Effects of Wireless Sensor Network Uncertainties on Output-Only Modal Analysis Employing Merged Data of Multiple Tests

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Abstract: The use of Wireless Sensor Networks (WSNs) for vibration-based 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 asynchronicity 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. Based on a brief review, this paper first reveals that Data Synchronization Error (DSE) is the most inherent factor amongst uncertainties of SHM-oriented WSNs. Effects of this factor are then investigated on outcomes and performance of the most robust Output-only Modal Analysis (OMA) techniques when merging data from multiple sensor setups. 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. Accelerations collected by a wired sensory system on a large-scale laboratory bridge model are initially used as benchmark data after being added with a certain level of noise to account for the higher presence of this factor in SHM-oriented WSNs. From this source, a large number of simulations have been made to generate multiple DSE-corrupted datasets to facilitate statistical analyses. The results of this study show the robustness of FDD and the precautions needed for SSI-data family when dealing with DSE at a relaxed level. Finally, the combination of preferred OMA techniques and the use of the channel projection for the time-domain OMA technique to cope with DSE are recommended.

Key words: wireless sensor networks (WSNs), data synchronization error (DSE), output-only modal analysis (OMA), multi-setup, frequency domain decomposition (FDD), data-driven stochastic subspace identification (SSI-data).

1. INTRODUCTION

The use of Wireless Sensor Networks (WSNs) for vibration-based 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 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, inaccurate synchronization

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and unreliable data transmission (Spencer *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 2009). Realizing such limitations, a number of research 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 (Rice and Spencer 2009; Pakzad *et al*. 2008; Nagayama *et al*. 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 in the Illinois Structural Health Monitoring Project (Rice and Spencer 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 techniques from prior studies. Then, effects of the most inherent uncertainty 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.

2. MAJOR UNCERTAINTIES OF SHM-ORIENTED WSNs

There are a number of technical uncertainties or challenges that have been identified by prior studies (Lynch and Loh 2006; Spencer *et al*. 2004). 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 acknowledgement 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 jitter-induced 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). Jitter-induced 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 (2009) customized a multi-metric sensor board named SHM-A in order to effectively mitigate the second and third source of jitter-induced DSE. The first source of jitter-induced 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 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. Nguyen *et al*. (2014) compared effects of different DSE levels on data collected from one real tower structure using the single sensor setup. Since previous research has mostly focused on simple structures such as cantilever and simply supported beams or on the use of the single sensor setup, effects of initial DSE on OMA of civil structures in larger scales, which in many cases need to employ multi-setup tests, need to be further studied. Such effects on the most popular (but in different domains) OMA techniques (i.e. FDD and SSI-data) definitely deserve a comparative investigation in order to uncover their strength and weakness. For the sake of completeness, FDD, SSI-data and associated strategies of data merging are briefly described in the next section.

3. OMA AND DATA MERGING METHODS

Representing non-parametric OMA is Frequency Domain Decomposition (FDD), proposed by Brincker *et al*. (2000). This technique starts with estimation of output power spectral density matrices each of which (G_{yy}) corresponds to one of the discrete frequencies (ω_i) in the frequency range of interest. These matrices are then decomposed by the Singular Value Decomposition (SVD) algorithm as follows

$$G_{yy}\left(j\omega_i\right) = U_i S_i U_i^H \tag{1}$$

Where $U_i = [u_{i1}, u_{i2}, \ldots, u_{im}]$ is a unitary matrix containing the singular vectors u_{ij}; S_i is a diagonal matrix containing singular values s_i; j and m are the index and total number of measured responses, respectively. Next, singular value lines are formed by assembling s_i for all discrete frequencies (ω_i) and plotted for implementing the peak-picking of modes. A mode is generally estimated as close as possible to the corresponding resonance peak of the first singular value line where the influence of the other modes is as small as possible. In the case of two orthogonally coupled modes occurring at one frequency, the previous step is carried out for the stronger mode whereas the peak on the second singular value line will be "picked" for the weaker mode (Structural Vibration Solutions A/S 2011). Mode shapes are finally derived from singular vectors (u_{ij}) corresponding to selected frequencies. Besides FDD, 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 later ones. Similar to traditional input-output non-parametric techniques, FDD family is said to be fast, simple and user-friendly as well as 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 families of OMA time domain techniques since it can take into account furious modes from measurement noise; cope well with dense and closely spaced modes and avoid spectrum leakage (Zhang *et al*. 2005; Brincker *et al*. 2001). This OMA family relies on directly fitting parametric state space models to the measured responses of a linear and time invariant physical system (Overschee and Moor 1996; Structural Vibration Solutions A/S 2011) as follows.

