A hybrid system identification methodology for wireless structural health monitoring systems based on dynamic substructuring

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ABSTRACT

System identification has been employed in numerous structural health monitoring (SHM) applications. Traditional system identification methods usually rely on centralized processing of structural response data to extract information on structural parameters. However, in wireless SHM systems the centralized processing of structural response data introduces a significant communication bottleneck. Exploiting the merits of decentralization and on-board processing power of wireless SHM systems, many system identification methods have been successfully implemented in wireless sensor networks. While several system identification approaches for wireless SHM systems have been proposed, little attention has been paid to obtaining information on the physical parameters (e.g. stiffness, damping) of the monitored structure. This paper presents a hybrid system identification methodology suitable for wireless sensor networks based on the principles of component mode synthesis (dynamic substructuring). A numerical model of the monitored structure is embedded into the wireless sensor nodes in a distributed manner, i.e. the entire model is segmented into sub-models, each embedded into one sensor node corresponding to the substructure the sensor node is assigned to. The parameters of each sub-model are estimated by extracting local mode shapes and by applying the equations of the Craig-Bampton method on dynamic substructuring. The proposed methodology is validated in a laboratory test conducted on a four-story frame structure to demonstrate the ability of the methodology to yield accurate estimates of stiffness parameters. Finally, the test results are discussed and an outlook on future research directions is provided.

Keywords. System identification, structural health monitoring, embedded numerical models, wireless sensor networks, dynamic substructuring.

1. INTRODUCTION

The primary goal of structural health monitoring (SHM) is to assess the condition of structures. In SHM systems, several condition assessment methodologies are employed depending on the monitoring objective. One such methodology, which has drawn significant research attention over the years, is system identification, which, in principle, encompasses the estimation of structural properties using response data collected from monitored structures. By obtaining an estimate of the properties of monitored structures, valuable insights are gained into the structural behavior, thus facilitating the accurate detection of unfavorable structural changes as well as the efficient design of remedial measures. System identification methods can be applied either directly to raw structural response data or to processed structural response data, the most common processing technique being the transformation of time domain data into the frequency domain.

Lots of research has been done in the field of system identification, most of which is related to the identification of modal properties of structures. Conventional system identification approaches are based on analysis techniques in the frequency domain. More specifically, Richardson and Formenti (1982) have used rational fraction polynomials for parameter estimation, while Brincker et al. (2000) have proposed the use of frequency domain decomposition for the identification of mode shapes. Other analysis techniques for system identification are applicable in the time domain. For example, Overschee and De Moor (1996) have introduced the stochastic subspace identification method for obtaining a state-space model of monitored structures, which has been further extended by Peeters and De Roeck (1999). Furthermore, in the random decrement method, originally presented by Cole (1973), the dynamic characteristics of the structure are identified by translating the structural response data into a sum of autocorrelation functions. Ibrahim (1977) has presented the Ibrahim time domain method for identifying the modal characteristics of structures by obtaining estimates of free responses of the structure from random responses of the same structure using the random decrement
method. Juang and Pappa (1984) have introduced the eigensystem realization algorithm for the estimation of model parameters as well as the reduction of the model using experimental data.

In traditional SHM systems employing cable-based sensors for data acquisition, system identification is performed on a centralized server (Park et al., 2013; Smarsly et al., 2012a,b). However, in wireless SHM systems, the processing power of wireless sensor nodes facilitates the on-board execution of various monitoring tasks through embedded algorithms with an aim to reduce the power consuming wireless communication of data. In the same context, embedded algorithms are also used to perform system identification in a distributed manner, i.e. directly on the distributedly installed sensor nodes (Dragos and Smarsly, 2015a). For decentralized identification of the structural properties, a model of the monitored structure needs to be considered, which is either data-driven, e.g. using artificial neural networks (Smarsly and Petryna, 2014), or physics-based, e.g. using finite element models (Dragos and Smarsly, 2015b). Deriving structural properties directly on-board the sensor nodes enhances the intelligence of wireless SHM systems, referred to as “smart structures” or “intelligent infrastructure” (Smarsly and Hartmann, 2007, 2009), hence facilitating the effective monitoring of structures, while preserving the inherently limited resources of wireless sensor nodes.

