td>-18.5338</td>
<td>-18.4851</td>
<td>-18.4350</td>
</tr>
</tbody>
</table>

Table 5.6: The largest wavelet modulus $\log_2(|Wf(u, s)|)_{max}$ using different mother wavelets
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Figure 5.21: Contour plot of the wavelet modulus calculated from sym4 and db4

Figure 5.22: Contour plot of the wavelet modulus calculated from coif2 and rbio4.4
5.3.6 Consideration of measurement noise

In order to test the robustness of the damage detection method, measurement noise in mode shapes should be considered.

A common practice is to add uncorrelated noise on the time domain responses at each sensor under the following form:

\[ y_i(t) = y^0_i(t) + \beta_1 \lambda (y^0_i(t)) \],

(5.12)

where \( y_i(t) \) and \( y^0_i(t) \) are the noisy and non-noisy responses of sensor \( i \) at time \( t \) respectively. \( \beta_1 \) indicates the level of noise and \( \lambda \) is the random parameter, with its continuous distribution \( f(\lambda) \) following a Gaussian distribution with zero mean and unitary standard deviation. By performing the modal identification on the noisy responses, the mode shapes which are corrupted by measurement noise can be extracted. To reduce the influence of the measurement noise, the mean \( \Phi^{\text{mean}} \) of the identified mode shapes from \( N \) samples is considered instead of a single mode shape.

\[ \Phi^{\text{mean}} = \frac{1}{N} \sum_{k=1}^{N} \Phi_k \]

(5.13)

This approach can represent the potential spatial correlation in the mode shape uncertainties, however, it would be quite time consuming, if the sample number \( N \) becomes very large. An alternative approach which has been adopted in several studies is to add spatially uncorrelated noise directly on the mode shapes:

\[ \phi_{ki} = \phi^0_i + \beta_2 \lambda \phi^0_i \],

(5.14)

where \( \phi_{ki} \) and \( \phi^0_i \) are respectively the noisy and reference component \( i \) of the \( k^{th} \) sample of the identified mode shape, \( \beta_2 \) is the level of noise and \( \lambda \) follows the \( f(\lambda) \) distribution (normal distribution with zero mean and unitary standard deviation). Because the effect on mode shapes of a noise introduced following Equation 5.12 or 5.14 is very different, \( \beta_1 \) and \( \beta_2 \) can not be set equal for the same order of the noise magnitude. Based on TONDREAU ET AL. (2011), \( \beta_2 = 0.858\% \) gives roughly the same effect as \( \beta_1 = 5\% \), this value of \( \beta_2 \) will be used in our case for the purpose of concept explanation.

For successful damage detection, the influence of the noise on mode shapes should be less than the changes due to damage. To assure this, the normalized modal difference (NMD) is taken as an indicator.

\[ NMD = \sqrt{\frac{1 - MAC}{MAC}} \]

(5.15)
Then, $NMD1 = NMD(\Phi_{S1D1}^0, \Phi_{S1D1}^{mean})$ denotes the normalized modal difference between the damaged mode shape without noise and the mean mode shape calculated from $N$ samples with noise, while $NMD2 = NMD(\Phi_{S1D1}^0, \Phi_{D0}^0)$ denotes the normalized modal difference between the damaged and intact mode shapes without noise. A precondition for successful damage detection is $NMD1 < NMD2$.

By observing the evolution of $NMD1$ for $\beta_2 = 0.858\%$ with the number of samples in Figure 5.23, the value of $NMD1$ is converged to $NMD2$ after $10^3$ samples. Choosing $N = 10^3$ leads to the result as shown in Figure 5.24, which demonstrates the robustness of the proposed method in consideration of measurement noise.

Figure 5.23: Evolution of $NMD1$ with the number of samples
Figure 5.24: Contour plot of the wavelet modulus using $\Phi_{m_{1}, n_{1}, D_{1}}^{m_{1}, n_{1}}$ from $10^3$ samples
5.4 Obtained insight

Based on the application results, the proposed damage detection method has been proved to be quite effective in the local damage identification of the WECs. The damage position is localized on the wavelet map by the line of wavelet modulus maxima, while the largest wavelet modulus is used for damage quantification, which may be later integrated into a more comprehensive process referred to damage prognosis.

The following advantages of the presented method can be concluded:

1. It is a global non-destructive evaluation technique for locating incipient damage, no prior knowledge of the damage position is required;

2. The method can be performed on the large-scale in-service structures under operational condition;

3. Intact modes are not necessary when the structure does not contain discontinuities or a reliable finite element model exists;

4. No need of higher order modes, only the first four modes are enough for the investigated wind turbine for instance;

5. Relatively small number of sensors are used;

6. Edge effect is eliminated so that damage near boundaries could also be detected;

7. Influence of measurement noise on mode shapes can be measured by the indicator of NMD and reduced using statistical methods.

In future work, validation through real measurement data is of particular interest since noise or measurement errors are present in the signals, which will examine the practicality of the method.
In this chapter, the model updating problem is dealt with and solved by means of simulation-based multi-criteria optimization. Representative numerical test cases are conducted to demonstrate the effectiveness of the proposed solution concept.

6.1 Parameter selection

The finite element (FE) model usually gives results that are not the same as the results given by an experiment. The reasons for the discrepancy between FE model data and measured data include (MOTTERSHEAD ET AL. 0 01):

- model structure errors: e.g., simplification of the structure; inaccurate assignment of mass properties; erroneous modelling of boundary conditions or joints.
- model order errors: e.g., discretisation errors when the finite element mesh is too coarse; truncation errors in order reduction methods.
- model parameter errors: material parameters such as Young’s modulus or mass density; cross section properties of beams such as area moments of inertia; shell/plate thicknesses; spring stiffnesses.
- errors in measurements.

Model updating is essentially a process of adjusting certain parameters of the FE model, therefore, some important issues should be settled before applying model updating,
i.e., determining the most appropriate mathematical structure model and the model order, because these modelling errors cannot be corrected by the process of model updating. When the model structure and model order have been decided upon, the problem of system identification reduces to the parameter estimation.

In the current research, some assumptions are taken into consideration to obtain appropriate results of model updating:

- The measurements are assumed to be correct and therefore the FE model is updated to match the measured data. However, measurements always imply uncertainty. It is necessary to use statistical methods to reduce the influence of measurement uncertainties.