$$\begin{aligned} x_{t+1} &= Ax_t + w_t \\ y_t &= Cx_t + v_t \end{aligned} \tag{2}$$

Here, x_t and y_t are the state vector and the response vector at time t, respectively. A is the system state matrix whereas C is the observation matrix. Amongst two stochastic processes, w_t is the process noise (i.e. the input) that drives the system dynamics whilst v_t is measurement noise of the system response.

In later phase, subspace models are first established for different dimensions up to the user-defined maximum value. Estimates of matrices A and C (i.e. $\hat{A}$ and $\hat{C}$, respectively) are then obtained by the least square solution. By performing the eigenvalue decomposition of the system matrix estimate ($\hat{A}$), its discrete poles (μ_i) and eigenvectors (Ψ) can be found as follows (Brincker and Andersen 2006):

$$\hat{A} = \Psi\left[\mu_i\right]\Psi^{-1} \tag{3}$$

The continuous time poles and subsequently modal frequencies and damping ratios are then obtained:

$$\lambda_i = \frac{\ln\left(\mu_i\right)}{\Delta t} \tag{4a}$$

$$f_i = \frac{\left|\lambda_i\right|}{2\pi} \tag{4b}$$

$$\zeta_i = \frac{\mathrm{Re}\left(\lambda_i\right)}{\left|\lambda_i\right|} \tag{4c}$$

where Δt is simply the sampling period. The mode shape matrix is finally derived from the observation matrix and eigenvectors:

$$\Phi = \hat{C}\Psi \tag{5}$$

By using increasing subspace model orders, multiple sets of modal parameters for each pole are obtained and their deviation can be used to examine whether the pole is as stable as a genuine structural mode. This leads to the extensive use of the stabilization diagram not only in SSI-data (see Figure 5 or 6 for illustration) but also in most parametric modal analysis methods. It might be worth noting that there is another SSI family that is based on covariance of data and therefore named covariance-driven SSI (SSI-cov) but this OMA approach is likely to confront higher computational errors due to the issue of matrix squared up in its calculation process (Zhang *et al*. 2005). Among different estimation algorithms for SSI-data (Structural Vibration Solutions A/S 2011), Un-weighted Principal Component (UPC), has been used most for OMA of civil structures. Another advantage of the SSI-data techniques over the FDD family is that they have potential to be operated in the automated manner.

Besides the use of a single dataset, it is not unusual in practice, to merge data from multiple setups 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 sensors (known as reference sensors) being kept fixed while the others are being roved along the structure. A common problem with this usage is the inconsistency and non-stationary amongst different datasets (for instance, due to different operational and environmental conditions) which may cause estimation errors in the OMA process (Reynders *et al*. 2009). Since DSE is a newer type of measurement uncertainty as previously mentioned, it is necessary that its impact be thoroughly investigated.

There are two most common ways of merging data in both SSI approaches in general and SSI-data family in particular from multiple tests, namely Post Separate Estimation Re-scaling (PoSER) and Pre Global Estimation Re-scaling (PreGER). By means of data of reference sensors, 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). Compared to PoSER, the advantage of PreGER is that only one stabilization diagram needs to be dealt with in the identification phase regardless of number of the setups while the user of PoSER may need to work with every single diagram of each setup. However, PreGER is likely to be less robust with respect to small non-stationarities (Reynders *et al*. 2009) which may be the case of DSE. The robustness of both methods and particularly PreGER with respect to DSE obviously deserves further investigation. For the sake of simplicity, SSI-data-UPC-PoSER and SSI-data-UPC-PreGER are hereafter shortened as UPC-PoSER and UPC-PreGER, respectively.

