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Application of artificial neural network for determination of wind induced pressures on gable roof

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Abstract. Artificial Neural Networks (ANN) have the capability to develop functional relationships between input-output patterns obtained from any source. Thus ANN can be conveniently used to develop a generalised relationship from limited and sometimes inconsistent data, and can therefore also be applied to tackle the data obtained from wind tunnel tests on building models with large number of variables. In this paper ANN model has been developed for predicting wind induced pressures in various zones of a Gable Building from limited test data. The procedure is also extended to a case wherein interference effects on a gable roof building by a similar building are studied. It is found that the Artificial Neural Network modelling is seen to predict successfully, the pressure coefficients for any roof slope that has not been covered by the experimental study. It is seen that ANN modelling can lead to a reduction of the wind tunnel testing effort for interference studies to almost half.

Key words: wind pressure coefficients; artificial neural network; interference factors and training data

1. Introduction

Wind loads on roofs of low buildings are significantly affected by the geometry of the building since it affects the flow pattern around the building. The usual practice for evaluating wind loads on buildings consists of using codes and standards whose specifications are based on wind tunnel tests performed in the ‘stand-alone’ configuration. However, buildings seldom exist in isolation being usually surrounded by other buildings. Thus, wind loads on buildings in actual environment differ from those measured on an isolated building. This is one of the main reasons due to which extensive testing is required for the determination of wind loads on low buildings, there being a large number of parameters with a wide range of values. To economise on the effort there is a need to explore ways of predicting wind loads from a comparatively reduced test programme. The ability of the neural network approach to train a given data set, and on that basis, to predict missing data and also to achieve possible normalisation, makes it an attractive proposition for knowledge acquisition for problems where there is no acceptable theory or empirical generalisation at present.

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Khanduri *et al.* (1995) presented the abilities of neural network for solving the wind interference problem among tall buildings. Sandri and Mehta (1995) applied neural network for predicting wind induced damage to buildings on the basis of simulated building damage data base. Girma (1999) used the neural network approach for determination of pressure distribution in buildings and found that errors were within 15% for predicted values. In the present study Artificial Neural Network is applied for predicting the design wind pressure coefficients for various zones on the low gable building in a stand-alone situation as well as for interference with another similar building. Data used for training and testing of neural network is obtained from wind tunnel tests carried out on the models of buildings.

2. Neural network model structure

Artificial neural network (ANN) models have been developed by artificial intelligence researchers and are being studied in the hope of simulating ‘human like’ performance in various fields such as for some complex multivariate and non-linear problems with incomplete or confusing information. The ANN models are composed of many non-linear computational elements (neurons) operating in parallel and are arranged in a pattern having extreme similarity with their biological counter part.