- The initial model already describes the reality basically correct (no model structure errors or model order errors), but only inaccurate in some of its components (parameter errors).

- Since the influence of non-linearities introduced by the gyroscopic effect and by crack is weak, it is assumed that the structural behaviour is linear and that damping is low enough not to require complex attention.

- It is important to compare the same extents of the model with the real world system. If physical boundary conditions affect the results, or additional parts are included in the measurement, both have to be considered in the numerical model as well.

### 6.1.1 Defect localization

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 unnecessary numerical effort and the possible danger of ill-conditioning. When choosing parameters it is always advisable to try to understand the behaviour of the structure globally and locally in those regions where local modelling inaccuracies might be responsible for discrepancies in predictions. Defect localization tries to locate main inaccuracies in a FE model according to experimental data. It usually serves as a preliminary step of the model updating process, which provides some helpful information in the selection of the updating parameters. The common defect localization methods include the Force Balance Method (FBM) (FISSETTE
ET AL. 1988) and the Error Matrix Method (EMM) (SIDHU AND EWINS 1984). FBM is simply a residual method, which produces residual force vectors by using the vibration equations in the frequency domain, while EMM is a system reconstruction methodology, which requires to reconstruct system matrices with incomplete modes.

ZANG ET AL. (2008) suggested a novel defect localization method using the information from a supermodel based on the concept of Equivalent Element Modal Strain Energy (EEMSE) and Equivalent Element Modal Kinetic Energy (EEMKE). A brief description of this method is now given. For each element of the FE model, the element strain energy and element kinetic energy due to each mode is

\[ EMSE_{ij} = \frac{1}{2} \phi_i^T K_{ej} \phi_i \] (6.1)

\[ EMKE_{ij} = \frac{1}{2} \omega_i^2 \phi_i^T M_{ej} \phi_i \] (6.2)

where \( M_{ej} \) and \( K_{ej} \) are the mass and stiffness matrices for the \( j \)th element, \( \omega_i \) is the \( i \)th natural frequency and \( \phi_i \) is the associated global mode shape at the degrees of freedom corresponding to the \( j \)th element. The EMSE and EMKE of a mode in Equation 6.1 and 6.2 give the energy distributions over all of the elements. However, since the energy distribution of a model is calculated using the modelled natural frequencies and mode shapes, the direct use of the EMSE and EMKE distributions may not able to locate the modelling errors.

To build a relationship between the FE model and the real structure, ZANG ET AL. (2008) proposed new metrics, called the Equivalent Element Modal Strain Energy (EEMSE) and the Equivalent Element Modal Kinetic Energy (EEMKE), in which the analytical eigensolution is replaced by the measured eigenvalues and expanded eigenvectors obtained from measurements. The element mass and stiffness matrices are still obtained from the FE model. The EEMSE and EEMKE metrics are calculated as:

\[ EEMSE_{ij} = \frac{1}{2} \{ \phi_i^m \}^T K_{ej} \phi_i^m \] (6.3)

\[ EEMKE_{ij} = \frac{1}{2} (\omega_i^m)^2 \{ \phi_i^m \}^T M_{ej} \phi_i^m \] (6.4)

where \( M_{ej} \) and \( K_{ej} \) are the mass and stiffness matrices for the \( j \)th element of the FE model, \( \omega_i^m \) is the natural frequency of the \( i \)th mode from measurements and \( \phi_i^m \) is the associated
measured mode at the degrees of freedom of the \( j \)th element of the FE model. The EEMSE and EEMKE use the eigenvalues and eigenvectors from the real structure and the element stiffness and mass matrices from the FE model, and hence combine information from the FE model and the real structure.

Based on the definitions of EEMSE and EEMKE, two indicators are proposed in order to localize errors in the FE model. The first indicator uses the difference of EEMSE and EMSE to localize the possible errors in the elemental strain matrix of the FE model. The second indicator uses the difference of EEMKE and EMKE to indicate possible errors in the elemental mass matrix of the FE model.

\[
IDS_{ij} = |EEMSE_{ij} - EMSE_{ij}|
\]  

(6.5)

\[
IDK_{ij} = |EEMKE_{ij} - EMKE_{ij}|
\]  

(6.6)

When using measurement data as the reference information about the actual structure, the common problem is the incomplete available data. The comparison of EMSE and EEMSE as well as EMKE and EEMKE should be based on the same physical areas, as the comparison of eigenvectors is based on the same DOFs. Since measurements on real structure are usually much coarser than the finite element discretization of the model, superelement is needed to cover the same region of the FE model as that between two measurements of the real structure. The wind turbine model is used as example to demonstrate the effectiveness of the method in Section 6.3.1.

6.1.2 Global sensitivity analysis

The result of defect localization implies the region with large modelling errors. An initial selection of the updating parameters still depends on engineering insight of the model. To ensure well-conditioned problem, the number of the updating parameters should not exceed the number of measurements. 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.
6.1. PARAMETER SELECTION

There are several different methods that belong to the class of global sensitivity analysis, as described in detail by SalteLLi (2008). 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 (Morris 1991). 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 (SalteLLi 2008):

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

(6.7)

The sensitivity measures, \( \mu \) and \( \sigma \), proposed by Morris, are respectively the mean and the standard deviation of the elementary effects calculated from finite randomly sampled inputs. The mean \( \mu \) assesses the overall influence of the factor on the output. The standard deviation \( \sigma \) estimates the ensemble of the factor’s effects, whether nonlinear and/or due to interactions with other factors. Campolongo et al. (2007) proposed replacing the use of the mean \( \mu \) with \( \mu^* \), which is defined as the mean of the absolute values of the elementary effects. The use of \( \mu^* \) can prevent cancellation effects when the model is nonmonotonic or has interaction effects. \( \mu^* \) is a practical and concise measure to use, especially when there are several output variables. Campolongo et al. (2007) has also shown that \( \mu^* \) is a good proxy of the total sensitivity index \( S_T \) of the variance-based method (SalteLLi 2008). With the aid of the global sensitivity analysis, the few decisive key parameters can be selected as updating parameters for the updating process.
6.2 Model updating framework

6.2.1 Multi-criteria optimization

As mentioned before, the objective function used in model updating evaluates the defect between measured and model predicted data. It is obvious that the choice of a suitable objective function is a key point for model updating. In real-world applications it is very difficult to find solely one single objective function to be sufficiently representative regarding the total performance of the structure. For this reason, it is advisable to consider simultaneously several objectives in the optimization, which is called multi-criteria or multi-objective optimization.