4. 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 another realistic sensor arrangement strategy (i.e. employing multiple sensor setups). To realize this aim, a sophisticated and 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 data herein was collected by a precisely synchronized wired sensing system, before being contaminated with an additional amount of measurement noise to account for the higher presence of this factor on WSNs in comparison with the wired sensing system employed herein. Serving as benchmark (or DSE-free) data, the noise-added accelerations are then introduced with a relaxed level of initial DSE for SHM-oriented WSN platform in a random manner. To investigate impact of DSE randomness, this pollution process was repeated fifty times to generate fifty sets of DSE-corrupted data for subsequent analyses. Both DSE-free and DSE-corrupted data are used for OMA utilizing FDD and two variants of 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 as 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 mitigate DSE impact. The basis for this is that the impact of DSE is generally higher for higher modes (see section 6.3) which is similar to the impact of conventional measurement uncertainties such as

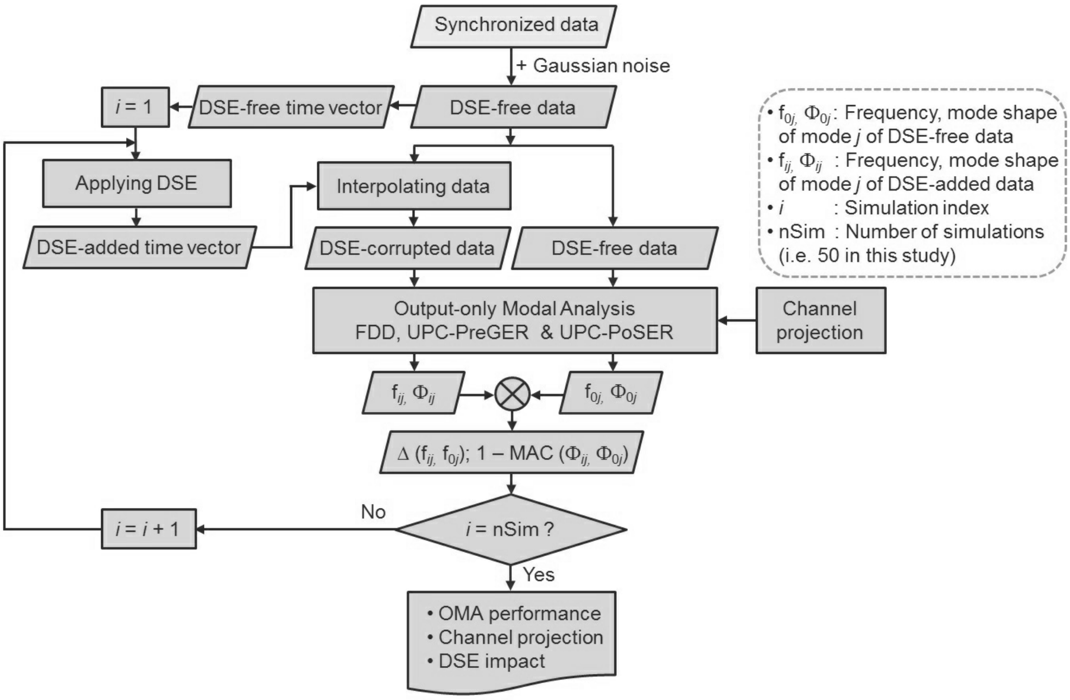

Figure 1. Flowchart of the investigation approach

measurement noise which can be handled by the use of the projection option. Figure 1 presents the flowchart of the investigation approach and further details can be found in section 5.

5. BRIEF DESCRIPTION OF TESTS AND ANALYSIS

5.1. The Bridge Model and Wired Sensing System

Object for data acquisition is the through-truss bridge model at the Queensland University of Technology (Figure 2). With almost 600 degrees of freedom and dimensions of 8550 mm by 900 mm for its foot print and the height of 1800 mm at the two towers, this bridge model can be one of the largest laboratory through-truss bridge models for SHM purposes. To simulate ambient excitation, three large industrial fans were used at three different positions along the structure. 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 high-quality uni-axial seismic ICP® accelerometers (www.pcb.com) with the sensitivity of 10 V/g. In each test, the sensors were divided into three groups each of which covers one cross section. This is 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 accelerometers (Structural Vibration Solutions A/S 2011). In each group, two accelerometers were used for vertical measurement and the other was to measure the lateral response. Of three groups, one was kept as the reference (i.e. near mid-span) and the other two were roved along the bridge model. Figure 3 illustrates two examples of the sensor setups. The total number of successive sensor setups was set at seven.

