Application of SHM Using an Autonomous Sensor Network

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ABSTRACT

Assessment of the condition of a structure in operation and subsequently its remaining maintenance free service time, is of increasing importance for various fields of engineering. The main drivers for this are cost effectiveness, increased system reliability, system safety and reduced environmental impact. The current generation of monitoring systems relies on active, power intensive excitation and wired communication. Systems based on operational vibrations of the structure and employing a network of smart, autonomously operating and wireless sensors offer new possibilities, but also pose new constraints. Damage identification methods are therefore sought that combine local low power usage and low data transmission with a high reliability. The focus of this paper is on operational vibrations and modal based Structural Health Monitoring damage identification methods, applied in large civil structures such as wind turbine towers and bridge decks and, to a lower extent, in large composite structures. Three methods are compared, both experimentally and numerically: Peak Picking (PP), Random Decrement – Frequency Domain Decomposition (RD–FDD) and Random Decrement – covariance based Stochastic Subspace Identification (RD–SSIcov). The RD–FDD method is found to be a suitable method for modal based damage identification, given the restrictions on smart wireless sensor networks.

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INTRODUCTION

Monitoring the structural integrity of infrastructure assets and offshore wind turbines receives an increasing amount of interest. The motivation is either the (safe) extension of the lifetime beyond the estimated lifetime (existing structures) or lowering the operational costs (new structures). Condition based maintenance strategies, also referred to as 'just-in-time' maintenance, are under development and rely on Structural Health Monitoring (SHM) techniques to monitor the current state of the structure. These systems are supposed to function without human intervention, implying a certain level of autonomy, and typically operate under in-service conditions.

The development of distributed wireless networks helps achieving the functionalities required [1–3]. However, they also set limitations in terms of data transmission, robustness and power consumption. A new strategy for developing structural health monitoring systems is needed [4]. This does not imply a need for the development of new methods, but for adaptations and different choices, as research of the past decades has delivered a significant amount of system identification and damage monitoring systems [5–7].

The objective of this paper is to investigate three vibration based methods for an SHM system in terms of their performance in a distributed wireless network. The key target is the balance between the robustness of the system on the one hand and the power consumption and data transfer on the other hand.

FREQUENCY DOMAIN SYSTEM IDENTIFICATION

A vibration based damage identification method starts with the identification of the dynamic characteristics of a system. An extensive list of output-only methods, as under investigation here, is available to transform the time response to one or multiple modal parameters such as the natural frequency, damping or mode shape [8]. A graphical overview of (a selection of) these methods is presented in Figure 1 [9].

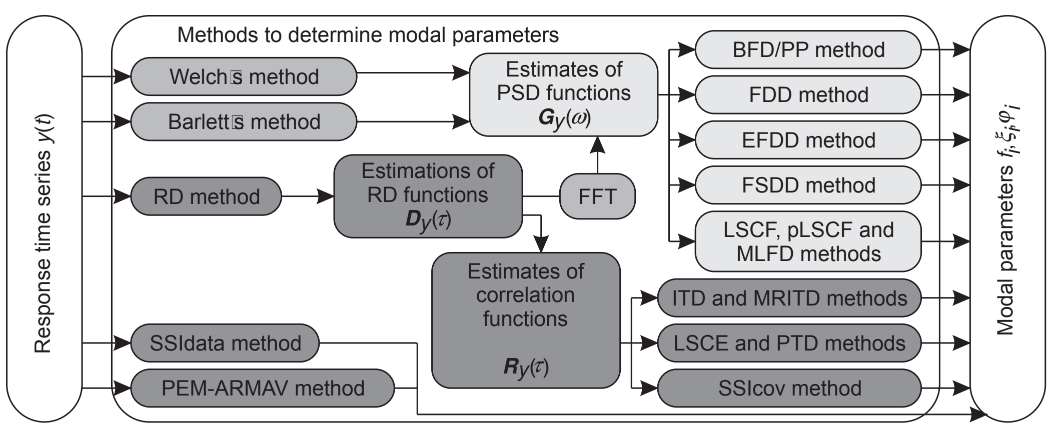

Figure 1: Schematic representation of output-only modal identification methods [9]. The dark gray blocks refer to time-domain functions and the light gray blocks to frequency domain functions, whereas the intermediate gray colored blocks refer to the transition from time to frequency domain.

