Structural health monitoring with a wireless vibration sensor network

T.G.H. Basten¹, F.B.A. Schiphorst¹²
¹ TNO Technical Sciences, Department Acoustics and Sonar
Oude Waalsdorperweg 63, 2597 AK, The Hague, The Netherlands
e-mail: tom.basten@tno.nl
² University of Twente, Department of Mechanical Engineering
P.O. Box 217, 7500 AE, Enschede, The Netherlands

Abstract
Advanced maintenance strategies for infrastructure assets such as bridges or offshore wind turbines require actual and reliable information of the maintenance status. Structural health monitoring based on vibration sensing can help in supplying the input needed for structural health monitoring applications. However, large structures require a sensor network with a large amount of sensors for vibration monitoring. Approaches with wired sensors and a central processing unit can raise scaling problems with respect to data processing and cabling. Wireless vibration sensors solve the cabling issues but due to limited communication bandwidth not all the data can be communicated, so the data processing has to be decentralized. Our goal is to develop a wireless sensor network which is capable to monitor the development of the eigenfrequencies and mode shapes over time using a decentralized approach. In this paper this network approach will be addressed and strategies for Operational Modal Analysis and decentralization aspects are examined. An experimental setup is available for performing experiments. This setup is a scale model of a wind turbine structure, which can be modified by adding masses at different locations. Experiments are performed with wired accelerometers to supply a dataset which can be used to study various approaches for distributed processing. In parallel, low cost wireless vibration sensors are being developed. The performance of these sensors will also be discussed.

1 Introduction
Monitoring the structural integrity of infrastructure assets has increasing interest. So have many civil structures which are in use today, reached the design life time. This asks for increased monitoring effort for the remaining life time. Another domain are offshore structures, where the costs of operational maintenance are very high. Alternative maintenance strategies such as condition based maintenance will directly result in substantial cost reductions. For such strategies, monitoring the current condition is critical. To be really useful for condition based maintenance, structural health monitoring should give answers to the following questions [1]:

- Is there damage present in the structure?
- What is the location of the damage?
- What is the severity of the damage?
- What is the remaining useful lifetime of the structure?

The complexity of the monitoring task increases with each question. Much research is focused on the development of methods to answer these questions. Among other techniques, vibration based techniques are widely studied for this purpose. However, large structures require a sensor network with a large
amount of sensors for vibration monitoring. Traditional approaches with wired sensors and a central processing unit can raise scaling problems with respect to data processing and cabling. Wireless vibration sensors solve the cabling issues, but due to limited communication bandwidth not all the data can be communicated, so the data processing has to be decentralized.

The goal of the current research is to set up a wireless sensor network to detect damage in various large structures, such as bridges and support structures of wind turbines. One of the challenges is to decentralize the data processing within the network. First, existing vibration based methods are discussed in section 2 and it will be examined whether and how they can be applied in a wireless sensor network in section 3. In section 4 an experimental setup is discussed which will be used to test various approaches in a later stage when the distributed algorithms are implemented. Finally, the wireless vibration sensors which will be used are examined in section 5. The paper ends with discussion and conclusions.

2 Vibration based structural health monitoring

Most popular vibration-based methods use the modal parameters of the structure to determine whether the structure is damaged or not. In case the analysis is done while the structure is in operation, this is called operational modal analysis (OMA).

The vibration based methods can be subdivided in a group of methods that is capable of detecting damage by comparing the modal parameters of the healthy and the damaged structure and a group that is capable of detecting damage using only the parameters of the damaged structure. The first group can be applied for new structures where the healthy parameters can be determined, while the second group is especially interesting to be applied to for example bridges that are already near the end of their lifetime. Two steps have to be taken to determine damage using OMA. The first step is to determine the modal parameters of the system. The second step is to process this data and to determine whether there is damage or not; the location; the severity and to estimate the remaining lifetime. Various algorithms are available for operational modal analysis, but not all of them are suitable to be implemented in a wireless sensor network. The second step probably has to be applied at a central processing unit, which is not a problem due to the limited data which is needed for this step. In the following section, methods for determining the modal parameters and damage detection methods will be discussed.