Several research approaches on the implementation of embedded system identification algorithms into wireless sensor networks have been proposed. For instance, Zimmerman et al. (2008) have presented the implementation of output-only system identification techniques (peak-picking, frequency domain decomposition, random decrement method) into prototype wireless sensor nodes. In their smart sensor framework (Illinois structural health monitoring project tool suite), Rice et al. (2010) have embedded system identification algorithms into the Imote2 sensor nodes. Embedded algorithms for system identification have also been proposed by Swartz et al. (2007) as part of embedded SHM software implemented into prototype wireless sensor nodes and the Narada sensor nodes.

The aforementioned embedded system identification algorithms are effective in obtaining estimates of the modal properties of the monitored structure. However, obtaining information on the physical parameters of the monitored structure directly on the sensor nodes has received little attention. In this paper, a hybrid approach towards system identification suitable for wireless SHM systems is presented. The “hybrid” nature of the approach is expressed by the use of “observed” variables to obtain estimates of “latent” variables inferred by mathematical models, which is implemented in distributed-cooperative software and hardware modules (wireless sensor nodes). The proposed approach is based on identifying physical parameters of structures by combining frequency domain decomposition with “dynamic substructuring”. Dynamic substructuring is a domain decomposition methodology introduced to accelerate the computationally intensive analysis of large structural systems through analyzing structures in segments and, subsequently, combining the results. The concept of dynamic substructuring has been applied extensively in system identification (Craig and Blades, 1997; Sjövall and Abrahamsson, 2008; Koh et al., 2003; Tee et al., 2004). In this study, drawing from the dynamic substructuring methodology, stiffness parameters (latent variables) of the structure are derived directly on the sensor nodes at a substructure level. First, by applying the Craig-Bampton method on “component mode synthesis” (a dynamic substructuring methodology), the structure is segmented into substructures and a numerical model for each substructure is embedded into the sensor node corresponding to the substructure under consideration. Second, acceleration response data is collected at each substructure, and local mode shapes are derived (observed variables) by applying frequency domain decomposition at a substructure level. Finally, the parameters of the local stiffness matrices, derived from the Craig-Bampton method, are optimized to fit the extracted mode shapes. The system identification methodology is validated through a laboratory test on a frame structure showcasing the ability of the proposed methodology to yield accurate estimates of the physical parameters of the structure.

In the first section of this paper, system identification is briefly discussed, and the mathematical background of the proposed methodology is illuminated. Section 2 covers the implementation of the methodology into embedded software, while section 3 presents the laboratory test devised for validation of the methodology. Finally, the results of the laboratory test are discussed and potential directions for future research are proposed.
### 2. A HYBRID METHODOLOGY FOR DECENTRALIZED SYSTEM IDENTIFICATION

While in conventional system identification methods direct estimates of the properties of the entire structural system are extracted, such a straightforward approach could be cumbersome for large structural systems (e.g., for structural systems in which particularly detailed information on the properties of each structural member is required). The computational burden associated with analyzing large structural systems can compromise the accuracy of the obtained results. To counteract this problem, a stepwise system identification process based on dynamic substructuring is proposed. In the following subsections, system identification in structural engineering is briefly discussed, including some examples of common system identification methods. In addition, the dynamic substructuring method is explained and the system identification methodology through dynamic substructuring, proposed in this paper, is presented.

#### 2.1 System identification through structural dynamics

In structural engineering, it is common to employ the principles of structural dynamics for system identification. In methods based on structural dynamics, the dynamic properties of monitored structures, such as eigenfrequencies, damping ratios, and mode shapes are obtained. The extraction of dynamic properties of a structure is achieved by collecting and processing acceleration response data from selected locations of the structure. The acceleration response data is either used in raw form (i.e., in the time domain) with minor processing needed to remove potential offsets and noise components, or transformed into the frequency domain, i.e., represented as combination of harmonic functions with different frequencies by using transformation algorithms such as the fast Fourier transform (FFT). In general, the goal is to inverse the problem posed by the equation of dynamic equilibrium (Eq. 1).

\[
m(w) \cdot \frac{\partial^2 x(w,t)}{\partial t^2} + c(w) \cdot \frac{\partial x(w,t)}{\partial t} + k(w) \cdot x(w,t) = F(w,t)
\]

In Eq. 1, \( m \) is the mass of the continuous structural system, \( c \) is the damping coefficient of the structural system, and \( k \) is the stiffness of the structural system. The displacement is denoted by \( x \), while \( w \) is the coordinate of the location of the structure, \( t \) is the time, and \( F \) is the external force applied to the structural system. In structural analysis, it is common to consider discrete structural systems with dynamic properties lumped at \( m \) discrete degrees of freedom (DOFs) of the structure. The discrete form of Eq. 1 is shown in Eq. 2.

