A stochastic analysis framework for a steel frame structure using wireless sensor system measurements

Yan Yu a,*, Won-Hee Kang b, Chunwei Zhang b,*, Jie Wang a, Jinping Ou c

a Faculty of Electronic Information and Electrical Engineering, Dalian University of Technology, Dalian 116024, China
b Institute for Infrastructure Engineering, University of Western Sydney, Australia
c School of Civil Engineering, Dalian University of Technology, Dalian 116024, China

A R T I C L E   I N F O

Article history:
Received 19 October 2014
Received in revised form 4 January 2015
Accepted 18 March 2015
Available online 25 March 2015

Keywords:
Stochastic analysis framework
Probability
Wireless sensor networks
Steel frame structure

A B S T R A C T

This paper presents a stochastic analysis framework for estimating the system-level first-passage probability of the structural responses of multi-degree-of-freedom structural systems based on experimentally measured uncertainties. The uncertainties are quantified by comparing the measured structural responses using a wireless sensor system and the predicted responses from an analytical model. The wireless sensor network is designed based on a modular design method, and the experimental program details for the measurement of structural responses are provided using the developed wireless sensor network. This framework employs a Monte Carlo simulation (MCS)-based first-passage probability estimation technique in which a structural dynamic analysis is performed in each simulation realization. The framework is applied to a 16-story steel frame structure, and the first-passage probability of 16 locations and the series system passage probability of the entire system have been estimated. The effect of the dependency between the structural responses is considered, and the improvements that need to be made to the presented framework in the future works are discussed.

1. Introduction

Structural systems should be designed to withstand natural and manmade hazards within allowable structural responses. These structural responses are often estimated using dynamic analyses with given hazard inputs. For realistic estimation of the response, the uncertainties due to the imperfectness of structural models need to be considered carefully, and accordingly, the responses should be represented in a probabilistic way. These uncertainties include inherent uncertainties in the random hazard inputs, modeling uncertainties in approximated design equations and model parameters, and statistical errors in a finite number of model evaluations. These uncertainties are considered in the stochastic dynamic analyses of structural systems, and the outputs are estimated in terms of the structural reliability, which is often expressed as the probability of exceedance in terms of the structural responses. This estimated structural reliability is of use to support decision making in structural design and control. However, stochastic structural dynamic analyses considering these uncertainties are statistically and computationally complex because of the sufficiently large amount of observation data required for the measurement of uncertainties, time-variant nature of structural responses, non-linearities in the geometry and material properties of structural members, correlation between structural components, and time-consuming repeated evaluation of structural simulations. Furthermore, theoretical difficulties are faced in stochastic dynamic analyses, such as the complex
calculation of the joint density functions between stochastic processes, unrealistic assumptions regarding the distribution of the stochastic process, and nonlinearity of a stochastic process. To overcome these challenges and to improve the computational accuracy and efficiency of the reliability analyses, there has been considerable research on such stochastic dynamic analysis to estimate the probability of first excursion, using various methodological attempts including analytical methods under special assumptions, crossing rate evaluation methods, Kolmogorov equation based methods, and advanced simulation based methods [1–5]. However, despite these theoretical developments, there are still limited research works on the integration of these stochastic structural analysis framework and the quantification of the uncertainties using real sensor measurements.

In addition, there are further challenges in structural response monitoring of a large structure. One important element for inspection system is the transmission of the measurement data from the sensors to the processing terminal; conventionally and most popularly, wired networks are used for this task. However, with a great number of sensors for a large structure, a huge amount of wires is needed. As a result, installation time and costs can be very high, and this may also affect the reliability of the data transmission. Moreover, there may be cases in which wires cannot be placed in certain locations of a structure. Fortunately, with the development of technologies in sensing, wireless communication, and Micro electro mechanical systems (MEMS), wireless sensor network (WSN) technique has been developed rapidly, and is being used gradually in structural health monitoring for civil engineering structures in an attempt to install quickly, inspect conveniently and lower the high capital costs associated with wire-based structural monitoring systems [6–8].

