Prediction of wind loads on a large flat roof using fuzzy neural networks

J.Y. Fu\textsuperscript{a,b}, Q.S. Li\textsuperscript{a,*}, Z.N. Xie\textsuperscript{c}

\textsuperscript{a}Department of Building and Construction, City University of Hong Kong, Hong Kong
\textsuperscript{b}Department of Civil Engineering, Jinan University, Guangzhou 510632, China
\textsuperscript{c}Department of Civil Engineering, Shantou University, Shantou 515063, China

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Abstract

Fuzzy neural networks (FNN) have capability to develop complex, nonlinear functional relationships between input–output patterns based on limited and sometimes inconsistent data, and are therefore suitable to predict wind loads on buildings on the basis of data obtained from model tests in wind tunnels. In this study, simultaneous pressure measurements are made on a large flat roof model in a boundary layer wind tunnel. An FNN approach is developed for prediction of mean pressure distributions on the roof model, and parts of the wind tunnel test results are used as the training sets for the FNN to recognize the pressure distribution patterns. The procedure is further extended to predict the power spectra and cross-power spectra of fluctuating wind pressures for some typical tap locations in the roof corners and leading edge areas under different wind directions. It is found that the developed FNN approach can generalize functional relationships of wind loads varying with incident wind directions and spatial locations on the roof, and can successfully predict the wind loads on the roof which are not fully covered by the wind tunnel measurements. It is demonstrated from this study that the adoption of the FNN approach can lead to a significant reduction of the pressure measurement programs (e.g., incident wind direction configurations and number of required pressure taps) in wind tunnel tests.

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1. Introduction

In recent years, more and more long-span roof structures have been built with increasing span and structural refinement. Roofs of such structures usually have the characteristics of light mass, high flexibility, slight damping and low natural frequency. As the span increases, the natural frequencies generally decrease, and the susceptibility of a roof structure with long-span to resonant excitation by turbulent wind action increases. Consequently, these structures have become progressively more wind sensitive, and wind loads generally control the design of such structures.

In designing such large roof structures, it is usually necessary to conduct wind tunnel tests to determine wind loads on rigid models by taking pressure measurements. In such wind tunnel experiments, it is necessary to install as many pressure taps as possible on the model surfaces in order to capture the detailed characteristics of wind loads on the structures. These experiments could be time consuming and expensive, but may only cover a limited number of basic configurations since wind pressure distributions on a long-span roof structure depend on several factors such as incident wind direction and wind turbulence characteristics, upstream terrain roughness, roof shape configurations, etc. Once experimental results are obtained, one strategy tries to look for an equation which best fits the results in order to incorporate an empirical equation in the analysis and design of structures \cite{1}. Such a procedure can be very cumbersome, especially for a large and complex roof structure.

Hence, there is a need to explore an effective way for predicting wind loads on large roof structures from a comparatively reduced pressure measurement programme in wind tunnel tests. The ability of the artificial neural network (ANN) approach to train a given data set, and on that basis, to predict missing data, makes it an attractive method for knowledge acquisition for problems which are difficult to solve by conventional theoretical and numerical methods.
In fact, ANN has been successfully applied to solve a number of wind engineering problems. Turkkan and Srivastava [2] used the neural network approach to predict the wind load distribution for air-supported structures. Khanduri et al. [3] applied the backpropagation neural networks to investigate the wind interference problem among tall buildings. Sandri and Mehta [4] applied a neural network for predicting wind-induced damage to buildings. Chen et al. [5] adopted an artificial neural network approach for prediction of mean and root-mean-square pressure coefficients on gable roofs of low-rise buildings. On the other hand, a fuzzy system based on the pioneering work of Zadeh [6] in fuzzy set theory has been an active research area with wide applications in civil engineering such as earthquake intensity evaluation [7], a fuzzy model for load combinations [8] and structural reliability assessment [9,10], etc.

In practice, there exists a very close relationship between neural networks and fuzzy systems, since they both work with degrees of imprecision in a space that is not defined by sharp deterministic boundaries. Hence, fuzzy and neural technologies can be fused into a unified methodology known as fuzzy neural networks.