\[
M_{mm} \cdot \ddot{\mathbf{x}}_m + C_{mm} \cdot \dot{\mathbf{x}}_m + K_{mm} \cdot \mathbf{x}_m = \mathbf{F}_m
\]

In Eq. 2, \( M, C, \) and \( K \) are the mass matrix, the damping matrix, and the stiffness matrix of the structure, respectively. The acceleration vector is denoted as \( \ddot{\mathbf{x}} \), \( \dot{\mathbf{x}} \) is the velocity vector, and \( \mathbf{x} \) is the displacement vector. The external force vector is denoted as \( \mathbf{F} \). Three major problems are observed when obtaining a direct inverse solution of Eq. 2: First, the external force (also referred to as “input”) is often unknown; second, the number of locations \( n \) of the structure, where acceleration response data is obtained, is typically lower than the usual number of DOFs considered in structural analysis \( (n \ll m) \) and is, generally, insufficient to obtain a detailed solution; third, due to unfavorable measurement factors (noise, round-off errors, etc.), the integration of acceleration response data for the derivation of the corresponding velocities and displacements is not stable. As a result, due to the ill-posed nature of the inverse problem, the estimation of dynamic properties directly from the equation of dynamic equilibrium is not possible. Alternatively, common analysis techniques in system identification rely on other mathematical tools to obtain estimates of the dynamic properties. The analysis tools of frequency domain decomposition, used in this paper, are briefly described in the next subsection.

#### 2.2 Frequency domain decomposition

Frequency domain decomposition is a modal identification technique based on the decomposition of the spectral density matrix of the acceleration response data collected from the monitored structure. The acceleration response data is first transformed into the frequency domain by applying a Fourier transform algorithm for discrete systems, such as the FFT, as shown in Eq. 3.

\[
F(\omega) = \int f(t) \cdot e^{2\pi i \omega t} dt \\
\text{discrete} \rightarrow \quad F_k = \sum_{n=0}^{N-1} f_n \cdot e^{-2\pi i n \frac{k}{N}} \quad k \in [0,N) \quad N \in \mathbb{Z} \quad \omega = \frac{k}{N}
\]

In Eq. 3, \( F \) is the continuous complex Fourier function of frequency \( \omega \), \( f(t) \) is a continuous time function, \( f_n \) is a the \( n \)th point of a discrete time series of \( N \) points, \( F_k \) is the discrete complex Fourier function at discrete frequency \( \omega = k/N \); and \( i \) is the imaginary unit. In signal processing, spectral density expresses the power (energy over time) carried by two signals.
over a range of frequencies. If the same signal is used twice, the “auto-spectral density” is calculated; if two different signals are used, the “cross-spectral density” is computed. Considering as signals \( r \) different sets of acceleration response data, the spectral density matrix \( G \) is populated by applying Eq. 4.

\[
G_j = \sum_{i=1}^{r} \sum_{j=1}^{r} F_i \overline{F_j} \quad (4)
\]

In Eq. 4, \( F_i \) and \( F_j \) are the discrete complex Fourier functions of acceleration response data sets (signals) \( i \) and \( j \), respectively, while the overbar and the superscript “*” denote complex conjugate. The relationship between the input spectral density matrix \( G_i \) and the output spectral density matrix \( G_j \) is given in Eq. 5.

\[
G_j = H(i\omega)G_i H(i\omega)^H \quad (5)
\]

In Eq. 5, \( H(i\omega) \) is the frequency response function matrix between the input and the output, and \( H \) denotes complex conjugate and transpose (“Hermitian” matrix). By performing singular value decomposition of the output spectral density matrix, a unitary matrix is obtained, which holds the singular vectors, as shown in Eq. 6.

\[
G_j = US^{-1} \quad U = [u_{j1} \quad u_{j2} \quad u_{j3} \quad u_{j4} \quad \cdots \quad u_{jp}] \quad (6)
\]

It has been proven by Brincker et al. (2000) that close to an eigenfrequency \( \omega_p \) of the structure, the first singular vector of Eq. 6 is an estimate of the \( p \)th mode shape, as shown in Eq. 7.

\[
\omega = \omega_p \iff u_{j1} \equiv \varphi_p \quad (7)
\]

Frequency domain decomposition is applied in this paper as a first step to extract local mode shapes at a substructure level. The extracted mode shapes are then used to perform system identification by applying the Craig-Bampton component mode synthesis method (Craig and Bampton, 1968). The concepts of the dynamic substructuring methodology as well as the Craig-Bampton method are described in the next subsection.

