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Operational modal analysis of Canton tower using a Bayesian method

Feng-Liang Zhang[1)], Yi-Qing Ni[2)] and Yan-Chun Ni[3)]*

[1)3)]*Research Institute of Structural Engineering and Disaster Reduction, Tongji University, 1239 Siping Road, Shanghai, China*
[1)] *fengliangzhang@tongji.edu.cn;* [3)]*yanchunni@gmail.com (*corresponding author)*
[2)]*Department of Civil and Environmental Engineering, The Hong Kong Polytechnic University, Hung Hom, Hong Kong*
[2)] *ceyqni@polyu.edu.hk*

ABSTRACT

Canton TV Tower is a high-rise slender structure with the height of 610 m. A structural health monitoring system has been instrumented on this structure, by which continuous data is measured. This paper presents the investigation on the identified modal properties of Canton TV Tower using ambient vibration data collected during a whole day (24 hours) based on a Benchmark problem. A recently developed fast Bayesian method is used for operational modal analysis based on the measured acceleration data. The approach views modal identification as an inference problem where probability is used as a measure for the relative plausibility of outcomes given a model of the structure and measured data. Focusing on the first several modes, the modal properties of the high-rise slender structure are identified on non-overlapping time windows during the whole day under norm wind speed. By defining the modal root-mean-square value using the power spectral density of modal force identified, the identified natural frequencies and damping ratios versus the vibration amplitude are investigated with the associated posterior uncertainty considered. Meanwhile, the relationships between modal parameters and temperature, modal parameters and wind speed are also studied.

1. INTRODUCTION

Structural health monitoring (SHM) has attracted increasing attention in the past few decades (Brownjohn 2005; Chang 2003; Sohn 2003;Ko 2005; Ni 2009; Yuen 2010; Ni 2011; Au 2013). For some large-scale structures, such as super tall buildings, long-span bridges, a SHM system is usually instrumented to perform real-time monitoring and provide valuable information for the evaluation of the structural performance. In the system, accelerometers play an important role in measuring the dynamic response of the subjected structures (Ni 2009; Au 2013). Based on the acceleration response collected, operational modal analysis can be conducted to identify the modal properties, i.e., natural frequency, damping ratio and mode shape. Many methods have been developed to perform operational modal analysis, among which, fast Bayesian FFT (fast Fourier Transform) method (Au 2011; Au 2012a; Au 2012b; Zhang 2013) developed recently is becoming popular and has been applied in different structures successfully. The approach views modal identification as an inference problem where probability is used as a measure for the relative plausibility of outcomes given a model of the structure and measured data. Using this method, the most probable value of modal parameters can be identified efficiently. Furthermore, the associated posterior uncertainty of these modal parameters can also be calculated analytically without resorting finite difference, which provide an important tool to evaluate the reliability of the modal properties. The identified modal parameters and their associated posterior uncertainty is significant for the future model updating, damage detection, structural health monitoring, etc.

In a benchmark problem of Canton Tower (Ni 2012; Kuok 2012), 24 hours acceleration, temperature, wind direction and wind speed response are recorded. Based on the Fast Bayesian FFT method, this paper presents the investigation on the operational modal analysis of Canton Tower. Focusing on the first several modes, the modal properties of the high-rise slender structure are identified on non-overlapping time windows during the whole day under norm wind speed. By defining the modal root-mean-square value using the power spectral density of modal force identified, the identified natural frequencies and damping ratios versus the vibration amplitude are investigated with the associated posterior uncertainty considered. Meanwhile, the relationship between the modal parameters and temperature, modal parameters and wind speed are also investigated.

2. CANTON TV TOWER

Canton TV Tower situated in the city of Canton, China, is high-rise slender structure with the height of 610 m. The detail information of the structure can be found in Ni (2012). Based on the design information, a full-order 3D finite element model of the tower is built using ANASYS with 122,476 elements, 84,370 nodes, and 505,164 degrees-of-freedom (DOFs) in total (Ni 2012). To improve the computational efficiency in SHM, a reduced 3D model is developed on the basis of the full model. The dynamic characteristics calculated using two models are consistent with each other and they can be used for the comparison with the modal identification results or further model updating.

A SHM system has been established in this structure with more than 700 sensors instrumented, including level sensors, thermometers, global position system, accelerometers, anemometers, fiber optic sensors and so on (Ni 2009; Chen 2011; Ni 2012). Among those, accelerometers were installed to collect the structural dynamic responses under ambient vibration conditions. There are 20 uni-axial accelerometers in total installed in 8 different sections of this structure. In Sections 4 and 8, four sensors are instrumented with two locations measured bi-axially while for other sections, two sensors are installed to measured two locations. The detail information of the instrumentation can be found in Chen (2011) and Ni (2012). Note that Sensors 01, 03, 05, 07, 08, 11, 13, 15, 17, 18 are used to collect the response in the short-axis of the inner tube and Sensors 02, 04, 06, 09, 10, 12, 14, 16, 19, 20 measure the response in the long-axis of the inner tube. In the benchmark study, 24 hours' acceleration data were collected from 18:00, 20th January 2010 to 18:00, 21th January 2010 under norm wind condition with wind and temperature information recorded simultaneously.

3. FAST BAYESIAN FFT METHED

In ambient modal identification, the loading and the response are modeled as stationary stochastic process. For this purpose, the whole 24 hours' data is divided into non-overlapping time windows of 30 min. It is found that 30-min time window is sufficient to balance between the accuracy in the identified modal parameters and the stationarity assumption in the stochastic wind. If the data is too short, the identified modal parameters may have a larger posterior uncertainty and the MPV may be unreliable. Oppositely, when the data used is too long, the stationary assumption cannot be satisfied well, which may increase the modelling error.

The Fast Bayesian FFT method is used to identify the modal properties with each set of data in 30-minute time window. The theory is outlined in the following. The original formulation can be found in Yuen (2003). For the recently developed fast algorithms that allow practical implementation, refer to Au (2011), Au (2012a), Au (2012b) and Zhang (2013).