In general, the multi-objective optimization problem is posed as follows:

\[
\begin{align*}
\min_x F(x) &= [F_1(x), F_2(x), \ldots, F_k(x)]^T \\
\text{subject to } g_j(x) &\leq 0, \ j = 1, 2, \ldots, m, \\
&\quad h_l(x) = 0, \ l = 1, 2, \ldots, e, \\
&\quad x^U_i \leq x_i \leq x^L_i, \ i = 1, 2, \ldots, n,
\end{align*}
\]

where \( k \) is the number of objective functions, \( m \) is the number of inequality constraints, and \( e \) is the number of equality constraints. \( x \) is a vector of design variables (updating parameters in the model updating problem) confined by a lower and an upper limits.

There are some basic concepts and definitions in the field of multi-objective optimization, e.g., Pareto optimality, preferences, utility function, necessary and sufficient conditions. These terms are shortly introduced in the following.

**Pareto optimality.** As opposed to single objective optimization problems which yield only one single optimum solution, multi-objective optimization problems do not have a single optimal solution, but rather a set of alternative solutions, named the Pareto-optimal points, which are optimal in the sense that no other solutions in the search space are superior to them when all objectives are considered. The predominant concept in defining an optimal point is defined as follows (MARLER AND ARORA 2004):

**Definition 1.** Pareto Optimal: A point, \( x^* \in X \), is Pareto optimal iff there does not exist another point, \( x \in X \), such that \( F_k(x) \leq F_k(x^*) \forall k \) and \( F_k(x) < F_k(x^*) \) for at least one \( k \).

**Definition 2.** Weakly Pareto Optimal: A point, \( x^* \in X \), is weakly Pareto optimal iff there does not exist another point, \( x \in X \), such that \( F_k(x) < F_k(x^*) \forall k \).
6.2. MODEL UPDATING FRAMEWORK

Definition 3. *Properly Pareto Optimal*: A point, \( x^* \in X \), is properly Pareto optimal iff it’s Pareto optimal and there is some \( M > 0 \) such that for each \( F_k \) satisfying \( F_k(x) < F_k(x^*) \) there exists at least one \( F_j \) such that \( F_j(x^*) < F_j(x) \) and \( \frac{F_k(x^*) - F_k(x)}{F_j(x) - F_j(x^*)} \leq M \).

The quotient is referred to as a trade-off. Properly Pareto optimal means the trade-off between each function and at least one other function is bounded. We cannot arbitrarily improve on one objective. The increment in one objective function results from a decrement in another objective function. The relationship of these three type points is: properly Pareto optimal \( \in \) Pareto optimal \( \in \) weakly Pareto optimal.

**Preference.** The term preference refers to decision-maker’s opinions concerning the relative importance of different objective functions.

**Utility function.** An individual utility function is defined for each objective and represents the relative importance of the objective. The utility function \( U \) is an amalgamation of the individual utility functions and is a mathematical expression that attempts to model the decision-maker’s preferences.

**Necessary and sufficient conditions.** If a formulation provides a necessary condition, every Pareto optimal point is attainable with adjustments in method parameters (exponents, weights, etc.), however, some solutions obtained may not be Pareto optimal. On the other hand, if a formulation provides a sufficient condition, then its solution is always Pareto optimal, although certain Pareto optimal points may be unattainable.

The common methods for multi-objective optimization problems can be divided into two categories: methods with a priori articulation of preferences, and methods with a posteriori articulation of preferences. The differences of two categories are listed in Table 6.1.

The methods with a priori articulation of preferences allow the user to specify preferences in the formulation of the utility function. One of the most general utility functions is expressed in its simplest form as the weighted exponential sum (Marler and Arora 2004):

\[
U = \left\{ \sum_{i=1}^{k} w_i [F_i(x) - z_i^*]^p \right\}^{\frac{1}{p}}, \tag{6.9}
\]

here, \( w \) is a vector of weights typically set by the decision-maker such that \( \sum_{i=1}^{k} w_i = 1 \) and \( w > 0 \). The utility function in Equation 6.9 can be viewed as a distance function that minimizes the distance between the solution point \( x \) and the ideal point \( z^* \). The parameter
CHAPTER 6. ROBUST MODEL UPDATING STRATEGY

Table 6.1: A priori articulation vs. a posteriori articulation of preference

<table>
<thead>
<tr>
<th></th>
<th>a priori</th>
<th>a posteriori</th>
</tr>
</thead>
<tbody>
<tr>
<td>when is</td>
<td>before optimization</td>
<td>after optimization</td>
</tr>
<tr>
<td>preference</td>
<td></td>
<td></td>
</tr>
<tr>
<td>expressed</td>
<td></td>
<td></td>
</tr>
<tr>
<td>output result</td>
<td>one solution</td>
<td>a set of solutions</td>
</tr>
<tr>
<td>advantages</td>
<td>use single-objective tools</td>
<td>user choose solution,</td>
</tr>
<tr>
<td></td>
<td></td>
<td>not formulation</td>
</tr>
<tr>
<td>main issues</td>
<td>eliciting preference,</td>
<td>computation,</td>
</tr>
<tr>
<td></td>
<td>necessary/sufficient cond.</td>
<td>even sampling</td>
</tr>
<tr>
<td>general approach</td>
<td>scalarization</td>
<td>genetic algorithm,</td>
</tr>
<tr>
<td></td>
<td></td>
<td>iterative methods</td>
</tr>
</tbody>
</table>

$p$ can take a value between 1 and $\infty$. This parameter influences the measure that is used. The commonly used values for $p$ and the resulting optimization problems are:

- $p=1$: the problem is equivalent to the standard weighted sum method;
- $p=2$: a weighted Euclidean distance is minimized;
- $p=\infty$: the weighted Chebyshev method (MIETTINEN 1999), the largest deviation should be minimized.