A literature search indicates that generally the authors of the previous investigations on the application of neural networks and fuzzy systems to wind engineering have mainly concentrated their studies to the predictions of pressure distributions on various building models. The usage of the neural network method to predict power spectra or cross-power spectra of fluctuating wind pressures on buildings and structures has received little, if any, attention in the literature in the past.

The objective of the present work is to develop a Fuzzy Neural Network (FNN) approach which is accurate and robust for the prediction of wind loads on a large flat roof. In order to obtain wind-induced pressure data for training and testing of the FNN, simultaneous pressure measurements are made on a large flat roof model in boundary layer wind tunnel tests. This study is concerned with not only the prediction of the mean pressure distributions on the roof model, but also the power spectra and cross-power spectra of fluctuating wind pressures using the FNN approach.

2. Wind tunnel experiment

2.1. Experimental arrangements

Wind tunnel experiments were carried out in the boundary layer wind tunnel at Shantou University with a working section 3 m wide × 2 m high and 20 m long. Spires and roughness elements were used to generate a simulated atmospheric boundary layer of suburban terrain specified in the China Load Code [11] as exposure B. This terrain type specifies a mean wind speed profile with a power law exponent of $\alpha = 0.16$ and a turbulence intensity of 18% at the model height. The measured mean wind speeds and turbulence intensities at various heights over the test section are illustrated in Fig. 1. The spectrum of longitudinal wind velocity at the model height ($z = 140$ mm in the wind tunnel and $z = 28$ m in full scale) is shown in Fig. 2. The Davenport, Kaimal, Karman and Harris type spectra are also expressed as non-dimensional forms in the figure for comparative purposes.

A flat roof model with square shape shown in Fig. 3 was made to represent a typical large flat roof structure with cantilevered parts. The roof was erected at a height of 140 mm above the wind tunnel floor. The model was made of Plexiglass and its dimensions are shown in Fig. 3. Fig. 4 shows a photo of the model mounted in the wind tunnel. The geometric length scale was selected as 1:200, so the prototype dimensions of the roof are thus 120 m × 120 m at a height of 28 m.

There were 144 and 108 pressure taps made on the upper and lower roof surfaces, respectively, for pressure measurements. In order to obtain the pressure differences between the both sides of the cantilevered roof parts, 108 pairs of the pressure taps were arranged at the same locations on both upper and lower cantilevered roof surfaces. The other 36 pressure taps on the upper surface were located on the enclosed section
of the roof. Simultaneous pressure measurements were made from the pressure taps. The layout of the pressure taps on the upper roof surface is shown in Fig. 5. In the wind tunnel tests, wind direction was defined as an angle $\beta$ from the east along anti-clockwise direction and $\beta$ varied from $0^\circ$ to $360^\circ$ with increment of $22.5^\circ$. Data sampling frequency was 330 Hz with sampling length of 32,768, and the measurements were carried out when the mean wind speed at the model height was 10.5 m/s.

### 2.2. Definitions of parameters

The pressure coefficient of the pressure tap $i$ on the roof surface is defined as follows:

$$C_{pi}(t) = \frac{p_i(t) - p_\infty}{p_0 - p_\infty}$$  \hspace{1cm} (1)

where $p_i(t)$ is the measured surface pressure at the tap $i$, $p_0$ and $p_\infty$ are the total pressure and the static pressure at reference height, respectively.

The convention for positive roof pressure and the corresponding pressure coefficient, on either the upper or lower roof surface, is always from the air side onto the roof surface. The net wind-induced pressure on the roof due to the combined action of pressures on the upper and lower roof surfaces are defined as positive in the downward direction.

$$\Delta C_{pi}(t) = C_{pu}^{i}(t) - C_{pl}^{i}(t) = \frac{p_u^i(t) - p_l^i(t)}{p_0 - p_\infty}$$  \hspace{1cm} (2)

where $\Delta C_{pi}(t)$ is the pressure coefficient difference of the tap $i$ between the upper and lower roof surfaces. $p_u^i(t)$ and $p_l^i(t)$ are respectively the measured upper and lower surface pressures at the tap $i$. In this study, the pressure coefficient $C_{pi}(t)$ defined in Eq. (1) and the pressure difference coefficient $\Delta C_{pi}(t)$ defined in Eq. (2) are both expressed as $C_{pi}(t)$. But, the pressure difference coefficients are used for the cantilevered roof parts and the pressure coefficients are adopted for the upper surface of the enclosed section.