The digitally measured acceleration data is modelled to be composed of structural dynamic response and prediction error:

$$\hat{\ddot{\mathbf{x}}}_j = \ddot{\mathbf{x}}_j + \mathbf{e}_j \tag{1}$$

where $\ddot{\mathbf{x}}_j \in R^n$ and $\mathbf{e}_j \in R^n$ (j=1,2,…, N) are the theoretical response a structure and prediction error, respectively; n denotes the number of measured DOFs; N is the number of sampling points. The FFT of $\hat{\ddot{\mathbf{x}}}_j$ is defined as

$$\mathcal{F}_k = \sqrt{\frac{2\Delta t}{N}} \sum_{j=1}^{N} \hat{\ddot{\mathbf{x}}}_j \exp[-2\pi \mathbf{i} \frac{(k-1)(j-1)}{N}] \tag{2}$$

where $\mathbf{i}^2 = -1$; $k = 1,\ldots,N_q$ with $N_q = \text{int}[N/2]+1$, $\text{int}[.]$ is the integer part of its argument; N_q denotes the index that corresponds to the Nyquist frequency; Δt denotes the sampling interval.

Let $\boldsymbol{\theta}$ denote the modal parameters to be identified, which includes natural frequencies, damping ratios, mode shapes, power spectral density (PSD) matrix of modal forces, and PSD of prediction error. Let $\mathbf{Z}_k = [\text{Re}\mathcal{F}_k; \text{Im}\mathcal{F}_k] \in R^{2n}$ denote an augmented vector of the real and imaginary part of $\mathcal{F}_k$. In practice, only the FFT data confined to a selected frequency band dominated by the target modes are used for modal identification. Such collection is denoted by $\{\mathbf{Z}_k\}$. Based on Bayes' Theorem, the posterior probability density function (PDF) of $\boldsymbol{\theta}$ given the data is expressed by:

$$p(\boldsymbol{\theta} \mid \{\mathbf{Z}_k\}) \propto p(\boldsymbol{\theta}) p(\{\mathbf{Z}_k\} \mid \boldsymbol{\theta}) \tag{3}$$

where $p(\boldsymbol{\theta})$ denotes the prior PDF that reflects the plausibility of $\boldsymbol{\theta}$ in the absence of data. Assuming uniform prior information, the posterior PDF $p(\boldsymbol{\theta} \mid \{\mathbf{Z}_k\})$ is proportional to the 'likelihood function' $p(\{\mathbf{Z}_k\} \mid \boldsymbol{\theta})$. The 'most probable value' (MPV) of the modal parameters $\boldsymbol{\theta}$ can be determined by maximizing $p(\boldsymbol{\theta} \mid \{\mathbf{Z}_k\})$ and hence $p(\{\mathbf{Z}_k\} \mid \boldsymbol{\theta})$.

For large N and small Δt, the FFT at different frequencies can be shown to be asymptotically independent and follow a Gaussian distribution (Schoukens 1991; Yuen 2003). The likelihood function $p(\{\mathbf{Z}_k\} \mid \boldsymbol{\theta})$ can be given by:

$$p(\{\mathbf{Z}_k\} \mid \boldsymbol{\theta}) = \prod_k (2\pi)^{-n} (\det \mathbf{C}_k)^{-1/2} \exp[-\frac{1}{2} \mathbf{Z}_k^T \mathbf{C}_k^{-1} \mathbf{Z}_k] \tag{4}$$

where $\det(.)$ is the determinant;

$$\mathbf{C}_k = \frac{1}{2} \begin{bmatrix} \boldsymbol{\Phi} & \\ & \boldsymbol{\Phi} \end{bmatrix} \begin{bmatrix} \operatorname{Re}\mathbf{H}_k & -\operatorname{Im}\mathbf{H}_k \\ \operatorname{Im}\mathbf{H}_k & \operatorname{Re}\mathbf{H}_k \end{bmatrix} \begin{bmatrix} \boldsymbol{\Phi}^T & \\ & \boldsymbol{\Phi}^T \end{bmatrix} + \frac{S_e}{2} \mathbf{I}_{2n} \tag{5}$$

denotes the covariance matrix of $\mathbf{Z}_k$; where $\boldsymbol{\Phi} = [\boldsymbol{\varphi}_1, \boldsymbol{\varphi}_2, ..., \boldsymbol{\varphi}_m] \in R^{n \times m}$ denotes the mode shape matrix; m is the number of modes in a selected frequency band; S_e denotes the PSD of the prediction error; $\mathbf{I}_{2n} \in R^{2n}$ is the identity matrix; $\mathbf{H}_k \in R^{m \times m}$ denotes the transfer matrix and the (i, j) element of this matrix is given by

$$\mathbf{H}_k(i, j) = S_{ij} [(\beta_{ik}^2 - 1) + 2\mathbf{i}\zeta_i \beta_{ik}]^{-1} [(\beta_{jk}^2 - 1) - 2\mathbf{i}\zeta_j \beta_{jk}]^{-1} \tag{6}$$

where $\beta_{ik} = f_i / \mathrm{f}_k$; f_k denotes the FFT frequency abscissa; f_i denotes the natural frequency of the ith mode; ζ_j denotes the damping ratio of the jth mode; S_{ij} denotes the cross spectral density between the ith and jth modal excitation. For analytical and computational purposes, it is convenient to work with the negative log-likelihood function (NLLF) $L(\boldsymbol{\theta})$:

$$L(\boldsymbol{\theta}) = \frac{1}{2} \sum_k [\ln \det \mathbf{C}_k(\boldsymbol{\theta}) + \mathbf{Z}_k{}^T \mathbf{C}_k(\boldsymbol{\theta})^{-1} \mathbf{Z}_k] \tag{7}$$

so that

$$p(\boldsymbol{\theta} \mid \{\mathbf{Z}_k\}) \propto \exp[-L(\boldsymbol{\theta})] \tag{8}$$

By this way, minimizing $L(\boldsymbol{\theta})$ is equivalent to maximizing $p(\boldsymbol{\theta} \mid \{\mathbf{Z}_k\})$.

