EFFECTS OF WIRELESS SENSOR NETWORK UNCERTAINTIES ON OUTPUT-ONLY MODAL ANALYSIS EMPLOYING MERGED DATA OF MULTIPLE TESTS

T. Nguyen[1*], T. H. T. Chan[1] and D. P. Thambiratnam[1]
[1] School of Civil Engineering and Built Environment,
Queensland University of Technology, Brisbane, Queensland, Australia.
*Email: theanh.nguyen@qut.edu.au

ABSTRACT

The use of Wireless Sensor Networks (WSNs) for Structural Health Monitoring (SHM) has become a promising approach due to many advantages such as low cost, fast and flexible deployment. However, inherent technical issues such as data synchronization error and data loss have prevented these distinct systems from being extensively used. Recently, several SHM-oriented WSNs have been proposed and believed to be able to overcome a large number of technical uncertainties. Nevertheless, there is limited research verifying the applicability of those WSNs with respect to demanding SHM applications like modal analysis and damage identification. This paper first presents a brief review of the most inherent uncertainties of the SHM-oriented WSN platforms and then investigates their effects on outcomes and performance of the most robust Output-only Modal Analysis (OMA) techniques when employing merged data from multiple tests. The two OMA families selected for this investigation are Frequency Domain Decomposition (FDD) and Data-driven Stochastic Subspace Identification (SSI-data) due to the fact that they both have been widely applied in the past decade. Experimental accelerations collected by a wired sensory system on a large-scale laboratory bridge model are initially used as clean data before being contaminated by different data pollutants in sequential manner to simulate practical SHM-oriented WSN uncertainties. The results of this study show the robustness of FDD and the precautions needed for SSI-data family when dealing with SHM-WSN uncertainties. Finally, the use of the measurement channel projection for the time-domain OMA techniques and the preferred combination of the OMA techniques to cope with the SHM-WSN uncertainties is recommended.

KEYWORDS

Wireless Sensor Networks (WSNs), Structural Health Monitoring (SHM), uncertainties, generic, SHM-oriented WSNs, Output-only Modal Analysis (OMA)

INTRODUCTION

The use of Wireless Sensor Networks (WSNs) for Structural Health Monitoring (SHM) has increasingly become popular due to many features such as low cost, fast and flexible deployment. Moreover, this sensing technology is capable of processing data at individual nodes and therefore enabling each measurement point to be a mini intelligent monitoring station (Lynch and Loh, 2006). As a result, many WSNs have been proposed for SHM applications and their capacity and features can be found in several comprehensive reviews (Lynch and Loh, 2006; Rice and Spencer Jr., 2009). In more recent time, SHM research community has paid more attention on commercial WSN platforms as they offer modular hardware and open software which can be further customized with ease to meet requirements of SHM applications.

However, the use of WSNs for SHM poses a number of technical challenges. Most WSNs have been initially designed for generic purposes rather than SHM (Ruiz-Sandoval et al., 2006). As a result, there are many limitations of such a generic platform such as low-sensitivity sensors, high noise, poor resolution of analog-digital converters (ADC), inaccurate synchronization and unreliable data transmission (Spencer Jr et al., 2004). Typical example can be seen in the case of the generic version of the Imote2 WSN, i.e. using basic sensors and sensor board ITS400 (Rice and Spencer Jr., 2009). Realizing such limitations, a number of researcher centers have begun enhancing capacity of selective WSN models in order to align them with requirements of SHM applications. High-fidelity sensor boards for SHM have been customized and specific middleware algorithms have been written to achieve tighter network synchronization and reliable wireless communication (Pakzad et al., 2008; Nagayama et al., 2009; Rice and Spencer Jr., 2009). This SHM-oriented WSN platform can be best illustrated in the combination of Imote2-based control & communication unit with SHM-A sensor board and middleware developed by the Illinois Structural Health Monitoring Project (ISHMP, see e.g. Rice and Spencer Jr., 2009). Since they are the most popular WSNs which have been used for SHM applications, the generic and SHM-oriented platforms of Imote2 are selected as representatives for this study hereafter.

Although SHM-oriented WSNs have achieved initial promising results, uncertainties of this platform have not been completely removed. Effects of SHM-oriented WSN uncertainties have not been studied in depth, particularly with respect to popular but demanding global SHM applications such as output-only modal analysis (OMA) and output-only modal-based damage identification (OMDI). It is worth noting that, OMA and OMDI have gained more popularity in comparison to their input-output counterparts in recent years as they are more applicable for monitoring in-service civil structures such as bridges under normal traffic operation (Brincker et al., 2003).