The weighted sum method uses linear combination of individual utility functions. It provides sufficient condition, but doesn’t provide necessary condition if the objective space is non-convex. Similarly, using Euclidean distance may not capture Pareto points in non-convex regions. The weighted Chebyshev method is also called weighted min-max method, in which the utility function can be reformed as:

$$U = \max_{i} \{ w_i [F_i(x) - z_i^*] \}. \quad (6.10)$$

This method can provide sufficient conditions for weakly Pareto optimality and necessary conditions for Pareto optimality in both of the convex and non-convex objective regions. Since the curvature of the objective space is unknown in the model updating problem, the weighted Chebyshev method is to be used.
6.2.2 Solution procedure

The complete model updating procedure can be illustrated by the flow chart in Figure 6.1.

![Flow chart of the proposed model updating procedure](image)

1. Select modal data $D^m$ generated from measurements on the real system.

$$D^m \equiv \{\omega_{m_1}, \ldots, \omega_{m_k}, \Phi_{m_1}, \ldots, \Phi_{m_k}\}, \ k \equiv \text{number of measured DOF}$$
2. Determine updating parameters (design variables) $x^n$ using the methods described in Section 6.1.

3. Establish objective function, constraints, as well as allowable upper and lower bounds of the design variables.

4. Apply simulation using appropriate initial input values.

5. Compute objective and constraint functions with the output from simulation.

6. Utilize powerful and adequate optimization algorithm to check the convergence and generate new input values if necessary.

7. If the convergence criteria is satisfied, stop and output the results; Otherwise, go back to step 4 and update the input values with the new generated ones.

As a rule, in simulation-based optimization, all or some of the objective and constraint functions depend on the simulation result. As can be seen in Figure 6.1, 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 (design variables) are created according to the logic of the optimization method 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.

In most cases, the respective simulations are accomplished using commercial finite element software because they are powerful numerical analysis tools providing high reliability and numerous capabilities. In this dissertation, the simulation tool applied is the commercial finite element software ANSYS.

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 provides no support for optimization or not powerful tools for optimization. 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 this dissertation, 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. (2010). It contains numerous robust optimization strategies,
including deterministic methods and stochastic methods. More details about the available methods in MOPACK can be found in NGUYEN ET AL. (2010). 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 needed for running optimization using external solvers in the simulation software and the optimization framework simultaneously. To this end, a simulation adapter is developed (MUSAYEV 2010) which is a general Java-based programming interface for coupling different simulation software with the optimization framework MOPACK. The working principle of the adapter is illustrated in Figure 6.2. The integration of multiple software in the optimization procedure makes the proposed model updating approach robust for complex structure problems.

![Figure 6.2: Working principle of the adapter in simulation-based optimization](image-url)
6.2.3 Optimization algorithm

In the optimization package of MOPACK, numerous optimization methods have been integrated with the ability of being accessed in a uniform manner. A complete list of the optimization methods available in MOPACK is reviewed in the following (Nguyen et al. 2010):

- Deterministic Methods: SCPIP (Sequential Convex Programming with Interior Point method), FSQP (Feasible Sequential Quadratic Programming), NLPQLP (Nonlinear Programming with Non-Monotone and Distributed Line Search), KNITRO (A Solver for Large-Scale Nonlinear Optimization), Polytop, IPOPT (Interior Point Optimizer), lp_solve and DOT (Design Optimization Tools).

- Stochastic Methods: EES (Extended Evolution Strategy), PSO (Particle Swarm Optimization), DE (Differential Evolution), HS (Harmony Search), SA (Simulated Annealing), CMA (Covariance Matrix Adaptation Evolution Strategy) and SOMA (Self-Organizing Migrating Algorithm).

It is crucial to choose a suitable optimization method for different problems, because the existence and correctness of the solution as well as the convergence speed largely depend on the optimization algorithm. The simulation-based optimization problem involved in the model updating procedure 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 least squares 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), which are derivative free methods, can be considered as a reliable alternative in such situations. Back and Schwefel (1993) and Eiben (2002) give overviews of 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. In order to compare results, two evolution strategies, EES and DE, in the broad class of EAs, are employed separately in the section of test implementation, within which the speed and efficiency of the two methods are revealed.

**Algorithm of Enhanced Evolution Strategy**

The Enhanced Evolution Strategy (EES) is the extended version of the Evolution Strategy (ES). The pre-runner ES as a stochastic method for global optimization, was developed in Germany by I. Rechenberg (RECHENBERG 1965, 1973) and H.-P. Schwefel (SCHWEFEL 1977, 1981)) and was firstly applied in engineering by D. Hartmann (HARTMANN 1978, 1984, 1985). Basic steps of the advanced population-based ES include:

1. Initialize $\mu$ individuals (candidate solutions) to form the initial parent population $P(0)$.

2. Repeat until TERMIN.COND is satisfied (convergence criteria or maximum number of generation).
   
   a) Select and recombine individuals from the parent population $P(0)$ to generate intermediate population $P'(t)$ of size $\lambda$ (usually $\lambda > \mu$).
   
   b) Mutate $P'(t)$ to get the offspring (children) population $P''(t)$ of size $\lambda$.
   
   c) Evaluate values of the fitness function for both children and parent populations.
   
   d) Select the best $\mu$ individuals.
   
   e) Use the selected $\mu$ children as parents for the next generation.

In the evolution process, the population is continuously modified by applying the operators of recombination, mutation and selection until the TERMIN.COND is fulfilled. The recombination is normally performed by combining randomly selected individuals of the parent population $P(t)$. Then the mutation operator $m$ modified the members of $P'(t)$ by adding a normally distributed random value. For each member of $P(t)$ and $P''(t)$, the
fitness is evaluated based on the numerical values of the problem function. Finally, the selection operator $s$ chooses individuals with best fitness values on the basis of either the set of children only ($(\mu, \lambda)$-selection) or the set of parents and children ($(\mu + \lambda)$-selection). Often $(\mu, \lambda)$-selection is preferred because it is better in leaving local optima and in following moving optima.

Enhanced Evolution Strategy (EES) is one of the variants of ES, within which the number of parents that will contribute to each new candidate solution is specified using a recombination operator, nominated as $(\mu/\rho, \lambda)$-ES and $(\mu/\rho + \lambda)$-ES (Bäck 1996).

**Algorithm of Differential Evolution**

The Differential Evolution (DE) is a fairly fast and reasonably robust method with the capability of handling nondifferentiable, nonlinear and multimodal objective functions. It is originally due to Storn and Price (1997). Books Price et al. (2005) Feoktistov (2006) Kacprzyk and Chakraborty (2008) have been published on theoretical and practical aspects of using DE in parallel computing, multiobjective optimization and constrained optimizations. The crucial idea behind DE is using vector differences for perturbing the vector population.