Time-history signals of wind-induced force on a roof surface were obtained from an integration of the simultaneous record of wind pressures over the corresponding surface, and the mean pressure coefficient $\bar{C}_p$ was determined from the pressure measurements.

Considering pressure signal attenuation due to the use of tubing systems for pressure measurements, correction to the signal output of fluctuating wind pressure is necessary [12,13]. Thus, the power spectrum of fluctuating wind pressure should be determined by

$$S_{C_p}(f) = \frac{S_{C_{px}}(f)}{|H(f)|^2}$$  \hspace{1cm} (3)

where $S_{C_{px}}(f)$ is the signal output of a pressure transducer, and $H(f)$ is the frequency response function of the tubing system.

### 3. Fuzzy neural networks

There have been various applications of fuzzy neural networks (FNN) in civil engineering [14,15]. Usually, models
based on neural networks for forecasting problems are less complex than systems based on fuzzy logic. However, the simplicity is achieved at the cost of an explicitly defined relationship between the individual inputs and overall model parameters.

This section presents a brief introduction to a fuzzy neural network approach [16] that combines the capability of neural networks with fuzzy logic reasoning attributes. In any case, the FNN can be viewed as elaborate, nonlinear systems which, given an external input, will estimate the corresponding output, even if the inputs are noisy or incomplete.

3.1. Fuzzy neural network model

The topology of the FNN used in the present work is shown in Fig. 6, which is comprised of four different layers: an input layer, a membership layer, an inference layer, and a defuzzification layer (an output layer). The network consists of \( n \) input variables with \( n \) neurons in the input layer, and \( m \) number of rules with \( m \) neurons in the inference layer; thus the number of neurons in the membership layer is \( n \times m \). Where \( m \) can be generated by using the K-mean clustering technique [16], of course, the values of \( m \) can also be adjusted with practical requirements.

In the membership layer, each node performs a membership function, and the activation function of \( u_i \) consists of a set of membership functions, i.e. \( u_i = (u_{i1}, u_{i2}, \ldots, u_{im}) \). The Gaussian function is adopted as the membership function. For the \( j \)th node of \( u_i \):

\[
u_{ij} = \exp \left( -\frac{(x_i - m_{ij})^2}{\sigma_{ij}^2} \right), \quad 1 \leq i \leq n, 1 \leq j \leq m \quad (4)
\]

where \( u_{ij} \) is the value of the fuzzy membership function of the \( i \)th input variable \( x_i \) corresponding to the \( j \)th rule; \( m_{ij} \) and \( \sigma_{ij} \) are, respectively, the mean and the standard deviation of the Gaussian function in the \( j \)th term of the \( i \)th input variable \( x_i \), and \( m_i = (m_{i1}, m_{i2}, \ldots, m_{im}), \sigma_i = (\sigma_{i1}, \sigma_{i2}, \ldots, \sigma_{im}) \).

The activation function in the inference layer uses multiplicative inference. For the \( i \)th rule node, the output is given by

\[
\pi_i = u_{1i} \times u_{2i} \times \cdots \times u_{ni} = \prod_{j=1}^{n} u_{ji}, \quad (1 \leq i \leq m). \quad (5)
\]

The defuzzification layer has the connecting weights \( (\omega_l) \) to the output from the inference layer, and these weights signify the strength of each rule in the output of the model. The output \( y \) is given as

\[
y = \omega_1\pi_1 + \omega_2\pi_2 + \cdots + \omega_m\pi_m. \quad (6)
\]

More detailed descriptions of the FNN can be found in [16].

3.2. Learning algorithm of FNN

The learning algorithm [16] of the FNN used in this study, which is based on the conventional BP algorithm [17,18], was adopted to train the network, and aims to minimize the mean square error (MSE), which is defined as

\[
E_p = \frac{1}{2}(y - Y)^2 \quad (7)
\]

where \( y \) is the model output, \( Y \) is the desired output.