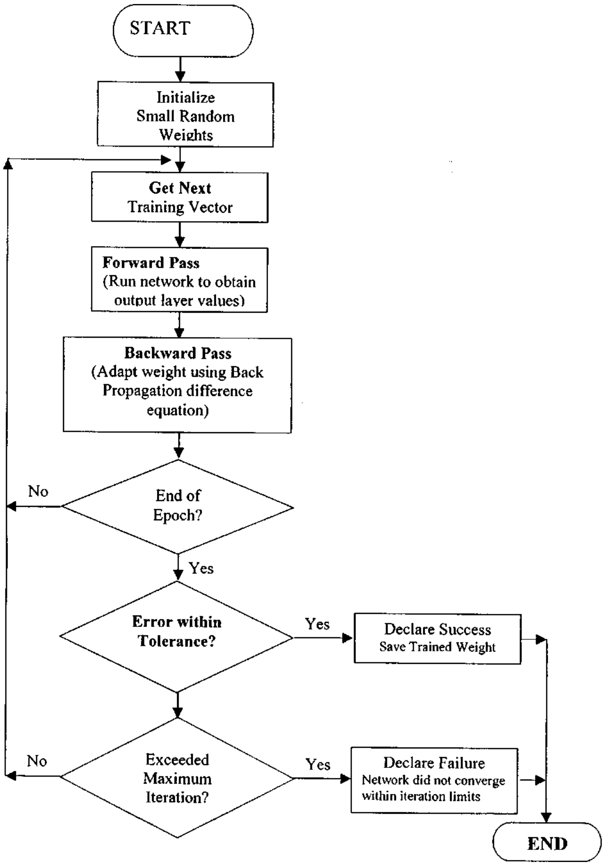

Fig. 1 Backpropagation flow chart

Neural Network representations are capable of developing functional relationship from discrete values of input-output quantities obtained from computational approaches or experimental results. This generalization property makes it possible to train a network on a representative set of input-output examples and get good results for a new set without training the network on all possible input-output examples.

The Backpropagation learning algorithm (Rumelhart and McCelland 1986) has been used to train the network in the present study. The overall process of Backpropagation learning algorithm including the forward and backward pass is presented in Fig. 1. A software (using C programming language) was developed for this algorithm specifically for this study. The software allows selection of number of neurons in the input layer, number of hidden layers, number of neurons in each hidden layer, and number of neurons in output layer. It also allows the selection of learning rate parameter and momentum factor. Software generates random numbered weights (as per specified range) depending upon the architecture of the network. This software has been tested on wide varieties of problems.

3. Experimental programme

A gable roof building ($13.5 \times 7 \times 5$ m) has been selected with the roof slope varying from 10^o to 35^o (with the increment of 5^o). Models were made to a geometric scale of 1:100. 72 pressure taps were used to cover the whole roof. The tubing system to measure the surface pressure consisted of 500-mm vinyl tubing with a 30 mm restrictor at 400 mm from pressure point, and a scanivalve pressure scanner. Pressure measurements were carried out by using Scanivalve ZOC12, a 32-port pressure transducer. The pressure measurement system has a linear response (constant magnitude and linear phase) up to 100 Hz. The sampling frequency was kept at 400 Hz. 8192 samples of pressure from each port were recorded thus giving a record of approximately 20 seconds, which corresponds to approximately 8 minutes for full scale assuming the velocity ratio of values in the wind tunnel and the field as 1/4. The roof area is divided into different zones as per the Indian Standard Code (IS875-1987, Part-3), (refer Fig. 2) with the purpose of making a direct comparison of codal values with those predicted experimentally. Zones 1, 2, 3 and 4 are defined as local pressure zones and zones 5, 6, 7 and 8 are defined as field zones. For local pressure zones worst pressures emerging from all wind direction from all four quadrants have been considered critical. Whereas for field zones 5-5′, 6-6′, 7-7′ and 8-8′ worst pressures emerging from all wind directions have been considered critical.

Experiments were also conducted to find out the effect of interference from a similar building on the building model of roof slope 20^o. The interfering building was moved in the longitudinal and transverse directions in a regular grid pattern as shown in Fig. 3. The interfering building was moved longitudinally 40 cm in steps of 5 cm whereas, it was moved upto 30 cm with the same step size transversely. Angle of wind attack was changed from 0^o to 90^o with increments of 15^o for every position of interfering building.

Atmospheric surface layer was developed in the wind tunnel over the building models by controlling the longitudinal turbulence intensity and its small scale turbulence content by using the combination of vortex generators, barrier wall and roughening blocks. The target values for these flow parameters were fixed on the basis of the findings of Cermak & Cochran (1992) and Tieleman *et al.* (1997).

The velocity fluctuations in the wind tunnel were measured by single hot wire probe.

