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Estimation of Coefficient of Pressure in High Rise Buildings Using Artificial Neural Network

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ABSTRACT
Tendency to build more slender and more flexible tall buildings have made these structures susceptible to action of wind. Therefore, wind force is one of the prime considerations in design of tall buildings. The prediction of wind-induced pressure coefficients on the surface of the buildings is of considerable practical importance. Wind tunnel testing is one of the main methods for wind load determination on structures. But this being, time consuming and costly wind tunnel tests can only cover a limited number of cases.

The present work focuses on the application of artificial neural networks (*ANNs*) to estimate pressure coefficients on surface of tall buildings. In the present study, two cases of training data set (consisting of geometrical coordinates of pressure points and angle at which wind strikes at the face of the building as the input to the network) has been used to predict the wind- induced `pressure coefficients Cp (mean) (output of the network) for the previously any wind incident angle. The performance of the network is assessed in terms of Root Mean Square Error (RMSE) and Correlation Coefficient R. From the present study, it is concluded that the value of Cp (Mean) goes on decreasing with increase in Wind Incidence Angle for the same pressure point. Also, suction effect is noticed near the corners of the building.

Keywords - Artificial Neural Networks, coefficients, Root Mean Square Error, Wind Incident Angle

I. INTRODUCTION

In recent years many tall buildings have been built or are being planned throughout the world. A tall building is defined herein as a building of sufficient height for the period of the first translational mode of vibration to exceed 4 seconds or for its height to exceed 50m [11]. Tall buildings are often regarded as being greater than 20 stories. A tall building is sometimes defined with respect to the height of the surrounding buildings.

The tall buildings are more susceptible to lateral loading and their design is essentially dictated by the behaviour of these structures under lateral loads. Lateral Loads can be of two types viz Earthquake loads and Wind loads. It is well known that light, flexible buildings are favourable for resisting seismic forces, while heavy, stiff buildings are favourable for resisting wind forces. Thus, tall buildings have to satisfy these two diametrically opposite design criteria and this can be one of the most difficult design issues. Buildings, bridges, large span roof structures and other civil structures must be able to withstand the external loads imposed by nature, at least to the extent that the disastrous damage of natural force is reduced to the acceptable limit [9].

II. WIND LOADS

Wind is one of the major forces responsible for the catastrophic failure and loss of life. Therefore, accurate evaluation and prediction of wind loads and proper mitigations are very important in reducing the adverse effects of wind in the built environment. Wind is air in motion relative to the surface of the earth. In general, as buildings grow taller and more slender, wind loading effects become more significant in comparison to earthquake effects. This is because whilst the wind overturning moment will typically increase as height cubed the elastic seismic base moment is unlikely to increase at more than height raised to the power 1.25 [11].

A. Factors Affecting Wind Loads

The response of a building to high wind pressures depends not only upon the geographical location and proximity of other obstructions to airflow but also upon the characteristics of the structure itself. Wind causes pressure or suction normal to the surface of a building or structure. The nature and magnitude of these pressures/suctions is dependent upon a large number of variables such as- Anticipated life span of the structure, Wind incidence angle, Influence of internal pressures etc.

B. Total Force on a Structure

Design wind load or force on a member is calculated from the following expression

$$F = A \times P \tag{1}$$

Where
F = wind force
P = pressure acting uniformly on area A;

$$P = 0.5 \times Cp \times \rho \times V^2 \tag{2}$$

ρ = density of air
C_p = pressure coefficient or Shape factor

C. Pressure coefficient

Pressure coefficient is the ratio of the difference between the pressure acting at a point on a surface and the static pressure of the incident wind to the design wind pressure, where the static and design wind pressures are determined at the height of the point considered after taking into account the geographical location, terrain conditions and shielding effect.

$$C_p\,(i) = \frac{P(i) - P(o)}{\frac{1}{2} \times \rho \times V^2} \tag{3}$$

where,
P(i) = Instantaneous surface pressure,
P(o) = Static (ambient, atmospheric) reference pressure,
ρ = Air density,
V = Mean wind velocity measured at boundary layer depth inside the wind tunnel.

Since the pressure at any point on the wall surface of the building is fluctuating with time, the pressure coefficient can also be treated as time-varying quantity. Following statistical quantity i.e. pressure coefficient is obtained from sample time history, $C_p(i)$:

$$\text{Mean Value} = C_{p,\,mean} = \frac{1}{N}\sum_{i=1}^{N} C_p\,(i) \tag{4}$$

where, N is the total number of samples.
The pressure coefficient is also given as

$$\left[1 - \left(\frac{V_P}{V_Z}\right)^2\right] \tag{5}$$

Where V_P is the actual wind speed at any point on the structure at a height corresponding to that of V_Z (design wind velocity).

