Substructure Identification for Shear Buildings Using Ambient Vibration

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Abstract. Due to the aging of materials and environment corrosion, important civil infrastructures, like high-rise buildings, gradually lose their carrying capacity. Such structural deterioration, if developed to severe extent and not detected in time, will post a great threat to structural safety. In recent years, there have been several tragic accidents around the world, in which old buildings suddenly collapsed without any early warning, resulting in significant casualties and property losses. In this paper, an innovative parameter identification and damage detection method is proposed for shear buildings using structural ambient vibration responses. A shear structure is partitioned into many two-story substructures; an inductive substructure identification procedure is then proposed, using the cross power spectral densities of structural responses, to estimate structural parameters from top to bottom iteratively. Because of inductive identification nature of the proposed method, an error analysis can be performed, which gives a simple analytical result, showing that the identification accuracy is greatly affected by some structural responses within a narrow frequency range. Based on this result, a reference selection rule is proposed which chooses the optimal reference response to improve the identification accuracy. Finally, a 6-story shear structure is used to verify the effectiveness of the proposed substructure method. Simulation results demonstrate that the proposed substructure method could very accurately identify the structural parameters even with quite large measurement noise disturbance.

Introduction

With the aging of materials and environmental corrosion, the carrying capacity of important infrastructures, like high-rise buildings, gradually decreases, which reduces the structural ability to withstand excessive loads in large natural hazards, such as strong earthquakes. Hence, it is important to develop structural damage detection method that can accurately detect structural degradation and give an early warning if necessary. Many researchers tried to utilize system/parameter identification methods to estimate structural parameters from measured structural responses; structural damage is detected by comparing the identified parameters at different times.

However, system/parameter identification methods are effectively to solve some inverse optimization problems, which are difficult to provide accurate results for complex real structures. First, a practical large structure usually requires a complex model that involves many degree-of-freedoms (DOFs) and unknown parameters to simulate the structural response. Due to the existence of many local minima/maxima, it is very likely that the optimization converges to local rather than global optima, resulting in significant identified error and, thus, unreliable damage detection. Second, a large number of unknown parameters often render the inverse problems more and more poorly ill-conditioned, making

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the parameter estimates very sensitive to small noise in the measured responses; the result, again, is an unreliable damage detection approach.

Confronting this difficulty, substructure identification methods, applying a "divide and conquer" strategy, provides a feasible solution to identify large complex structures [1]. Basically, substructure identification methods divide a large structure into many smaller substructures, each of which has far fewer DOFs and unknown parameters, and perform parameter identification for each substructure independently. Since substructure identification methods greatly reduce the size of unknown parameter search space for the optimization; thus, convergence and ill-conditionedness problems are alleviated. Second, since only the structural responses related to the identified substructure are required in substructure identification, there is no need to monitor all DOFs simultaneously, which may greatly reduce the cost of structural health monitoring system.

Since Koh *et al.* [1] first presented the idea of substructure system identification, many new substructure methods have been proposed. Yun *et al.* [2] and Tee *et al.* [3] proposed several time-domain based substructure methods. Koh *et al.* put forward a substructure method in the frequency-domain that does not need to measure the structural responses at substructure boundary DOFs. Yuen *et al.* [4] further combined this method with a Bayesian identification framework to provide a probability measure of the identification accuracy. Hou *et al.* [5] proposed to isolate the concerned substructures from the global structure by adding virtual forces on the boundary of the substructure.

In the author's previous studies [6, 7, 8], an innovative substructure identification method for a shear structure is proposed. The Fourier transform of two or three adjacent floors acceleration responses are utilized to formulate a substructure identification problem in which the stiffness and damping coefficient of a certain story are identified. Repeating this procedure, the stiffness and damping coefficients of the whole structure can be identified from top to bottom in an iterative manner. Because of the noisy nature of the acceleration measurements, using the Fourier transform can provide accurate results only when the measurement noise is not too large. To improve identification accuracy in the presence of large noise, the author [8] proposed an alternate improved substructure method based on the transfer functions among the substructure responses. However, the implementation of this method requires several strict constraints that prevent its wide application.

In this paper, a new substructure identification method based on the cross power spectrum density of structural responses is derived from the differential equation governing the structural random responses. This approach not only overcomes the previous constraints imposed on the transfer function method, but also further improves the identification accuracy. A reference response, which is jointly wide sense stationary (WSS) with all structural responses, is introduced; the cross power spectral densities between structural accelerations and this reference response, calculated by averaging long wide sense stationary responses in frequency domain, are used in formulating the new substructure identification. The result is a great improvement of the identification accuracy by reducing the effect of measurement noise through averaging. Moreover, a smart selecting rule is formed, based on the identification error analysis for this new method, to choose the best reference response candidate, from a set of possible candidates, to further reduce the effect of measurement noise and, thus, improve the identification.