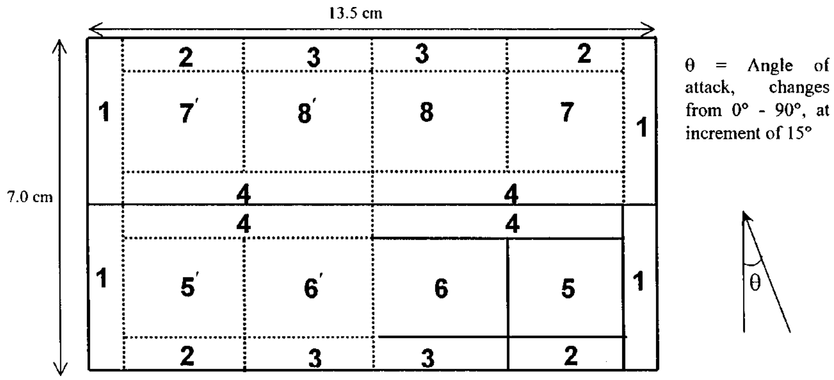

Fig. 2 Location of various zones on the roof of building model

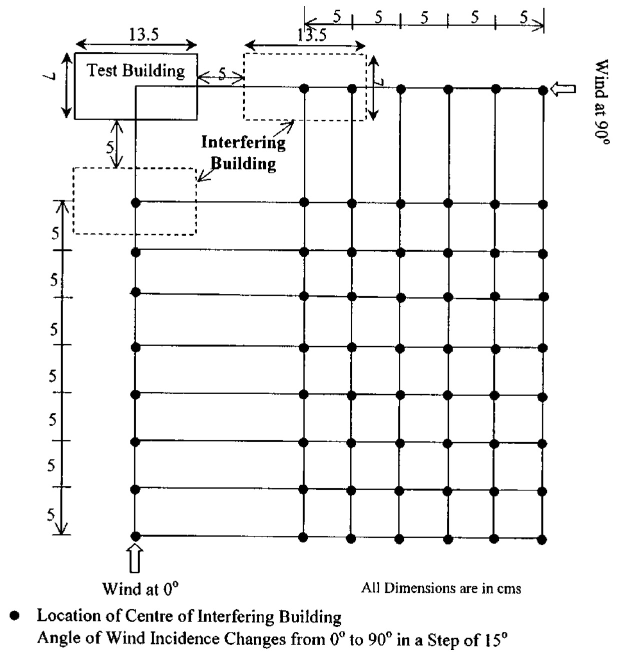

Fig. 3 General layout of interference with a single similar building

Instantaneous velocity fluctuations were recorded at a sampling frequency of 4 KHz. The mean velocity and longitudinal turbulence intensity at the eaves height of models were 8.9 m/s and 19% respectively with the velocity profile index being 0.136. The longitudinal integral scale at the same height was found to be 0.436 m. The small scale turbulence content was defined as (Tieleman *et al.* 1997).

$$S = (nS_u(n) / Su^2)(Su/U)^2 \times 10^6 \text{ evaluated at } n = 10U / L_p$$

where n is frequency, $S_u(n)$ is the spectral density, Su is the standard deviation of the longitudinal velocity, U is the mean velocity and L_p is the characteristic model dimension. In the present study model height is taken as the characteristic model dimension. Small-scale turbulence parameter of incident flow is evaluated at the frequency $n = 10U / L_p$ as per above mentioned equation. L_P is taken as model eaves height, i.e., 5.1 cm. This gives the value of frequency equal to 1745 Hz, at U = 8.9 m/s. Average value of $S_u(n)$ is taken for frequency range 1743 to 1747 Hz for the calculation of small scale turbulence parameter. The value obtained for this parameter is 73*. Tieleman *et al.* (1999) have reported values of same order for small scale turbulence content in their wind tunnel studies and has obtained good correlation between full scale and wind tunnel model results for mean and peak pressure coefficients.

4. Data reduction

Design pressure coefficient for any zone of the roof of the building is deduced from the most critical value of the peak pressure coefficient measured in the experiment, but is not taken equal to the peak value itself. It is unlikely that the maximum wind speed will be experienced from the most critical wind direction for each point of the building, and thus it will be more logical to take a reduced value for design. Different codes have used different approaches to deduce the design pressure coefficient from experimental studies. In the present study, a method based on probability distribution of measured pressure peaks has been used.