D. Computation of Cp

Wind tunnel testing is the main source of simulation of atmospheric boundary layer. In these wind tunnel experiments, one needs to install as many pressure taps as possible on model surfaces in order to capture the detailed characteristics of wind loads on the structures, in order to provide wind induced pressure on the building for the calculation of the wind- induced vibration and the equivalent wind load [5]. The ANNs have the capability to learn and generalize the complex, nonlinear functional relationships by training sample data obtained from experimental results, even given noisy or incomplete information[4,6], thus providing an efficient alternative solution to common prediction problems.

III. ARTIFICIAL NEURAL NETWORKS

Artificial neural networks (ANNs) are a functional abstraction of the biologic neural structures of the central nervous system [1, 2, 3, and 13]. They are powerful pattern recognizers and classifiers. They operate as blackbox, model-free, and adaptive tools to capture and learn significant structures in data.

A. Feed-Forward Back Propagation Neural Network (BPNN)

The most common ANN learning algorithm is the Multi Layer Perceptron (MLP), also termed as Back Propagation Neural Network (BPNN), an extension of the original perceptron model that included only an input and output layer and was originally developed by Werbos (1974) and later reintroduced by Rumelhart et al(1986). Such networks contain an extra layer(s) termed as hidden layer(s) in their architecture to overcome the problems of the perceptron model. The number of hidden layers and the number of neurons in each hidden layer are usually determined by a trial-and-error procedure.

B. METHODOLOGY

The aim of present study is to determine the wind pressure coefficients on the front face of a tall building by developing a Back Propagation Neural Network (BPNN). The data comprising of wind pressure coefficients considered for the analysis is obtained from experimental tests conducted in Boundary Layer Wind Tunnel (BLWT). The building is square in plan with dimensions as 30m×30m×180m.

The wind pressure measurements are made by varying wind incidence angle from 0° to 90° at an interval of 15° i.e. at 0°, 15°, 30°, 45°, 60°, 75° and 90° and pressure measurements are taken on all the faces of the model. Mean, maximum and RMS values of wind pressure coefficients were evaluated from the experimental data. But in the present study face of building named A2 is taken into account only and the mean values of wind pressure coefficients Cp (mean) are considered.

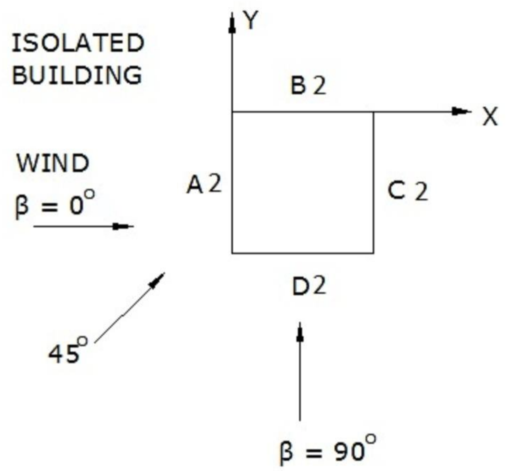

Fig 1 Direction of wind incidence angle

C. *Preparation of Training and Testing Data*

The Neural Network Tool in MATLAB was used to develop the BPNN model for the prediction of wind-induced pressure coefficients on a tall building. More detailed description of this can be found in [12]. In preparing the training data different conditions have to be considered. Increasing the number of training patterns increases the potential level of accuracy that can be achieved by the network.

The training data which consists of the experimental input- output data pairs under the incident wind angles, taken in two cases I and II as mentioned below were used to train the BPNN.

I. 0°, 15°, 75° and 90°
II. 0°, 30°, 60° and 90°

The remaining experimental data which were not used in the training were chosen as the new test data to evaluate the prediction accuracy of the developed BPNN model i.e. the pressure coefficients corresponding to unseen wind incidence angles for case I and case II as mentioned below

I. 30°, 45° and 60°
II. 15°, 45° and 75°

Initially the network selected, consisted of two hidden layers which were later increased. However, for a given network structure, the number of neurons in the hidden layers can significantly affect the prediction performance of the BPNN [7, 8]. For better appreciation of the generalization ability of the developed neural network, the prediction performance of a specific network is evaluated in terms of the following two parameters:

A correlation coefficient R is estimated between the ANN predictions and the experimental data.