### 2.3 Dynamic substructuring and component mode synthesis

Dynamic substructuring is a domain decomposition method introduced to accelerate the computationally intensive analysis of large structural systems. The main idea of dynamic substructuring is to segment the entire structure into substructures and interfaces. Each substructure is analyzed separately, and the analysis results are synthesized to obtain a “global” solution for the entire structure by fulfilling the interface compatibility criteria. Dynamic substructuring is typically applied in avionics and aerospace engineering (Seshu, 1997); however, extensions to other engineering disciplines, such as civil engineering, for the analysis of complex structures are also common (Blachowski et al., 2015).

Several dynamic substructuring methods have been proposed, the main difference between them being the parameters used to characterize the structural system. A general framework has been proposed by De Klerk et al. (2008) for the classification of dynamic substructuring methods. According to this framework, dynamic substructuring analysis can be performed in the physical domain, in the frequency domain, or in the modal domain. In the physical domain, a discretized model of the structure is formulated and each substructure is represented by the mass, stiffness, and damping parameters of the part of the model corresponding to the substructure under consideration. In the frequency domain, each substructure is represented by the frequency response functions (FRFs) between the input and the output from the measured locations of the substructure. The FRFs are used for the calculation of a “dynamic” stiffness matrix, which is a function of the mass matrix, the stiffness matrix, and the damping matrix of the structure (Jetmundsen et al., 1988; Crowley et al., 1984). In the modal domain, each substructure is regarded as a combination of modal responses. In all aforementioned methods, the synthesis of the global solution is based on the equilibrium of interface forces.

In this paper, for system identification through dynamic substructuring, the Craig-Bampton method based on component mode synthesis (CMS) is considered (Craig and Bampton, 1968). According to the Craig-Bampton method, the structure is segmented into \( N \) components each discretized to \( m \) DOFs, while the interfaces among the components are assumed to be fixed. To obtain the global solution of the structure, both vibration (normal) modes of the \( q \) internal DOFs of each substructure and constraint (static) modes of the \( b \) interface DOFs must be considered. The formulation of the Craig-Bampton method for an arbitrary substructure \( s \) with at least one interface is given in Eq. 8 and Eq. 9.
\[
M_{mn}^{(i)} \ddot{u}_m^{(i)} + K_{mn}^{(i)} u_m^{(i)} = F_m \iff \begin{bmatrix} M_{qq} & M_{qb} \\ M_{bq} & M_{bb} \end{bmatrix} \ddot{u}_q + \begin{bmatrix} K_{qq} & K_{qb} \\ K_{bq} & K_{bb} \end{bmatrix} u_q = \begin{bmatrix} F_q \\ 0 \end{bmatrix}
\]

(8)

\[
\begin{bmatrix} u_s \\ u_b \end{bmatrix} = \begin{bmatrix} \Phi_{qq} & \Phi_{qb} \\ 0_{bq} & I_{bb} \end{bmatrix} \begin{bmatrix} q_s \\ q_b \end{bmatrix}, \quad \Phi_{by} = -K_{yb}^{-1} K_{bb}^{-1}
\]

(9)

In Eq. 8 and Eq. 9, \(M\) is the mass matrix, \(\ddot{u}\) is the acceleration vector, \(u\) is the displacement vector, \(F\) is the external force vector, \(\Phi_{qq}\) is the matrix of vibration modes of the internal DOFs, \(\Phi_{qb}\) is the matrix of constraint modes of the boundary DOFs, \(0_{bq}\) is a \((b \times q)\) matrix of zeroes, and \(I_{bb}\) is an \((b \times b)\) unitary matrix. The mass matrix and the stiffness matrix of substructure \(s\) in the generalized coordinate space are obtained through the transformation using the modal matrix \(\Psi\), as shown in Eq. 10.