The MPV of $\boldsymbol{\theta}$ can be determined by numerically minimizing the NLLF. However, the minimization process is ill-conditioned. On the other hand, the computational time grows drastically with the number of measured degree of freedoms. Therefore, in real applications, fast algorithms have been developed recently which allows the MPV to be obtained almost instantaneously in the case of well separated modes (Au 2011; Zhang 2013) and closely-spaced modes (Au 2012a; Au2012b). The posterior uncertainty can also be obtained directly, which makes it possible to assess the accuracy of the MPV and decide if additional data is needed for quality improvement. On the other hand, in the modal identification, for separated or closely-spaced modes cases, a frequency band will be selected. Considering the limited bandwidth in physical processes and the fact that the resonance band accounts for the major contribution, the root-mean-square

(RMS) value of the acceleration response can be calculated according to (Au 2012c), which can be used to represent the vibration level of a given mode.

In the traditional operation modal analysis methods, the power spectral density of modal force is usually assumed to be a constant up to the Nyquist frequency. However, this may be not true in reality, especially for the wind loading. In the fast Bayesian method presented in this work, it is instead assumed that the PSD of modal force in a selected frequency band is a constant, which makes it possible to analyze the data reasonably.

4. ANALYSIS RESULTS

4.1 Typical 30-min window

As aforementioned, the 24 hours data was separated into 48 time windows with 30 min for each. The analysis of a typical time window of data is presented first and the same procedure is applied to other time windows. Figure 1 shows the root power spectral density spectra of the structure, which corresponds to the second half hour of the response. Below 2 Hz, fifteen obvious peaks can be found in the spectrum. The first mode is less than 0.1 Hz, which is the foundational mode of the tower. In the operational modal analysis, all these 15 modes are investigated.

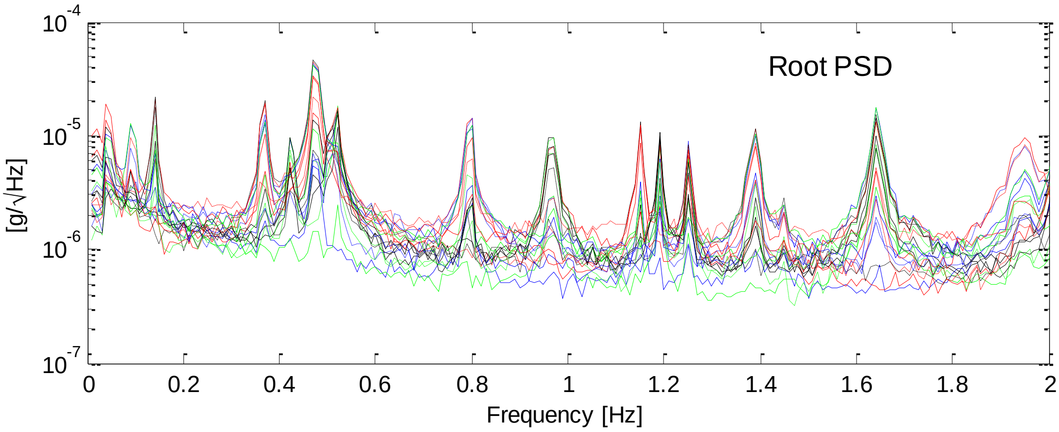

Figure 1 Power spectral density of a typical 30-min window

Table 1 shows the identified modal parameters of the fifteen modes. From the second to the ninth column, every two columns are taken as one group with the first one denoting the MPV and the second one denoting the associated posterior c.o.v. (coefficient of variation=standard derivation/MPV). It is seen that the c.o.v. of natural frequency is quite small (less than 0.5%), implying that the MPVs are quite accurate. The damping ratios for this structure are quite small and only the ones of the first and fourth modes are larger than 1%. This is consistent with the results in Chen (2011) under ambient condition. The posterior uncertainty of damping ratio is relatively high compared with the natural frequency with an order of magnitude of a few tens percent. The other two parameters, i.e., PSD of modal force and PSD of prediction error, are related to the environments around. From the table, the c.o.v. of former are obvious larger than those of latter.

Table 1 Identified modal parameters and the associated posterior uncertainty

Mode	f	cov (%)	Z (%)	cov (%)	S(g^2/Hz)	cov (%)	Se(g^2/Hz)	cov (%)
Mode 1	0.094	0.39	1.28	32.2	1.044	18.7	5.9	5.3
Mode 2	0.138	0.22	0.56	42.3	0.062	27.6	3.9	5.8
Mode 3	0.366	0.08	0.25	32.8	0.210	11.1	1.7	3.8
Mode 4	0.424	0.42	2.16	38.0	0.057	54.5	2.1	5.4
Mode 5	0.475	0.05	0.11	41.9	0.556	11.8	1.7	4.3
Mode 6	0.506	0.03	0.06	70.3	0.006	29.3	9.4	6.5
Mode 7	0.523	0.11	0.50	25.3	0.025	20.0	1.9	5.0
Mode 8	0.796	0.05	0.23	23.2	0.069	7.9	0.8	2.6
Mode 9	0.965	0.10	0.66	17.5	0.005	14.8	0.7	2.5
Mode 10	1.151	0.03	0.13	26.9	0.011	11.7	0.5	3.9
Mode 11	1.191	0.03	0.07	40.5	0.000	26.8	1.0	4.1
Mode 12	1.250	0.03	0.10	28.1	0.003	10.9	0.7	3.2
Mode 13	1.388	0.05	0.33	16.1	0.033	8.5	0.5	2.7
Mode 14	1.642	0.04	0.28	16.7	0.004	9.8	0.5	2.2
Mode 15	1.946	0.07	0.74	11.6	0.074	10.3	0.6	2.5