Mathematically, it is defined as:

$$R = \frac{\sum_{i=1}^{N} T_i P_i}{\sqrt{\sum_{i=1}^{N} T_i^2}\sqrt{\sum_{i=1}^{N} P_i^2}} \qquad (6)$$

Where *N* is the number of samples;

$$T_i = Y_i - \bar{Y}$$

$$P_i = y_i - \bar{y}$$

Root Mean Square Error (RMSE) between the ANN predictions and the experimental data is evaluated as follows:

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - Y_i)^2} \qquad (7)$$

Network is trained to fit the inputs and outputs using Levenberg- Marquardt Backpropagation (trainlm). The data is randomly divided in three kinds of samples:

Training- These are presented to the network during training and the network is adjusted according to its error. About 60% of the data samples i.e. approximately 51 points are chosen for training by default.

Validation- These are used to measure network generalization and to halt training when generalization stops improving. 20% of data i.e. 17 points are used for validation purpose.

Testing- These have no effect on training and so provide an independent measure of network performance during and after training. The remaining 20% of the data is used to test the network's performance.

Regression R values measure the correlation between outputs and targets. An R value of 1 means a close relationship and R value of 0 indicates a random relationship. Mean Squared Error is the average squared difference between outputs and targets. Lower values are better. Zero means no error. The performance plot for both the sets were obtained and for set I it is shown in Fig 2

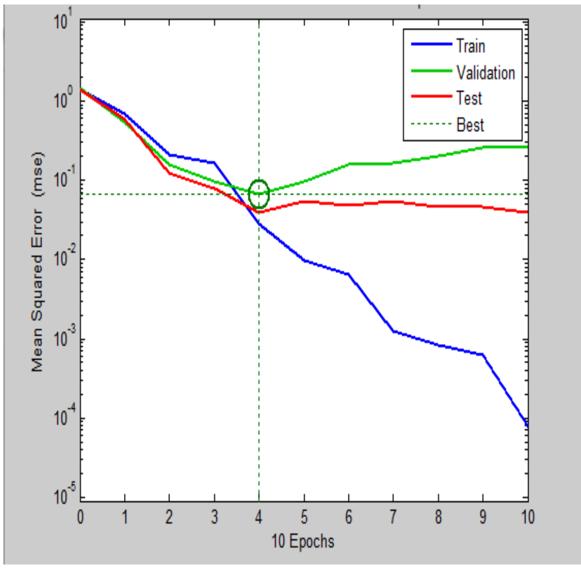

Fig 2 Performance Plot during training of BPNN model using data set of case I (0°, 15°, 75° and 90°)

IV. RESULT & DISCUSSIONS

Cp(mean) values were calculated using ANN for both the sets i.e. Set I & Set II. The R^2 and RMSE values were calculated for both the sets and is shown in Table No. 1 for Set I. R2 value has been shown graphically in Fig. [3,4 & 5]

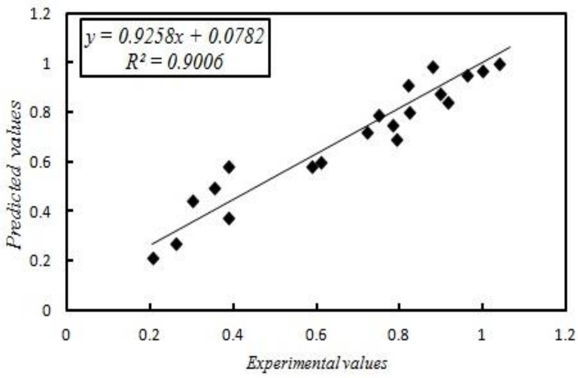

Fig. 3 Scatter plot of Cp (mean) between Experimental and predicted values for test wind incident angle 30° for Set I

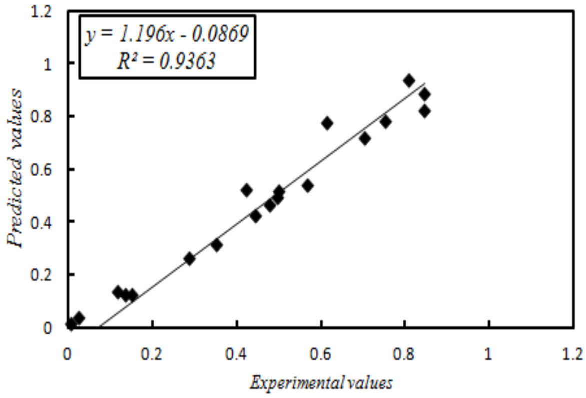

Fig.4 Scatter plot of Cp (mean) between Experimental and predicted values for test wind incident angle 45° for Set I