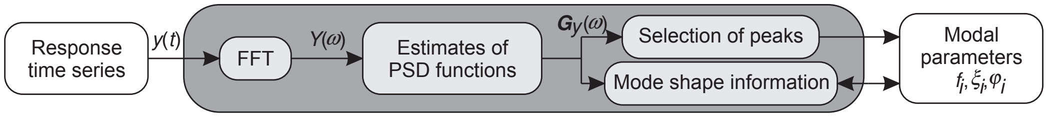

Figure 2: Flow chart of the PP method.

The choice of methods heavily depends on the application in terms of the structure and the environmental conditions. In this case, the applicability of the method in a distributed wireless network is a leading constraint. Therefore, three methods are investigated in more detail:

1. Peak picking (PP)
2. Random Decrement – Frequency Domain Decomposition (RD–FDD)
3. Random Decrement – Covariance based Stochastic Subspace Identification (RD–SSIcov)

The first method is a rather basic method, implemented here without time averaging. It will serve as a reference for the other two methods. The RD–FDD and RD–SSIcov both rely on the Random Decrement method [10] for the time signal averaging. The RD method is selected for its noise reduction capabilities.

A rudimentary form of Peak Picking (PP) is implemented here (see Figure 2) for referencing purposes. The main advantage of PP for a distributed sensor network is that the data can be processed locally, saving data transfer [11], while the requirements for local processing are limited (only FFT). The downside of the method is that it is likely to miss natural frequencies or to find spurious natural frequencies. Generally, the PP method is not suitable for more complex structures with a high modal density: closely separated peaks cannot be distinguished.

The Random Decrement (RD) method is used to acquire the average of an output-only time signal. The RD method does not rely on a fixed interval between time windows, as in [12, 13], but on time windows with a common initial or triggering condition. The method is based on the concept that the response of a system is composed of three parts: (1) the response to an initial displacement; (2) the response to an initial velocity; and (3) the response to an initial random input load during the time window period. The random part in the signal disappears if the signal is averaged over sufficient time windows. The resulting response can be considered as the response of the system to the initial condition, as defined by the trigger and hence contains information on the dynamic behaviour of the system.

The RD signatures can be employed for both time domain (SSIcov) and frequency domain (FDD) methods. A direct relation exists between the RD functions and the

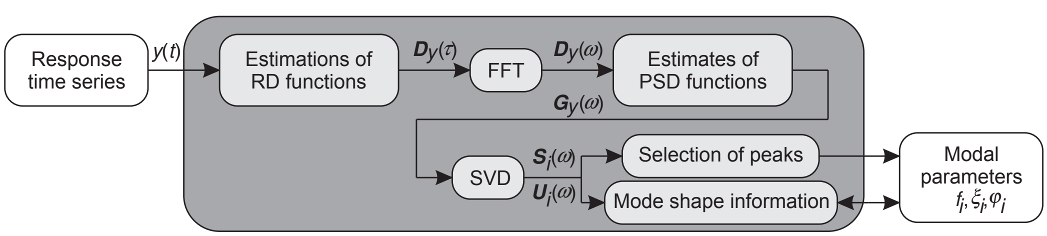

Figure 3: Flow chart of the RD–FDD method.