This paper is organized as follows: the second section shows the formulation of the substructure identification. The third section demonstrates an error analysis that examines how the uncertainties in the measurement will affect the identification accuracy. According to the error analysis result, a smart reference selection rule is proposed in the fourth section, which chooses the best reference candidate to improve the accuracy of the substructure identification. In the fifth section, a numerical example of 6-story structure is given to illustrate the efficacy of proposed substructure identification method. Finally, the conclusions summarize the paper and give some direction for future research.

Substructure Identification for Shear Structures

Figure 1a shows an n-story shear structure subject to ground excitation. The dynamic equation of this structure can be written for each story substructure as follows

top floor ($i = n$):

$$m_n\ddot{x}_n(t) + c_n[\dot{x}_n(t) - \dot{x}_{n-1}(t)] + k_n[x_n(t) - x_{n-1}(t)] = 0 \tag{1}$$

middle floor ($1 \le i \le n-1$):

$$m_i\ddot{x}_i(t) + c_i[\dot{x}_i(t) - \dot{x}_{i-1}(t)] + k_i[x_i(t) - x_{i-1}(t)] + c_{i+1}[\dot{x}_i(t) - \dot{x}_{i+1}(t)] + k_{i+1}[x_i(t) - x_{i+1}(t)] = 0 \tag{2}$$

where m_i, c_i and k_i are mass, damping coefficient and stiffness of the i^{th} story, respectively; $x_i(t)$ is the displacement of the i^{th} floor and ground relative to an inertial reference frame at time t ($x_0(t)=u_g(t)$ denotes the ground displacement response); overdots represent derivatives with respect to time t. It is assumed herein that the mass of the structure is known.

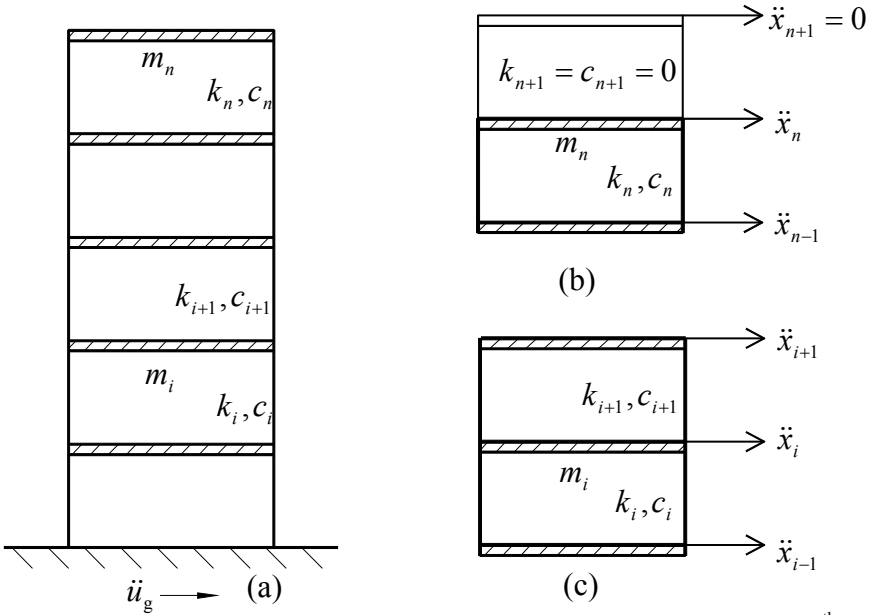

Figure 1. (a) An n-story shear structure with (b) a top story substructure and fictitious $(n+1)^{\text{th}}$ story and (c) a non-top story

