Journal of Wind Engineering & Industrial Aerodynamics 170 (2017) 1–17

Contents lists available at ScienceDirect

Journal of Wind Engineering & Industrial Aerodynamics

journal homepage: www.elsevier.com/locate/jweia

Prediction of wind loads on high-rise building using a BP neural network combined with POD

Huang Dongmei [a,b,*], He Shiqing [a], He Xuhui [a,b], Zhu Xue [a]

[a] School of Civil Engineering, Central South University, Changsha, Hunan, 410075, China
[b] High-speed Railway Construction Technology National Engineering Laboratory, Central South University, Changsha, Hunan, 410075, China

ARTICLE INFO

Keywords:
High-rise building
POD
BPNN
Rigid model synchronisation pressure wind tunnel test
Time series of wind-induced pressures

ABSTRACT

According to the limited wind tunnel test results to obtain detailed data of surface wind pressure on buildings has important significance for the accurate calculation of cladding wind pressure and wind-induced response of structures. In this paper, a backpropagation neural network (BPNN) combined with proper orthogonal decomposition (POD-BPNN) is proposed for the prediction of the mean, root-mean-square (RMS) pressure coefficients and the time series of wind-induced pressures on a building surface, respectively. In this study, simultaneous pressure measurements are made on a high-rise building model in a boundary layer wind tunnel and parts of the model test data are used as the training input–output sets for BPNN and POD-BPNN models. Comparisons of the prediction results by the POD-BPNN approach and those from the wind tunnel test demonstrate that the BPNN combined with POD method can successfully and efficiently predict the time series of pressure data on all surfaces of a high-rise building on the basis of wind tunnel pressure measurements from a certain number of pressure taps.

1. Introduction

With the development of construction technology and engineering materials, more super tall buildings and large-span roof structures have been built all over the world. These structures are super-flexible, lightweight, have low damping ratios, and low fundamental frequencies, which make them very sensitive to wind load. Under the action of strong typhoons, failures in glass curtain walls and roofs have happened frequently, and the fact that such structures suffer strong wind-induced vibration is commonplace. Therefore, it is necessary to understand the detailed characteristics of such wind effects on such structures.

In design of some slender structures such as super-tall, large-span roof structures, and so on, usually it is necessary to obtain more detailed wind load information: this generally comes from wind tunnel tests of rigid model pressure measurement. In these wind tunnel tests, to obtain sufficient detailed wind load characteristics to meet the requirements of engineering design and research, enough measurement points should be placed on the surface of the model. With the progress of synchronous acquisition technology for pressure scanning valves, it is not a significant problem to obtain synchronous wind pressure time histories for more than 1000 points on a rigid model in a wind tunnel test; however, with some of the more complex high-rise buildings (Huang et al., 2014, 2015a) and large span structures (Fu et al., 2007), the number of points is still far from the design requirement. In addition, for some dynamic tests with simultaneous pressure measurement, it is inappropriate to arrange too many points on the model which would cause data distortion (Kato and Kanda, 2014). Therefore, it is necessary to explore effective ways to predict, or extend, the wind-induced pressures on the entire surface of a structure according to the limited pressure data from the taps.

At present, there are many ways to build a multi-variable linear/nonlinear forecasting model, such as inverse distance weighting (IDW) (Lu and Wong, 2008), kriging (Franke, 1982), regression polynomials (*e.g.* ARMA) (Kho et al., 2002), artificial neural networks (ANNs) (Turkkan and Srivastava, 1995), *etc*. In these methods, the conventional IDW method has relatively simple and fixed forecasting model, which simplifies the interpolation process, however makes it not well adaptive to the variation of wind pressure distribution of different regions and different structures; the kriging method, based on the theory of spatial statistics, uses the variogram to measure the spatial correlation and weight of near sampling points, thereby it can well adapt to the variation of wind pressure distribution. However, the variation function should be selected by human experience, and when the variance function is a combination, it is difficult to select and the amount of calculation is increased; the regression polynomials is a most commonly used method for selecting different empirical formula to accommodate to the wind pressure distribution with different characteristics, however, when many