2.1 Algorithms for operational modal analysis

Operational modal analysis aims at determining the modal parameters of the system, while this system is excited by unknown, operational forces. The algorithms rely on only the measured response and are therefore called output-only methods. Because the modal parameters cannot be measured directly, it is necessary to derive these parameters from measurements of, for example, the accelerations at several points on the structure. Important output-only system identification methods for the extraction of modal data (i.e. natural frequency, damping ratio and mode shapes) are schematically represented in Figure 1, which is taken from reference [2]. The methods used for OMA can be roughly divided in frequency domain and time domain methods.
2.2 Frequency domain methods

The classical frequency-domain approach for OMA is the Peak Picking (PP) technique. Modal frequencies can be directly obtained from the peaks of the Auto Spectral Density plot. Then, the mode shapes can be extracted from the column of the spectral matrix which corresponds to the same frequency. The peak picking method gives reasonable estimates of the modes and it is fast and simple to use. However, PP can be inaccurate when applied to complex structures, especially in the case of closely spaced modes. The Frequency Domain Decomposition (FDD) is an extension of PP which aims to overcome this disadvantage. The FDD technique estimates modes from spectral density matrices by applying a Singular Value Decomposition. This corresponds to a single-degree-of-freedom identification of the system for each singular value. The modal frequencies can then be obtained from the singular values. The mode shapes follow from the singular vectors. The Enhanced Frequency Domain Decomposition (EFDD) is a further development of the FDD. In addition to modal frequencies and shapes, the EFDD can estimate modal damping.

2.3 Time domain methods

In multi-input multi-output (MIMO) Experimental Modal Analysis (EMA) impulse response functions (IRF) are used to extract the modal parameters of a system. This methodology is adopted by the Natural Excitation Technique (NExT), but uses correlation functions (COR) instead of IRF. IRF and COR can both be expressed as a summation of exponentially decayed sinusoids. The modal parameters of each decaying sinusoidal are identical to those of the corresponding structural mode [3]. The correlation functions can be obtained by different techniques such as the random decrement technique (see section 2.4) or by direct estimates of the random response of a structure subjected to broadband natural excitation. Another type of procedures used in the time domain (TD) to determine modal parameters are the procedures based on the Auto-Regressive Moving Average (ARMA). In the case of a multivariate system, the model is called Auto-Regressive Moving Average Vector (ARMAV). The parametric ARMAV model describes the relation of the system’s responses to stationary zero-mean Gaussian white noise input and to AR (auto-regressive) and MA (moving-average) matrices. The AR component describes the system dynamics on the basis of the response history and the MA component regards the effect of external noise and the white noise excitation. The ARMAV model can be expressed in the state-space form, from which natural frequencies, damping ratios and mode shapes can be extracted. The Prediction-Error Method (PEM) algorithms are capable of extracting modal parameters from the ARMAV models. These PEM-ARMAV models are computationally intensive and require an initial guess [3].
Stochastic Subspace Identification (SSI) methods are another type of modal identification methods. These methods do not require a non-linear search, which reduces the computational complexity compared to the ARMAV-based methods. Furthermore, these methods are numerically reliable and have shown to give good results [4]. The two most common methods in this area are the covariance based SSI (SSI-COV) and the data driven SSI (SSI-data). The SSI-COV is based on the covariance matrix of the output and the SSI-data uses the stochastic response data directly to identify modal parameters [4].

2.4 Random decrement method

The RD technique is a time domain procedure to extract the system response. The structural responses to operational loads are transformed into random decrement functions, which are proportional to the correlation functions of the system operational responses. Equivalently, they can be considered as free vibration responses [5]. The RD technique averages time signals of the measured structural responses, with a common initial or triggering condition. The RD technique can be applied for both time domain methods, like the SSI-COV method, but also for the frequency domain methods, like PP, FDD and EFDD.