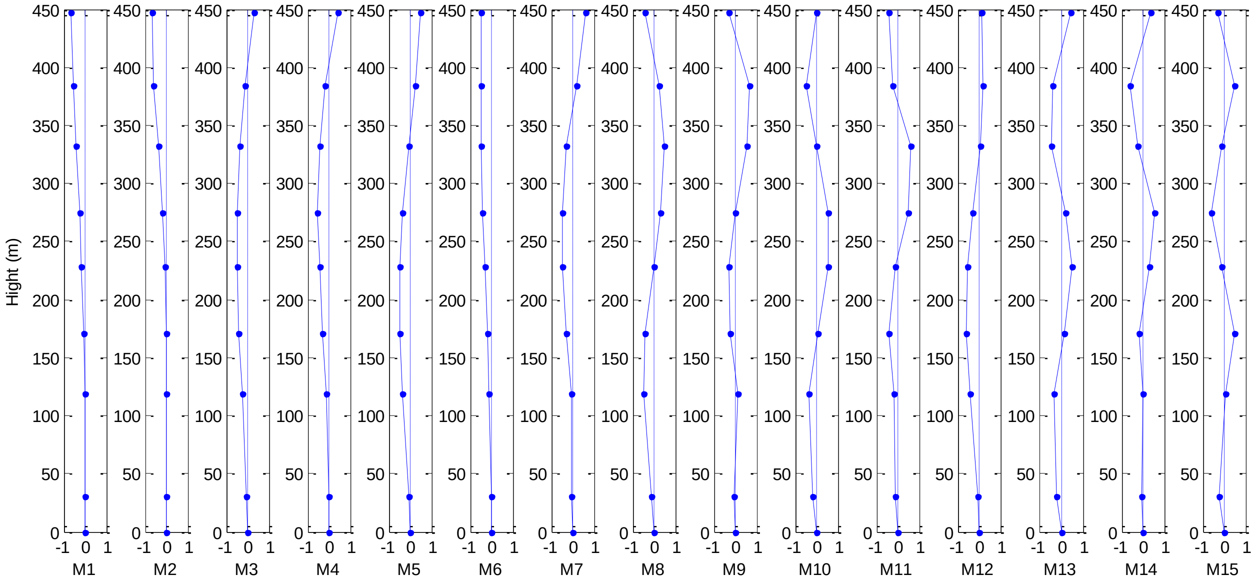

Figure 2 The mode shapes for the first 15 modes in short-axis direction

Figure 2 and Figure 3 show the identified mode shapes of the fifteen modes in short and long axis direction, respectively. It is seen that the mode shapes of some modes are similar, for example in short axis direction, Mode 1, Mode 2 and Mode 6; Mode 3, Mode 4, Mode 5, Mode 7 and Mode 12; Mode 8; Mode 9, Mode 10, Mode 11 and Mode 13; Mode 14 and Mode 15. The modes in long axis are similar. The similarity of the mode shapes in short and long axis direction indicates that the weak and strong directions of this tower is not evident from this point of view.