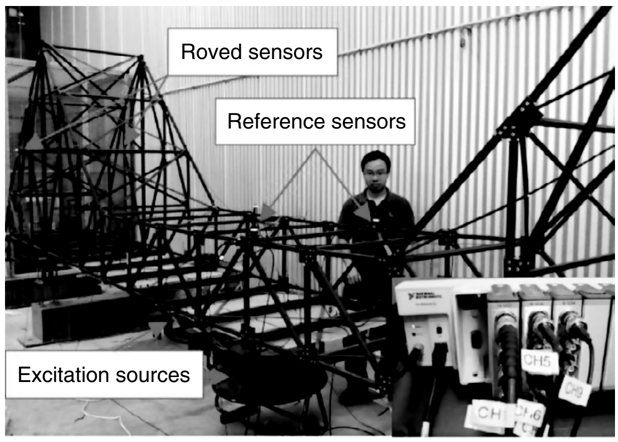

Figure 2. Physical bridge model and its wired sensing system

The sensing system was controlled by a National Instruments (NI) data acquisition system including NI

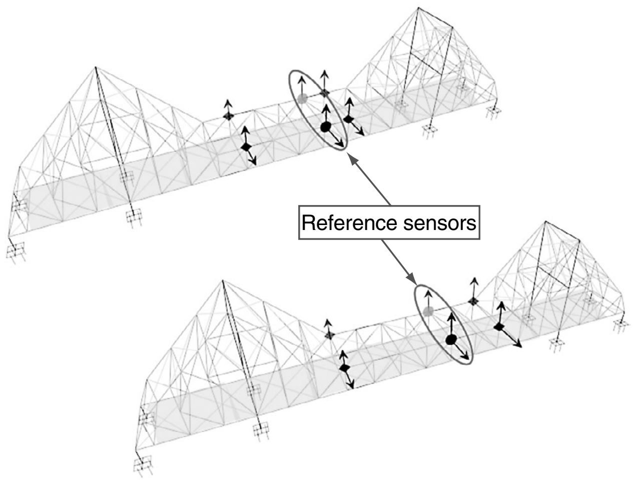

Figure 3. Two examples of the sensor setups

cDAQ 9172 chassis, NI 9234 dynamic signal acquisition modules and LabVIEW Signal Express software (www.ni.com). To achieve precise synchronization, the internal timebase of one module is selected to be shared with the other modules so that all modules can use the same timebase in the sampling process. 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 illustration purpose, the data used hereafter was 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.

5.2. Simulation of Noise and Initial DSE

All seven-subset data were added with relatively high level of Gaussian noise (i.e. 20 percent in root-mean-square sense) to account for the presence of higher noise in WSNs in comparison with the wired sensing system used herein. In this step, the MATLAB function named "randn" was utilized to create sequences of Gaussian distributed numbers with the specified root-mean-square values (MathWorks 2011). Acting as the DSE-free source, each noise-added acceleration sequence is then contaminated with an initial DSE which was randomly assigned between zero and the effective sampling period in the simulation process. To do so, the DSE value was first added to the initial time vector of each time series to obtain the (DSE-induced) delayed time vector and based on these two time vectors, the DSE-corrupted data was then derived from the DSE-free acceleration sequence by means of the MATLAB one-dimensional interpolation function named "interp1". The "interp1" function has a number of options which are actually the methods of interpolation including popular ones such as linear or cubic spline interpolation methods. It is worth noting that the linear interpolation method 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. Since the simulations herein are not subjected to such a computational constraint, the cubic spline interpolation method in the "interp1" function was adopted to achieve more accurate simulation results (MathWorks 2011). This process was run fifty times to generate fifty DSE-corrupted datasets to facilitate statistical analyses.

5.3. OMA and Analyses of Effects of DSE

The DSE-free and fifty DSE-corrupted datasets were used as the input for FDD, UPC-PoSER and UPC-PreGER techniques. The analysis was conducted using ARTeMIS Extractor software (Structural Vibration Solutions A/S 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.

For each OMA technique, fifty sets of modal parameters (i.e. frequencies and mode shapes) were estimated at each mode and can be used to compare with the benchmark modal parameter set (i.e. from the DSE-free data). As this direct comparison is the same as level 1 of modal-based damage identification process (Brincker *et al*. 2001), popular damage indices such as frequency changes and the deviation from unity of Modal Assurance Criterion (MAC) of mode shape pairs can be used as primary indicators for assessment of DSE impact. Interested readers could refer to Allemang (2003) for more details of the MAC index.