To address this need, this paper first presents a brief review of major uncertainties of the SHM-oriented WSN platform and their effects on OMA approach from prior studies. Then, effects of the most inherent uncertainties are investigated with respect to one of the frequent OMA applications, i.e. OMA employing merged data from multiple tests (Dohler et al., 2010). Frequency Domain Decomposition (FDD) and Data-driven Stochastic Subspace Identification (SSI-data) are selected for this investigation as each of them has been considered as the most robust technique for either frequency domain or time domain.

MAJOR UNCERTAINTIES OF SHM-ORIENTED WSNs

There are a number of technical uncertainties or challenges that have been identified by prior studies (Spencer Jr et al., 2004; Lynch and Loh, 2006). However, from a perspective of SHM applications, two major and distinct WSN uncertainties that can directly degrade data quality are data loss and data synchronization error (Nagayama et al., 2007). Brief review and discussion regarding these two factors are presented below.

Data loss has been seen as a serious problem for the generic WSN platform and resulted from unreliable wireless communications between sensor nodes (Nagayama et al., 2007). In SHM-oriented WSNs, reliable communication protocol based on selective negative acknowledgement (NACK) approach have been developed in middleware services so that lost data packets can be resent (Nagayama et al., 2009). Wireless data transmission without loss is currently achievable though it has not been available in a real-time manner.

Data synchronization error (DSE) is another well-known uncertainty in WSNs which consists of two main components, namely initial DSE and incremental DSE. Major sources of initial DSE include the timing offset among local clocks and the random delay in start time of sensing in sensor nodes (Nagayama et al., 2009). Incremental DSE is mainly due to (1) clock drift, (2) fluctuation in sampling frequency of each sensor node and (3) difference in sampling rate among sensor nodes. In the SHM-oriented WSN platform, there are a number of solutions in both hardware and software customization efforts to cope with DSE. Rice and Spencer Jr (2009) customized a multi-metric sensor board named SHM-A in order to effectively mitigate the second and third source of incremental DSE. The first source of incremental DSE, clock drift, can be effectively dealt with using clock drift compensation algorithm (Nagayama et al., 2009). As a result, the remaining synchronization error for SHM-oriented Imote2 platform is mainly initial DSE which is random in range of a single sampling period (Linderman et al., 2011). Even though a lower initial DSE can be further achieved with re-sampling algorithm (Nagayama et al., 2009), this algorithm costs more computation effort at leaf nodes. Tolerance capacity of SHM applications with respect to relatively small DSE in SHM-oriented WSNs needs to be assessed in order to avoid unnecessarily excessive computational burden.

There are limited studies that have investigated effects of DSE on SHM applications and almost all of them focused on effect of DSE on OMA techniques. The rationale for that is, as a global SHM approach, OMA generally requires data from different measurement points to be well-synchronized with each other (Nagayama et al., 2007). It is worth noting that this requirement can be easily met in the traditional wired sensing system but not in case of WSNs with inherent synchronization errors. Nagayama et al. (2007) noted substantial effects of initial DSE on modal phases detected from simulation model by one parametric OMA method, whereas Krishnamurthy et al. (2008) observed considerable influence of initial DSE on mode shape magnitudes estimated by FDD in an experiment. Yan and Dyke (2010) confirmed effects of DSE on mode shapes in both simulation and experimental studies. Since previous research have mostly focused on simple structures such as cantilever and simply supported beams with a few degree-of-freedoms (DoFs) using mostly non-parametric OMA techniques working on single dataset, effects of initial DSE on OMA of more complex structures with more realistic scenarios including having a wider range of modes and using data merged from multiple tests need to be further studied. Such an effect on popular parametric OMA techniques like SSI-data also deserves an investigation. For sake of completeness, FDD, SSI-data and associated merging techniques are briefly described in the next section.

