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Structural Parameter Identification of Wind-Excited High-Rise Buildings with Limited Output Measurements

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Abstract: In this paper, an algorithm is proposed for the identification of structural parameters of tall buildings under unknown wind loading with limited measurements of acceleration response outputs. Dynamic wind loading on tall buildings at typical levels is estimated based on the fluctuating properties of wind. A tall building is decomposed into small size substructures based on its finite element formulation. Interconnection effects between adjacent substructures are considered as 'additional unknown inputs' to substructures. For each substructure, the identification algorithm is based on sequential application of extended Kalman estimator for the extended state vector of the substructure and least-squares estimation of its unknown external excitations. It is shown that the 'additional unknown inputs' can be estimated by the algorithm without the measurements of the substructure interface degree-of-freedoms, which is superior to previous substructural identification approaches. The proposed algorithm is straightforward and simpler since it can identify structural parameters and unknown excitations in a sequential manner. To validate the feasibility of the proposed algorithm, structural parameters of a 20-story shear-type building and the unknown wind loading are identified in a numerical example. It is shown that the proposed algorithm is effective.

Keywords: Structural Parameter Identification, Wind Loading, Unknown Inputs, Substructure Approach, Extended Kalman Estimator, Least-squares Estimation

1 Introduction

With the innovations of new technologies, materials and design application, civil engineering structures become more and more light, high and complex, which make structures very sensitive to wind loading. For tall buildings, long-span bridges, high towers and mast structures, wind loading is essential in the structural design. Thus, it is important to explore the dynamic characteristics of wind loading and its effect on the excited large-scale structures. In general, it is difficult to directly measure the external wind loading on a structure in real time, and the response measurement is more accurate. So, identification of time-varying force from measured responses has been the main stream of indirect methods. When a proper wind loading model is assumed and applied to the structure, the wind loading can be identified based on the measurements of the structural responses [1]. Some approaches have been proposed for the identification of wind loading acting on buildings together with the unknown structural parameters based on the measurements of the structure responses, including the displacements, velocities and accelerations at all degrees-of-freedom (DOFs) [2]. However, it's often impossible to deploy so many sensors in order to accurately measure all outputs of systems, and thus it is highly desirable to deploy fewer sensors. In this case, only limited structural response outputs are measured.

Extended Kalman filter (EKF) has been studied and shown to be useful for structural identification with limited response outputs [3,4,5,6], but the traditional EKF approaches require that all excitation inputs are measured or available. Recently, Yang et al. proposed an extended Kalman filter with unknown excitation inputs, referred as EKF-UI, for the identification of structural parameters as well as the unmeasured excitation inputs [7]. But the analytical recursive solutions by the EKF-UI are obtained with rather complex mathematical

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derivations since the unknown excitation and structural parameters are identified simultaneously. Identification of structural parameters without excitation information has also been explored by some researchers [8,9,10,11,12,13,14]. However, assumptions are adopted in these approaches that information of structural displacement and velocity response signals are available or can be obtained through integration of measured acceleration responses. In practice, dynamic responses are usually measured by accelerometers, and error is incurred in obtaining velocity and displacement signals by integration. Hence, acceleration signal is preferred to velocity and displacement signals.

Identification of tall building with a large number of unknown parameters is more difficult due to ill-condition and computation convergence problems [15]. In addition, along with the size of a structural system increases, its computational efforts increase tremendously [16]. Therefore, substructural identification approaches, in which a large size structure is decomposed into several small size substructures with fewer DOFs and unknown parameters [15,17,18], have been proposed. Interaction effects between adjacent substructures are accounted by interaction forces at the interfaces between adjacent substructures [19,20,21,22]. However, previous substructural identification approaches require that measurements of all response signals at the substructure interface DOFs are available. Although the aforementioned EKF-UI algorithm can identify the unmeasured excitation inputs of the structure, it still requires deploying sensors and measuring all DOFs of responses at the substructure interface for identification of the interaction forces as the EKF-UI is based on a Kalman filter approach. In practice, it is often impossible to measure all responses at the interface DOFs between substructures, e.g., it's very difficult to measure the rotational DOFs at the substructure interfaces.

In this paper, an algorithm is proposed for the identification of structural parameters of tall buildings and the unknown wind loading with limited measurements of acceleration response outputs. Dynamic wind loading on the structure at typical levels is simulated based on the fluctuating properties of wind. A tall building is decomposed into small size substructures based on its finite element formulation. Interconnection effects between adjacent substructures are considered as 'additional unknown inputs' to substructure. An algorithm is proposed based on sequential application of extended Kalman estimator for the extended state vector of the substructure and least-squares estimation of its unknown external excitations. A numerical example of identification of a 20-story shear building subject to unknown wind loading is used to demonstrate the proposed algorithm.