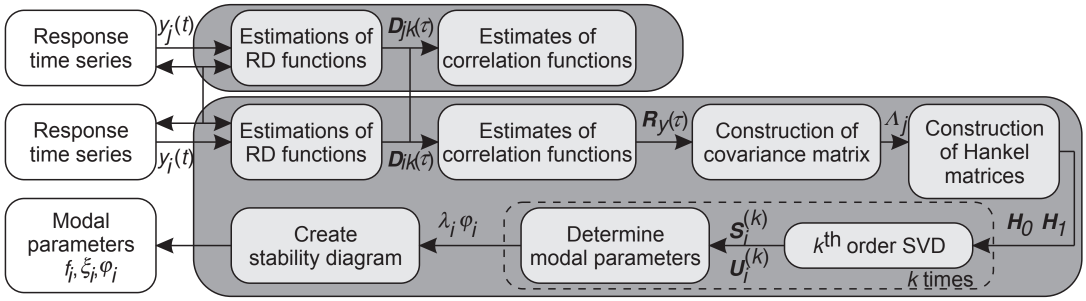

Figure 4: Flow chart of the RD–SSIcov method.

correlation functions. The auto–correlation function can be determined directly from the RD response of a single node, while the cross–correlation functions depend on the response functions of multiple nodes, triggered at the same time.

The Random Decrement – Frequency Domain Decomposition (RD–FDD) [8] relies on a Singular Value Decomposition (SVD), see Figure 3, increasing the separation between signal and noise and allowing for the identification of peaks of closely spaced natural frequencies. The singular values of the SVD grow significantly at each natural frequency. A peak identification algorithm is used to extract the natural frequencies. The mode shapes can be obtained from the corresponding singular vectors. Narrowly separated peaks can be identified by investigating the second largest singular value close to a peak in the first singular value. This should be carried out carefully, to avoid spurious modes being identified as real modes.

The most powerful method investigated here is the Random Decrement – covariance based Stochastic Subspace Identification (RD–SSIcov) [8, 14]. This method (Figure 4) relies on the correlation functions and uses a state space formulation for the dynamic model. The RD–SSIcov method has proven to be powerful, but it is computationally heavy, has limited possibilities for decentralised processing (as it relies on cross-correlations) and requires tuning.

DAMAGE IDENTIFICATION – NUMERICAL EXAMPLE

The Modal Strain Energy – Damage Identification method [15] is employed, as it is proven to be a powerful method for vibration based damage detection and localisation. The performance of the three methods is assessed with a 10 degree of freedom mass–spring–damper model. The masses are all set to 1 kg, the spring constants to $1.0 \cdot 10^6$ N m^{-1} and the damping to 20 Ns m^{-1}. The damage is modelled as a stiffness reduction of the spring between the 6th and the 7th degree of freedom. Each degree of freedom is loaded with a white Gaussian noise with zero mean. The resulting normalised damage indices are shown in Figure 5.

The RD–FDD and RD–SSIcov clearly outperform the PP method - according to the expectations. The difference between the two methods is assessed by varying the amount of stiffness reduction (1%, 3%, 5% and 10%), see Figure 6. The RD–SSIcov does perform better, but both methods fail for the lowest stiffness reduction of 1%.

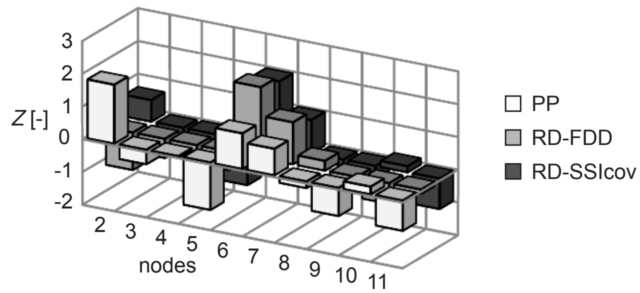

Figure 5: Normalised damage indices for a 10–dof system with a 5% stiffness reduction of the spring element between the 6th and 7th degree of freedom.