OMA AND DATA MERGING TECHNIQUES

Representing for non-parametric OMA is Frequency Domain Decomposition (FDD), proposed by Brincker et al. (2000). In this technique, each spectral matrix is decomposed, using Singular Value Decomposition (SVD) method, into a set of auto spectral functions each of which corresponds to a single-degree-of-freedom system. Then, singular value lines are assembled for all discrete frequencies and the first (and sometimes the second) line can be used to estimate resonant frequencies using the pick-peaking method. Mode shape vectors are derived from the corresponding singular vector. There are two variants of this technique, i.e. Enhanced FDD and Curve-fit FDD but three techniques work similarly except the fact that estimation of damping ratios is only implemented in the two variants. Similar to traditional input-output non-parametric techniques, FDD family is said to be fast, simple and user-friendly as well immune to computational modes (Zhang et al., 2005). However, difficulties may arise in the case that dense and close modes are simultaneously present.

On the other hand, Data-driven Stochastic Subspace Identification (SSI-data) has been considered as one of the most robust techniques in time domain since it can take into account furious modes from measurement noise; cope well with dense and closely spaced modes and avoid spectrum leakage (Brincker et al., 2001; Zhang et al., 2005). This method relies on directly fitting parametric state space models to the measured time histories with a user-defined range of model orders, extracting a subspace (also by SVD technique) which holds structural modes. Modes are estimated through a tool called stabilization diagram of the estimated state space models Among different estimation algorithms for SSI-data (SVS, 2011), Un-weighted Principal Component (UPC), has been used most for OMA of civil structures.

Besides the use of a single dataset, it is not unusual, in practice, to merge data from multiple tests in both input-output and output-only modal analysis (Reynders et al., 2009). Such a usage is able to cover a large number of measurement points using a limited number of sensors for the denser measurement which is always desirable in modal analysis, particularly for mode shape estimation. Multiple successive test setups are employed with a few of sensors (i.e. reference sensors) being kept fixed while the others are being roved along the structure. In order to reduce effects of measurement noise and the computational effort, the use of projection channels can be adopted aiming at projecting large and arbitrarily noisy data onto some well-positioned (and least noisy) channels.

There are two most common ways of merging data in SSI-data-UPC from multiple tests, namely Post Separate Estimation Re-scaling (PoSER) and Pre Global Estimation Re-scaling (PreGER). The former merges secondary data (i.e. mode shapes) estimated by SSI of all individual tests whilst the latter relies on merging the correlation of all primary sub-datasets (i.e. time series) into a unified set before performing SSI techniques (Dohler et al., 2010). For the sake of simplicity, SSI-data-UPC- PoSER and SSI-data-UPC-PreGER are hereafter shortened as UPC- PoSER and UPC- PreGER, respectively.

RESEARCH METHODOLOGY

As previously discussed, effects of common initial DSE on OMA approach especially on two most popular OMA techniques (i.e. FDD and SSI-data-UPC) need to be investigated more thoroughly on more complex structures with sufficiently realistic scenarios. To realize this aim, a large-scale laboratory bridge model is selected for data acquisition with multiple successive tests using limited number of sensors. In order to have DSE-free data, the original datasets herein were collected by wired sensing system, before being contaminated with relatively high noise level to account for the presence of this factor on practical WSNs. Serving as benchmark data, the noise-corrupted (but DSE-free) datasets are then introduced with a random initial DSE as previously reviewed. Both DSE-free and DSE-corrupted datasets are used for OMA utilizing FDD and SSI-data-UPC techniques, to identify modal frequencies, mode shapes and their changes with respect to DSE. Damping ratios are not under consideration of this study based on the fact that their estimation can be inaccurate in OMA approach and they are not among commonly-used damage indices for SHM (Brincker et al., 2001). The use of projection channels is also explored to see whether it can reduce effects of DSE.

BRIEF DESCRIPTION OF TESTS AND ANALYSIS

The Bridge Model and Wired Sensing System

Object for wired data acquisition is the through-truss bridge model with almost 600 DoFs which can be one of the largest laboratory models for SHM purpose. To simulate ambient excitation, three large industrial fans were used at three different positions along the structure (fig. 1). Fan speed and direction were altered from one test to another to take into account changes of wind speed and wind direction in reality.

The bridge model was instrumented with nine uni-axial accelerometers divided into three groups each of which cover one cross section. Based on the assumption of the cross-section moving as a rigid body, the movement of one rectangular cross section can be described by three uni-axial sensors (SVS, 2011). In each sensor group in this test, two sensors were therefore used for vertical measurement and the other was to measure the lateral response. Of three groups, one is kept as the reference sensor group near mid-span and the other two were roved along the bridge model. Figure 1 shows two examples of the sensor layouts. The total number of successive datasets was set at seven.