The substructure identification begins with Eq. (2). Subtracting $m_i\ddot{x}_{i-1}$ from both side of Eq. (1), multiplying both sides by a reference response $y(t-\tau)$ at a different time and taking the expectation, will give

$$\begin{aligned} &m_i R_{(\ddot{x}_i - \ddot{x}_{i-1})y}(\tau) + c_i R_{(\dot{x}_i - \dot{x}_{i-1})y}(\tau) + k_i R_{(x_i - x_{i-1})y}(\tau) \\ &\quad = -m_i R_{\ddot{x}_{i-1}y}(\tau) + c_{i+1} R_{(\dot{x}_{i+1} - \dot{x}_i)y}(\tau) + k_{i+1} R_{(x_{i+1} - x_i)y}(\tau) \end{aligned} \tag{3}$$

where $R_{xy}(\tau) = \mathrm{E}[y(t-\tau)\, x(t)]$ is the cross correlation function between the responses $y(t)$ and $x(t)$. Here, it is assumed that the reference response $y(t)$ and all structural responses are jointly WSS. If $y(t)$ and $x(t)$ are joint WSS process, the cross correlation satisfies [9]

$$R_{x^{(m)}y}(\tau) = R_{xy}^{(m)}(\tau) \tag{4}$$

assuming that the associated mean square derivatives exist, where $x^{(m)}$ denotes the m^{th} derivative of random process $x(t)$ with respect to time t; $R_{xy}^{(m)}(\tau)$ denotes the m^{th} derivative of the correlation function with respect to τ. Therefore, Eq. (4) can be converted into a differential equation with respect to the correlation functions

$$
\begin{aligned}
&m_i \ddot{R}_{(x_i - x_{i-1})y}(\tau) + c_i \dot{R}_{(x_i - x_{i-1})y}(\tau) + k_i R_{(x_i - x_{i-1})y}(\tau) \\
&\quad = -m_i \ddot{R}_{x_{i-1}y}(\tau) + c_{i+1} \dot{R}_{(x_{i+1} - x_i)y}(\tau) + k_{i+1} R_{(x_{i+1} - x_i)y}(\tau)
\end{aligned} \tag{5}
$$

Taking a Fourier transform of both sides, rearranging the order of the equation, and exploiting the property $\mathcal{F}(\ddot{R}) = (j\omega)^2 \mathcal{F}(R)$ (where $j^2 = -1$; $\mathcal{F}(\cdot)$ denotes Fourier transform operation), gives

$$
\frac{1}{1 - j\, c_i / (m_i \omega) - k_i / (m_i \omega^2)} = \frac{S_{\ddot{x}_{i-1}y} - S_{\ddot{x}_i y}}{S_{\ddot{x}_{i-1}y} + (S_{\ddot{x}_{i+1}y} - S_{\ddot{x}_i y})[\, j c_{i+1} / (m_i \omega) + k_{i+1} / (m_i \omega^2)]} \tag{6}
$$

where $S_{\ddot{x}_i y} = S_{\ddot{x}_i y}(j\omega)$ is the cross power spectral density (CPSD) between the structural acceleration response $\ddot{x}_i$ and the reference response y (herein, $j\omega$ is often omitted for the notational simplicity).

Assuming that structural parameters $[k_{i+1} \;\; c_{i+1}]^{\mathrm{T}}$ in Eq. (6) are known, the right side of Eq. (6) can be computed from the measured responses. Using the equilibrium condition in Eq. (6), an optimization problem can be formulated to identify structural parameters $[k_i \;\; c_i]^{\mathrm{T}}$:

$$
\arg\min_{k_i, c_i} \quad J(k_i, c_i) = \sum_{l=1}^{N} \left| \begin{aligned} &1 \Big/ \left[1 - j c_i / (m_i \omega_l) - k_i / (m_i \omega_l^2) \right] - \\ &\left(\hat{S}_{\ddot{x}_{i-1}y,l} - \hat{S}_{\ddot{x}_i y,l} \right) \Big/ \left\{ \hat{S}_{\ddot{x}_{i-1}y,l} + (\hat{S}_{\ddot{x}_{i+1}y,l} - \hat{S}_{\ddot{x}_i y,l})[\, j c_{i+1} / (m_i \omega_l) + k_{i+1} / (m_i \omega_l^2)] \right\} \end{aligned} \right|^2 \tag{7}
$$

where $\hat{S}_{x_i y,l} = \hat{S}_{x_i y}(j\omega_l)$ ($i = 1, \ldots, n$) denotes the CPSD at frequency ω_l between reference response y and the i^{th} floor acceleration $\ddot{x}_i$ as estimated from the measured (noise contaminated) responses; the $\omega_l = l\,\Delta\omega$ ($l = 1, \ldots, N$) are discrete frequencies at which the CPSD are calculated on frequency interval $\Delta\omega$.