2 Dynamic Wind Loading

The longitudinal wind loading is considered in the following analysis by neglecting the transverse and vertical wind loading components. The wind speed at level z above the ground, $v(z,t)$ can be written as [2]:

$$v(z,t) = \bar{v}(z) + v_f(z,t) \tag{1}$$

Where $\bar{v}(z)$ and $v_f(z,t)$ denote the average wind speed and fluctuating wind speed, respectively. Then, wind pressure on the structure at level z can be written as

$$\omega(z,t) = \frac{1}{2}\rho\mu_s(z)v^2(z,t) \tag{2}$$

Where ρ is the density of air, $\mu_s(z)$ is the drag coefficient of the structure at level z. Substituting Eq. (1) into Eq. (2) yields

$$\begin{aligned} \omega(z,t) &= \bar{\omega}(z) + \omega_f(z,t) = \bar{\omega}(z)[1+2\frac{v_f(z,t)}{\bar{v}(z)}] \\ &= \mu_s(z)\mu_z(z)\omega_0[1+2\frac{v_f(z,t)}{\bar{v}(z)}] \end{aligned} \tag{3}$$

where $\bar{\omega}(z)$ is the average wind pressure on the structure at level z, $\mu_z(z)$ is the wind pressure altitude change coefficient on the structure at level z; ω_0 is the wind pressure at 10m. Then the wind loading $P(z,t)$ on the structure at level z can be written as

$$\begin{aligned} P(z,t) &= A_z\mu_s(z)\mu_z(z)[1+2\frac{v_f(z,t)}{\bar{v}(z)}]\omega_0 \\ &= J(z)[1+2\beta v_f(t)]\omega_0 \end{aligned} \tag{4}$$

where A_z is the orthogonal exposed wind area at level $z, \beta = \frac{v_f(z,t)}{\bar{v}(z)}$ is a quotient of the max fluctuating wind speed and the average wind speed, $J(z) = A_z\mu_s(z)\mu_z(z)$, $v_f(t)$ is a stationary random process and it can be simulated by using the trigonometric series method, it can be written as [23].

$$v_f(t) = a_k\sum_{k=1}^{N}\sin(\omega_k + \phi_k) \tag{5}$$

where a_k is a Gaussian random variable which the average value is 0 and standard deviation is σ_x, ϕ_k is statistically independent random variable uniformly distributed between 0 and $2\pi, \omega_k = \omega_l + (k-\frac{1}{2})\Delta\omega, \omega_l$ is the limit of frequency ω, N is the total number of sampling frequencies, $\Delta\omega = \frac{(\omega_u - \omega_l)}{N}$ and ω_u is the limit on of frequency ω. Assume that ρ_l is fluctuating wind related length coefficient, for example, $\rho_l = 3$ is said that three levels of fluctuating wind is completely related [2].

Because the influence of the structure of fluctuating wind is far outweighing its average wind, the dynamic wind loading is only consider the fluctuating wind. The fluctuating wind load can be written as

$$w(z,t) = 2J(z)\beta v_f(t)\omega_0 = J(z)w(t) \tag{6}$$

where $w(t)$ is the fluctuating wind load only related with time. Thus, dynamic wind loading on tall buildings at typical levels is estimated based on the above fluctuating properties of wind.

3 Identification Algorithm for Unknown Structural Parameters and Wind Loading

Based on the finite element model, the equation of motion of a tall building structure under unknown wind loading can be written as

$$\boldsymbol{M}\ddot{\boldsymbol{x}}(t)+\boldsymbol{C}\dot{\boldsymbol{x}}(t)+\boldsymbol{K}\boldsymbol{x}(t)=\boldsymbol{B}\boldsymbol{w}(t) \tag{7}$$

in which $\boldsymbol{x}(t),\dot{\boldsymbol{x}}(t)$ and $\ddot{\boldsymbol{x}}(t)$ are vectors of displacement, velocity and acceleration response of the structure, respectively; $\boldsymbol{M},\boldsymbol{C}$ and $\boldsymbol{K}$ are the mass, damping and stiffness matrices of the structure, respectively; $\boldsymbol{w}(t)$ is a vector of the stationary random process of unknown wind loading; and $\boldsymbol{B}$ is the influence matrices associated with $\boldsymbol{w}(t)$. Usually, the mass of a structural system can be estimated accurately based on its geometry and material information. For simplicity, it is assumed that the mass matrix M is a diagonal matrix.