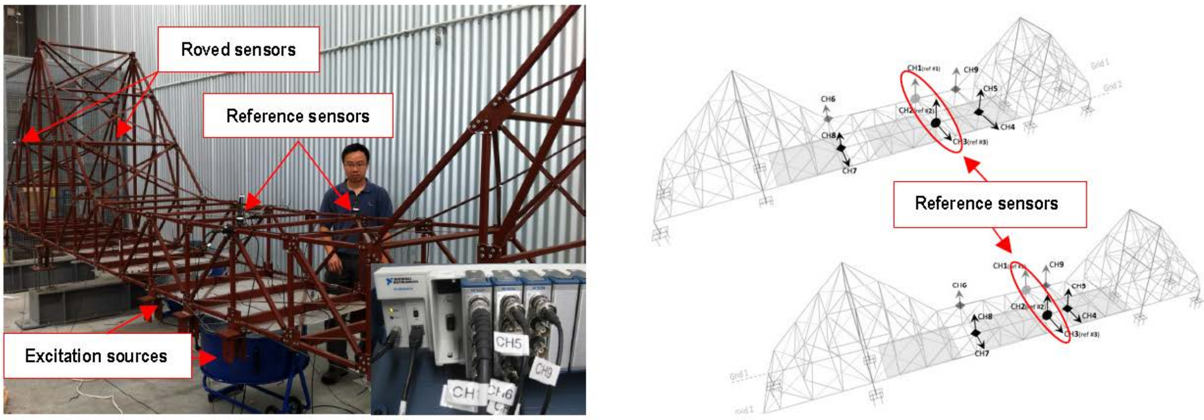

Figure 1 Physical bridge model, sensing system and two examples of the sensor layouts

The sensing system was controlled by a National Instruments (NI) data acquisition system including NI cDAQ 9172 chassis and NI 9234 dynamic signal acquisition modules and LabVIEW Signal Express software (www.ni.com). Sampling rate was set at relatively high value, i.e. 1766 Hz which allows the use of different decimation factors to achieve different lower sampling rates. For the illustration purpose, the data used hereafter were obtained by decimating ten times the original data, therefore resulting in 176.6 Hz as the effective sampling rate. This effective rate can be considered belonging to a common range for practical SHM applications.

Simulation of Noise and Initial DSE

All seven datasets were polluted with relatively high level of noise (i.e. 20 percent root-mean-square) to account for the presence of higher noise in SHM-oriented WSNs. Each noisy time series is then contaminated with one initial DSE which is randomly selected between zero and the effective sampling period. The corresponding DSE-polluted time was derived by one of the one-dimensional interpolation algorithms of Matlab software. It is worth noting that the linear interpolation technique has already been utilized in the re-sampling algorithm for SHM-oriented WSN middleware (Nagayama et al., 2009) due to the fact that it requires less computational effort from sensor resources. In this simulation, the cubic spline interpolation technique was adopted to achieve more accurate simulation results.

OMA using FDD and SSI-data-UPC Techniques

The DSE-free and DSE-corrupted datasets were used as the input for FDD, UPC-PoSER and UPC-PreGER techniques. The analysis was conducted using ARTeMIS Extractor software (SVS, 2011) with two options for channel projection as previously mentioned (i.e. enable and disable). It is worth noting that the use of channel projection is mainly recommended to the case that has many sensors. After several trials, the number of projection channels selected was four as they provided the best results. Also, the dimension for the state space model (i.e. the maximum model order) was set 180 as it was found to be sufficient for both UPC-PoSER and UPC-PreGER. In ARTeMIS Extractor software, UPC-PoSER is simply called UPC or Un-weighted Principal Component (see also Figure 4) whilst UPC-PreGER is known as UPC Merged Test Setups.

RESULTS AND DISCUSSIONS

__Common Results of OMA for DSE-free Data__

The first four modes detected are purely (or almost purely) lateral modes, at around 6.5, 7.7, 13.2 and 14.2 Hz, respectively (Figure 2) whilst three higher modes detected (at around 18.2, 22.2 and 23.4 Hz) are mostly coupled ones like between lateral and vertical responses. Figure 2 also shows, for instance, such a coupled mode (mode 7).