Because Eq. (7) can be used to estimate any intermediate story parameters, given that the parameters of the story above are known, an inductive identification is effectively established. Moreover, as shown in figure 1b, the top story substructure can be actually treated as a special case of a non-top story substructure with the condition that the parameters $[k_{n+1} \;\; c_{n+1}]^{\mathrm{T}}$ of the imaginary $(n+1)^{\text{th}}$ story are zeros. With this condition, a simplified identification problem for the top story substructure can be formulated as follows:

$$
\arg\min_{k_n, c_n} \quad J(k_n, c_n) = \sum_{l=1}^{N} \left| 1 \Big/ \left[1 - j c_n / (m_n \omega_l) - k_n / (m_n \omega_l^2) \right] - \left(\hat{S}_{\ddot{x}_{n-1}y,l} - \hat{S}_{\ddot{x}_n y,l} \right) \Big/ \hat{S}_{\ddot{x}_{n-1}y,l} \right|^2 \tag{8}
$$

Clearly, the top story parameters $[k_n \;\; c_n]^{\mathrm{T}}$ can be directly estimated from Eq. (8), which can be used to start the inductive identification procedure in Eq. (7). Consequently, the parameters of all stories of the structure can be identified from top to bottom in an iterative manner.

The proposed identification method has several advantages: (*i*) There is no need to measure all structural responses simultaneously. For each identification step, only the two or three floor accelerations and one reference measurement are needed, potentially reducing the cost of SHM system. (*ii*) In each step of the substructure identification, there are only two parameters, making the optimization procedure much easier to execute and converge. (*iii*) During the method formulation, no special assumption is made on the reference response $y(t)$ except that it is joint WSS with all the structural responses involved in the substructure identification; thus this approach provides wide flexibility in selecting the reference response. In a subsequent section, a smart selection rule is proposed, based on the results of an error analysis for this substructure identification method, to choose the best reference response candidate such that the identification error can be greatly reduced. (*iv*) For each step, the substructure identification only makes use of the dynamic equilibrium of one floor substructure to formulate the identification problem; hence, any excitation forces applied outside the floor being identified need not be measured nor will they affect the accuracy of this step identification. This property provides an easy way to conduct substructure

identification with little interference to normal use of the building (when substructure identification is performed on one floor, other floors can still be open to normal use).

Identification Error Analysis

An important feature of the above substructure method is that an inductive identification procedure was adopted; therefore, all identification steps (except for the top story substructure) have the same formulation and also quite simple, only having two parameters to estimate in each step. This feature makes it easy to conduct an identification error analysis for this method. Using the linearization method, the author showed [10] that the relative identification error for the identification problem (7) can be approximated by

$$\begin{bmatrix} \theta_{k_i} \\ \theta_{c_i} \end{bmatrix} \approx \sum_{l=1}^{N} \mathrm{Re}\left\{ \begin{bmatrix} U_{11,l}^{i} & U_{12,l}^{i} & U_{13,l}^{i} \\ U_{21,l}^{i} & U_{22,l}^{i} & U_{23,l}^{i} \end{bmatrix} \cdot \begin{bmatrix} N_{\ddot{x}_{i-1}y,l} / S_{(\ddot{x}_i - \ddot{x}_{i-1})y,l} \\ N_{\ddot{x}_i y,l} / S_{(\ddot{x}_i - \ddot{x}_{i-1})y,l} \\ N_{\ddot{x}_{i+1}y,l} / S_{(\ddot{x}_i - \ddot{x}_{i-1})y,l} \end{bmatrix} \right\}$$
$$+ \sum_{l=1}^{N} \mathrm{Re}\left\{ \begin{bmatrix} U_{14,l}^{i} & U_{15,l}^{i} \\ U_{24,l}^{i} & U_{25,l}^{i} \end{bmatrix} \cdot \begin{bmatrix} \dfrac{S_{(\ddot{x}_{i+1} - \ddot{x}_i)y,l}}{S_{(\ddot{x}_i - \ddot{x}_{i-1})y,l}} \theta_{k_{i+1}} \\ \dfrac{S_{(\ddot{x}_{i+1} - \ddot{x}_i)y,l}}{S_{(\ddot{x}_i - \ddot{x}_{i-1})y,l}} \theta_{c_{i+1}} \end{bmatrix} \right\} \tag{9}$$

where $[\theta_{k_i} \quad \theta_{c_i}]^{\mathrm{T}}$ and $[\theta_{k_{i+1}} \quad \theta_{c_{i+1}}]^{\mathrm{T}}$ are the relative identification errors of the i^{th} and $(i+1)^{\mathrm{th}}$ story parameters, respectively; $N_{\ddot{x}_i y,l} = \hat{S}_{\ddot{x}_i y,l} - S_{\ddot{x}_i y,l} \ \ (i = 1, \ldots, n)$ is the measurement uncertainty of the CPSD $S_{\ddot{x}_i y}$ at frequency ω_l due to the effect of measurement noises; $U_{jk,l}^{i}$ are some deterministic factors that are functions of structural parameters m_i, k_i, c_i, k_{i+1} and c_{i+1} as well as frequency ω_l [10].