\[
\begin{align*}
\Psi^{(s)} &= \begin{bmatrix} \Phi_{qq} & \Phi_{qb} \\ 0_{bq} & I_{bb} \end{bmatrix} \\
\mu^{(s)} &= (\Psi^{(s)\top})^T M_{qq}^{(s)} \Psi^{(s)} \\
\kappa^{(s)} &= (\Psi^{(s)\top})^T K_{qq}^{(s)} \Psi^{(s)}
\end{align*}
\]

(10)

Considering a total of \(N_b\) substructures, the synthesis and the global solution are shown in Eq. 11 and Eq. 12. A transformation matrix \(S\) is used to invoke the interface compatibility criteria (i.e. by mapping the interface DOFs from each substructure to the global structure).

\[
\begin{bmatrix} u_{q1} \\ u_{b1} \\ u_{q2} \\ u_{b2} \\ \vdots \\ u_{qn} \\ u_{bn} \end{bmatrix} = S \begin{bmatrix} q_{s1} \\ 0 \\ q_{s2} \\ 0 \\ \vdots \\ q_{sn} \\ 0 \end{bmatrix}
\]

(11)

\[
M = S^\top \mu S \quad K = S^\top \kappa S \quad [K - \lambda_p^2 M] \Phi_s = 0 \quad \lambda_p = \omega_p^2
\]

(12)

In Eq. 11 and Eq. 12, \(\mu\) and \(\kappa\) are the block diagonal mass and stiffness matrices of all substructures, \(M\) and \(K\) are the transformed mass matrix and the transformed stiffness matrix, respectively, \(\lambda_p\) are the eigenvalues of the global solution, and \(\Phi_s\) are the mode shapes in the generalized coordinate space. To convert the mode shapes to the physical coordinate space, a final transformation step, using the modal matrix \(\Psi\) of each substructure, needs to be taken, as shown in Eq. 13.

\[
\begin{bmatrix} \Phi_1^s \\ \Phi_2^s \\ \vdots \\ \Phi_{n_s}^s \end{bmatrix} = \begin{bmatrix} \Psi_1^s \\ \Psi_2^s \\ \vdots \\ \Psi_{n_s}^s \end{bmatrix} \begin{bmatrix} \Phi_1^{s_1} \\ \Phi_2^{s_1} \\ \vdots \\ \Phi_{n_s^{s_1}}^{s_1} \end{bmatrix} \begin{bmatrix} \Phi_1^{s_2} \\ \Phi_2^{s_2} \\ \vdots \\ \Phi_{n_s^{s_2}}^{s_2} \end{bmatrix} \ldots \begin{bmatrix} \Phi_1^{s_{n_b}} \\ \Phi_2^{s_{n_b}} \\ \vdots \\ \Phi_{n_s^{s_{n_b}}}^{s_{n_b}} \end{bmatrix}
\]

(13)

In Eq. 13, \(\Phi_s\) are the mode shapes in the physical coordinate system. By extracting estimates of the mode shapes from frequency domain decomposition and by applying Eq. 10 to Eq. 13 in an iterative manner (i.e. for several combinations of values), the substructure mass matrix and stiffness matrix can be optimized to fit the extracted mode shapes. To be applied in a wireless SHM system, the theoretical framework presented in this section is implemented into embedded software. The implementation details are given in the next section.
3. IMPLEMENTATION OF THE SYSTEM IDENTIFICATION METHODOLOGY INTO A WIRELESS SHM SYSTEM

The proposed system identification methodology is implemented into a prototype wireless SHM system. In this section, the components of the SHM system are briefly described, and the embedded software, which implements the system identification methodology, is presented.

3.1 Architecture of the wireless SHM system

The wireless SHM system is composed of wireless sensor nodes, a server, and a gateway sensor node (“base station”) that serves as an interface between wireless sensor nodes and server. As mentioned previously, one of the major drawbacks of wireless sensor networks is power consumption, particularly due to extensive wireless transmission. Therefore, in the SHM system used on this study, the monitoring tasks are allocated in a way that wireless transmission is minimal. The monitoring tasks supported by the SHM system are shown in Figure 1.

![Figure 1. Monitoring tasks of the wireless SHM system.](image)

As shown in Figure 1, the initial model parameters are defined on the server. Then, the parameters of the model of each substructure are wirelessly transmitted to the corresponding sensor nodes. Upon receipt of the initial model parameters, the sensor nodes obtain the initial model of the substructure by applying the Craig-Bampton method. Subsequently, acceleration response data from each substructure is collected and, on-board the sensor nodes, transformed into the frequency domain. The experimental mode shapes of the substructure are extracted by the sensor nodes by applying frequency domain decomposition on the transformed acceleration response data. Finally, the parameters of the Craig-Bampton model are optimized using the extracted mode shapes.