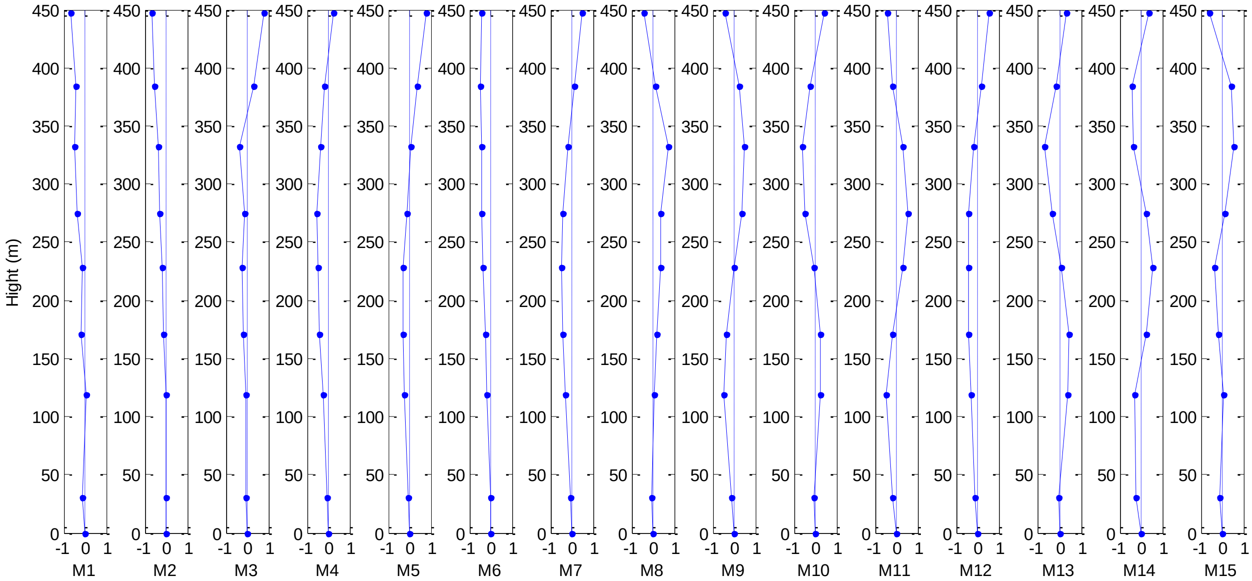

Figure 3 The mode shapes for the first 15 modes in long-axis direction

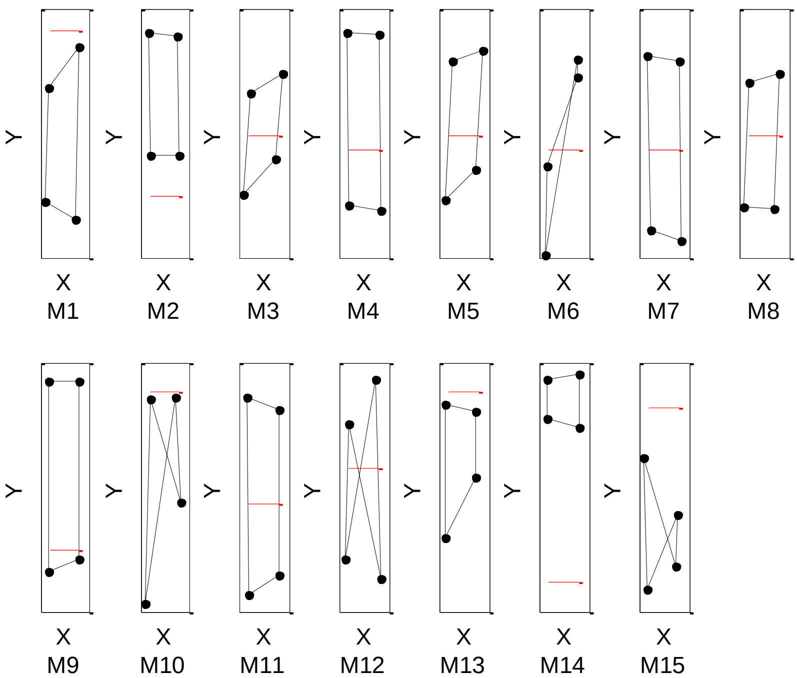

Figure 4 XY view of the mode shape for four measured locations in Sections 4 and 8

Recall that in Sections 4 and 8, biaxial sensors are instrumented in two locations for each section. This makes it possible to investigate the torsional behaviors of these modes. Figure 4 shows the top view (XY view) of the mode shapes for these four locations, where the red and black lines denote the undeformed and deformed shape, respectively. It is seen that although the mode shapes of some modes in Figure 2 and Figure 3 are similar, they are different in this view, where Modes 6, 10, 12, 15 exhibits significant torsional behaviors.

4.2 Modal parameters in long period (24 Hours)

We next investigate the behavior of modal parameters in a whole day under ambient conditions. Figure 5 shows the 10-min averaged wind speed, wind direction and temperature measured by the sensors installed in the tower, where the wind speed is relative stable with a fluctuation from about 1.5 to 4 m/s and there is no much change for the wind direction, while the temperature changes from 14 to 18 degrees gradually. Overall, the environment is relatively stationary during this 24 hours. The 48 segments of acceleration data is analyzed separately with the similar procedure in Section 4.1. In this study, only the first three modes are investigated.

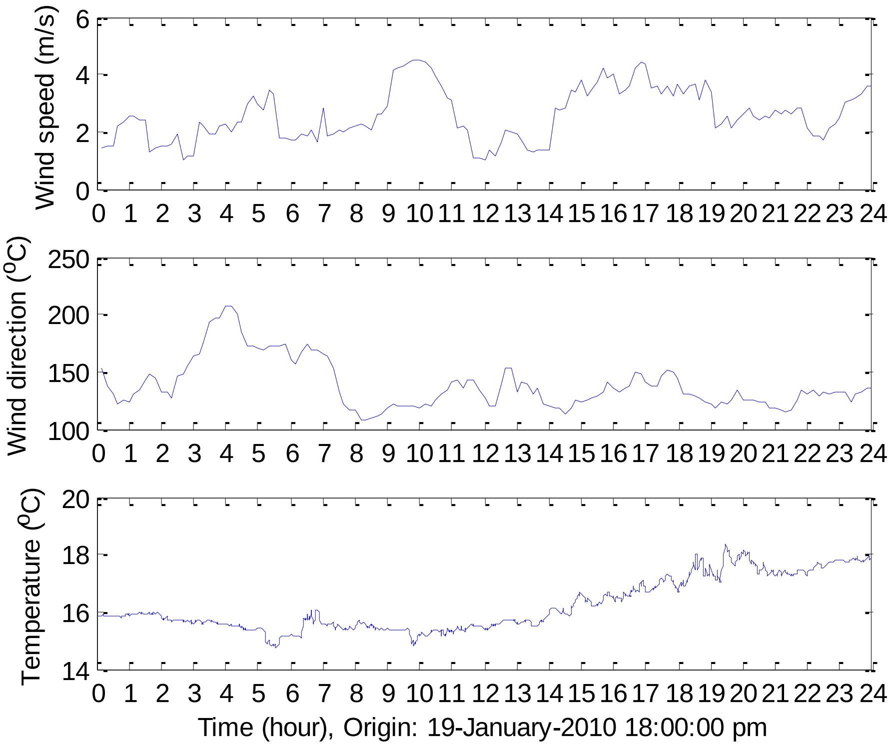

Figure 5 Wind and temperature information collected in the Canton Tower

Figure 6 to Figure 8 show the modal parameters identified using the 48 sets of data and the associated uncertainty for Mode 1 to Mode 3, respectively. The identified result for each data set is shown with a dot at the posterior MPV and an error bar covering two posterior standard deviations. It is seen that the natural frequencies of three modes change slightly with time, while the damping ratios have a relatively larger variation but still have same order of magnitude. The sudden change of modal parameters may reflect the quality of the data used. Take the data corresponding to 16.5 hour for example. It is seen that the posterior uncertainty of natural frequency and damping ratio in the second mode are larger than other ones. To look for the reason, the time history of the data is shown in Figure 9, where some strange peaks can be found. These peaks could come from the sensor noise, the electric noise or some noise in the environment, which may influence the stationary assumption of the excitation and then lead to the inaccuracy of the identified result (say, larger uncertainty).