* Corresponding author. School of Civil Engineering, Central South University, Changsha, Hunan, 410075, China.
E-mail address: huangdongmei_tumu@163.com (H. Dongmei).

http://dx.doi.org/10.1016/j.jweia.2017.07.021
Received 3 January 2017; Received in revised form 26 July 2017; Accepted 30 July 2017

0167-6105/© 2017 Elsevier Ltd. All rights reserved.

parameters are involved, it is very difficult to obtain an ideal empirical formula for the function form between them is complicated and unknown. Fortunately, ANNs with multilayer perceptrons are the equal of a multi-mapping black box analysis function (Turkkan and Srivastava, 1995), which can describe the complex and non-linear functional relationships of a large number of parameters by training some input-output pairs from tests, even with noisy or incomplete information (Haykin, 1999): thus it has the characteristics of self adjustment and robustness and has been widely used in interpolation problems in various fields (Chen et al., 2003; Yu and Xu, 2014; Ahmed et al., 2015). At the same time, ANNs in some wind engineering interpolation problems are also gradually becoming more widely used. For example, to investigate wind interference between tall buildings (Khanduri et al., 1997; English and Fricke, 1999), to predict the mean and root-mean-square (RMS) pressure coefficients on gable roofs of low-rise buildings and large span space structures (Chen et al., 2003; Fu et al., 2007; Gavalda et al., 2011), and even to predict the wind-induced pressure time series on structures (Chen et al., 2002; Fu et al., 2007), and so on (Chen et al., 2008, 2016; Wu, and Kareem, 2011).

Although a neural network can commendably predict the mean and RMS wind pressures on the structure, it is inadequate to predict the wind pressure time series for too enormous input-output trained data set with time parameter *t*. Therefore, it is necessary to seek an appropriate method to transform the time-variant wind pressure field and then to let the input-output trained data of the ANN be time-independent. Proper orthogonal decomposition (POD) is just one of the approaches based on this objective. Using POD, spatially-distributed multivariable random loads can be reconstituted through a linear combination of a series of orthogonal load modes (Azam and Mariani, 2013) weighted by the corresponding, unrelated modal coordinates (*i.e.* loading principal coordinates), respectively. The orthogonal load modes are space-related and time-independent, and the loading principal coordinates are time-varying and space-independent. The POD involves a covariance proper transformation (CPT) and uses proper vectors to form a covariance matrix of random fluctuating wind loads at zero time lag as the load modes. Armitt (1968) and Lumley (1970) firstly introduced the POD technique to deal with turbulence and wind-related issues. Subsequently, some researchers used POD in reconstructing wind fields (Tamura et al., 1999; Bienkiewicz et al., 1995; Holmes et al., 1997), finding some systematic structures hidden in the random fields (Kikuchi et al., 1997; Wang and Zhou, 2014), and calculating structural wind-induced responses (Solari and Carassale, 2000; Solari et al., 2007; Carassale et al., 2007; Huang et al., 2015b).

In our work, a back-propagation neural network (BPNN), combined with a proper orthogonal decomposition (POD-BPNN) approach is used for the prediction of the mean, the root-mean-square (RMS) pressure coefficients, and even the time series of wind-induced pressures on a structure, respectively. A high-rise building is taken as an example to conduct wind tunnel testing to obtain wind-induced pressure data for training, and then it is used to show the validity of POD-BPNN for the prediction of wind-induced pressures, not only the statistics relating to the pressure data but also the time series, the spectra, and the coherence functions thereof.

2. Wind tunnel experiments

2.1. Overview of experiments

Wind tunnel experiments were carried out in the boundary layer wind tunnel at Central South University in China, which belongs to the High-speed Railway Construction Technology National Engineering Laboratory. It is a double test section reflux type wind tunnel, in which, the low speed test section is with a working section of 12 m width, 3.5 m height, and 18 m length, with a wind speed of 2–18 m/s (continuously adjustable), and the high-speed test section is with a working section of 3 m width, 3 m height, and 15 m length, with a wind speed of 2–90 m/s (continuously adjustable). All the experiments in this paper are carried out in the high-speed test section.