To evaluate changes of modal parameters with different bases like frequencies under DSE impact, basic statistical measures are employed including root-mean-square error (RMSE) of DSE-corrupted frequencies (with respect to the DSE-free frequency) and relative difference of DSE-corrupted frequency estimates. With MAC deviations which share the same base (i.e. zero), box-plot function (MathWorks 2011) was adopted to visualize some useful statistical properties (such as

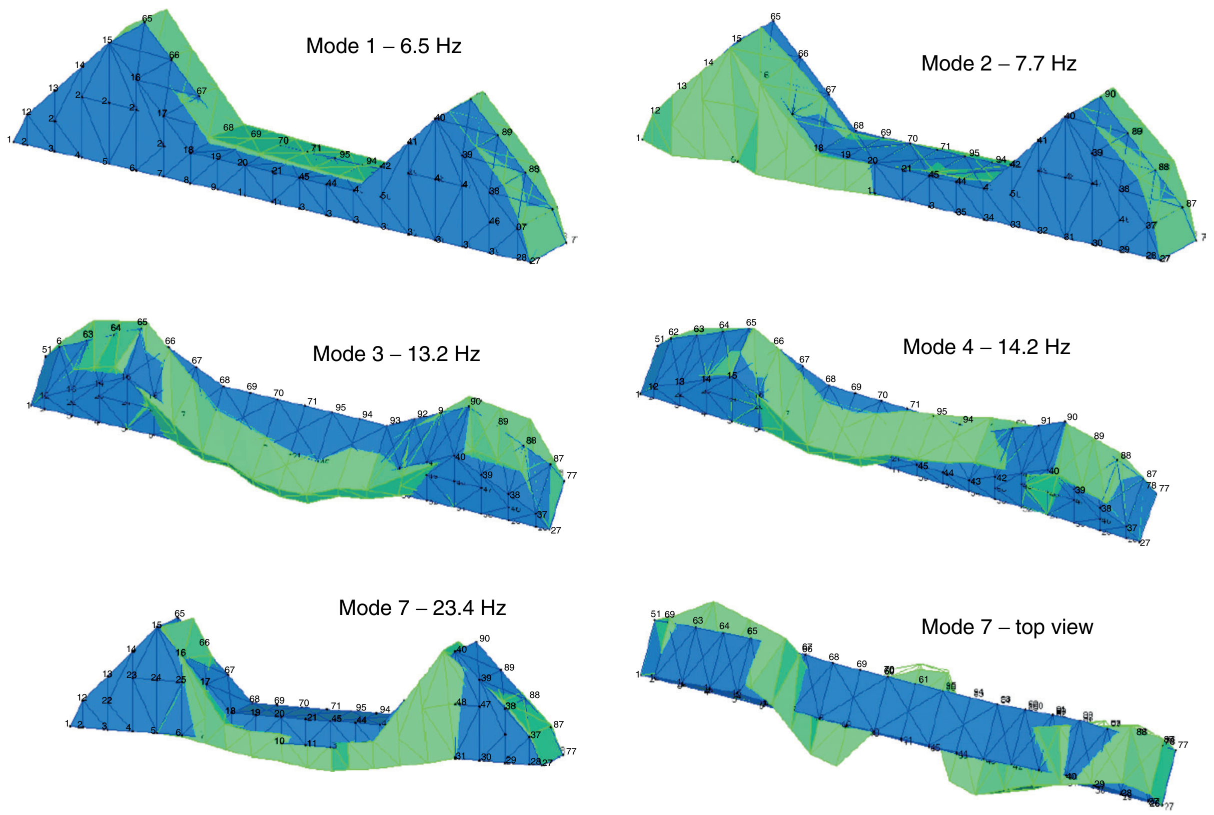

Figure 4. Typical mode shapes estimated from DSE-free data

median, quartiles and extremes) of MAC deviations at a number of first modes.

6. RESULTS AND DISCUSSIONS

6.1. 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 4) whilst three higher modes detected (at around 18.2, 22.2 and 23.4 Hz) are mostly coupled ones between lateral and vertical responses. Figure 4 shows such a coupled mode (mode 7).