The population used for each generation is defined by a total of $NP$ parameter vectors of dimension $D$.

$$ x_{i,G}, i = 1, 2, \ldots, NP $$

The number $NP$ does not change during the minimization process. The initial vector population is chosen randomly and should cover the entire parameter space. Normally a uniform probability distribution is applied for the random decisions. In the mutation process, new vectors are generated by adding the weighted difference between two population vectors randomly chosen from the current population.

$$ v_{i,G+1} = x_{r1,G} + F (x_{r2,G} - x_{r3,G}) $$

$r1, r2, r3$ are random indexes $\in \{1, 2, \ldots, NP\}$. $F$ is a real and constant factor $\in [0, 1]$ which controls the amplification of the differential variation $(x_{r2,G} - x_{r3,G})$. Figure 6.3 shows a two-dimensional example that illustrates the different vectors which play a part in the generation of the mutated vector $v_{i,G+1}$.

The mutated vector’s parameters are then mixed with the parameters of the predetermined target vector, to yield the so-called trial vector. Each population vector has to serve
6.3. APPLICATION ON WEC

6.3.1 Test of defect localization

In this section, the application of the proposed defect localization method on the wind turbine model is presented. As aforementioned, measurements on real structure are usually much coarser than the finite element discretization of the model, therefore superelement (substructure) is needed to cover the same region of the FE model as that between two
measurements of the real structure. ANSYS provides the technique of substructuring, which condenses a group of finite elements into a single element represented as a matrix. The single-matrix element is called a superelement. In general, the only restriction is that elements within the superelement are assumed to be linear and cannot use Lagrange multipliers. The condensation is done by identifying a set of master degrees of freedom, i.e., reduced matrices and the reduced DOF solutions are calculated in terms of the master DOFs. The master DOFs serve as the interface between the superelement and other elements. They should also be chosen that they can characterize the dynamic behavior of the model. The ANSYS program uses the Guyan Reduction procedure (GUYAN 1965) to calculate the reduced matrices. The key assumption in this procedure is that for the lower frequencies, inertia forces on the slave DOFs (those DOFs being reduced out) are negligible compared to elastic forces transmitted by the master DOFs. Therefore, the total mass of the structure is apportioned among only the master DOFs. The net result is that the reduced stiffness matrix is exact, whereas the reduced mass and damping matrices are approximate. Based on this, the indicator IDS proposed in Section 6.1.1, which makes use of the stiffness matrix, will be applied in the following tests to localize modelling error.

Figure 6.4: Illustration of the superelements on the wind turbine model
As shown in Figure 6.4a, totally 21 superelements (SE) are generated. SE1 represents the part of foundation. SE2 to SE20 covers the tower and SE21 contains the rotor including three blades. The master DOFs of SE2 to SE21 are taken from two end nodes of each superelement, and each end node has six DOFs, including three translational and three rotational DOFs. While for SE1, more nodes have to be chosen for master DOFs, because the nodes on the solid elements have only three translational DOFs but no rotational DOFs. The selected nodes are distributed as shown in Figure 6.4b, five on top surface of the foundation and five on bottom.

Since stiffness is generally more difficult to model than mass, it is therefore more likely that errors in stiffness modelling are responsible for inaccurate predictions than mass errors. Three test cases are used to demonstrate the effectiveness of the method.

- In the first case, a modelling error is assumed to be located in the tower. Simulated measurements are taken from a model the same as the FE model developed in Chapter 4, but with stiffness reduction of the element near the lower connection (at 21m). The stiffness reduction factor takes the value of 0.9.

- In the second case, parameter errors of the foundation are considered. The concrete foundation of the wind turbine is placed on the ground. To include the influence of soil, an elastic foundation model using the winkler foundation is used. According to ENERCON GMBH (1997), the stiffness $E_s,dyn$ of the ground in place may vary from 70 MN/m$^2$ to 150 MN/m$^2$. While $E_s,dyn = 80 MN/m^2$ is taken for the initial FE model, $E_s,dyn = 150 MN/m^2$ is used to generate the simulated measurements.

- Then in the third case, the stiffness of the nacelle is changed by 10% to simulate a modelling error in the rotor.

If we only compare the eigen frequencies and mode shapes, the modelling errors can be hardly revealed. Taking case 1 as an example, Table 6.2 lists the first 6 “measured” bending modes of the structure with comparison with the initial FE model. The natural frequency differences are quite small, and the MAC values are all close to 1, which indicates very good agreement between the mode shapes of the initial and “measured” models.

In order to localize the error in the model, the EMSE of the initial FE model and the EEMSE using the “measured” eigen vectors are calculated based on the 21 generated superelements. Figure 6.5 shows the EMSE distribution of the FE model for different modes. It is known that, the strain energy is higher for more complex mode shapes in
Table 6.2: Comparison of the modes from “measurements” and initial FE model

<table>
<thead>
<tr>
<th>mode</th>
<th>mode shape</th>
<th>“measurements”</th>
<th>FE model</th>
<th>MAC</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>$f_m$ [Hz]</td>
<td>$f_n$ [Hz]</td>
<td>$\frac{</td>
</tr>
<tr>
<td>1</td>
<td>1st bending in X dir.</td>
<td>0.3597</td>
<td>0.3599</td>
<td>0.056%</td>
</tr>
<tr>
<td>2</td>
<td>1st bending in Y dir.</td>
<td>0.3612</td>
<td>0.3612</td>
<td>0</td>
</tr>
<tr>
<td>3</td>
<td>2nd bending in Y dir.</td>
<td>2.229</td>
<td>2.250</td>
<td>0.942%</td>
</tr>
<tr>
<td>4</td>
<td>2nd bending in X dir.</td>
<td>2.437</td>
<td>2.437</td>
<td>0</td>
</tr>
<tr>
<td>5</td>
<td>3rd bending in Y dir.</td>
<td>5.555</td>
<td>5.713</td>
<td>2.844%</td>
</tr>
<tr>
<td>6</td>
<td>3rd bending in X dir.</td>
<td>6.258</td>
<td>6.258</td>
<td>0.659%</td>
</tr>
</tbody>
</table>