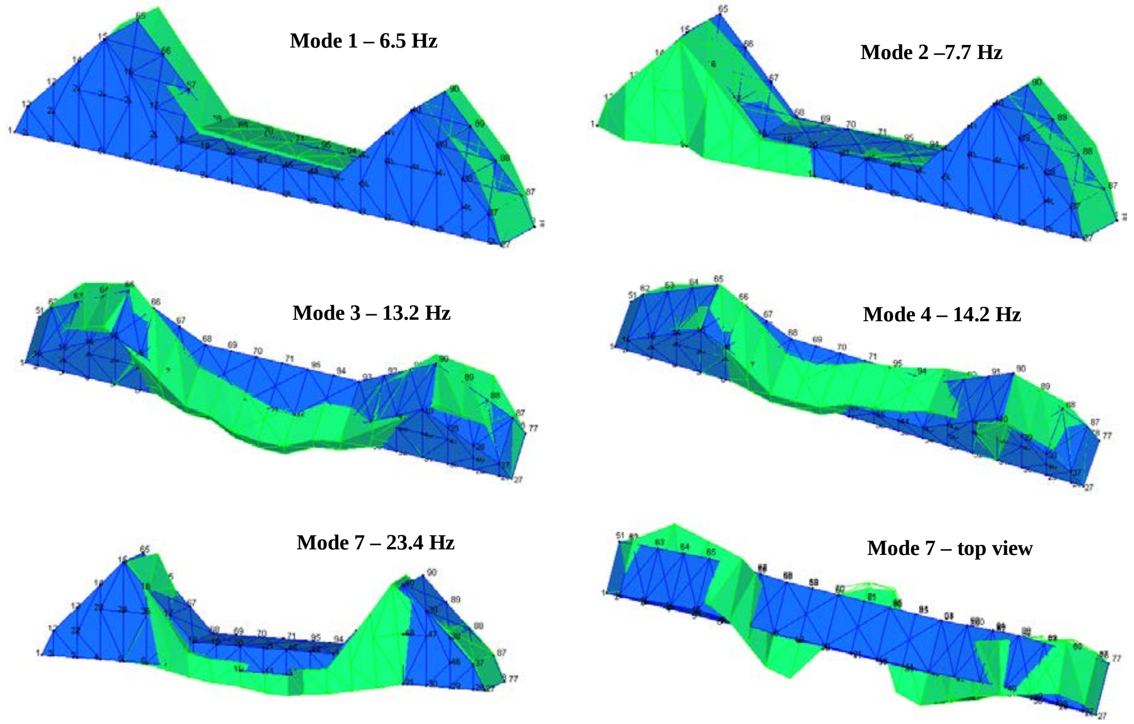

Figure 2 Typical mode shapes estimated from DSE-free data by FDD/SSI-data-UPC

__The Use of Channel Projection__

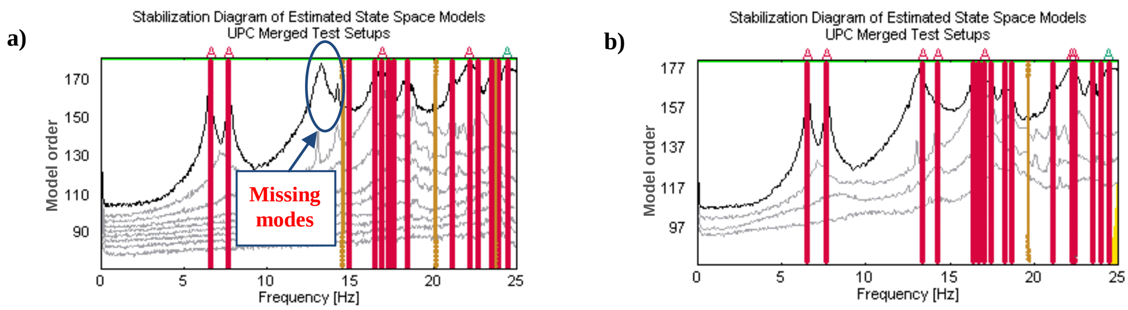

Figure 3 Stabilization diagram of UPC-PreGER with projection: a) disabled & b) enabled