The method works as follows: at each time instant, the response of the system is composed of three parts: the response to an initial displacement; the response to an initial velocity and the response to the random input loads during the time period between the initial state and the time instant of interest [5]. By averaging many of those time series, the random part will disappear, while the result can be interpreted as the system’s response to the initial condition defined by the trigger, thus, containing information about the system’s behavior. There is a direct relation between RD signatures and the correlation functions. The concept is easily extended from autocorrelation functions to the estimation of cross-correlation functions between two system outputs. This is simply achieved by averaging time blocks from one system output while the averaging process is triggered by another output.

2.5 Damage characterization

After the modal parameters (i.e. eigenfrequencies, modal shapes and modal damping) are determined, these parameters are analyzed to determine whether there is damage present in the structure or not. There are numerous methods presented in literature regarding damage detection based on the modal parameters. The most common ones can be subdivided in the following categories [6]:

- Natural frequency-based methods;
- Mode shape-based methods;
- Mode shape curvature-based methods;
- Modal strain energy-based methods;
- Flexibility matrix and flexibility shape curvature-based methods

2.5.1 Natural frequency-based methods

The natural frequency-based methods are based on the fact that damage in a structure causes changes in the natural frequencies of the structure. These methods, however, have some major drawbacks. Natural frequencies have a relatively low sensitivity to damage, and therefore only higher levels of damage can be detected and measurements with high accuracy are needed to achieve reliable results [7]. This makes these methods very sensitive to noise and environmental influences.

2.5.2 Mode shape-based methods

Mode shape-based methods have some clear advantages compared to the natural frequency-based methods. The mode shapes contain local information, which makes it possible to determine the location of the damage and multiple damage detection is possible. Next to this, the mode shapes are less sensitive to environmental factors like temperature. The disadvantage of mode shape-based methods is that they are sensitive to noise. This is because changes in mode shapes induced by damage are of similar magnitude as changes in mode shapes induced by noise [6], [8].

2.5.3 Mode shape curvature-based methods

For beam type structures, like a wind turbine and a simple bridge, modal curvatures can be used as an indication of damage. The curvature of the mode shape is inversely proportional to the flexural stiffness [8]. Damage like cracks and corrosion are assumed to cause a reduction in cross-sectional moment of inertia, which will lead to an increase of the curvature at the location of the damage. The mode shape curvature is more sensitive to damage than the mode shape itself [6], [8]. The traditional mode shape curvature-based methods are based on the change in the modal curvature between the healthy and damaged structure. There are, however, also methods based on the curvature that only need the output of the damaged structure. In [6] these methods are compared and it is concluded that the latter is not as robust as the first, but still is a good choice in the case that only the damaged system parameters can be measured.

2.5.4 Modal strain energy-based methods

A popular category of damage identification methods use the modal strain energy change for damage identification. These methods need information about the modal parameters of the healthy structure. These can be obtained by measurements done with the healthy structure or by a numerical model. A damage index (DI) is defined, which represents the ratio of the stiffness parameters of the healthy and damaged structure. For beam-type or plate-type structures, the modal strain energy can be directly related to mode shape curvatures [6]. The strain energy can also be directly measured by measuring the strain mode shapes. These methods are generally very effective in localizing damage.

2.5.5 Flexibility matrix and flexibility shape curvature

In [6], [7] and [8] also methods that are based on the flexibility and the flexibility shape curvature of the system are discussed. In [7] and [8] it is concluded that these methods are less suited as a damage identification method, because of their sensitivity to measurement noise. Improvements of the methods are complex, which make these methods less attractive.