In this context, in this paper, a simple Monte Carlo simulation (MCS) based stochastic analysis framework for calculating a first-passage probability based on the observed responses is presented. This framework proposes to quantify the uncertainties in dynamic analysis through the comparison with the measurements by using wireless sensor network. The design details of the wireless sensor network are also proposed in the framework. This simulation-based method provides a robust way to handle the nonlinearity and various types of distributions of a stochastic process. In this study, a 16-story frame structure example is considered to demonstrate the framework. The uncertainties of the computational model of the structure are measured as the differences between the computational analysis results and the sensor observations of the structural responses. A system-level reliability analysis with correlated joint passage failure modes is performed using a simulation-based method for simple implementation, and the effect of considering correlation is briefly discussed.

2. Theoretical analysis

2.1. First passage problem using simulation method

This study aims to estimate the reliability of a frame structure based on the evaluation of the first passage probability, defined as the probability of first passage into the failure domain where the failure domain is defined by the given threshold value of the structural responses. In this section, the process for evaluating the first-passage probability based on a crude MCS is reviewed.

Let \( X(t) \) be a random process. The calculation of the first passage probability is started from the evaluation of the mean upcrossing rate. Let \( M(T) = \max(X(t); 0 \leq t \leq T) \) denote an extreme value of the response process \( X(t) \) over the time interval of length \( T \). The distribution of \( M(T) \) under the Poisson assumption is given in terms of the averaged mean upcrossing rate by the following relation [9,10]:

\[
F_{M(T)}(\xi) = \text{prob}(M(T) \leq \xi) = 1 - \exp(-\bar{v}^+(\xi)T) \tag{1}
\]

where \( \xi \) = threshold value for \( X(t) \) and \( \bar{v}^+(\xi) \) is the averaged mean upcrossing rate defined by

\[
\bar{v}^+(\xi) = \frac{1}{T} \int_0^T v^+(\xi,t)dt \tag{2}
\]

where \( v^+(\xi,t) = \text{mean upcrossing rate of } X(t) \text{ at time } t \). In most nonlinear systems, analytical or numerical solutions for calculating \( v^+(\xi,t) \) are not available, and therefore, empirical time series need to be used. By generating \( k \) time histories of \( X(t) \) within time length \( T \), the empirical estimation of the averaged mean upcrossing rate is calculated to be

\[
\hat{v}^+(\xi) = \frac{1}{kT} \sum_{j=1}^{k} \frac{1}{T} \sum_{t=1}^{T} n_j^+(\xi,0,T) \tag{3}
\]

where \( n_j^+(\xi,0,T) = \text{counted number of upcrossings of level } \xi \text{ for time history number } j \). This empirical averaged mean upcrossing rate can replace the analytical or numerical solution of Eq. (2) when a sufficient number of simulations are conducted. By using this statistical estimator of the averaged mean crossing rate, we can avoid the derivation of analytical solutions for the mean upcrossing rate of the stochastic process for nonlinear systems.

2.2. A target steel frame structure and dynamic analysis results

As an application for the first-passage probability estimation procedure presented in the previous section, we consider a structural model: the 16-story steel frame structure shown in Fig. 1. This structural model represents a transverse section of atypical steel building at 1:8 geometrical scale ratio. The structure measures 2.25 m × 1.05 m in plane and 8 m in height as shown in Fig. 1. The cross-section types of the column, girder and brace of the structure are 50 mm × 50 mm × 4 mm, 160 mm × 4 mm × 30 mm × 5 mm and 2L25 mm × 3 mm (with/without braces located within the middle span on each story, including 122 beams and 68 nodes), respectively. Approximately 300 kg of mass is added to each story of the structure. Joint-bolt connections are assumed to be rigid connections. A 36 steel material is chosen as the structural member’s main materials. Payload concrete slab’s compressive strength is chosen to be 20.7 MPa; however, this will not affect the dynamic analysis results of the structure.
For this structure, a dynamic analysis is firstly performed for the input ground acceleration shown in Fig. 2. The structural seismic responses (accelerations) are calculated as shown in Fig. 3, where the accelerations of 16 stories are plotted.

3. Validation experiments using wireless sensor system

3.1. Wireless sensor system

3.1.1. The overall architecture of the system

The overall architecture of the wireless acquisition system is shown in Fig. 4, which consists of one coordinator, repeaters and several wireless nodes. Meanwhile, each wireless node can also be connected multiple high-performance servo acceleration sensors [11,12].