comparison to simpler mode shapes. Just as in Figure 6.5, the EMSE takes values of a few tenths for the first bending modes, a few for the second bending modes, and dozens for the third bending modes. EMSE is also different from element to element in a certain mode. Elements with large EMSE values in one mode indicate high sensitivity to the change in the structure. Figure 6.6 to 6.8 display values of the indicator $IDS = |EMSE - EEMSE|$ for the three test cases as described before. In case 1, the modelling error is introduced to the lower connection of the tower. With large IDS values at SE8 in all of the first six modes, the erroneous region in the FE model is correctly identified. The identification results in mode 3 and mode 4 are not as confident as in the other modes, because the EMSE of SE8 in mode 3 and mode 4 are too small compared to the other elements (see Figure 6.5). The modelling errors in the foundation in case 2 and in the rotor in case 3 have also been correctly located by the IDS indicator. The results from the test cases are very encouraging. Rather than using solely engineer’s judgement, the defect localization method using the IDS indicator is straightforward and more reliable for selection of updating parameters.
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Figure 6.5: EMSE distribution of the FE model for different modes

Figure 6.6: IDS distribution for different modes in case 1
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Figure 6.7: IDS distribution for different modes in case 2

Figure 6.8: IDS distribution for different modes in case 3
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6.3.2 Test of model updating

As stated before, model updating can be used to validate the FE model through measurements. Instead of considering the complete model, it is more reasonable to validate the model components in the first step. Taking the blade as an example, the following test substantiates the effectiveness of the proposed model updating strategy.

![Figure 6.9: Input parameters of the blade cross section](image)

<table>
<thead>
<tr>
<th>Updating parameters</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>thickness of the skin $t_1$ [m]</td>
<td>0.003</td>
<td>0.01</td>
</tr>
<tr>
<td>thickness of the two shear webs $t_2$ [m]</td>
<td>0.003</td>
<td>0.01</td>
</tr>
<tr>
<td>thickness of the top and bottom spar caps $t_3$ [m]</td>
<td>0.003</td>
<td>0.01</td>
</tr>
<tr>
<td>location of the forward shear web $x_1$</td>
<td>0.1c</td>
<td>0.3c</td>
</tr>
<tr>
<td>location of the after shear web $x_2$</td>
<td>0.4c</td>
<td>0.6c</td>
</tr>
</tbody>
</table>

c: chord length

Table 6.3: Updating parameters and constraint range

Five geometrical parameters of the blade cross section are used as updating parameters as illustrated in Figure 6.9 and Table 6.3. Structural properties including eigenfrequencies and mode shapes of the first five modes and the blade weight are measures of the measurements and the FE model:

$$f_1, f_2, f_3, f_4, f_5, \Phi_1, \Phi_2, \Phi_3, \Phi_4, \Phi_5, m.$$  

The reference measures take means of the measured structural properties. However, due to the lack of real measurement, simulated structural properties using the following parame-
ters are slightly contaminated by noise to generate simulated means of measurements.

\[ t_1 = 0.008, \ t_2 = 0.005, \ t_3 = 0.005, \ x_1 = 0.15c, \ x_2 = 0.5c. \]

The objective function using the weighted Chebyshev method is formulated in terms of the frequency shift, the normalized modal difference and the mass difference, as seen in Equation 6.11.

\[
\mathbf{F} = \max (\mathbf{F}_f, \mathbf{F}_\Phi, \mathbf{F}_m)
\]

\[
\mathbf{F}_f = (w_1 \Delta f_1, \ldots, w_5 \Delta f_5), \quad \Delta f_i = \frac{|f_i^r - f_i^{FE}|}{f_i^r}
\]

\[
\mathbf{F}_\Phi = (w_1 \text{NMD}_1, \ldots, w_5 \text{NMD}_5), \quad \text{NMD}_i = \sqrt{1 - \frac{\text{MAC}_i}{\text{MAC}_i}}
\]

\[
\mathbf{F}_m = w_m \frac{|m_i^r - m_i^{FE}|}{m_i^r}
\]

\[
\mathbf{w} = [w_1, \ldots, w_i, \ldots, w_5]
\]

The weighting vector \( \mathbf{w} \) is set by user to specify preferences and to represent the relative importance of each objective. If the reference measures are not equally reliable (different standard deviation), it is convenient to give them different weights, whereby relatively higher weights are assigned to the measured terms that are trusted more. The coefficient of variation \( cv \) is the ratio of the standard deviation to the mean and often presented as the given ratio multiplied by 100. It describes the dispersion of the variable. The higher the \( cv \), the greater the dispersion in the variable. Specifically to this test example, the “measured” frequencies are supposed to have different coefficients of variation: \( cv_1 = 0.1, \ cv_2 = 0.2, \ cv_3 = 0.3, \ cv_4 = 0.4, \ cv_5 = 0.5 \). The weighting factor is proposed to use the reciprocal of \( cv \), so that higher weights are assigned to the frequencies with more reliability.

\[
\frac{100 \cdot \sigma_i}{f_i}
\]

\[
\mathbf{w} = [w_1, \ldots, w_i, \ldots, w_5] = [\frac{1}{cv_1}, \ldots, \frac{1}{cv_i}, \ldots, \frac{1}{cv_5}]
\]

Two optimization algorithms, the Differential Evolution (DE) and the Enhanced Evolution Strategy (EES), are employed separately with the purpose of comparison. The initial values of the updating parameters are chosen randomly from the constraint range. Thus, a uniform probability distribution for all random decisions is assumed unless more information is available. The control parameters of the DE method are set as: population size
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\( PN = 20 \), crossover constant \( CR = 0.9 \) and weighting factor \( F = 0.9 \). In the EES algorithm, the parent population size \( \mu = 7 \) and the descendent population size \( \lambda = 35 \). For both algorithms, the running mean number is set as 50 and the maximum number of iterations is 1000. Totally 5 runs are executed for each algorithm, because the initial parameters vary in each run and may influence the optimization result. To execute a higher number of runs, parallelization is required to speed up the optimization.