6.2. The Use of Channel Projection

Of the three techniques, the channel projection has the most substantial influence on robustness of UPC-PreGER with respect to DSE presence. While the projection-disabled version of UPC-PreGER works properly with DSE-free data estimating all aforementioned modes, it completely fails detecting modes 3 and 4 from most of the fifty sets of DSE-corrupted data [Figure 5(a)] even though higher dimensions of the state space model were tried. However, the use of channel projection has enhanced UPC-PreGER so that these two modes can be

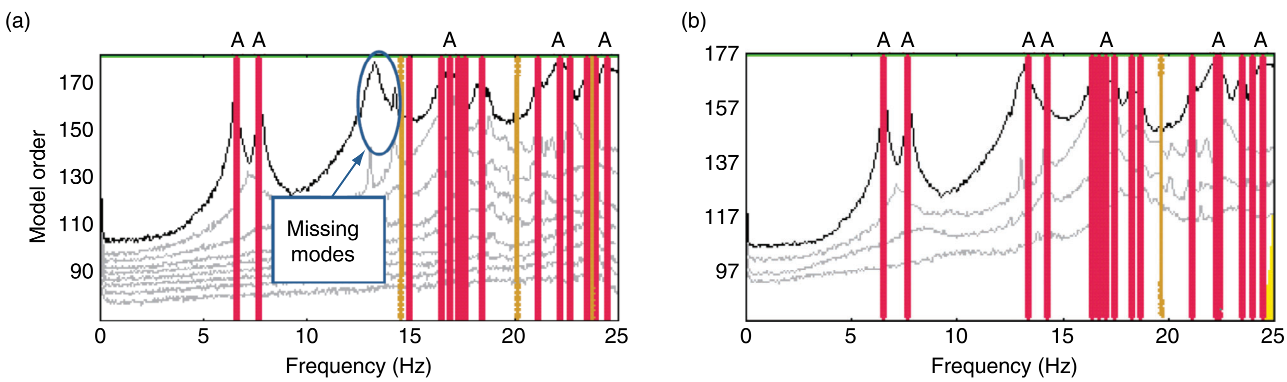

Figure 5. Stabilization diagram of UPC-PreGER with projection: (a) disabled; (b) enabled

estimated again in the projection-enabled version [Figure 5(b)]. Besides, the channel projection has also certain effect on the way UPC-PoSER copes with DSE. Some noise modes are mistakenly detected at locations of true modes [see Figure 6(a) for the case of mode 2] if the channel projection is not used. This problem is also resolved once the projection option is enabled [Figure 6(b)]. 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 the projection option on performance of FDD technique is presented in the next section.

6.3. 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. Besides, it is necessary to examine whether FDD is under the same impact of the projection. Therefore, in each OMA round, the projection method was applied for two UPC-PreGER and UPC-PoSER whilst the robustness of FDD was also examined for both cases i.e. with the channel projection being enabled and disabled. The remaining of this section will present and discuss the results of DSE impact on estimates of frequencies and mode shapes.

There is no change in frequencies estimated by FDD for both DSE-free and DSE-corrupted data. This once again reinforces the prior findings that DSE does not affect frequencies estimated by FDD (Krishnamurthy *et al*. 2008; Yan and Dyke 2010) and highlights the robustness of this technique with respect to DSE impact on frequency estimation.

Frequency estimates by SSI family are subjected to certain influence from DSE but the effects are fairly different for two SSI-data-UPC sub-techniques as illustrated in Table 1. Whilst UPC-PoSER experiences the maximum frequency RMSE of less than 0.01 Hz,