According to the gradient descent method [18], the weights in the output layer are updated by the following equation:

\[
\omega_l(n + 1) - \omega_l(n) = -\eta \frac{\partial E_p}{\partial \omega_l} \quad (8)
\]

where \( \eta \) is the learning-rate parameter of the weights and is a positive constant to be determined.

The update laws of \( m_{ij} \) and \( \sigma_{ij} \) can also be obtained by the gradient descent method, i.e.

\[
m_{ij}(n + 1) - m_{ij}(n) = -\eta \frac{\partial E_p}{\partial m_{ij}} \quad (9)
\]

\[
\sigma_{ij}(n + 1) - \sigma_{ij}(n) = -\eta \frac{\partial E_p}{\partial \sigma_{ij}}. \quad (10)
\]

Here, assuming the learning-rate parameters of the mean and the standard deviation of the Gaussian function are also \( \eta \).

Then, substituting Eqs. (8) and (9), or (10), respectively, into Eq. (7), the following equations are obtained:

\[
\omega_l(n + 1) - \omega_l(n) = -\eta(y - Y)\pi_i \quad (11)
\]

\[
m_{ij}(n + 1) - m_{ij}(n) = -\eta(y - Y)\omega_j \prod_{l=1,l\neq i}^{n} u_{lj}^2 \frac{x_i - m_{lj}}{\sigma_{ij}^2} \quad (12)
\]

\[
\sigma_{ij}(n + 1) - \sigma_{ij}(n) = -\eta(y - Y)\omega_j \prod_{l=1,l\neq i}^{n} u_{lj}^2 \frac{(x_i - m_{lj})^2}{\sigma_{ij}^3} \quad (13)
\]

The overall process of this learning algorithm is shown in Fig. 7. Software (made by C and MATLAB programming languages) on the basis of this algorithm was developed for this study.
4. Prediction of wind loads on the roof

The process of training the FNN using the above-mentioned data obtained from the wind tunnel tests is presented below for prediction of the wind loads on the roof.

4.1. Prediction of mean pressure coefficients

In this case, in order to determine whether the FNN is sufficiently generalized to be of practical use, the mean pressure coefficients for zone A in the roof shown in Fig. 5 for an incident wind direction of 292.5° were chosen to train the FNN and test its performance. The contours of the measured mean pressure coefficients on the roof for this wind direction are shown in Fig. 8. The zone A was chosen because it is located in the area under high negative pressure actions associated with corner vortices. It is noted that the wind pressure distributions in this area are difficult to predict by conventional theoretical or numerical methods.

The zone A contained 60 pressure taps. 80% of the taps (those in the zone A without marked with ●, as shown in Fig. 5) were used in training of the FNN, and the data from the remaining pressure taps were used for evaluation of the prediction accuracy of the developed FNN.

During the training process, the input and output data were the positions and the mean pressure coefficients of these pressure taps in training, respectively. By training the FNN with the input–output example patterns, the multivariate nonlinear functional relationships were captured and generalized. Then, given the values of the input variables \((x, y)\) from the testing pressure taps (those in the zone A marked with ●, as shown in Fig. 5), the corresponding output, \(C_p\), can be obtained. It must be mentioned that the testing data for the FNN prediction were not used in the training process.

Fig. 8. Contours of \(C_p\) for a wind direction of 292.5°.

Fig. 9 shows the comparison of \(C_p\) between the experimental data and the FNN prediction for the testing pressure taps in the zone A. It can be seen from this figure that the FNN predictions are in good agreement with the experimental data. Actually, the average of the mean square error (MSE) of all the 12 testing pressure taps is less than 3% for the prediction of \(C_p\). This indicates that the prediction of the mean pressure coefficients for these taps in the area under high negative pressure actions associated with corner vortices is acceptable.