3.1 Substructure Approach

A tall building structure involves a large number of DOFs. To reduce the number of DOFs, the large-scale structure can be divided into a set of small size substructures based on its finite-element model. The equation of motion of a substructure concerned can be extracted from the equation of motion of the whole structure, Eq. (7), to yield

$$\boldsymbol{M}_{rr}\ddot{\boldsymbol{x}}_r(t)+[\boldsymbol{C}_{rr}\boldsymbol{C}_{rs}]\begin{bmatrix}\dot{\boldsymbol{x}}_r(t)\\ \dot{\boldsymbol{x}}_s(t)\end{bmatrix}+[\boldsymbol{K}_{rr}\boldsymbol{K}_{rs}]\begin{bmatrix}\boldsymbol{x}_r(t)\\ \boldsymbol{x}_s(t)\end{bmatrix}=\boldsymbol{B}_r\boldsymbol{w}_r(t) \tag{8}$$

where subscript 'r' denotes internal DOFs of the substructure concerned, subscript 's' denotes interface DOFs. Treating the inter-connection effects as 'additional unknown inputs' to the focused substructure, the above equation can be re-arranged as

$$\boldsymbol{M}_{rr}\ddot{\boldsymbol{x}}_r(t)+\boldsymbol{C}_{rr}\dot{\boldsymbol{x}}_r(t)+\boldsymbol{K}_{rr}\boldsymbol{x}_r(t)=\boldsymbol{B}_r\boldsymbol{w}_r(t)+\boldsymbol{B}_r^*\boldsymbol{f}_r^*(t) \tag{9}$$

where $\boldsymbol{f}_r^*(t)$ is the s-'unknown input' vector at the substructure interface, $\boldsymbol{B}_r^*$ is the influence matrix associated with the 'unknown inputs' $\boldsymbol{f}_r^*(t)$, and

$$\boldsymbol{B}_r^*\boldsymbol{f}_r^*(t)=-\boldsymbol{C}_{rs}\dot{\boldsymbol{x}}_s(t)-\boldsymbol{K}_{rs}\boldsymbol{x}_s(t) \tag{10}$$

Therefore, the substructure is excited by both the unmeasured external wind loading $\boldsymbol{w}_r(t)$ and the 'additional unknown inputs' $\boldsymbol{f}_r^*(t)$ due to substructure inter-connection.

3.2 Extended Kalman Estimator

Introducing an extended state vector $\boldsymbol{X}_r=[\boldsymbol{x}_r,\dot{x}_r,\boldsymbol{\theta}_r]^T$, in which $\boldsymbol{\theta}_r$ is a vector of the n-unknown structural parameters, such as damping and stiffness parameters, one can transform Eq. (9) into a state equation as:

$$\dot{\boldsymbol{X}}_r=\begin{Bmatrix}\dot{\boldsymbol{x}}_r\\ \boldsymbol{M}_r^{-1}\begin{bmatrix}\boldsymbol{B}_r\boldsymbol{w}_r(t)+\boldsymbol{B}_r^*\boldsymbol{f}_r^*(t)-\\ (\boldsymbol{C}_{rr})_{\boldsymbol{\theta}_r}\dot{\boldsymbol{x}}_r-(\boldsymbol{K}_{rr})_{\boldsymbol{\theta}_r}\boldsymbol{x}_r\end{bmatrix}\\ \boldsymbol{0}\end{Bmatrix} \tag{11}$$

In which, $(\boldsymbol{C}_{rr})_{\boldsymbol{\theta}_r}$ represents that elements in the damping matrix $\boldsymbol{C}_{rr}$ are composed by the unknown parameters of damping in the parametric vector $\boldsymbol{\theta}_r,(\boldsymbol{K}_{rr})_{\boldsymbol{\theta}_r}$ represents the constitution of stiffness matrix $\boldsymbol{K}_{rr}$ analogously. As observed from Eq. (11), the extended state equation is a nonlinear equation of the extended state vector $\boldsymbol{X}_r$. Thus, Eq. (11) can be rewritten in the following general nonlinear differential state equation as:

$$\dot{\boldsymbol{X}}_r=\boldsymbol{g}_r(\boldsymbol{X}_r,\boldsymbol{w}_r,\boldsymbol{f}_r^*) \tag{12}$$

Some sensors are deployed on the substructure to measure the response signals. Usually acceleration signals are measured and the observation vector of the focused substructure can be expressed in the discretized form as

$$\begin{aligned}\boldsymbol{y}_r[k]&=\boldsymbol{D}_r\ddot{\boldsymbol{x}}_r[k]+\boldsymbol{v}_r[k]\\ &=\boldsymbol{h_r}(\boldsymbol{X}_r[k],\boldsymbol{f}_r^*[k])+\boldsymbol{G}_r\boldsymbol{w}_r[k]+\boldsymbol{v}_r[k]\end{aligned} \tag{13}$$

where,

$$\begin{aligned}&\boldsymbol{h}_r(\boldsymbol{X}_r[k],\boldsymbol{f}_r^*[k])=\\ &\boldsymbol{D}_r\boldsymbol{M}_r^{-1}\{\boldsymbol{B}_r^*\boldsymbol{f}_r^*[k]-(\boldsymbol{C}_{rr})_{\theta_r}\dot{\boldsymbol{x}}_r[k]-(\boldsymbol{K}_{rr})_{\theta_r}\boldsymbol{x}_r[k]\}\end{aligned} \tag{14}$$