Eq. (9) demonstrates that the identification errors $[\theta_{k_i} \quad \theta_{c_i}]^{\mathrm{T}}$ of the i^{th} story parameters are composed by two parts: the first part is due to the measurement uncertainties of the structural responses; the second part is related to the uncertainties of the above story parameters. Each error consists of a product of two kinds of terms: deterministic factors $U_{jk,l}^{i}$ and corresponding uncertain terms. Working as weighting factors, factors $U_{jk,l}^{i}$ represent the relative importance of these uncertainty terms. The author showed [10] that all factors $U_{jk,l}^{i}$ share a common feature that their magnitudes are significantly large near the i^{th} story substructure natural frequency $\omega_{i0} = \sqrt{k_i / m_i}$ and very small when leave from that frequency, indicating that uncertainty terms near frequency ω_{i0} plays a dominant role in determining the identification accuracy. Moreover, since there are two common structural responses in the uncertainty terms: $S_{(\ddot{x}_i - \ddot{x}_{i-1})y,l}$ serves as the common denominator for all three measurement uncertainty terms ($N_{\ddot{x}_{i-1}y,l} / S_{(\ddot{x}_i - \ddot{x}_{i-1})y,l}$, $N_{\ddot{x}_i y,l} / S_{(\ddot{x}_i - \ddot{x}_{i-1})y,l}$ and $N_{\ddot{x}_{i+1}y,l} / S_{(\ddot{x}_i - \ddot{x}_{i-1})y,l}$); $S_{(\ddot{x}_{i+1} - \ddot{x}_i)y,l} / S_{(\ddot{x}_i - \ddot{x}_{i-1})y,l}$ is a common structural response in the uncertain terms related to the accumulation error. Therefore, largely amplifying the former response and, meanwhile, reducing the latter response can significantly improve identification accuracy.

Reference Selection Rule

The choice of reference $y(t)$ affects the values of uncertainty terms in Eq. (9), so does the accuracy of the estimated parameters. Utilizing the error analysis results, the author proposed an optimal reference selection rule to choose the best reference to improve the identification accuracy, which is reviewed thereafter.

To simplify the reference selection, it is assumed that 1) measurement noises are zero-mean processes, independent of true (noise free) structural response and independent of

one another at different locations; 2) there is only one excitation applying to the structure. Based on the above two assumptions, the optimal reference $y(t)$ for the i^{th} story substructure identification should satisfy the following two conditions: 1) it does not involve in this step substructure identification (*i.e.*, $y(t)$ is none of the following: $\ddot{x}_{i-1}(t)$, $\ddot{x}_i(t)$ and, for the non-top story, $\ddot{x}_{i+1}(t)$); 2) it gives the smallest performance index value in Eq. (10)

$$J[y_k] = \int_0^\infty \left| W(j\omega_l) / S_{(\ddot{x}_i - \ddot{x}_{i-1})y_k,l} \right|^2 d\omega_l \tag{10}$$

where $W(j\omega_l) = [k_i/(m_i\omega_l^2)]^2 / [1 - jc_i/(m_i\omega_l) - k_i/(m_i\omega_l^2)]^4$ is a frequency weighting function, which is very large in magnitude near frequency ω_{i0} and very small when away from that frequency.

The first condition is to ensure that the measurement uncertainty terms ($i.e., N_{\ddot{x}_j y,l} / S_{(\ddot{x}_i - \ddot{x}_{i-1})y,l} \quad j \in [i-1, i, i+1]$) are zero-mean; the second condition is to amplify response $S_{(\ddot{x}_i - \ddot{x}_{i-1})y,l}$ as large as possible near frequency ω_{i0} and, thus, improve the identification accuracy (because when there is one excitation applying to the structure, the CPSD ratio $S_{(\ddot{x}_{i+1} - \ddot{x}_i)y,l} / S_{(\ddot{x}_i - \ddot{x}_{i-1})y,l}$, affecting the accumulation error, will be unchanged for the choice of reference $y(t)$; consequently, the selection of reference $y(t)$ only needs to amplify response $S_{(\ddot{x}_i - \ddot{x}_{i-1})y,l}$ near frequency ω_{i0}). For more detailed discussion about the reference selection rule, readers may refer to the author's previous work [10].