3.2 Embedded software

The system identification methodology is implemented through embedded software written in Java programming language. From the mathematical formulation of the methodology presented in the previous section, it is clear that the methodology encompasses several distinct tasks, the programming of which is facilitated by the object-oriented paradigm of Java. The embedded software comprises two packages, one package to manage the tasks of the server and one package to manage the tasks of each sensor node. Each package contains several Java classes, which include the information for constructing “objects”, each corresponding to an individual task of the system identification methodology.
The package designed to handle the tasks of the server contains Java classes that read the parameters of the initial model from a text file and send the model parameters of each substructure to the corresponding sensor nodes. The wireless communication between the server and the sensor nodes is achieved by establishing reliable wireless peer-to-peer communication links through the base station. The package also allows the user to request the results of the optimized model parameters from the sensor nodes.

The package developed to handle the tasks of the sensor nodes, termed “sensorNode”, contains several Java classes that execute the monitoring tasks shown in Figure 1. More specifically, in the “MainNode” the initial model parameters are received and the collection of acceleration response data is managed. In addition, in the MainNode, the execution of the rest of the monitoring tasks (defined by other classes) is handled. The “FrequencySpectrum” class and the “FFT” class, as well as some helper classes, are responsible for the transformation of the collected acceleration response data into the frequency domain. The “FrequencyDomainDecomposition” class performs the extraction of experimental mode shapes. The “CraigBampton” class derives the parameters of the initial model by applying the Craig-Bampton method. Finally, the optimized Craig-Bampton model parameters are calculated by fitting the initial model to the extracted mode shapes. For matrix operations, such as singular value decomposition, eigenvalue decomposition, etc., further helper classes as well as classes from the open-source “JAMA” (JAMA, 2016) library are used. An extract of the sensorNode package is given in Figure 2.

4. VALIDATION TEST

The system identification methodology is validated through a laboratory test, devised to showcase the ability of the methodology to yield accurate estimates of the substructure stiffness matrices. First, the experimental setup, i.e. the laboratory structure and the sensor node specifications, is described. Then, the test procedure is presented and, finally, the test results are discussed.

4.1 Experimental setup

The test structure used for the validation test is a 4-story frame structure. A different system identification approach using the same frame structure has been presented by Dragos and Smarsly (2015b). The previous approach follows the concept of coupling in the frequency domain, i.e. between the frequency response functions of the collected acceleration response data, for the derivation of stiffness parameters.
The slabs of the frame structure are made of steel plates of 250 mm × 500 mm × 0.8 mm (length × width × thickness), resting on M5 steel-threaded columns of circular cross sections (5 mm diameter). The height of a story is 230 mm, and the overall height is 920 mm. The columns are clamped into a solid block of 400 mm × 600 mm × 300 mm; the degree of fixity is adequate to consider that all DOFs at the base of the columns are fully restrained. The instrumentation of the frame structure is illustrated in Figure 3. The structure is divided into two substructures with an overlapping interface. Specifically, substructure α consists of the first story and the second story, and substructure β comprises the second, the third, and the fourth story. As shown in Figure 3, both substructures are interfaced at the second story. Following this substructuring concept, one sensor node is placed at the center of each story. Sensor nodes A and B belong to substructure α, while sensor nodes B, C, and D belong to substructure β. For the sake of simplicity output-only data processing is considered, i.e. the excitation force is not measured.

For the instrumentation illustrated above, the sensor nodes and the base station used are of type “Oracle Sun SPOT” (Oracle Corp., 2009, 2010). The SunSPOT sensor node platform includes a Java-programmable 400 MHz ARM microprocessor, 512 kB volatile memory (RAM) used for data storage and runtime. 4 MB flash memory used for storing applications, and an IEEE 802.15.4 radio transceiver. The dimensions of the sensor node are 41 mm × 70 mm × 23 mm (length × width × height), while the weight the sensor node is 54 g. It should be noted, that since the weight of each story slab is comparable to the weight of the sensor node, the mass of the sensor nodes is accounted for at the definition of the initial model parameters. In terms of sensing boards, the sensor nodes are equipped with an MMA7455L digital output accelerometer of microelectromechanical systems (MEMS) type, a light sensor, and a temperature sensor. With respect to acceleration sampling, the integrated accelerometer can sample at either 125 Hz or 250 Hz, with selectable measurement ranges of ±2 g, ±6 g, or ±8 g.