$\boldsymbol{D}_r$ is the matrix associated with the locations of accelerometers, $\boldsymbol{G}_r=\boldsymbol{D}_r\boldsymbol{M}_r^{-1}\boldsymbol{B}_r$, and $\boldsymbol{v}_r[k]$ is the measured noise vector.

Based on the extended Kalman estimator [24,25], the extended state vector at time $t=(k+1)\times\Delta t$ can be estimated with the observation of $(\boldsymbol{y}_r[1],\boldsymbol{y}_r[2],\ldots,\boldsymbol{y}_r[k])$ as follows:

$$\begin{aligned}&\hat{\boldsymbol{X}}_r[k+1|k]=\tilde{X}_r[k+1|k]\\ &+\boldsymbol{K}_r[k]\begin{Bmatrix}\boldsymbol{y}_r[k]-h_r\left(\hat{\boldsymbol{X}}_r[k|k-1],\hat{\boldsymbol{f}}_r^*[k|k-1]\right)\\ -\boldsymbol{G}_r\hat{\boldsymbol{w}}[k|k]\end{Bmatrix}\end{aligned} \tag{15}$$

in which,

$$\tilde{X}_r[k+1|k]=\hat{\boldsymbol{X}}_r[k|k-1]+\int_{t[k]}^{t[k+1]}\boldsymbol{g}_r(\boldsymbol{X}_r,\boldsymbol{w}_r,\boldsymbol{f}_r^*)dt \tag{16}$$

where $\hat{\boldsymbol{X}}_r[k+1|k]$ and $\hat{\boldsymbol{w}}[k|k]$ are the estimation of $\boldsymbol{X}_r[k+1]$ and $\boldsymbol{w}[k]$ given $(\boldsymbol{y}[1],\boldsymbol{y}[2],\ldots,\boldsymbol{y}[k])$, respectively and $\boldsymbol{K}[k]$ is the Kalman gain matrix [22,24]:

However, since the wind loading $\boldsymbol{w}_r(t)$ and the 'additional unknown inputs' $\boldsymbol{f}_r^*(t)$ due to substructure inter-connection are unknown, it is impossible to obtain the recursive solution for the extended state vector by the classical extended Kalman estimator alone.

3.3 Estimation of Unknown Excitation Inputs

As shown by the extended Kalman estimator, the extended state vector of the focused substructure at time $t=(k+1)\times\Delta t$ can be estimated given the observation signal $(\boldsymbol{y}_r[1],\boldsymbol{y}_r[2],\ldots,\boldsymbol{y}_r[k])$ and the unknown excitations at time $t=k\times\Delta t$. Then, it is possible to estimate the 'additional unknown inputs' $\boldsymbol{f}_r^*$ at time $t=(k+1)\times\Delta t$ based on their formulations in Eq. (10), i.e.,

$$\begin{aligned}\boldsymbol{B}_r^*\hat{\boldsymbol{f}}_r^*[k+1|k] = &-\hat{\boldsymbol{C}}_{rs}[k+1|k]\hat{\dot{\boldsymbol{x}}}_s[k+1|k]\\ &-\hat{\boldsymbol{K}}_{rs}[k+1|k]\hat{\boldsymbol{x}}_s[k+1|k]\end{aligned} \tag{17}$$

where $\hat{\boldsymbol{x}}_s[k+1|k]$ and $\hat{\dot{\boldsymbol{x}}}_s[k+1|k]$ are the estimation values of corresponding state vectors at the interface DOFs, $\hat{\boldsymbol{C}}_{rs}[k+1|k]$ and $\hat{\boldsymbol{K}}_{rs}[k+1|k]$ can be constructed by the estimated values of structural parameters from the finite element model of the structure.

In the proposed algorithm based extended Kalman estimator, recursive solutions for the extended state vector of each substructure is initially obtained with the observation signals and unknown excitation values at a former time instant, followed by the estimation of unknown excitation values. Due to this superiority, the 'additional unknown inputs' to each substructure can be estimated based on the formulation of 'additional unknown inputs' without all measurement signals on the substructure interfaces.