Table 6.4 and 6.5 list the optimization results. It can be seen that, for both methods, all runs generate successful results, although the optimized objective and the convergence speed vary a little bit. The best result for each method is selected by choosing the minimum converged objective, as underlined in Table 6.4 and 6.5. These two selected results provide very close optimized updating parameters (see Table 6.6), indicating consistent results from the DE and EES methods. Besides, the optimized individual objectives have been examined in Table 6.7, from which the influence of the weighting factors can be observed. The weighting vector \( \mathbf{w} = [1/cv_1, 1/cv_2, 1/cv_3, 1/cv_4, 1/cv_5] = [1/0.1, 1/0.2, 1/0.3, 1/0.4, 1/0.5] \), it decreases from \( w_1 \) to \( w_5 \), that means higher weights are assigned to \( f_1 \) and \( \Phi_1 \) than to \( f_5 \) and \( \Phi_5 \). The optimization results show that the accuracies from \( \Delta f_1 \) to \( \Delta f_5 \) and from \( NMD_1 \) to \( NMD_5 \) keep the same trend as the weighting factors, demonstrating that higher accuracies are ensured for the terms with more reliabilities.

For the two selected runs, the iterative courses of the objective function and the updating parameters are shown in Figure 6.10 to 6.13. It can be seen in the EES method, parameter values may be generated out of the constrain range in the beginning of the iterations. To avoid meaningless or wrong parameter values (e.g. negative values for thickness), some check criteria should be applied before each call of the simulation.

In order to integrate structural damage or deteriorations into the FE model, a prior knowledge of possible damage position can be achieved from the wavelet-based damage detection method, so that the damage can be parameterized with a limited set of parameters, e.g., parameter of location in a small range and stiffness reduction factor. In the objective function, the space-scale-domain data (wavelet modulus) are utilized in addition to the modal-domain data (eigenfrequencies and mode shapes). With the same procedure as used in the above example, the difference between the FE model and the damaged structure is minimized and the damage extent can be estimated by the optimized stiffness reduction factor.
### Optimization result using DE method

<table>
<thead>
<tr>
<th>Termination reason</th>
<th>running mean criterion satisfied</th>
</tr>
</thead>
<tbody>
<tr>
<td>Result status</td>
<td>success</td>
</tr>
<tr>
<td>Objective</td>
<td>8.470e-03 8.258e-03 7.803e-03 8.393e-03 8.541e-03</td>
</tr>
<tr>
<td>Iteration number</td>
<td>186 206 299 297 155</td>
</tr>
<tr>
<td>Evaluation</td>
<td>3741 4141 6001 5961 3121</td>
</tr>
<tr>
<td>Total time [hr]</td>
<td>2.52 2.78 4.06 4.06 2.13</td>
</tr>
</tbody>
</table>

Table 6.4: Optimization result using DE method

### Optimization result using EES method

<table>
<thead>
<tr>
<th>Termination reason</th>
<th>running mean criterion satisfied</th>
</tr>
</thead>
<tbody>
<tr>
<td>Result status</td>
<td>success</td>
</tr>
<tr>
<td>Objective</td>
<td>9.200e-03 8.515e-03 8.440e-03 1.061e-02 1.452e-02</td>
</tr>
<tr>
<td>Iteration number</td>
<td>180 168 125 150 211</td>
</tr>
<tr>
<td>Evaluation</td>
<td>7560 7056 5250 6300 8862</td>
</tr>
<tr>
<td>Total time [hr]</td>
<td>3.56 3.59 2.26 2.94 5.09</td>
</tr>
</tbody>
</table>

Table 6.5: Optimization result using EES method

### Updating parameters

<table>
<thead>
<tr>
<th>Updating parameters</th>
<th>DE</th>
<th>EES</th>
</tr>
</thead>
<tbody>
<tr>
<td>thickness of the skin $t_1$ [m]</td>
<td>7.999299e-03</td>
<td>7.991846e-03</td>
</tr>
<tr>
<td>thickness of the two shear webs $t_2$ [m]</td>
<td>4.568836e-03</td>
<td>4.533992e-03</td>
</tr>
<tr>
<td>thickness of the top and bottom spar caps $t_3$ [m]</td>
<td>5.403323e-03</td>
<td>5.434789e-03</td>
</tr>
<tr>
<td>location of the forward shear web $x_1$</td>
<td>1.259454e-01c</td>
<td>1.259630e-01c</td>
</tr>
<tr>
<td>location of the after shear web $x_2$</td>
<td>4.797485e-01c</td>
<td>4.794155e-01c</td>
</tr>
</tbody>
</table>

Table 6.6: Results of updating parameters
### Table 6.7: The optimal results comparisons

<table>
<thead>
<tr>
<th>Individual objective</th>
<th>DE</th>
<th>EES</th>
<th>Individual objective</th>
<th>DE</th>
<th>EES</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta f_1$</td>
<td>0.000776</td>
<td>0.000755</td>
<td>$NMD_1$</td>
<td>0.000446</td>
<td>0.000444</td>
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<tr>
<td>$\Delta f_2$</td>
<td>0.000237</td>
<td>0.000370</td>
<td>$NMD_2$</td>
<td>0.001560</td>
<td>0.001584</td>
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<tr>
<td>$\Delta f_3$</td>
<td>0.002341</td>
<td>0.002489</td>
<td>$NMD_3$</td>
<td>0.000735</td>
<td>0.000718</td>
</tr>
<tr>
<td>$\Delta f_4$</td>
<td>0.002271</td>
<td>0.002426</td>
<td>$NMD_4$</td>
<td>0.001920</td>
<td>0.001985</td>
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<tr>
<td>$\Delta f_5$</td>
<td>0.003869</td>
<td>0.004220</td>
<td>$NMD_5$</td>
<td>0.001793</td>
<td>0.001633</td>
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<tr>
<td>$\Delta m$</td>
<td>0.007618</td>
<td>0.006971</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Figure 6.10: The iterative course for the objective function (DE)
Figure 6.11: The iterative course for the parameters (DE)

Figure 6.12: The iterative course for the objective function (EES)
Figure 6.13: The iterative course for the parameters (EES)
Due to the worldwide demand for green energy and increasing use of wind energy converters, the accurate assessment of the WEC performance and service life is becoming more and more paramount in both economical and ecological aspects. It is indispensable to know the structural condition of the WEC at each point in time during operation, therefore, this dissertation presents the implementation of a comprehensive system identification concept for continuous structural health monitoring of WECs.