3 Decentralized approaches

Large structures require a sensor network with a large amount of sensors for vibration monitoring. Approaches with wired sensors and a central processing unit can raise scaling problems with respect to data processing and cabling. To apply wireless vibration sensors, the data processing has to be decentralized. Zimmerman et al [9] discuss some decentralized approaches for the peak picking, random decrement and frequency domain decomposition algorithms. The PP and RD methods are relatively easy to decentralize. For the FDD method some adaptations and assumptions have to be made to make it applicable in a wireless sensor network. Zimmerman et al examine the wireless data transmission, which
is needed in a network with 20 Nodes where 4,096 data points are used to calculate the modal information for four modes. A central approach requires 170,880 bytes, where the PP method only needs 2,128 bytes to communicate, which makes PP method a very efficient method. However there are some drawbacks. The main problem is that the PP method hardly finds closely spaced modes. Also the PP procedure is rather subjective and therefore difficult to implement perfectly in software [9]. The SSI-COV approach is not examined yet in the paper from Zimmerman, but its performance is very good [4]. Therefore, this algorithm is studied further and efforts will be made to decentralize this algorithm. As a first start centralized versions of the PP, FDD and SSI-COV algorithms are implemented and tested with a test structure. Decentralized versions will be implemented and tested in a later stage.

4 Scale model for vibration monitoring

4.1.1 Wind Turbine

Monitoring offshore wind turbine installations with a wireless sensor network has increasing interest, see for example [10], [11] and [12]. Recently also a strategic research agenda was set up for distributed, hierarchical sensor networks enabling park wide control of operation and maintenance-on-demand [13], which addresses the need for wireless sensor networks for structural health monitoring for offshore wind turbines.

To follow the aforementioned research agenda, a test structure was made to test various algorithms for structural health monitoring. The test structure is a scale model of a wind turbine, see Figure 2. The support structure is a steel rod of 1.8 m high and 5 mm thickness which is bolted to a concrete plate. The structure can be modified by adding steel rings (mass: 2.6 kg) to the structure. In this way the mass distribution is modified which reflects in changing eigenfrequencies and mode shapes. The test structure is excited by means of a small shaker on top of the wind turbine. In the first stage only wired sensors are applied. Ten accelerometers are placed on the support structure at equal distance. They all measure in the same direction, which corresponds with the excitation direction of the shaker.

Figure 2: Test structure for operational modal analysis
4.1.2 Initial test results with wired sensors

Some test results are given in Figure 3 where the transfer functions between the excitation signal and the ten accelerometers are given for five different situations: no added mass, one added mass at three different locations and two added masses. The peaks in the transfer functions clearly change, which is caused by the shift in the system eigenfrequencies.

As a first start, the three different methods (PP, FDD and SSI-COV) are applied in a centralized form to determine the lowest eigenfrequencies. First the peak picking method was applied based on only the autospectra. Then the FDD method based on the full spectral matrix determined with the RD method was applied. Finally the SSI-COV method was applied, where the covariance matrix was determined by means of the RD method. The results of the 5 lowest frequencies for the undamaged (no extra masses applied) and a damaged situation (mass attached to the top side of the structure) are given in Table 1.

<table>
<thead>
<tr>
<th>n</th>
<th>PP</th>
<th>Damaged</th>
<th>Undamaged</th>
<th>Damaged</th>
<th>Undamaged</th>
<th>Damaged</th>
<th>Undamaged</th>
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<td>13.9</td>
<td></td>
<td>11.5</td>
<td>14.0</td>
<td></td>
<td></td>
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<tr>
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<td>101.3</td>
<td></td>
<td>95.0</td>
<td>101.0</td>
<td>95.6</td>
<td>101.1</td>
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<tr>
<td>3</td>
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<td></td>
<td>915.7</td>
<td>949.7</td>
<td>920.6</td>
<td>951.6</td>
</tr>
</tbody>
</table>

Table 1: Eigenfrequencies in [Hz] of damaged and undamaged structure determined with three different methods for operational modal analysis

The change in eigenfrequencies is clearly observed by the three different techniques. At higher frequencies, for this structure the SSI covariance method finds some more eigenfrequencies than the other
two methods due to some closely spaced modes which cannot be found by the peak picking and FDD method (not given in the Table 1).