From Eq. (13), it is noted that the observation vector, such as the acceleration measurement, is a linear function of external wind loading $\boldsymbol{w}_r(t)$. Under the conditions that the number of output measurements is greater than that of the unknown excitations, the unknown external excitations at time $t=(k+1)\times\Delta t$ can be estimated from Eq. (13) by least -squares estimation as:

$$\begin{aligned}&\hat{\boldsymbol{w}}_r[k+1|k+1] = [(\boldsymbol{G}_r)^T\boldsymbol{G}_r]^{-1}(\boldsymbol{G}_r)^T\\ &\left\{\boldsymbol{y}_r[k+1]-\boldsymbol{h}_r\left(\hat{\boldsymbol{X}}[k+1|k],\boldsymbol{f}_r^*[k+1]\right)\right\}\end{aligned} \tag{18}$$

in which, $\hat{\boldsymbol{w}}_r[k+1|k+1]$ is the estimation of $\boldsymbol{w}_r[k+1]$ given the observation of $(\boldsymbol{y}[1],\boldsymbol{y}[2],\ldots,\boldsymbol{y}[k+1])$.

So, the proposed algorithm can identify structural parameters and unknown excitation in a sequential manner, which simplifies the identification problem and reduce both computational effort and storages compared with other existing work. Based on the proposed algorithm, identification of substructures of a tall building structural system and unknown wind loading can be conducted concurrently with parallel computing; however, signal transmission between adjacent substructures is needed for estimating the inter-connection forces.

4 Numerical Example

As shown by Figure 1, a numerical example of identification of a 20-story shear building subject to unknown wind loading is used to demonstrate the proposed algorithm.

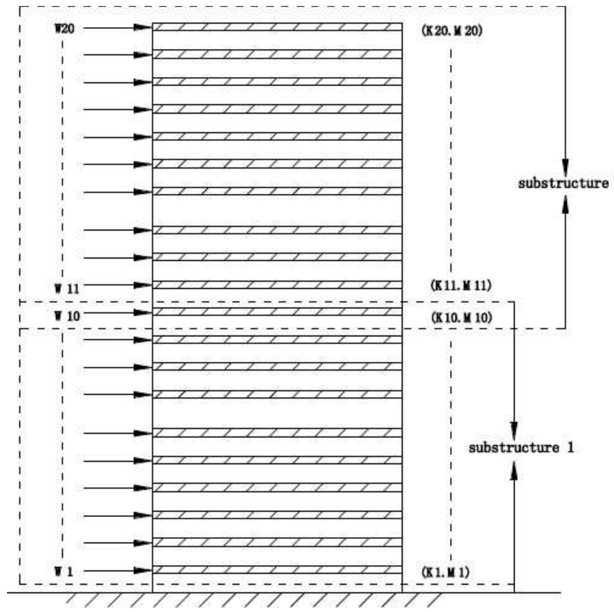


Fig. 1: The model of a 20-story shear building.

Wind loading is simulated based on the procedures in section 2. In the numerical example, the time step of date is 0.001s. The mean wind velocity at 10 m above the ground is chosen to be 15 m/sec. The landscape level is B, the density of air ρ is taken as 1.25kg/m^3. And $\rho_l=20$. The qualities and stiffness of each story of the building are assumed to be the same with floor mass M = 5000 kg and the floor stiffness $K=1.2\times105$ N/m, each story is 3m high.

Rayleigh damping assumption is employed and the damping matrix is assumed as

$$\boldsymbol{C}=\alpha\boldsymbol{M}+\beta\boldsymbol{K} \tag{19}$$

In the substructure approach, the building is divided into two substructures with floor 1-10 being the 1st substructure and floor 10-20 being the second one, as shown by Figure 2.

In the 1st substructure, accelerometers are installed at 1st, 3rd, 4th, 6th, 7th, 8th and 9th floors. In the 2nd substructure, accelerometers are installed at 10th, 11th, 13th, 14th, 15th, 16th, 17th, 18th and 20th floors. In the 1st substructure, accelerometers are not installed at 2nd and 10th floors; in the 2nd substructure, accelerometers are not installed at 12th and 19th. Thus, only limited acceleration responses are measured and the responses at the two substructural interface DOFs are not all available.