4.2 Test procedure

As discussed previously, the application of the system identification methodology requires the a priori definition of an initial numerical model of the structure. To this end, the structure illustrated in Figure 3 is modeled as a 4-DOF oscillator; the modeling concept follows the experimental setup with one sensor node on each story. The numerical model of the structure is shown in Figure 4.
As can be seen from Figure 4, the segmentation of the numerical model follows the substructuring logic of Figure 4. Initially, the structure is assumed to behave as a “shear frame”, i.e. internal force distribution is restricted to adjacent DOFs. The shear frame assumption implies that the slab functions as a “diaphragm”, i.e. the slab is non-deformable under in-plane stresses and deformable under out-of-plane stresses. Based on the dimensions of the structure, the assumption, given the low rotational stiffness of the slab, seems coarse at a first glance. However, in frame structure analysis, it is not an uncommon assumption. Furthermore, the discrepancy between the optimized stiffness parameters and the initially assumed stiffness parameters is indicative of whether the “shear frame” assumption holds for the tested frame structure. The first eigenfrequency of the initial mode, computed from finite element analysis, is $f_1,\text{in} = 9.30\, \text{Hz}$, while the initial stiffness matrix is given in Eq. 14. Since the shear frame assumption has been used in the previous system identification approach on the same structure (Dragos and Smarsly, 2015b), the results of the stiffness parameters, shown also in Eq. 14, are used for comparison purposes.

$$
K_{\text{initial}} = \begin{bmatrix}
50.83 & -25.42 & 0 & 0 \\
-25.42 & 50.83 & -25.42 & 0 \\
0 & -25.42 & 50.83 & -25.42 \\
0 & 0 & -25.42 & 25.42
\end{bmatrix}
$$

The stiffness matrices of substructures $\alpha$ and $\beta$ are extracted from the stiffness matrix of Eq. 14. The stiffness matrices of the substructures embedded into the sensor nodes are given in Eq. 15.

$$
K^\alpha_{\text{initial}} = \begin{bmatrix}
50.83 & -25.42 \\
-25.42 & 25.42
\end{bmatrix}
$$

$$
K^\beta_{\text{initial}} = \begin{bmatrix}
25.42 & -25.42 & 0 \\
-25.42 & 50.83 & -25.42 \\
0 & -25.42 & 25.42
\end{bmatrix}
$$

For small scale laboratory structures, the values of the structural mass can be easily derived. In this validation test, the mass values (including the mass of the sensor nodes) are given in Eq. 16 and Eq. 17.

$$
M = \begin{bmatrix}
8.56 \cdot 10^{-4} & 0 & 0 & 0 \\
0 & 8.56 \cdot 10^{-4} & 0 & 0 \\
0 & 0 & 8.56 \cdot 10^{-4} & 0 \\
0 & 0 & 0 & 8.20 \cdot 10^{-4}
\end{bmatrix}
$$

$$
M^\alpha = \begin{bmatrix}
8.56 \cdot 10^{-4} \\
0 \\
0 \\
4.28 \cdot 10^{-4}
\end{bmatrix}
$$

$$
M^\beta = \begin{bmatrix}
8.20 \cdot 10^{-4} & 0 & 0 \\
0 & 8.56 \cdot 10^{-4} & 0 \\
0 & 0 & 4.28 \cdot 10^{-4}
\end{bmatrix}
$$
As shown in Eq. 17, the mass of the interface DOF (story 2) is halved between the two substructures. According to the Craig-Bampton method, the distribution of the interface DOF mass could be done in any combination; the optimal distribution in this study is obtained through trial and error.