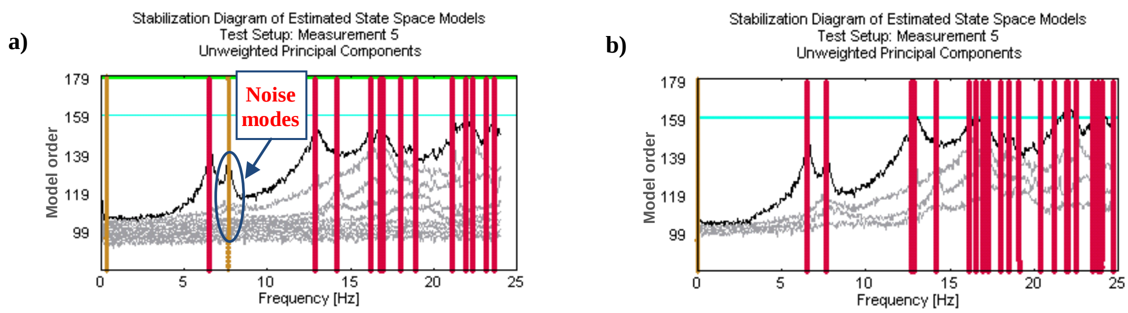

Figure 4 Stabilization diagram of UPC-PoSER with projection: a) disabled & b) enabled

Of the three techniques, the channel projection has the most substantial influence on robustness of UPC-PreGER with respect to DSE presence. While this technique works properly with DSE-free data estimating all aforementioned modes, it completely fails detecting modes 3 and 4 from DSE-corrupted data (Figure 3a) even though higher dimensions of the state space model were tried. However, the use of channel projection has assisted UPC-PreGER so that these two modes can be estimated again (Figure 3b). Besides, the channel projection has also certain effect on the way UPC-PoSER copes with DSE. Some noise modes are mistakenly detected by at locations of true modes (see Figure 4a for the case of mode 2) if the channel projection is not used but this situation is resolved once the projection selection is enabled (Figure 4b). Obviously, channel projection is needed for two SSI-data-UPC techniques in order to effectively detect genuine modes under the presence of DSE. Impact of this projection method on performance of FDD technique is presented in the next section.

Effects of DSE on Outcomes of three OMA Techniques

The previous section has proven the necessity of applying the channel projection for UPC-PreGER and UPC-PoSER when DSE is present in the sensing system. It is also necessary to examine whether FDD is under the same impact of the projection. This projection method was therefore applied for two UPC-PreGER and UPC-PoSER whilst the robustness of FDD was also examined for both cases i.e. when the channel projection is enabled and disabled. In each case, frequencies and mode shapes estimated from two data (i.e. DSE-free and DSE-polluted data) at seven aforementioned modes of interest were used to calculate the relative frequency change and Modal Assurance Criterion (MAC), respectively, for the ultimate assessment of effects of DSE. Interested readers could refer to Allemang (2003) for details of MAC indicator. Higher MAC values (which are, in other words, closer to unity) indicate the lower deviations of the mode shapes under DSE impact.

Table 1 Effects of DSE on outcomes of three studied OMA techniques

	Mode ordinal		**1**	**2**	**3**	**4**	**5**	**6**	**7**
FDD-Projection disabled	Frequency of DSE-free data (1),	(Hz)	6.55	7.67	13.25	14.20	18.16	22.16	23.39
	Frequency of DSE-polluted data (2)	(Hz)	6.55	7.67	13.25	14.20	18.16	22.16	23.39
	Relative frequency change (2 vs 1)	**(%)**	**No change for all modes**						
	MAC (2 vs 1)	**-**	**0.9921**	**0.9962**	**0.9518**	**0.9595**	**0.9569**	**0.9555**	**0.9378**
FDD-Projection enabled	Frequency of DSE-free data (1),	(Hz)	6.55	7.67	13.25	14.20	18.16	22.16	23.39
	Frequency of DSE-polluted data (2)	(Hz)	6.55	7.67	13.25	14.20	18.16	22.16	23.39
	Relative frequency change (2 vs 1)	**(%)**	**No change all modes**						
	MAC (2 vs 1)	**-**	**0.9928**	**0.9963**	**0.9518**	**0.9626**	**0.9728**	**0.9553**	**0.9402**
UPC-PoSER-Projection enabled	Frequency of DSE-free data (1),	(Hz)	6.55	7.70	13.19	14.27	18.17	22.21	23.43
	Frequency of DSE-polluted data (2)	(Hz)	6.55	7.70	13.19	14.28	18.19	22.21	23.43
	Relative frequency change (2 vs 1)	**(%)**	**0**	**0**	**0**	**0.07**	**0.11**	**0**	**0**
	MAC (2 vs 1)	**-**	**0.9928**	**0.9946**	**0.9527**	**0.9605**	**0.9585**	**0.9524**	**0.9303**
UPC-PreGER-Projection enabled	Frequency of DSE-free data (1),	(Hz)	6.55	7.71	13.22	14.29	18.21	22.09	23.43
	Frequency of DSE-polluted data (2)	(Hz)	6.59	7.71	13.24	14.34	18.17	22.02	23.46
	Relative frequency change (2 vs 1)	**(%)**	**0.61**	**0**	**0.15**	**0.35**	**-0.22**	**-0.32**	**0.13**
	MAC (2 vs 1)	**-**	**0.9456**	**0.9618**	**0.8943**	**0.8190**	**0.8242**	**0.7847**	**0.7356**