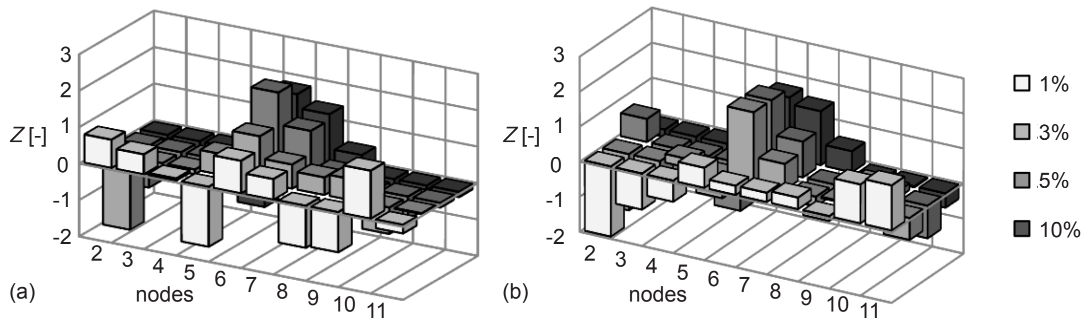

Figure 6: Normalised damage indices for: (a) various stiffness reductions using RD-FDD; (b) various stiffness reductions using RD-SSIcov.

DISTRIBUTED SENSOR SYSTEMS

One of the key issues in the success of wireless autonomous sensor networks is the level of distribution of tasks. In general, the bottleneck is the local power supply, combined with the relative high power consumption of data transfer [11]. Local processing reduces the amount of data transferred and therewith lowers the power requirements. The PP method allows for a high level of local processing: the time data $y(t)$ acquired at a node is converted to a frequency response $Y(\omega)$ by an FFT (see Figure 2). A peak identification algorithm is then applied, after which only the frequencies at which a peak is identified are sent to the central unit. The frequency response $Y(\omega)$ is only requested by the central unit for those frequencies that are identified as real (rather than spurious) natural frequencies and are considered to be relevant for the problem. This information is used to construct (for example) the mode shapes.

The distribution of tasks is slightly more complex for the RD–FDD method. The nodes collect time signals $y(t)$ of length Δt and construct the decrement functions $\boldsymbol{D}_y(\tau)$ (see Figure 3) both depending on a trigger signal of the nodes itself and on those of other nodes. The Fourier transformation, the estimation of the power spectral density $\boldsymbol{G}_y(\omega)$, the SVD and identification of peaks are performed locally. The result is sent to the central processing unit, after which a similar procedure follows as for the PP method to acquire the relevant mode shape information. Synchronisation is important, due to the triggering, but appropriate protocols are available for that purpose [11, 16].

TABLE I: DATA TRANSFER AND DECENTRALISATION OF TASKS FOR THE PP, RD–FDD AND RD-SSICOV METHODS.

	Function		Data transfer		
	Local	Central	Data	Amount	Direction
PP	FFT	Select ω_n	ω_{peak}	$N_P N_N N_b^f$	Node→central
	PSD	Request $Y(\omega_n)$	ω_n	$N_F N_N N_b^f$	Central→nodes
	Peak picking		$Y(\omega_n)$	$N_F N_N N_b^f$	Node→central
RD–FDD	auto–RD	Select ω_n	Trigger	$N_N N_b^t$	Node→nodes
	FFT	Request $Y(\omega_n)$	ω_{peak}	$N_P N_N N_b^f$	Node→central
	PSD		ω_n	$N_F N_N N_b^f$	Central→nodes
	SVD		$Y(\omega_n)$	$N_F N_N N_b^f$	Node→central
	Peak picking				
RD–SSIcov	auto–RD	Select ω_n	Trigger	$N_N N_b^t$	Node→nodes
	cross–RD	Build mode shape	$\boldsymbol{D}_{ji}(\tau)$	$2N_\tau N_N N_b^f$	Node→node
	Covariance		ω_{stab}	$N_P N_N N_b^f$	Node→central
	Hankel matrix		$\varphi_{\text{2DOF}}(\omega_n)$	$2N_P N_N N_b^f$	Node→central
	SVD				
	Stability diagram				

The RD–SSIcov relies on cross-correlations, implying a relative large amount of internodal communication. The random decrement auto- and cross-correlations $\boldsymbol{D}_{ji}(\tau)$ are determined (see figure 4). These can be sent to the neighbouring node, after which the covariance matrix $\boldsymbol{\Lambda}_m$ and the Hankel matrices $\boldsymbol{H}_0$ and $\boldsymbol{H}_1$ are determined. The modal parameters are locally extracted by an SVD and a stability diagram procedure and sent to the central unit. Alternatively, the random decrement functions can be sent to the central unit, where the subsequent steps of the procedure are performed for all nodes, requiring a significantly higher amount of data transfer.