The plots of probability density function of measured pressure fluctuations of different taps over the roof show that the taps close to the edge and ridge of the building roof have significant deviation from Gaussian distribution as shown by Xu *et al.* (1990). Different approaches are in vogue to transform the observed data to follow the Gaussain distribution. In the present study, Box-Cox transformation (Box and Cox 1964) has been used to normalise the independent peaks of pressure history of each pressure tap, the independent peaks having been obtained using criterion suggested by Peterka (1983). Further the pressure coefficients were estimated at different probability levels as described above, and finally the design pressure coefficients (*Cpq*) at 99% probability of non exceedance were selected. The observed values of *Cpq* in the presence of interfering building have been compared with those for stand-alone case for all zones of building roof and expressed in terms of Interference Factor (IF), defined as

$$\text{IF} = \frac{\text{Response in Interference Configuration}}{\text{Response in Stand-alone Configuration}}$$

5. Use of ANN and results

5.1. ANN application for predicting wind Loads on buildings

Data obtained from the wind tunnel testing of different models has been used for the training of the neural network. The neural network has been trained using the roof slope and location of different zones on the building as the input and design wind pressure coefficients on the same as output parameter. The trained network is then expected to predict the design wind

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*If evaluated at the frequency of 1745 Hz, this value works out to be 216 as reported in Kwatra *et al.* (1999)

pressure coefficients for different zones on the buildings for roof slopes not covered in the training set.

5.1.1. Selection of neural network architecture and training data

The neural network architecture for the present study was selected by trial and error to minimize the error and to obtain speedy convergence. The network used for the training of data consists of two hidden layers with a input and a output layer. Input layer has two neurons representing the input parameter which are (i) zone number and (ii) roof slope. Output layer has one neuron which represent output parameter as design wind pressure coefficients for the concerned zone. Each hidden layer consists of twenty neurons. Nonlinear sigmoid function has been used as activation function.

For training of the network, roof slopes of 10^o, 15^o, 20^o and 30^o have been used. Design pressure coefficients (*Cpq*) of respective zones for these roof slopes have been considered as output parameter. All the input and output data have been normalised by the maximum value (which is termed as normalising factor) for each parameter, so that the values remain between 0 to +1. The output of the network is obtained in the form of normalised output, which is then converted to actual values by multiplying each value by corresponding normalising factor as used for preparing the training data set. The initial weights of the network have been set as random number between

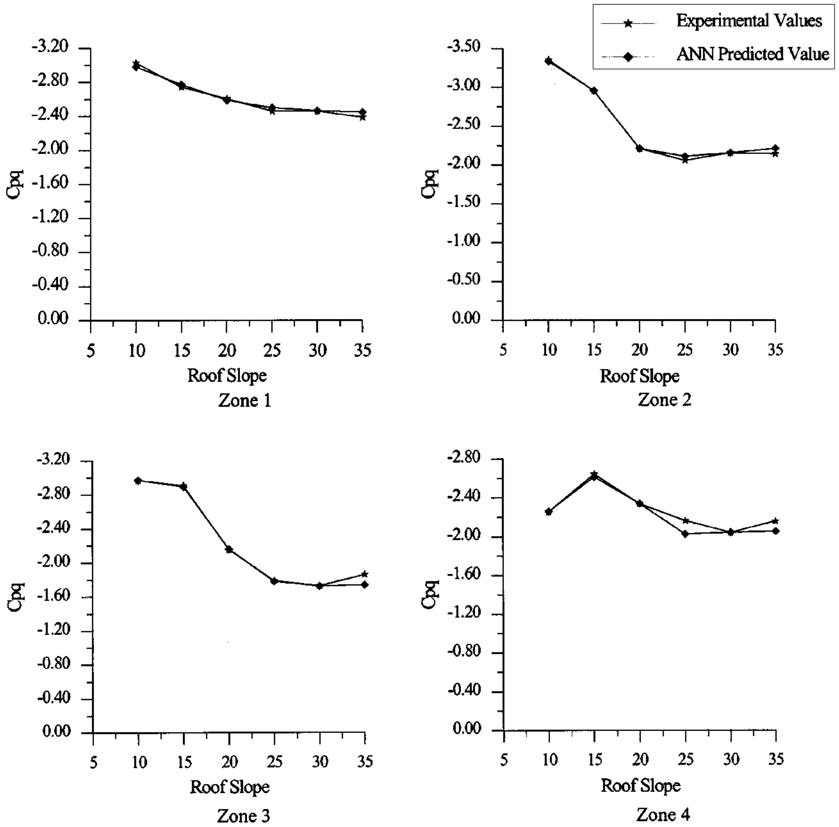


Fig. 4 Comaprison of *Cpq* for local pressure zones obtained by experiment and predicted by ANN

the range -0.3 to 0.3. The learning rate parameter (η) and momentum factor (α) are kept 0.15 and 0.85 respectively.