The structure is deflected and acceleration response data is collected at a sampling rate of 125 Hz by each sensor node. Then, experimental mode shapes are automatically extracted by applying frequency domain decomposition. The experimental mode shapes are normalized with respect to the interface DOF. The first extracted eigenfrequency is $f_{1,ext} = 2.38$ Hz, while the first normalized experimental mode shapes at each substructure are given in Eq. 18.

$$
\varphi_1^a = \begin{bmatrix} 0.37 \\ 1.00 \end{bmatrix}, \quad \varphi_1^b = \begin{bmatrix} 2.21 \\ 1.79 \\ 1.00 \end{bmatrix}
$$

(18)

The extracted mode shapes are converted to generalized coordinates; the converted mode shapes are used to fit an optimized version of the Craig-Bampton model. Depending on the optimization algorithm used, different sets of optimized parameters for the initially assumed model can be derived. In this study, optimization is performed by multiplying the initial stiffness matrices with a scalar value and by minimizing the residuals of the eigenvalue problem of Eq. 12 at a substructure level, using the generalized mode shapes. It is well known that the stiffness of structures depends on the elastic modulus and on the length of the structural elements. The multiplication of the matrices with a scalar value is related to potential variations of the elasticity modulus and the length of the elements of each substructure. Due to the similarity between the two substructures, it is reasonable to assume that the same scalar should minimize the residuals at both substructures. The optimized matrices are given in Eq. 19.

$$
K_{\text{optimized}}^a = \begin{bmatrix} 1.88 & -0.94 \\ -0.94 & 0.94 \end{bmatrix}, \quad K_{\text{optimized}}^b = \begin{bmatrix} 0.95 & -0.95 & 0 \\ -0.95 & 1.90 & -0.95 \\ 0 & -0.95 & 0.95 \end{bmatrix}
$$

(19)

4.3 Discussion of the results

The deviations between the initial and the optimized matrices are significant. The size of the deviations leads to the conclusion that the shear frame assumption does not hold for the tested structure. Adding to this conclusion, the eigenfrequency of the extracted mode shape is significantly lower than the eigenfrequency of the initially assumed model. With respect to the accuracy of the results, as can be seen from Eq. 19, the results of the optimized stiffness parameters between the two substructures are quite consistent. In addition, the results of the optimized stiffness parameters are very close to the results obtained from the previous system identification study on the same frame structure, which has been performed using a different coupling technique. Hence, it is concluded that the stiffness parameters of the system have been successfully identified at a substructure level and with minimal wireless transmission.

5. SUMMARY AND CONCLUSIONS

In civil engineering, traditional system identification methods are applied on structural response data typically collected on a centralized server. However, wireless SHM systems performing centralized monitoring tasks can be detrimental to the inherently limited resources of wireless sensor nodes. To preserve the resources of wireless sensor node against the power-consuming wireless transmission, the processing power collocated with sensing modules on wireless sensor node platforms is utilized to embed algorithms that perform several monitoring tasks. In this direction, several embedded algorithms that perform system identification in a distributed manner have been proposed. While the embedded system identification algorithms are efficient in estimating dynamic properties of structures, only few studies have been reported that focus on obtaining information on the physical parameters of monitored structures on the sensor nodes. In this paper, a distributed system identification methodology suitable for wireless sensor networks has been proposed, based on a combination of the frequency domain decomposition method and the Craig-Bampton method on component mode synthesis. According to the proposed methodology, the monitored structure is analyzed into substructures (following the Craig-Bampton method), and a numerical model of each substructure is embedded into the corresponding sensor nodes. Then, experimental acceleration response data is derived, and experimental mode shapes are derived by applying
frequency domain decomposition. The extracted mode shapes are used to optimize the stiffness parameters of the embedded numerical model of each substructure at sensor node level.

The proposed methodology has been validated through a laboratory test on a 4-story frame structure. An initial numerical model of the structure (4-DOF oscillator) has been defined following the shear frame structure concept. For analysis purposes, the structure has been divided into two substructures, one wireless sensor nodes mounted on each story. The numerical model has been segmented and each segment has been embedded into the corresponding sensor nodes. In a test procedure, experimental acceleration data has been collected and, on board the sensor nodes, transformed into the frequency domain. Experimental mode shapes have been extracted and converted to generalized coordinates. Finally, the initial stiffness parameters of the numerical model of each substructure have been optimized to fit the experimental mode shapes.

In conclusion, the results of the validation test have demonstrated the applicability of the proposed system identification methodology. The optimized stiffness parameters are consistent between the two substructures. Also, the optimized parameters have been compared to the results of a previous study on the same frame structure and have proven to be in good agreement. Furthermore, even with a coarse initial assumption about the behavior of the structure, optimal stiffness parameters that fit with the experimental data could be derived. Future research will address the optimization part of the proposed methodology. Furthermore, quality assessment of dynamic substructuring methods, on the basis of prediction accuracy in system identification, will be performed.

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