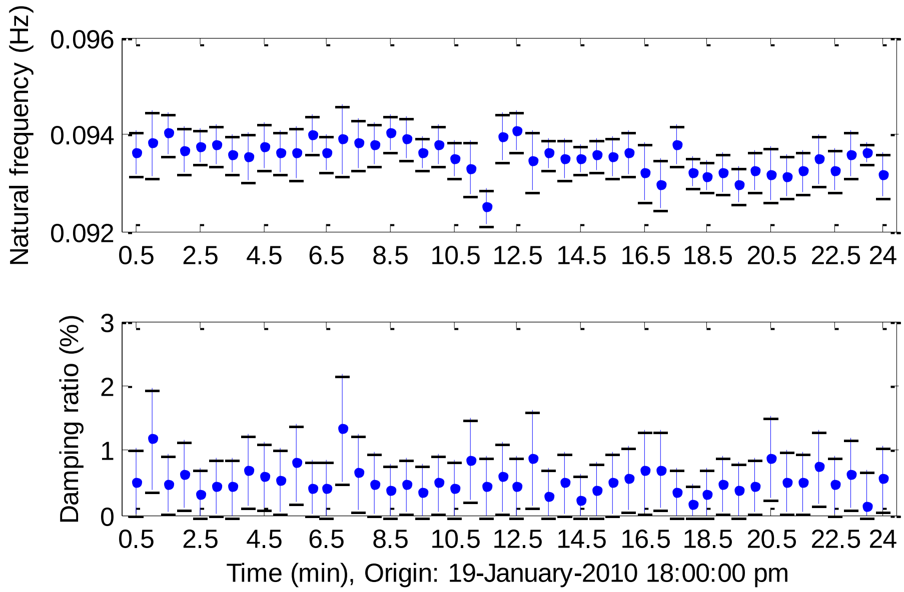

Figure 6 Modal parameters in different setups, Mode 1

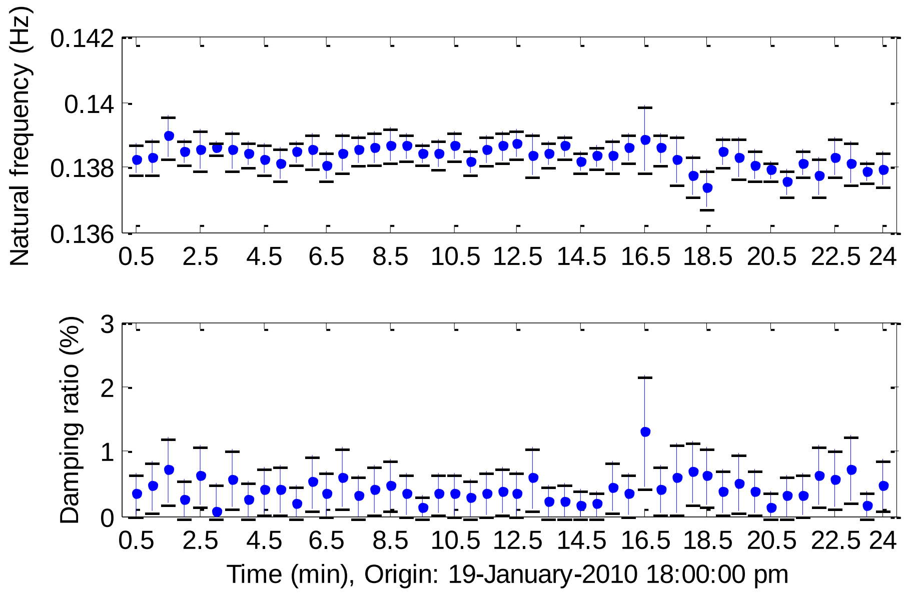

Figure 7 Modal parameters in different setups, Mode 2

From Figure 6 to Figure 8, it is difficult to find the correlation between the modal parameters and wind speed, modal parameters and temperature directly. To perform further investigation, Figure 10 and Figure 11 show the modal parameters identified in different data sets versus the temperature and wind speed, respectively. It is seen that there is slightly descending trend for the natural frequency with the increase of temperature. Similar trend can also be found in the relationship between the natural frequency and wind speed, although it is also not obvious. The trend for damping ratio is difficult to investigate since the changes of temperature and wind speed are too slight.