5.1.2. Comparison of ANN predictions with experimental values

The network has been trained with above-mentioned data set and the average mean square error of the network was reduced to 0.0003. The network performance has been tested by checking the output of the network for the same input data set used for the training of the network. The ouput values of the network for this data set have been found to be in close agreement with the target values of the same. These results ensure the successful training of the network. The values of *Cpq* for all roof zones for the roof slope 25^{o} and 35^{o} have been predicted by ANN. The predicted values of design pressure coefficients are compared with the experimental values. These comparisons have been presented in Fig. 4 for local pressure zones and in Fig. 5 for other zones. It can be seen from these figures that the predicted values of *Cpq* for all zones for 10^{o}, 15^{o}, 20^{o} and 30^{o} roof slopes are found to match perfectly with experimental values, as these values were present in training data set. The predicted values of *Cpq* for all zones of roof slope 25^{o} and 35^{o} are also observed to be in close agreement with the experimental values. The maximum error found for the ANN predicted values of *Cpq* for roof slope

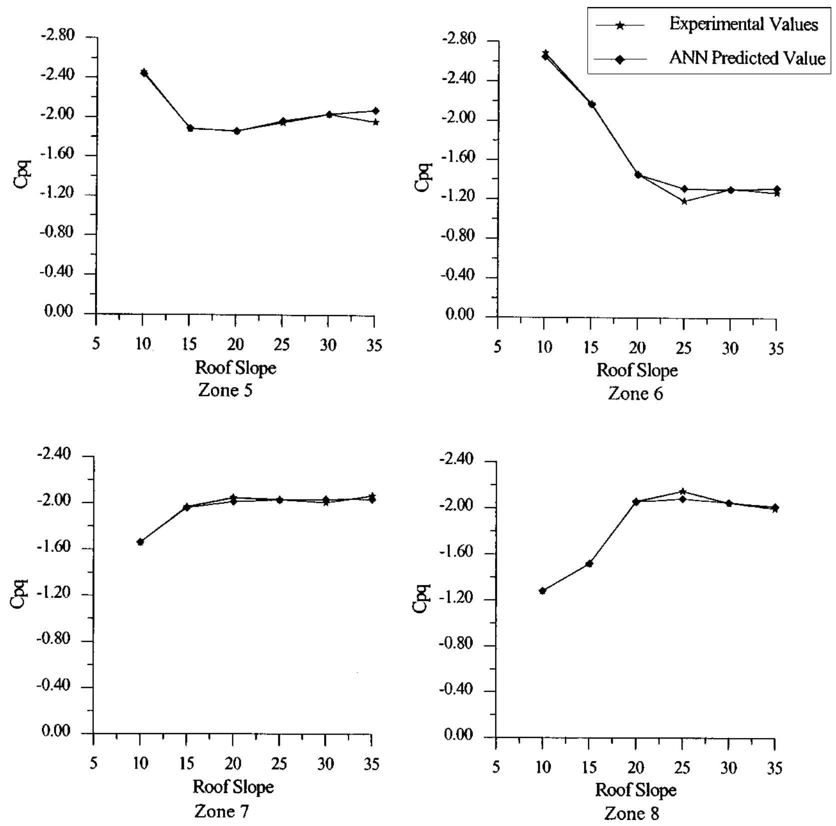


Fig. 5 Comparison of *Cpq* for other than local pressure zones obtained by experiment and predicted by ANN

of 25° and 35° is around 7%, which occurs for zone 4 of the roof with 25° roof slope.