Such system structure is easy to implement a centralized control, and due to this characteristic, it also brings advantages of ease of maintenance and safety.

3.1.2. Design of wireless node and base station

The wireless node uses a modular design method [13,14], which includes the signal conditioning circuits, storage unit, a wireless transmission unit, micro processing unit, power management unit, etc. A block diagram of the wireless node is shown in Fig. 5. In the designed system, force-balance sensor is used for the low frequency vibration sensing unit because civil engineering structures usually belong to low frequency vibration ones. 24 bit high accurate ADC chip ADS1248 is selected to convert analog signal to digital signal; MSP430F5438 is used for micro processor, which has the lowest operating power consumption. The performance is up to 25MIPS at 1.8–3.6 V operating voltage range and can meet the design needs of wireless sensor in low power consumption and high rapid data processing. Storage unit uses NAND large capacity flash memory. Wireless transceiver unit is for data wireless transmission, consisting of CC2520 RF chip and enlarge front CC2591. CC2520 RF chip is 2.4 GHz license-free ISM band Zigbee/IEEE 802.15.4 RF transceiver. CC2591 is 2.4 GHz RF front end unit for low power consumption and low voltage wireless application, which can improve the transmission power and receiving sensitivity and increase the wireless signal strength and transmission distance. In the system, 24 V battery is selected as wireless node’s power source for rapid measurement and continued power supply. Because each unit in the system needs different power supply, such as ±15 V, ±12 V, +3.3 V, and analog circuits require a higher voltage ripple, energy design has two-stage transformation structure. The first stage uses DC/DC chips for the transformation from +24 V to

---

Fig. 1. A 16-story steel frame structure.

(a) Structural elevation sketch  (b) Cross section of columns and beams  (c) FEM models

Fig. 2. Input ground acceleration by an earthquake.
± 15 V and +3.3 V. The second stage uses LDO chips 7812 and 7912 for the transformation from ±15 V to ±12 V.

The base station, which is composed of wireless modules, MCU, and communication protocol conversion unit, is responsible for the formation and maintenance of the network and used to send commands and receive data. It is shown in Fig. 6.

3.2. Experimental program

Test object is a 16-story frame structure model. Its story is 0.5 m and the used steel material is Q235. Parameters are as follows: elasticity modulus $E = 206 \times 10^3$ N/mm$^2$; shear model $G = 79 \times 10^3$ N/mm$^2$; mass density $\rho = 7850$ kg/m$^3$. Large concrete blocks are used as loads: $M = 0.2 \times 0.1 \times 2.5 \times 2500 = 125$ kg.

An accelerometer is installed on each story, and therefore, a total of 16 sensors are installed in the entire structure to measure the acceleration of each story. The wireless control center and layout scheme of the wireless nodes are shown in Figs. 7–9 is a zoomed-in partial schematic view of the Fig. 8.

3.3. Analysis of experimental results

The measured accelerations using the wireless sensor system in the previous sections are shown in Fig. 10, based on the same earthquake input in Fig. 2.

Based on the calculated and measured accelerations shown in Figs. 3 and 10, a stochastic analysis based on the procedures introduced in the previous section has been carried out. First, from these results, it is observed that both of them fluctuate around zero at all sensor locations, and we assume that we can regenerate them using a zero-mean Gaussian process. In other words, at a certain time point, the structural response can be represented by a random variable following a normal distribution with zero mean. The calculated and measured structural responses do not need to be identical. By assuming that the sensors used in this test are perfect and have no measurement error, we can measure the modeling error for the calculation results shown in Fig. 3. This error is simply defined as

$$e_{\text{modeling}}(t) = \text{acc}_{\text{cal}}(t) - \text{acc}_{\text{measured}}(t)$$

where $e_{\text{modeling}}(t) =$ modeling error at time $t$, $\text{acc}_{\text{cal}}(t) =$ calculated acceleration at time $t$, and $\text{acc}_{\text{measured}}(t) =$ acceleration measured by an accelerometer at time $t$. The modeling errors at 16 sensor locations are calculated according to Eq. (4) and plotted in Fig. 11.
In this figure, it is noted that this modeling error also follows a zero-mean Gaussian process because the modeling error is defined by a linear function of these two accelerations and the calculated and measured accelerations follow a zero-mean Gaussian process.