Table 1 clearly shows that FDD is the most robust technique among those studied herein with respect to DSE effects. Its frequency estimates stay unchanged under the impact of DSE regardless of whether the channel projection is applied or not. The mode shape magnitudes estimated by this technique have also changed the least. It appears, with reasonable number of sensors like those used in this research, that FDD does not necessarily require the assistance from projection method even though a slight improvement in MAC values can be seen if the projection option is enabled. UPC-PreGER is the worst possibly due to the fact that this technique merges the correlation of data before performing SSI and errors may be exaggerated during this merging phase. With help of the channel projection, UPC-PoSER also overcomes negative impact of DSE on local sets of data and achieves considerable robustness to cope with this uncertainty.

It can also be seen from table 1 that, impact of DSE on estimates of mode shapes generally increases with the order of modes which is similar to effects of measurement noise. One simple way to combat this negative influence is to limit number of modes of interest and this fact has become a fundamental axiom to achieve a feasible modal-based SHM solution in practice. MAC deviation (from unity) of around 0.05 at the sixth mode might be considered as an acceptable fluctuation threshold for monitoring of structural damage in real civil structures (see, for instance, Brincker et al., 2001).

Repetition Check

Since the main uncertainty presented in each time series of the DSE-corrupted data was randomly generated at one time, it is necessary to examine whether the trend previously investigated is repeated for more than other similar datasets. To cater to this need, two more data sets were randomly generated with the same maximum DSE value and analysed in the same way. The results were quite similar, but they are not presented herein due to the constraint of the paper space. Impact of DSE randomness will be addressed in an extension of this study (to be published in Journal of Civil Structural Health Monitoring).

CONCLUSIONS

This paper has presented an intensive investigation of effects of uncertainties of SHM-oriented WSNs on performance and outcome of several popular OMA techniques considering frequent realistic applications. Based on a brief review, the paper has first revealed that whilst data loss can be effectively treated using reliable communication protocols, DSE is still unavoidable and can be considered as the most inherent uncertainty. However, the review has also shown that the DSE magnitude has been considerably alleviated in the SHM-oriented WSN platform such as the combination of Imote2 and the SHM-A sensor board, and will possibly help avoiding the use of costly computational methods for compensation of DSE impact. Since OMA has been identified as one of SHM approaches possibly suffering the most from negative impact of DSE, effects of the updated DSE level on three most frequently-used OMA techniques have been investigated with respect to one of the common usages i.e. employing data merged from multiple tests. A combination of experimental data from a large-scale bridge model excited by means of artificial wind and simulation of SHM-oriented WSN uncertainties including noise and DSE has been adopted to facilitate the assessment process. The results have shown that, of the three OMA techniques, FDD is the most robust technique possibly because it avoids working directly with time-domain data like the other two and impact of DSE is the least at spectral peaks. Without using channel projection, both UPC-PoSER and UPC-PreGER have been found to suffer from unreliable estimation of modal characteristics but effects of DSE on UPC-PreGER are much more severe than those on UPC-PoSER. The use of the channel projection has been proven to help improve the robustness of these two time-domain OMA techniques with respect to adverse influence of the remaining DSE in SHM-oriented WSN. Since parametric and non-parametric OMA techniques have always recommended to be used together to complement each other, combination of both FDD and UPC-PoSER is highly recommended for reliable OMA outcome under presence of DSE.

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