4.2. Prediction of mean pressure distributions

Wind pressure distributions on large cantilevered roof structures depend on several factors such as incident wind direction and turbulence characteristics, roof shape configurations, building plan dimensions, and upstream terrain, etc. Under similar flow conditions, the flow pattern around a building strongly depends on wind direction and roof shape configurations. Accordingly, the distributions of wind loads on

Fig. 9. Comparison of \(C_p\) between the experimental data and the FNN prediction for a wind direction of 292.5°.
roofs change significantly with these parameters. In the present study, wind direction, $\beta$, and the positions of pressure taps $(x, y)$ were considered as input variables in the FNN, and the output was $C_p$.

Considering the symmetry of the flat roof, attention was paid to the experimental data obtained for the wind directions varying from $270^\circ$ to $360^\circ$. These available experimental data were allocated into two subsets: training data and testing data. The training data which consist of the experimental input–output data pairs from $270^\circ$ to $360^\circ$ (except $315^\circ$), were used to train the FNN functions. The experimental data for the wind direction ($315^\circ$) that were not used in the training process were chosen as the testing data and were used for evaluating the prediction performance. In other words, the developed FNN model will be used to interpolate or expand the current database into this new wind direction ($315^\circ$).

Fig. 10 shows comparison of the distribution of $C_p$ on the roof surface between the experimental data and the FNN prediction for wind direction of $315^\circ$.

It can be seen from Fig. 10(a) and (b) that the FNN predictions are in good agreement with the experimental data over the whole roof surface, including the leading edge and roof corner areas. Pressure distributions on such areas are difficult to predict by conventional theoretical or numerical methods, because of our imperfect knowledge about the structure of separating/reattaching flows and conical vortices and their sensitivity to incident flow characteristics [19]. The worst suction often occur in these regions due to the strong flow separation at the leading edges [20–22]. The effects of the conical vortices are clearly visible in the contour distribution of $C_p$ predicted by the FNN, as shown in Fig. 10(b). It is observed that the sharp pressure gradients in the leading edge and roof corner areas were captured by the FNN.

Fig. 10(a) and (b) also reveal an important fact, i.e., for $\beta = 315^\circ$, the contour distribution of $C_p$ should be symmetrical due to the symmetry of the flat roof, but the contour distribution of $C_p$ from the wind tunnel tests is not fully symmetrical, as shown in Fig. 10(a), which implies that the experimental measurements may contain some noisy or erratic signals. However, it is observed from Fig. 10(b) that the FNN predictions tend to yield a smooth contour plot and the contour distribution of $C_p$ predicted by the FNN is symmetrical, which indicates that the trained FNN did not memorize every data point, but recognized and generalized the informative and meaningful patterns [5,18]. Therefore, the performance of the trained FNN is quite satisfactory for the prediction.

4.3. Prediction of power spectra of fluctuating wind pressures for some typical taps

Since the pressure distributions on the corner and leading edge areas are not easily predicted by conventional theoretical or numerical methods, it is difficult to predict power spectra of fluctuating pressures in these regions by such methods. Therefore, it is desirable to seek an effective approach for this purpose. In this study, the FNN is applied to predict the power spectral density of fluctuating wind pressures for some typical tap locations in the corner and leading edge areas to examine the predictive performance of the FNN. To the authors’ best knowledge, this is probably the first attempt to use the neural network method to predict power spectra of fluctuating wind pressures on buildings.

For a corner pressure tap (marked with $\Delta 10$ in Fig. 5), wind direction, $\beta$, and frequency, $f$, were considered as input variables in the FNN, and the output was the power spectral density of fluctuating wind pressures which was expressed as a non-dimensional form, $\frac{f}{\sigma_3}(\beta)$. The experimental data for the wind direction varying from $180^\circ$ to $360^\circ$ were considered herein. These available experimental data were also allocated into two subsets: training data and testing data. The training data which consist of the experimental input–output data pairs from $180^\circ$ to $360^\circ$ (except $225^\circ$, $270^\circ$ and $315^\circ$), were used to train the FNN functions. The experimental data of the three typical wind directions ($225^\circ$, $270^\circ$ and $315^\circ$) that were not
used in the training process were chosen as the new test data and were used for evaluation of the performance of the trained FNN.