The next step is to calculate the probability of exceedance in terms of accelerations. The limit states of the structural responses are simply defined using the arbitrarily defined criteria in terms of a threshold acceleration value, and the corresponding exceedance probabilities are calculated at all 16 sensor locations using the framework provided in the previous section. In this analysis, the threshold value has been set to be 1.7 m/s². According to Eqs. (1)–(3), MCS has been performed 1000 times, and for each realization of the simulations, only the actual vibrating time period of 20 s has been considered. The input acceleration for each simulation has been generated using a zero mean Gaussian process with the statistical estimation of the standard deviation of the original input acceleration. After carrying out a dynamic analysis using this random input, the structural responses at 16 locations are estimated and the modeling error has been added as a zero-mean Gaussian process with the statistical standard deviation estimation from the results shown in Fig. 11. Then, an outcrossing rate was statistically obtained to calculate the probability of exceedance at each of the 16 locations. The probabilistic analysis results are plotted in Fig. 12.

In Fig. 12, the calculated probabilities of exceedance values are different at all 16 locations because the responses of the structure and the modeling errors are different at those locations. The probability of exceedance is especially higher at locations 15 and 16 compared to the other locations, mainly because they have larger modeling errors. The sources of these modeling errors include the errors ignored in the simple structural model such as errors from simplified modeling and ignorance of important parameters, and parameter errors such as variations in geometric and material parameters. However, the quantified modeling error in this study only shows the sum of these possible sources of errors and does not provide the relative importance or quantified contributions. The measurement error of each sensor has not been considered in this analysis as they are often much smaller than the modeling errors, and the consideration of them will create larger variations in the structural responses and the greater values of the failure probabilities. In this analysis, system reliability analysis has also been carried out, and the result is shown in the last bar at the right-hand side. This system is defined by a series system where the system fails if simultaneous exceedance of structural responses is observed at not less than one location. The occurrence of simultaneous exceedance and the corresponding system failure probability can be evaluated based on the concept of a joint first-passage probability [15]. The joint first-passage probability is defined by the probability that each of the component processes exceeds its respective double-sided threshold during the specified interval. According to this definition, the empirical estimation of the averaged upcrossing rate in Eq. (3) can analogously be extended for the case with two random processes as

\[
\hat{v}_{12}^{\ast} (\xi_1, \xi_2) = \frac{1}{kT} \sum_{j=1}^{k} n_{ij}^{12} (\xi_1, \xi_2; 0, T)
\]  

(5)
where \( n_{12,j}(\xi_1, \xi_2; 0, T) \) = the counted number of simultaneous upcrossings of the two random processes for time history number \( j \), and \( \xi_1 \) and \( \xi_2 \) are the threshold values of these two random processes. By extending this equation and using De Morgan’s rule, the averaged upcrossing rate for the system event of \( m \) random processes can be calculated where the system exceedance is defined as at least one exceedance being observed at a certain time point. The result for the series system in Fig. 12 shows obviously higher failure probability than the other component failures because the system definition is stricter than component event definitions. No significant effects from the consideration of component correlations are found in this analysis. The system probability considering the joint passage probability is 0.8380, whereas that with the assumption that all components are independent and their chance of exceedance is not affected by the other components is 0.8385; these two values are almost identical. This means that all components are almost statistically independent. For these analyses, MCS have been repeated 1000 times and 15.69 s was required for all of these analyses using MATLAB\textsuperscript{®} on a computer with an Intel I7 CPU (2.80 GHz each) and 3 GB of RAM.
Fig. 10. Measured accelerations of 16 stories.

Fig. 11. Modeling errors at 16 sensor locations.
sensors, dynamic analysis, different types of structural uncertainty distribution assumptions, measurement error of sensors, dynamic analysis, different types of structural responses, and development of a computationally efficient stochastic analysis framework using machine-learning techniques will be required in future works.

Acknowledgements

The authors gratefully acknowledge that this work is supported by the National Natural Science Foundation of China (Project Nos. 5116120359, 61301130, 61401059), the University of Western Sydney under the UWS Research Partnerships Program, the IIE International Research Initiatives Scheme, the IIE Research Grant Scheme, and the National Key Technology Research and Development Program during the Twelfth Five-Year Plan Period (Project No. 2011BAK02B01).

References