Firstly, the monitoring system is a qualified basis for continuous checking of the WEC structure. Measured acceleration time histories serve to extract structural dynamic properties by means of the modal identification technologies. As an essential part of the system identification, the accuracy and reliability of the modal identification play a vital role. While the Enhanced Frequency Domain Decomposition (EFDD) method is popular in use due to its properties of being simple and straightforward, the Stochastic Subspace Identification (SSI) technique is considered to be the most powerful class of the known identification techniques although it has been only recently emerged in civil and mechanical engineering field. By applying both methods on the measurements, the identified eigenfrequencies and mode shapes prove to be quite similar, only the damping ratios have large deviations, this is because the EFDD method uses the half-power bandwidth damping estimation, which is not very reliable. The consistency of the results are examined by using 16 different data sets. For the detected modes in Y direction (forward-aft), the coefficients of variation of the first three eigenfrequencies are $cv_1 = 0.7\%$, $cv_2 = 1.9\%$, $cv_3 = 0.4\%$. Considering the inevitable measurement uncertainties, the dispersion of the eigenfrequencies from different samples are very small, demonstrating quite close results from different
samples. The MAC values between the mean and the individual mode shapes fall all between 0.99 and 1, which represents identical mode shapes. Only the corresponding modal damping estimates show relatively higher dispersion. This is because it is very difficult to get accurate estimation of modal damping ratios under ambient loads. The modal damping ratios vary with the amplitude of the structural response and are influenced by the wind characteristics, which lead to the existence of aerodynamic damping. Therefore when the accurate identification of modal damping ratios is required, complementary free vibration tests are recommended.

The computation of the structural and dynamic behavior of the WEC is carried out by means of appropriate finite element software. Currently, the finite element program ANSYS is applied, which particularly allows for computing different variants of the structural model. Two individual finite element models of the wind energy converter have been created. In the first model, the tower and blade structure are generated by solid and shell elements in accordance with the real world geometry. Highly realistic finite element models of course yield a large number of elements and enormous numerical effort in dynamic analysis. Therefore in the second model, an intentionally simplified approximation model of the tower as well as the rotor blades has been established. By comparing the structural dynamic characteristics, the reliability of the approximation model has been verified. Simulation of the structural responses including rotating blades under stochastic wind field is performed on the simplified FE model on the basis of DIN1055-4:2005-03 and blade element momentum theory for load calculation. With the aid of the structural response simulation, the gyroscopic effect due to the rotating rotor has been investigated. From an increase of 5% of the maximum equivalent stress during the rotating state, the gyroscopic torque is considered to be quite small compared to the bending moment caused by the wind load. However, the gyroscopic force induces cyclic stresses to the blade root, hub and axle of the turbine, which can quickly fatigue and crack the components, leading requirements for further analysis.

In the frame of system identification, the most challenging and difficult part is the damage identification. Based on the demand of an efficient and robust non-destructive damage detection method for WECs as well as the distinct advantages of the wavelet transform, an integrated wavelet-based damage detection method is presented. The method uses the identified mode shapes as spatial signals and takes synergistic advantages of the stationary wavelet transform and the continuous wavelet transform. The procedure consists of signal decomposition, damage localization and damage quantification. It has been conducted on
several numerical tests, leading to the following conclusions: The method is a global non-destructive evaluation technique for locating incipient damage, no prior knowledge of the damage position is required. The method can be performed on the large-scale in-service structures under operational condition. Intact modes are not necessary if the structure does not contain discontinuities or a reliable finite element model exists. No need of higher order modes, only the first four modes are enough for the investigated WEC for instance. Relatively small number of sensors are used, e.g., 19 sensors are simulated in the test case. Edge effect is eliminated so that damage near boundaries could also be detected. Influence of measurement noise on mode shapes can be measured by the indicator of normalized modal difference and reduced using statistical methods.

One thing needs to be mentioned is that, the damage pattern used in the numerical tests is a simulation of decreased stiffness reduction, which actually can result from different reasons, e.g., corrosion, loosening bolts, failed welds, etc. In order to identify initialization and propagation of cracks, the proposed damage detection method should be applied locally, that means, the scanning density should be drastically increased in the damage region, then the similar process is performed. Based on the current study, following research may concentrate on local observation of the damage, e.g., fracture analysis of cracks including fatigue crack propagation analysis, with which the fatigue lifetime can be estimated for the damage sensitive part. Besides, verification through real measurement data is of particular interest since noise or measurement errors are present in the signals, which will examine the practicality of the proposed method.

To obtain highly qualified finite element models of the observed structure, model updating is successively requested in continuous SHM. The success of model updating strongly depends on accurate parameterisation, suitable definition of the objective function, and an effective robust optimization algorithm. Two methods are proposed to contribute to an efficient parameterisation: one is location-based method using the equivalent element modal strain energy (EEMSE) and the other is parameter-based method using global sensitivity analysis. By representative numerical tests, the proposed method indicates the erroneous region in the FE model correctly. Rather than using solely engineer’s judgement, the error indicator IDS based on EEMSE has proven to be straightforward and reliable for selection of updating parameters. The model updating process is dealt with as a simulation-based multi-criteria optimization problem. Formulation of the objective function involves a priori articulation of preferences and the weighted Chebyshev method. Defects between the model and the real structure are measured by modal-domain data (eigenfrequencies and
mode shapes) and space-scale-domain data (wavelet modulus), in which the latter is more
damage-sensitive and specially used in the process of damage integration. If the refer-
ence measures are not equally reliable, different weights are assigned from the reciprocal
of the coefficients of variation, so that higher accuracies are ensured for the terms with
more reliabilities. Besides, coupling finite element software and the optimization package
MOPACK, which provides numerous robust optimization strategies, leads to a powerful
tool for model updating of complex real world structure.

Based on the proposed system identification strategy, an accurate structural evaluation
and damage assessment as well as prediction of the structural responses can all be realized
in the continuous SHM. Reliable lifetime prediction for damage sensitive parts can also be
implemented in future work based on the continuously improved numerical model.
Bibliography

ALLEMANG, R. J. (August, 2003). The modal assurance criterion – Twenty years of use and abuse. Sound and vibration 37(8), 14–21. [cited at p. 38]


ANSYS INC (2007). Theory reference for ANSYS: Chapter 14: element library. [cited at p. 34]


LARSEN, G. C., A. M. HANSEN, AND O. J. D. KRISTENSEN (2002). Identification of damage to wind turbine blades by modal parameter estimation. [cited at p. 3]


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<td>4.2</td>
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