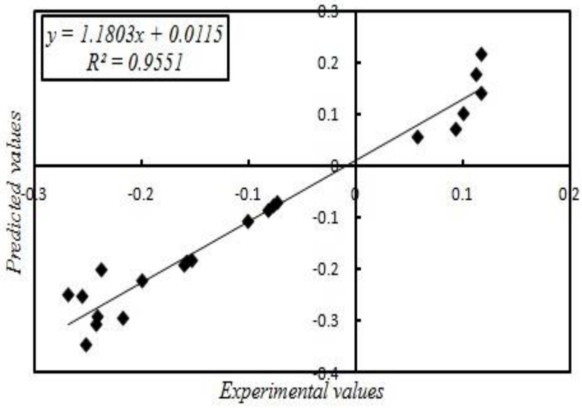

Fig 5 Scatter plot of Cp (mean) between Experimental and predicted values for test wind incident angle 60° for Set I

Table1 Summarizing the value of correlation coefficient R and RMSE for the test data set of case-I

Wind direction (degrees)	Correlation Coefficient R	RMSE (%)
30	0.94898	8.87
45	0.96761	6.74
60	0.97729	4.43

From Table 1 it is noticed that the value of R is more than 0.9 which indicates that the agreement between the experimental values and BPNN predicted values is generally good. Also from the scatter plots between the experimental and predicted values of Cp (mean) for the test wind incident angles 30°, 45° and 60° (Fig. 3,4 & 5), it is clear that there is close approximation between the two values. The root mean square error is observed maximum for wind incidence angle 45° while minimum for the angle of 60°.

Similarly, the results for data set corresponding to case II are discussed, for this set. the wind incident angles 0°, 30°, 60° & 90° were used to train the BPNN and angles 15°,45° & 75° were chosen as the new test incident angles to evaluate the prediction accuracy of the developed BPNN model. The results are shown below in table No 2

Table 2 summarizing the value of correlation coefficient R and RMSE for the test data set of case II

Wind direction (degrees)	Correlation Coefficient R	RMSE (%)
15	0.95852	7.81
45	0.94919	8.75
75	0.93263	9.87

For set II also the value of R is more than 0.9 for all the three angles which indicates that the agreement between the experimental values and BPNN predicted values. is generally good. Also from the scatter plots between the experimental and predicted values of Cp (mean) for the test wind incident angles 15°, 45° and 75°, it is observed that there is close approximation between the two values. The root mean square error is observed maximum for wind incidence angle 75° while minimum for wind incidence angle of 15°.

Thus from the above results it can be concluded that the artificial neural network technique can provide satisfactory predictions of wind- induced pressure coefficients on the tall buildings.

Reasons for Discrepancies in Results

Discrepancy between set of ANN results and experimental data can be because of some of the possible reasons listed below:

- Different network structures, learning rates, and inputs are believed to result in different prediction accuracies.
- The step size problem occurs because the standard backpropagation method computes only the first partial derivative of the overall error function with respect to each weight in the network. Given these derivatives, gradient descent is performed in weight space, reducing the error with each step. It is straightforward to show that if we take infinitesimal steps down the gradient vector, running a new training epoch to recompute the gradient after each step, we will eventually reach a local minimum of error function. But somewhere else in the weight space there exists another set of synaptic weights for which error function δ_k is smaller than the local minimum in which the network is stuck. It is clearly undesirable to have the learning process terminate at a local minimum, especially if it is located far above a global minimum.
- There is no foolproof method for setting architectural and learning parameters beforehand to achieve the optimal model for a specific problem. The approach generally adopted is trial-and-error, with a reasonable architecture selected initially.

V. CONCLUSION

In the present research, ANN-BPNN model has been used to estimate mean value of Cp at various pressure points with varying wind incident angles. It has been shown that ANN can be used for estimation of wind pressure distribution on buildings surface. The application of artificial neural networks for the prediction of pressure coefficients on tall buildings was observed to be successful in the present study. The ANN was trained with wind tunnel experimental data involving wind incident angles and geometrical coordinates of pressure points in order to predict the Cp (mean). The value of correlation coefficient between the experimental Cp and ANN predicted Cp values come out to be more than 0.9 in all the test cases. The value of RMSE is less than 10% in all the case tested so far.

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