An estimate of the data transfer of the three methods is summarised in Table I. The number of extracted peaks N_P is not necessarily equal to the number of natural frequencies N_F, especially if only a subset is used for the extraction of other modal parameters such as the mode shapes. N_N is the number of sensor nodes, N_τ the number of timesteps in an RD time window and N_b^f and N_b^t are the number of bytes required for a floating point number and a trigger signal respectively. The location (at the node or at a central unit) where the different function in each procedure is performed is also indicated. The amount of data transfer is higher for the RD–FDD and RD–SSIcov methods, but it also involves data transfer between nodes, which is likely to require less power than sending the information directly to the central unit. Furthermore, the number of decentralised operations to be performed increases, although it should also be noted that the work required cannot be compared directly, as the PP takes the FFT from the entire time signal, whereas the RD–FDD and RD–SSIcov calculate the FFT from multiple significantly shorter time windows. However, it can still be concluded that the number of decentralised operations is increasing with the complexity of the method.

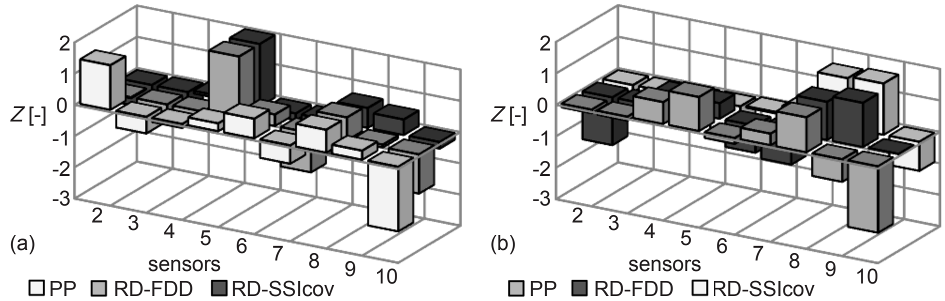

Figure 7: The normalised damage index for the PP, RD–FDD and RD–SSIcov for two different damage cases: added mass (a) between node 4 and 5 and (b) between node 7 and 8.

EXPERIMENTAL RESULTS

The three methods were also tested in the lab on a small scale wind turbine tower [7]. The model consists of a 1.8 m high steel tube with a wall thickness of 5 mm and is bolted to a concrete plate. The structure can be modified by adding steel rings of 2.6 kg (16.25% of the weight of the pole), to mimic a damage, similar to the procedure followed in [17, 18]. The measurements were performed with wired sensors and the three methods discussed are applied in centralised form. The objective of the test is to validate the methods. The normalised damage index is shown in Figure 7. The added mass is placed at two different location (between node 4 and 5 and between node 7 and 8). Once again, the RD–FDD and RD–SSIcov outperform the PP method, whereas the difference between the RD–FDD and RD-SSIcov is marginal.

CONCLUSIONS

It is shown in this article that the design of a distributed wireless sensor network for SHM applications requires the evaluation of the level of decentralisation: which functions can be performed locally and how can the amount of data transfer be kept at a minimum, without losing robustness of the system. Two methods, the RD–FDD and RD–SSIcov were proven to be suitable solutions for an output-only based application in terms of robustness, but the RD–FDD (1) requires a lower amount of data transfer, (2) does not rely on cross–correlations and (3) requires significantly less local operations and is therefore favourable in a wireless network in which power resources are generally a limiting factor. Current research within TNO is focussed on implementing the algorithms in wireless sensor nodes and applying and testing them on a steel bridge deck, together with other SHM techniques [19].

ACKNOWLEDGEMENTS

This research is supported by the TNO Enabling Technology Program “Adaptive Multi Sensor Networks” (AMSN).

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