Based on the proposed algorithm, structural responses, structural parameters and the unknown wind loading can be identified with parallel computation. The influence of measurement noise on the results of system identification and damage detection is considered by

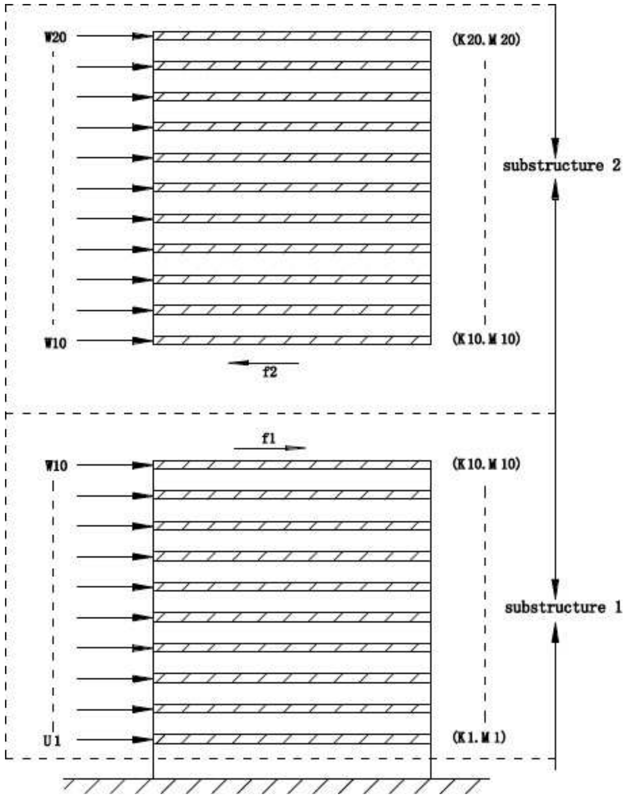


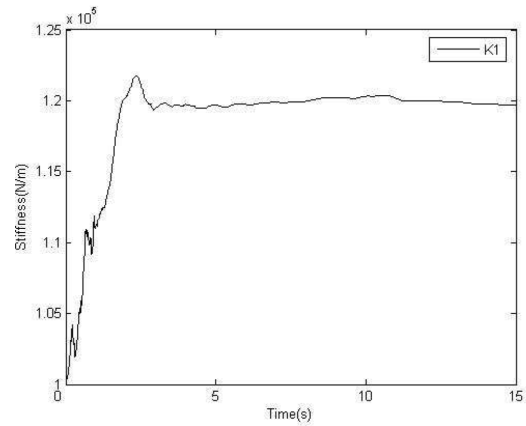
Fig. 2: The model of substructure with“unknown inputs”.

Table 1: Identified structural stiffness parameters and relative errors

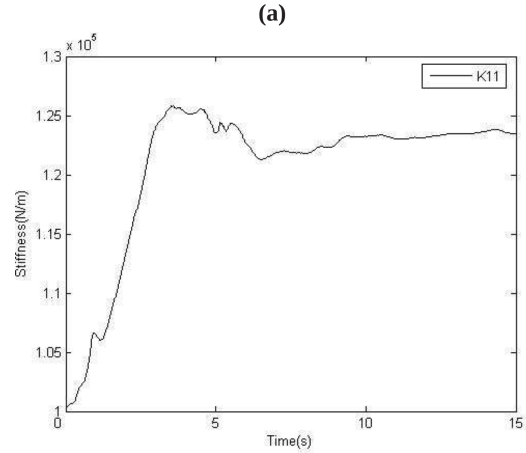
stiffness parameter	without noise		5% noise	
	recognition value ($\times 10^5$ N/m)	error (%)	recognition value ($\times 10^5$ N/m)	error (%)
k_1	1.2004	0.033	1.2011	0.094
k_1	1.2011	0.095	1.1950	−0.416
k_3	1.2014	0.115	1.2029	0.242
k_4	1.2023	0.194	1.1944	−0.464
k_5	1.2005	0.039	1.2016	0.132
k_6	1.2102	0.853	1.2095	0.794
k_7	1.1996	−0.030	1.1997	−0.021
k_8	1.1798	−1.682	1.1806	−1.618
k_9	1.1608	−3.264	1.1784	−1.800
k_{10}	1.1865	−1.124	1.1898	−0.849
k_{11}	1.1786	−1.781	1.1699	−2.509
k_{12}	1.2279	2.326	1.2144	1.198
k_{13}	1.2191	1.588	1.2139	1.155
k_{14}	1.2342	2.848	1.2167	1.393
k_{15}	1.2199	1.660	1.2136	1.137
k_{16}	1.2283	2.356	1.2314	2.614
k_{17}	1.2143	1.196	1.2031	0.261
k_{18}	1.1979	−0.174	1.1942	−0.486
k_{19}	1.1937	−0.529	1.1890	−0.913
k_{20}	1.1734	−2.217	1.1650	−2.919

superimposition of noise process with the theoretically computed response quantities. In this example, all the measured acceleration responses are simulated by the theoretically computed responses superimposed with the corresponding white noise with 5% noise- to- signal ratio in root mean square (RMS). Structural parameters are identified in the case without noise and with 5% noise in measured structural responses.