5 Wireless sensors

To monitor large structures the sensors have to be low cost and easy to install with sufficient data quality. Wireless sensors have important advantages above wired sensors, especially regarding installation aspects. Within TNO Technical Sciences the current platform for wireless sensor technology is from SOWNet Technologies [14]. The current G-Node platform is used (G-Node G301). This platform contains a microcontroller, a radio, a USB interface and some flash memory. The radio operates in the free ISM 868 MHz radio band. The G-node can be powered from a PC USB port or from a 2.7 to 3.6 Volt battery pack.

On top of the G-Node platform a sensor board (GColta) can be connected via a 10pins connector. This GColta sensor board contains a digital accelerometer, a light sensor, a temperature sensor and a humidity sensor, see Figure 4.

![Figure 4: SOWNet G-Node G301 with attached GColta sensor board](image)

The vibration sensor on the GColta sensor board is a digital 3-axis accelerometer from Analog Devices (Analog Devices ADXL345). The sensor is small, thin and ultralow power. The accelerometer has a high resolution (13-bit) and has a user selectable range up to +/-16g. The output data is accessible through either a SPI or I2C interface. In the current research the SPI interface is used. The output bandwidth is user selectable up to 3200 Hz. Radio messages are used to communicate between the nodes and a central computer. The task of the nodes is to perform measurements, while the central computer is used to store the collected data and assign new tasks to the nodes. A root node is connected with USB to the computer as a gateway.

Decentralized algorithms for operational modal analysis are not implemented yet on these nodes. However some preliminary tests were performed to asses the performance of the cheap vibration sensors on board of these nodes. The sensors were compared with the output of high quality wired accelerometers from Brüel&Kjaer (B&K 4514) by putting them on top of a shaker table. Some results are given in Figure 5 were the power spectral density of the measured output is given for four different signals, tones of 10 and 200 Hz respectively and white noise with respectively 100 and 400 Hz bandwidth.
From the data it is clearly observed that the noise floor of the wireless sensor is higher than for the wired sensor. Also it is clear from this figure that some distortion occurs (clearly visible in upper right picture). This may be caused by the sensor fixation and needs some further attention.

From the first observation of the sensor output it is clear that the performance of the low cost sensor is less than that of high quality vibration sensors, which is not surprising. However, the sensors give very reasonable output and seem to be applicable for determining the modal parameters. To completely understand the behavior of the wireless sensors further research is needed, but the feasibility of the sensors for monitoring purposes is clearly shown. A prototype housing was made using rapid manufacturing. The sensors can be attached with magnets to the steel support structure of the wind turbine, see Figure 6.
6 Discussion and conclusions

Vibration based structural health monitoring has increased interest. There are various interesting algorithms, but not all of them are suitable to be applied in a wireless sensor network. With the known limitations, it is certainly possible to apply vibration based structural health monitoring with a wireless vibration network.

Vibration based structural health monitoring is a global method, with relatively limited accuracy. Research is performed to combine these vibration based methods with local methods, such as ultrasonic testing to make it possible to monitor large scale structures with sufficient accuracy which is needed for condition based maintenance strategies. Therefore, at TNO various structural health monitoring techniques will be combined in a large steel test structure, which will be subjected to fatigue loading. An approach with corresponding architecture is being set up for combining the different techniques. Vibration based monitoring with a wireless sensor network will be part of this architecture. Therefore, decentralized algorithms which are discussed in this paper will be implemented in the network and tested with the small wind turbine and also with the large steel structure. An important issue which is not discussed yet, but needs further attention is energy management of the wireless sensors.

Acknowledgements

The research is performed in the framework of the TNO Enabling Technology Program Adaptive Multi Sensor Networks. We thank our TNO colleagues Henk Hakkesteegt and Puneeth Nekkundi for their contributions to the wireless sensor and Dorien Lutgendorf for carrying out the experiments with the wind turbine setup.

References