Fig. 11(a)–(c) show comparison of the power spectral density of fluctuating wind pressure for the tap marked with Δ10 in Fig. 5 between the experimental data and the FNN prediction under three typical wind directions (225°, 270° and 315°).

It can be seen from Fig. 11(a)–(c) that all the FNN predictions are in excellent agreement with the experimental data. It is found that the FNN has learned smaller-scale fluctuations of signals and reproduced them in the simulation, and the FNN predictions tend to yield a smooth contour plot. This is because the FNN has the ability to capture the underlying nonlinear dynamics [5,23]. With enough neurons, in theory, the FNN can approximate any nonlinear continuous function to any desired degree of accuracy. This is one of the most significant features of the FNN.

In addition, Fig. 11(c) demonstrates an important fact, i.e., for the experimental data, it is found that at higher frequency range (about 60–100 Hz), there is a small growth in spectral amplitudes because these experimental measurements may contain some noisy or erratic signals; but the FNN predictions show that at these higher frequencies, the amplitudes of pressure spectra still decrease as the frequency increases, which is consistent with the observation made in Ref. [24], though the declines are not very obvious. This indicates that the trained FNN did not memorize these noisy or erratic signals, and is able to provide a satisfactory prediction.

For the leading edge areas, the power spectral density of fluctuating wind pressures for some typical taps (marked with Δ7–Δ11 in Fig. 5) under a wind direction of 270° were chosen to train the FNN and test its performance. The positions of these taps (x, y), and the frequency, f, were considered as input variables in the FNN, and the output is the power spectral density.

In this case, the power spectral density of fluctuating wind pressures for the previously “unseen” taps will be predicted by using the experimental data from some adjacent taps. For the previously “unseen” tap Δ8, the four adjacent taps are Δ7, Δ9, Δ10 and Δ11. The results are shown in Fig. 12. It can also be seen that the FNN predictions are in good agreement with the experimental data and the FNN predictions also tend to yield a smooth curve plot, which indicates that the FNN is sufficiently generalized to be of practical use.
4.4. Prediction of cross-power spectra of fluctuating wind pressures between different taps

The cross-power spectral density of fluctuating wind pressures between different taps plays important roles in determining wind-induced dynamic responses of large cantilevered roofs. It is thus desirable to provide such predictions. An attempt is made herein to predict the cross-power spectral density under one wind direction between the “seen” tap and the “missing” tap by using the cross-power spectral density data between some “seen” taps.

For a wind direction of 270°, the “seen” taps are Δ7, Δ8, Δ9 and Δ11, and the “missing” tap is Δ10, as depicted in Fig. 5. The positions of these taps (x, y), and the frequency, f, were considered as input variables in the FNN, and the output was the cross-power spectral density between these taps, which was also expressed as the non-dimensional form.

The cross-power spectral density of fluctuating wind pressures between the “missing” tap Δ10 and the “seen” taps Δ8 and Δ11 were obtained by the FNN, as shown in Fig. 13(a) and (b), respectively. It is clear that the two predicted cross-power spectral densities are both close to the actual measurements. All the results indicate that the FNN has a good prediction performance, and thus it can be concluded that the FNN approach is robust when it is applied to predict the wind loads on a large cantilevered roof.

5. Conclusions

The application of a fuzzy neural network approach for the prediction of mean pressure distributions, power spectra of fluctuating wind pressures for some typical taps, and cross-power spectra of fluctuating wind pressures between different taps on a large cantilevered flat roof was observed to be successful. To the authors’ best knowledge, this was probably the first attempt to use the neural network method to predict power spectra of fluctuating wind pressures on buildings.

The present results indicate that the developed FNN is capable of generalizing nonlinear functional relationships among a number of variables such as wind-induced pressure, approaching wind direction, positions of pressure taps and the frequency so that it is able to predict wind loads on a large cantilevered flat roof with good accuracy for any combination of these variables. It was observed that this approach has the potential to reduce the pressure measurement programs (approaching wind direction configurations and number of required pressure taps on building models) in wind tunnel tests. In fact, the FNN approach can also be used for solving other similar wind engineering problems which involve many variables and the relationships among these variables are unknown and complex.

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