In Figures 3(a)-3(b), convergences of the identified stiffness k_1 in the 1st substructure and k_{11} in the 2nd substructure are shown as dashed line. It can be seen from this figure that the identified stiffness parameter converges very fast.



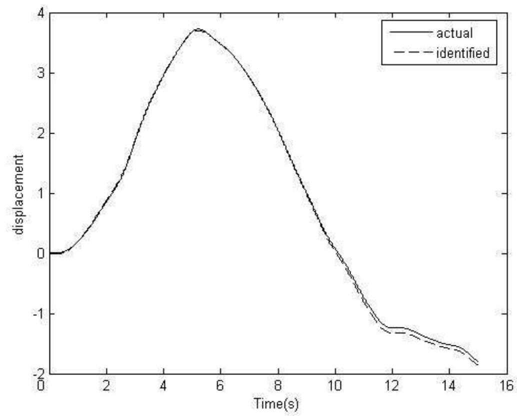
(a)



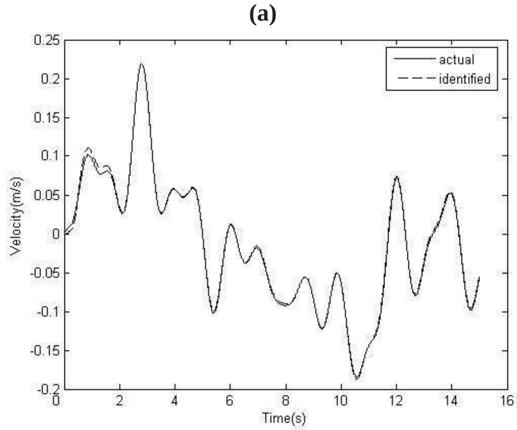
(b)

Fig. 3: (a). Convergences of the identified stiffness k_1 (b). Convergences of the identified stiffness k_{11}.

For clarity of comparisons, the identified displacement and velocity responses of the 1 floor in 1st substructure for a segment from 0.0 to 15s are presented in Figure 4(a) and Figure 4(b) as dashed curves, respectively, while the corresponding actual results are also shown as solid curves in these two figures. From these comparisons, it is shown that displacement and velocity responses can be identified by the proposed algorithm, which ensures the identification of inter-connection effect between adjacent substructures.



(a)



(b)

Fig. 4: (a). The identified displacement of the 1st floor (b). The identified displacement of the 1st floor.

Both of the identified stiffness parameters and relative errors to real ones are listed in Table 1. It can be found that the errors are small even in the case with 5% noise. The results indicate that the identified structural stiffness parameters have a good accuracy. Furthermore, the wind loading identified from the case with 5% noise is compared with the true one and shown in Figure 5. In the figure, “identified results1” and “identified results 2” are identified from the first and the second substructure, respectively. The results of identified wind loading in the case with 5% noise can fit the real wind loading quite well.

5 Conclusions

In this paper, an algorithm is proposed for the identification of structural parameters of tall buildings and the unknown excitation wind loadings with limited output measurements. Based on the substructure approach, a tall building is decomposed into small size substructures. Inter-connection effect between adjacent substructures is considered as ‘additional unknown inputs’ to each substructure. The proposed algorithm is based on sequential estimation of the extended state vector by the extended Kalman estimation and least squares estimation for the unknown inputs. It can identify structural parameters and unknown excitation in a sequential manner, which simplifies the identification problem compared with other available algorithms. Also, the proposed technique can estimate the ‘additional unknown inputs’ without all measurement signals at the substructure interface.

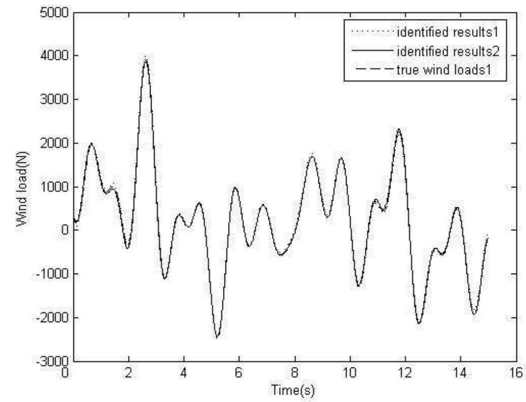


Fig. 5: The results of identified wind loadings.

Identification of the structural parameters of a 20-story shear-type building and the unknown excitation wind loading with limited measurements of acceleration responses demonstrates that the proposed algorithm can identify tall building parameters and the unknown wind loading with good accuracy.