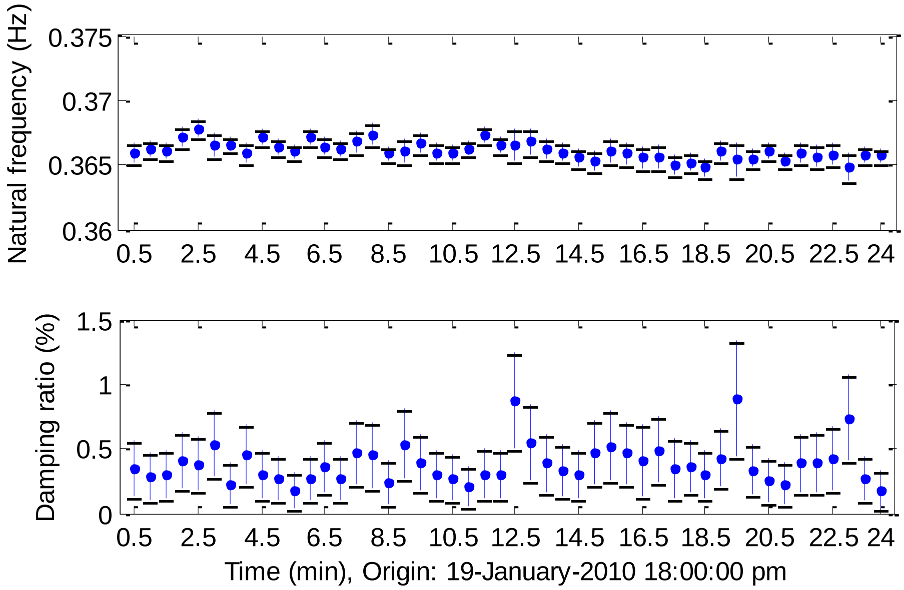

Figure 8 Modal parameters in different setups, Mode 3

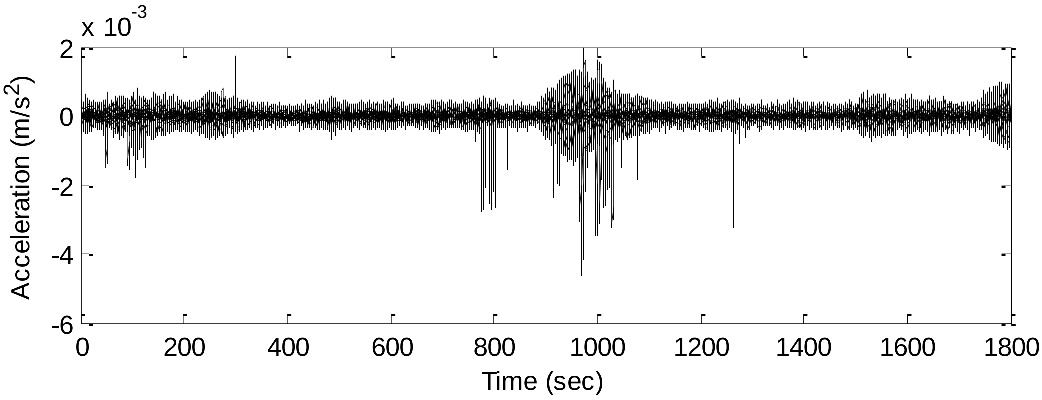

Figure 9 Time history of the acceleration corresponding to 16.5 hour

Using Fast Bayesian FFT method, one important merit is that the PSD of modal force can be identified directly. This makes it possible to calculate the modal root mean square (RMS) value of ith mode according to the following equation (Au 2012c):

$$RMS_i = \frac{\pi f_i S_i}{4\zeta_i} \tag{9}$$

where f_i, ζ_i, and S_i denotes the natural frequency, damping ratio and PSD of modal force of ith mode. The RMS value of the modal response in a given time window is utilized to represent the vibration level in a given mode.

Figure 12 shows the relationship between the natural frequency and modal RMS, the damping ratio and modal RMS in Modes1 to 3. The natural frequency decreases with the increase of vibration level for each mode. This result is consistent with the investigation in Au (2012c), where two tall buildings are studied under strong wind events. Similar to Figure 10 and Figure 11, there is no obvious trend for the damping ratio. To exam the rationality of the definition of modal RMS, the relationship between wind speed and modal RMS for Modes 1 to 3 is plotted in Figure 13. It is seen that the modal RMS increases with the wind speed in a manner approximated to be linear for each mode, implying that the wind speed has an evident correlation with the modal RMS. This is consistent with our intuition.