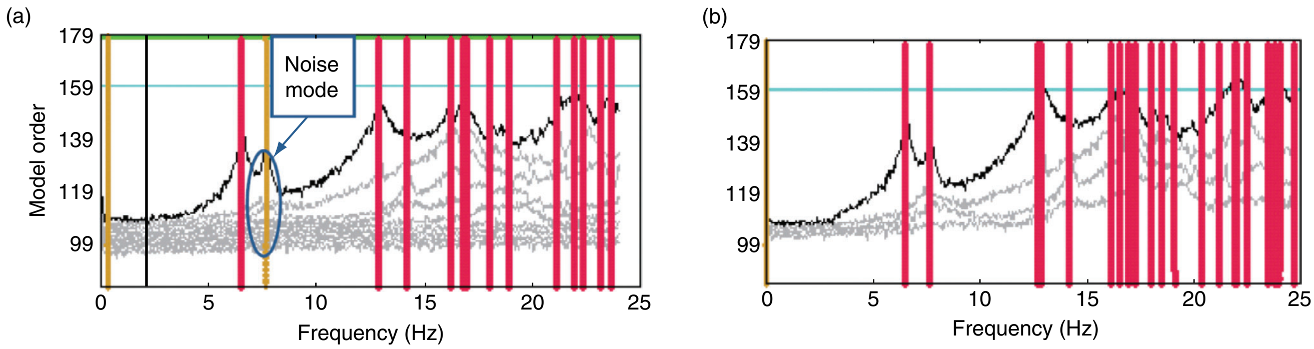

Figure 6. Stabilization diagram of UPC-PoSER with projection: (a) disabled; (b) enabled

Table 1. Effects of DSE on frequency estimates by UPC-PoSER and UPC-PreGER

Technique	Mode	DSE-free (Hz)	RMSE (mHz)	Min (Hz)	Max (Hz)	RD (%)
UPC-PoSER	1	6.550	0.04	6.550	6.550	0.00
	2	7.700	0.15	7.700	7.701	0.01
	3	13.187	6.36	13.167	13.183	0.13
	4	14.271	2.32	14.272	14.278	0.04
	5	18.171	7.41	18.158	18.180	0.12
	6	22.207	1.29	22.203	22.208	0.02
	7	23.425	6.23	23.426	23.447	0.09
UPC-PreGER	1	6.547	19.33	6.573	6.616	0.66
	2	7.705	3.05	7.706	7.718	0.15
	3	13.215	89.66	13.290	13.643	2.67
	4	14.288	65.04	14.348	14.540	1.35
	5	18.210	70.63	18.304	18.601	1.63
	6	22.094	109.89	21.913	22.273	1.63
	7	23.433	101.45	23.339	23.676	1.44

* RD = (Max-Min)×100/DSE-free

that figure of UPC-PreGER can be as large as 0.1 Hz. Similarly, the upper bound for relative frequency difference of the former technique is only 0.13 percent whereas that of the latter is up to 20 times larger.

Figure 7 shows the distribution of MAC deviations (from unity) of mode shapes estimated by FDD (with two options for the channel projection), UPC-PoSER and UPC-PreGER. Obviously, the results of these four cases can be seen to be classified into two groups. MAC indices of mode shapes estimated by FDD with two cases and UPC-PoSER mainly experience drops of less than 0.1 and their trend clearly show that DSE impact increases along with the increase in the mode order. However, those from UPC-PreGER can be as large as 0.3 or even higher for extreme cases and their trend is somewhat non-stationary at transitions between certain modes. These trends are reflected not only via median value of MAC deviations but also in general through the dispersion statistics such as the inter-quartile range (i.e. the height of the box in Figure 7).

The results above show 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. Amongst three techniques, 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 the 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 the above results that, impact of DSE on estimates of mode shapes generally increases