A numerical example

A 6-story shear structure excited by ground motion is used herein to verify the effectiveness of the proposed substructure identification method. The parameters of the structure are chosen to be $m_i = 1\times10^5$ kg, $c_i = 8\times10^5$ N·sec/m, $k_i = 16\times10^7$ N/m (i = 1, …, 6). The ground excitation $\ddot{u}_g$ is generated by a white Gaussian random process passed through a 4-th order low-pass Butterworth filter with a 12 Hz cut-off frequency. 3,600 seconds of ground and floor acceleration responses, with a sampling rate of 200 Hz, are simulated to carry out substructure identification. To test the effectiveness of the proposed method as would be typical with only ambient excitation source, fairly large measurement noise is added to each true structure response. It is assumed herein that the magnitude of the measurement noise of all acceleration responses is the same, with root-mean-square (rms) magnitude equal to 50% of that of the ground excitation.

To examine the effect of choosing different reference responses $y(t)$ on the identification accuracy, two scenarios are considered here. (1) For each step of the substructure identification, $y(t)$ is selected among the measurement floor accelerations and ground acceleration, using the selection rule given previously. (2) $y(t)$ is fixed as the top story acceleration for all story substructure identifications. The MATLAB® command `cpsd` is used to calculated the CPSDs between the reference response $y(t)$ and structural acceleration responses $\ddot{x}_j$. In both scenarios, the total structural responses are equally divided into frames of 30 second duration. A Hanning window is applied to each frame to reduce the effect of leakage when calculating CPSD. The measurement noise is also assumed to band limited Gaussian white noise with a 200 Hz cut-off frequency.

To verify that the proposed identification method works consistently well, 100 identification tests are performed. The statistics of the identification results of both scenarios are listed in Table 1 and Table 2. From the results, it can be seen that by using the smart selection method (scenario 1), the proposed substructure identification method can offer very accurate results in spite of fairly large measurement noise (50%). The largest relative root-mean-square-error (RMSE) of all story stiffnesses is just 1.45%; even for the damping parameters, which are usually difficult to identify, the largest relative RMSE is only 5.8%. However, if the reference response is the roof acceleration as in scenario 2, the reference will involved in the substructure identification of 5th and 6th story parameters, resulting in biased estimation of the CPSDs used in the identification and, thus, biased identified parameters.

Table 1. Statistics of relative identification errors in percentage (scenario 1).

floor #	reference $y(t)$	Story stiffness		Story damping	
		mean	RMSE	mean	RMSE
1	$\ddot{x}_3$	-0.23	0.90	2.15	4.39
2	$\ddot{u}_g$	0.02	0.56	0.60	3.20
3	$\ddot{u}_g$	-0.14	0.60	0.31	3.02
4	$\ddot{u}_g$	-0.18	1.46	-1.14	5.80
5	$\ddot{u}_g$	0.01	0.40	-0.20	2.17
6	$\ddot{u}_g$	0.05	0.25	-0.0	1.38

Table 2. Statistics of relative identification errors in percentage (scenario 2).

floor #	reference $y(t)$	Story stiffness		Story damping	
		mean	RMSE	mean	RMSE
1	$\ddot{x}_6$	-0.98	1.79	15.47	19.91
2	$\ddot{x}_6$	-2.36	3.20	3.84	7.14
3	$\ddot{x}_6$	-2.95	3.75	-4.81	8.99
4	$\ddot{x}_6$	2.03	3.69	-31.89	40.61
5	$\ddot{x}_6$	5.61	5.63	-1.30	2.63
6	$\ddot{x}_6$	0.61	0.66	-4.50	4.68

Conclusion

In this paper, a substructure identification method for shear structures is proposed. By utilizing the dynamic equilibrium of each floor, a series of inductive identification problems are formulated, using the CPSD between sub-structural responses and a reference response, to identify the structural stiffness and damping parameters. An identification error analysis, based on the linearization of the identification problem, is performed for the proposed substructure method, showing that the identification error is mainly determined by the measurement uncertainty and upper story parameter uncertainty (for non-top story identification only) near the substructure natural frequency. Based on this result, a smart selection rule is designed to choose the best reference response candidate such that the identification error can be greatly reduced. A 6-story shear building is used to demonstrate that the proposed substructure method can provide very accurate identification results in spite of the disturbance of fairly large noise and that the smart reference response selection proposed herein does make the identification much more accurate.

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