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References

[1] S S Law, J Q Bu and X Q Zhu. Time-varying wind load identification from structural responses. Engineering Structures. Vol.27, (2005), 1586-1598.
[2] J Chen and J Li. Study on the inverse wind load identification of tall building. Chinese Quarterly of Mechanics. Vol.22, No.1, (2001), 72-77(in Chinese).
[3] M Hoshiya, E Saito. Structural identification by extended Kalman filter. Journal of Engineering Mechanics (ASCE). Vol.110, No.12, (1984), 1757–1771.
[4] O Maruyama, M Hoshiya. System identification of an experimental model by extended Kalman filter. Proceedings of the Structural Safety and Reliability, ICOSSA 2001[C]. Swet & Zeitinger: Lisse 7 (2001).
[5] C D Petersena, R Fraanjeb, B S Cazzolatoa, A C Zandera, C H Hansen. A Kalman filter approach to virtual sensing for active noise control. Mechanical Systems and Signal Processing. Vol.22, (2008), 490–508.

[6] J N Yang, S Lin, H W Huang and L Zhou. An adaptive extended Kalman filter for structural damage identification. Journal of Structural Control and Health Monitoring. Vol.13, No.4, (2006), 849–867.

[7] J N Yang, S W Pan, H W Huang. An adaptive extended Kalman filter for structural damage identification II: unknown inputs. Journal of Structural Control and Health Monitoring. Vol.14, No.3, (2007), 497–521.

[8] J N Yang, S W Pan, S L Lin. Least square estimation with unknown excitations for damage identification of structures. Journal of Engineering Mechanics (ASCE). Vol.133, No.1, (2007), 12–21.

[9] X L Ling, A Haldar. Element Level System Identification with Unknown Input with Rayleigh Damping. Journal of Engineering Mechanics (ASCE). Vol.130, No.8, (2004), 877–885.

[10] H Kathuda, R Martinez, A Haldar. Health Assessment at local level with unknown input excitation. Journal of Engineering Mechanics (ASCE). Vol.131, No.6, (2005), 956-965.

[11] Y Lei, J Y Lei, Y Song. Element level structural damage detection with limited observations and with unknown inputs. Proceedings of SPIE's Conference on Health Monitoring of Structural and Biological Systems. Vol.6532, (2007), 65321X1-X9

[12] X Zhao, Y L Xu, J Chen, J Li. Hybrid Identification method for Multi-story Buildings with Unknown Ground Motion: theory. Journal of Sound and Vibration. Vol.291, (2006), 215-239

[13] M A Demetriou. Using unknown input observers for robust adaptive fault detection in vector second-order systems. Mechanical Systems and Signal Processing. Vol.19, (2005), 291-309.

[14] D Wang, A Haldar. System identification with limited observations and without input. Journal of Engineering Mechanics (ASCE). Vol.123, No.5, (1997), 504–511.

[15] C G Koh, L M See, Balendra T. Estimation of structural parameters in time domain: a substructure approach. Earthquake Engineering and Structural Dynamics. Vol.20, No.8, (1991), 787–801

[16] C G Koh, B Hong, C Y Liaw. Substructural and progressive structural identification method. Engineering Structures. Vol.25, (2003), 1551-1563.

[17] P Sjövall, T Arahamsson. Substructure system identification from coupled system test data. Mechanical Systems and Signal Processing. Vol.22, (2008), 15-33.

[18] K F Tee, C G Koh, S T Quek. Substructural first- and second-order model identification for structural damage assessment. Earthquake Engineering and Structural Dynamics. Vol.34, (2005), 1755-1775.

[19] B Xu. Time Domain Substructural Post-earthquake Damage Diagnosis Methodology with Neural Networks. Lecture Note in Computer Science. Vol.3611, (2005), 520-529.

[20] W D Ambrogio, A Fregolent. The role of interface DOFs in decoupling of substructures based on the dual domain decomposition. Mechanical Systems and Signal Processing. Vol.24, (2010), 2035-2048.

[21] C Gontier, M Bensaibi. Time domain identification of a substructure from in situ analysis of the whole structure. Mechanical Systems and Signal Processing. Vol.9, NO.4, (1995), 379-396.

[22] J N Yang, H W Huang. Substructure damage identification using a damage tracking technique. Proceedings of SPIE's Conference on sensors and Smart Structures Technologies for Civil, Mechanical, and Aerospace Systems. Vol. 6529, (2007), 6529R1-R10.

[23] X T Zhang. Structure wind engineering. China architecture & building press. (2006), 168-170(in Chinese).

[24] P Kettle, A Murray and F Moynihan. Moynihan Sensor less Control of a Brushless DC motor using an Extended Kalman estimator. Proceedings of PCIM'98 Intelligent Monitoring. (1998), 385-392.

[25] C S Hsieh, F C Chen. Optimal Solution of the Two-Stage Kalman Estimator. IEEE Transactions on Automatic Control. Vol.44, No.1, (1999), 194-199.

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