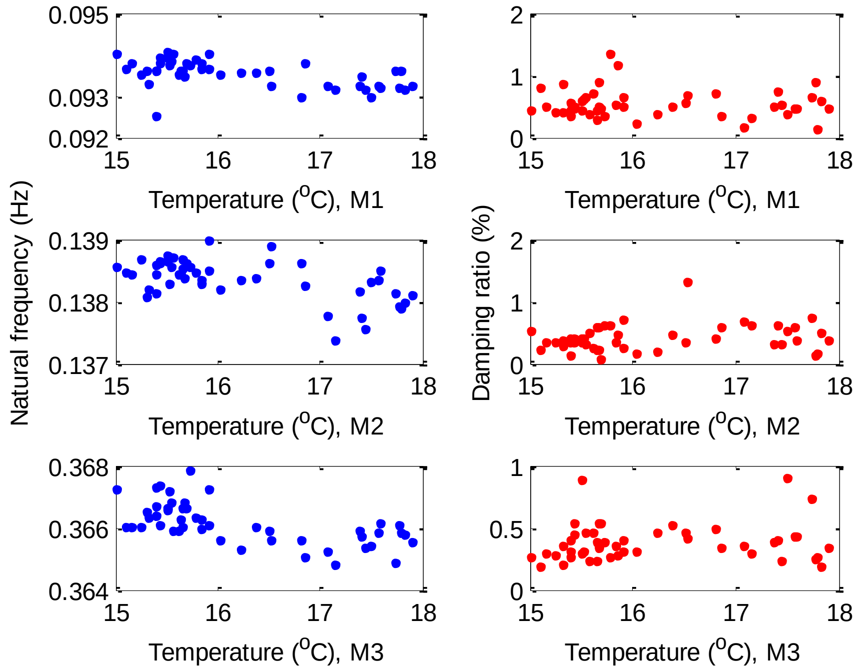

Figure 10 Modal parameter in different data sets versus temperature

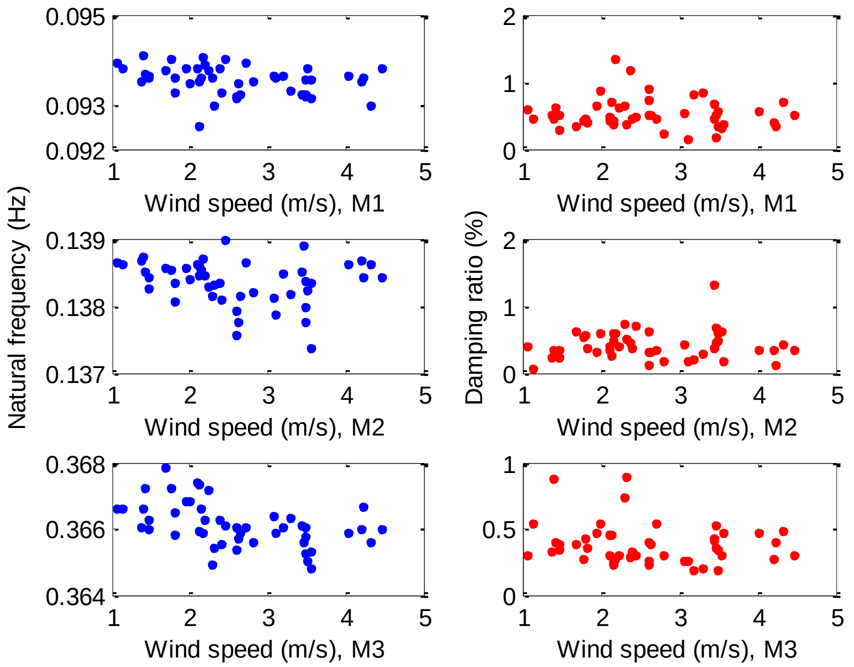

Figure 11 Modal parameter in different data sets versus wind speed

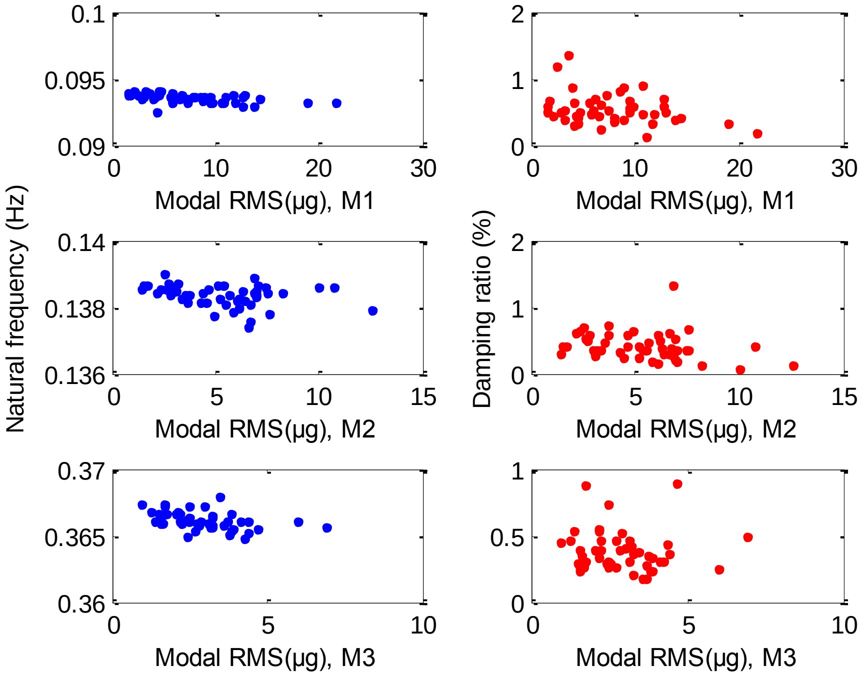

Figure 12 Modal parameter VS vibration amplitude

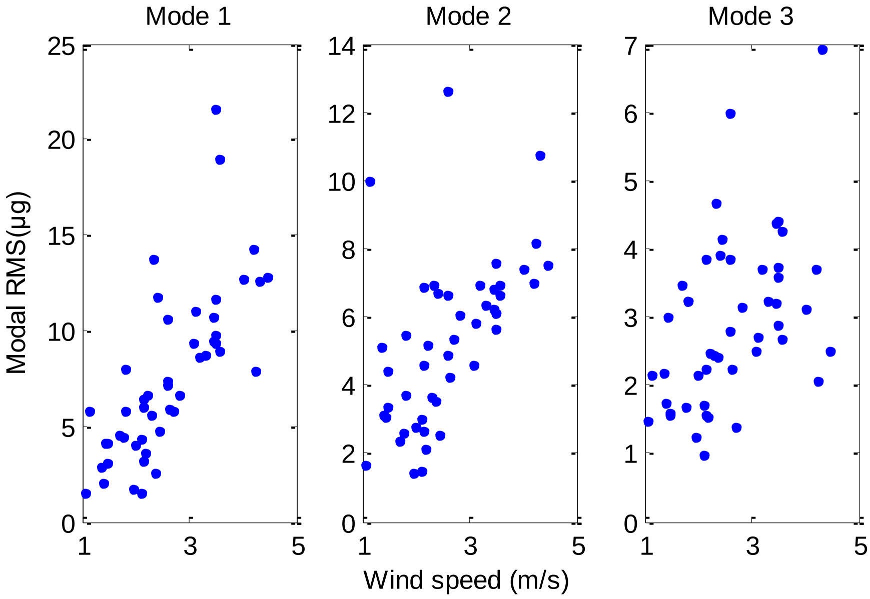

Figure 13 Wind speed VS vibration amplitude

5. CONCLUSIONS

This paper presents the work on the operational modal analysis of Canton tower using a new developed fast Bayesian FFT method. In addition to the most probable value of modal parameters, the method also makes it possible to calculate the associated posterior uncertainty. The modal parameters of fifteen modes are identified, including the natural frequency, damping ratio, mode shape, modal force PSD and prediction error PSD. The natural frequency of the first mode is very small (less than 0.1 Hz), and it is consistent with the properties of the super-tall structure. The damping ratios of these modes are all not large under ambient condition. The identification of natural frequency is more accurate than those of damping ratio with a small posterior uncertainty. It is interesting to find that the mode shape of some modes are similar in translational direction and the main difference is situated in their torsional behaviors. The weak and strong directions of this tower are not evident, since the mode shapes of the same mode in short and long axis are similar.

On the basis of 24 hours' acceleration, wind speed, wind direction and temperature response collected in a whole day, 48 sets of modal parameters are identified to investigate the relationship with the wind speed, temperature and modal RMS of the acceleration response. By plotting the MPV and the associated posterior uncertainty of all the identified results together, the questionable data may be detected by comparing the posterior uncertainty of some modal parameters with others and checking the consistency. It is also seen that the natural frequency has a slightly descending trend with the temperature, wind speed and modal vibration amplitude, while this is not true for the damping ratio under stable ambient condition. Finally, by comparing the correlation between modal RMS and wind speed, a linear relationship between these two quantities is investigated, implying that the definition of the modal RMS is reasonable with the PSD of modal force considered.

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