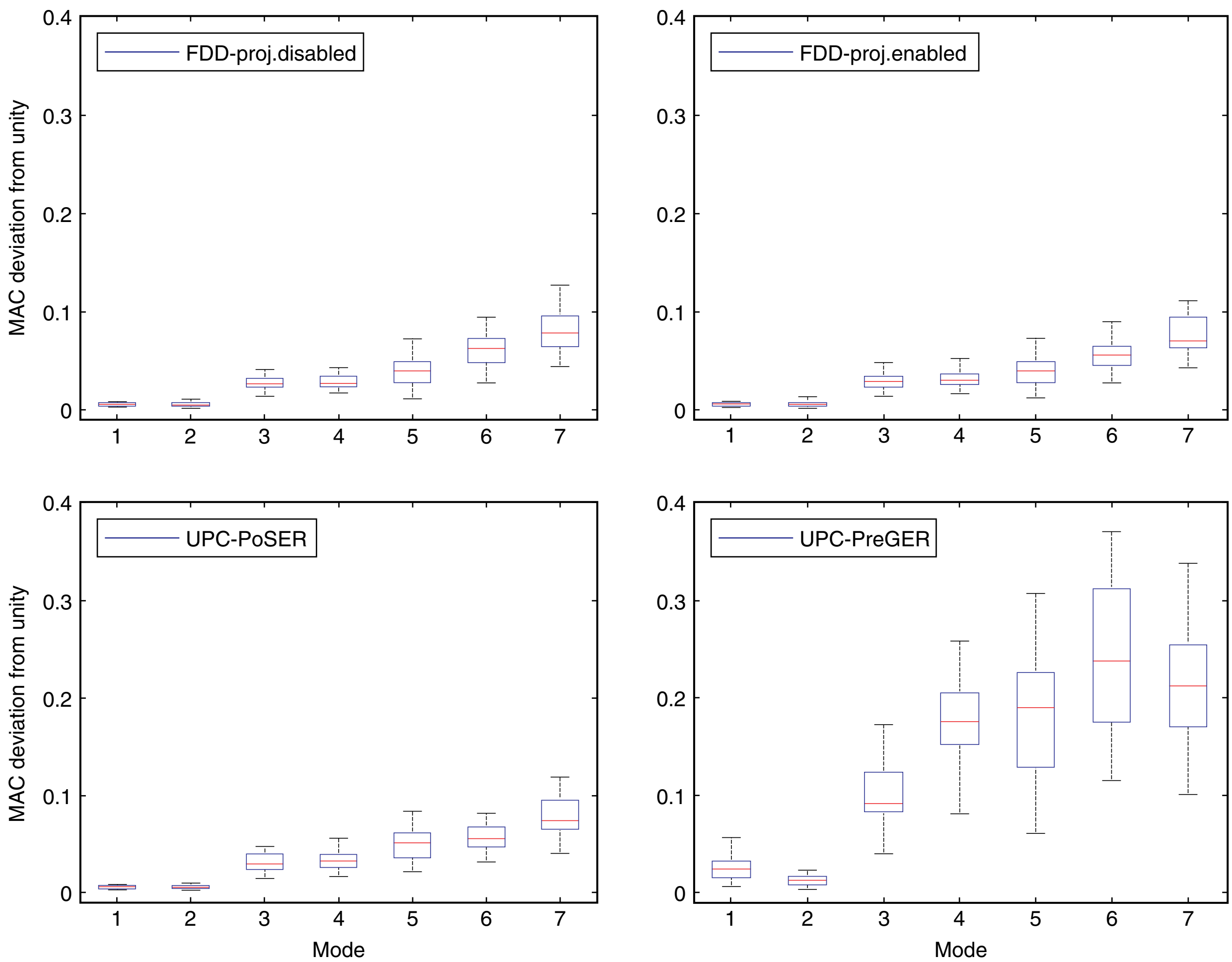

Figure 7. Box-plots of MAC deviations (from unity) of mode shapes for four cases

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 estimated by FDD or UPC-PoSER might be considered as an acceptable fluctuation threshold for monitoring of structural damage in real civil structures, see for instance (Brincker *et al*. 2001).

7. 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 a frequent realistic application. 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. Since OMA has been identified as one of the SHM approaches possibly suffering the most from negative impact of DSE, effects of a relaxed DSE level on three most frequently-used OMA techniques have been investigated with respect to one of the common usages i.e. merging data from multiple tests. A combination of precisely synchronized experimental data of a large-scale laboratory structure, simulation of SHM-oriented WSN uncertainties including random noise and random DSE and commonly-used statistical tools such as the box-plot has been adopted to facilitate the assessment process. The results have first shown that the impact of DSE on modal parameters (except frequencies estimated by FDD) tends to be more severe for higher-order modes and this trend is similar to conventional measurement uncertainties such as measurement noise. 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 at spectral peaks is the least. Without using channel projection, both variants of SSI-data (i.e. UPC-PoSER and UPC-PreGER) have been found to suffer from unreliable estimation of modal characteristics under disturbance of DSE. In this regard, the use of the channel projection has been proven to be able to enhance the performance of the two SSI-data variants to some extent. Nevertheless, the remaining impact of DSE on the outcome of UPC-PreGER is still considerable while that of UPC-PoSER is reduced to be more or less the same as the impact on the outcome of FDD. Since parametric and non-parametric OMA approaches have always been recommended to be used together to complement each other, the combination of both FDD and UPC-PoSER with the channel projection option has been shown to be effective and highly recommended for OMA of multi-setup datasets subjected to DSE such as those collected by WSN.

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