Fig. 1 shows a photo of the model (a square building) mounted in the wind tunnel. The wind field and model were all made with a geometric length scale of 1:350. As shown in Fig. 1, spires, grids, and roughness elements were used to simulate a boundary layer wind flow of urban terrain type stipulated in the Load Code of China (2012) as exposure C category. This terrain type specifies a mean wind speed profile with a power law exponent of $a = 0.22$. The non-dimensional measured mean wind speeds profile, longitudinal turbulence intensities profile, and lateral turbulence intensities profile are shown in Fig. 2(a) and (b), and (c), respectively (the reference point is located at 1.2 m and the corresponding wind speed is 14 m/s). Meanwhile, the mean wind speeds profile stipulated in the Load Code of China (2012) and the turbulence intensity profile stipulated in the Japanese Load Code (AIJ, 1996) are also shown in Fig. 2(a) and (b), respectively. As seen, the simulated wind field is in good agreement with theoretical requirements. Moreover, the spectra of longitudinal and lateral wind speeds at the reference point (gradient wind height) are shown in Fig. 2(d) and (e), respectively, which match the von Karman type spectrum. In addition, longitudinal and lateral turbulence integral scales are shown in Fig. 2 (f) and (g), respectively. According to the scale ratio, they are corresponding to 60–200 m and about 70 m of the actual wind field, respectively. That is consistent with the actual situation. Moreover, it can be noted that the vertical profiles of the u-turbulence intensity and integral length scale are both greater than v-ones, and the u-and v-turbulence intensities and the u-integral length scale decrease as height increases, the v-integral length scale basically does not vary with altitude.

The size and pressure measuring taps arrangement of the model are shown in Fig. 3. The model height is about 1.4 m and width is about 0.163 m (the wind tunnel obstruction is about 2.5% (less than 5%), and the blockage effect thereof is negligible). There are 14 measurement layers on the model, on each of which is arranged 36 measuring points and the position of each layer is consistent (a total of 504 taps). In this way, label M10-1 represents the measured value of the 1st measured point in the 10th layer. To evaluate the prediction effect of the method proposed in our paper for surface wind pressure with limited measurement points, it is firstly necessary to determine which data are to be used for training, and which data for prediction. As shown in Fig. 3, the measurement points labeled '●' were accepted as training data (a total of 120 points), and those marked as 'O' were untrained but can be used as verified data for the prediction results by the proposed POD-BPNN approach only using the limit training data. The electronic scanvalve (ZOC-33, produced by Scanivalve Company in United States) is used to gather wind pressures, its gathering frequency is 625 Hz, and the each

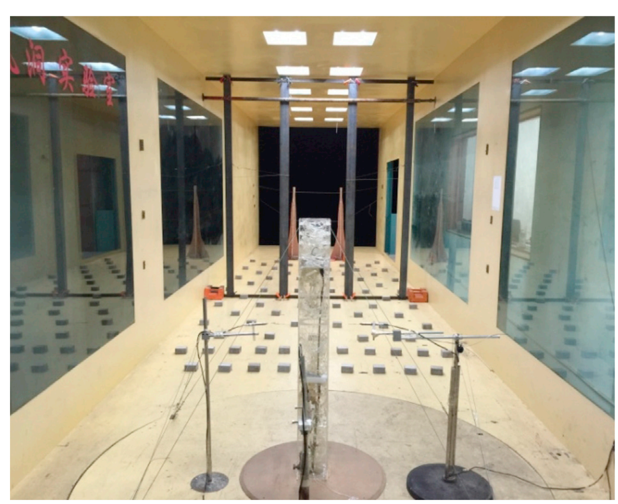

Fig. 1. Rigid model pressure measurement wind tunnel test.

Download English Version:

https://daneshyari.com/en/article/4924744

Download Persian Version:

https://daneshyari.com/article/4924744

Daneshyari.com