5.2. ANN modelling for interference studies

The Interference Factors (IF) for worst design pressure coefficients irrespective of wind direction for each zone of the roof on the building for single building interference have been taken as output parameter of the neural network. Locations of interfering building have been considered as input parameter. Training of the neural network is carried out by the data set, which consists of some selected locations of interfering building and the values of IF for *Cpq* for each zone of the roof at those locations. The trained network is then expected to predict the IF for *Cpq* for each zone of the roof for locations of interfering building not covered in the training data set. Training of the neural network has been carried out separately for each zone of the roof.

5.2.1. Selection of neural network architecture

Neural network used for training for each zone of the roof consists of two hidden layers with an input and an output layer. Input layer has two neurons representing the input parameters which are X and Y coordinates of position of interfering building. These positions on interfering have been discussed earlier in the section 3. Output layer has one neuron, which represents the Interference Factor (IF) for *Cpq* for the concerned zone for the corresponding position of interfering building.

5.2.2. Selection of learning rate parameter and momentum coefficient

The values of learning rate parameter and momentum coefficient has been changed during the training of the network. Training of the neural network has been started with a value of 0.05 for learning rate parameter (η) and 0.65 for momentum coefficient (α). After some cycles of training, when the convergence of the network become slow, the values of these parameters have been increased with a step of 0.05. The values of η and α have changed from 0.05 to 0.35 and 0.65 to 0.95 respectively. Training of the network is carried out till the average mean square error of the network is reduced to 0.0005.

5.2.3. Selection of training data set

Selection of the training data set for the training of the neural network is the most important step. In preparing the training data different conditions have to be considered which include the size of the network, learning rate parameter and momentum coefficient. Increasing the number of training patterns increases the potential level of accuracy that can be achieved by the network. A large number of training patterns, however can sometimes overwhelm training algorithm. Consequently, there is no guarantee that adding more training patterns leads to improved solutions. A study has been carried out for selecting the training samples. This has been performed for zone 1 and zone 4 of the building roof. In the experimental study for single building, the interfering building has been placed on 63 different locations. In the first step, 23 positions of interfering building have been selected. In the second step 6 additional positions of interfering building have been included in the training set, which makes the training data set of 29 samples. Finally 4 more positions have been added to the training data set which makes the training data set of 33 samples. These positions of interfering building have been shown in Fig. 6. Training

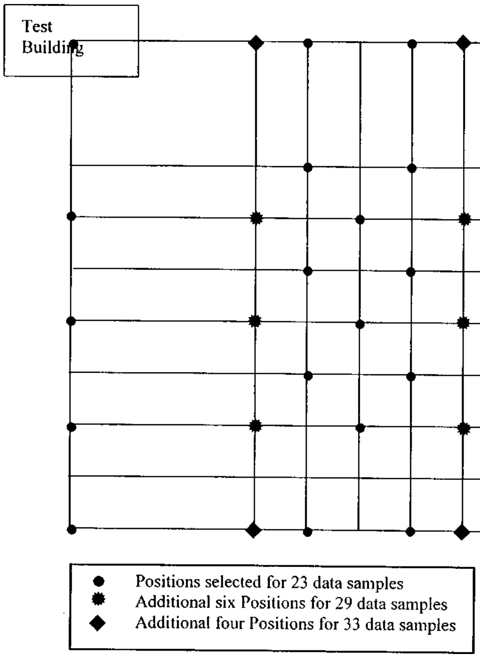


Fig. 6 Positions of interfering building selected for different training data set (For single building interference)

of the neural network has been carried out by using these training data sets and the average mean square error for all the cases is reduced to 0.0005.

5.2.4. Comparison of measured and predicted data

The values of IF for *Cpq* for zone 1 and zone 4 have been predicted for all positions of interfering building. Correlation between predicted values and experimental values of IF for *Cpq* for zone 1 and zone 4 for different training data set have been plotted and presented in Figs. 7 and 8. It can be seen from these correlation plots that as the number of samples in the training set is increased to 33 the

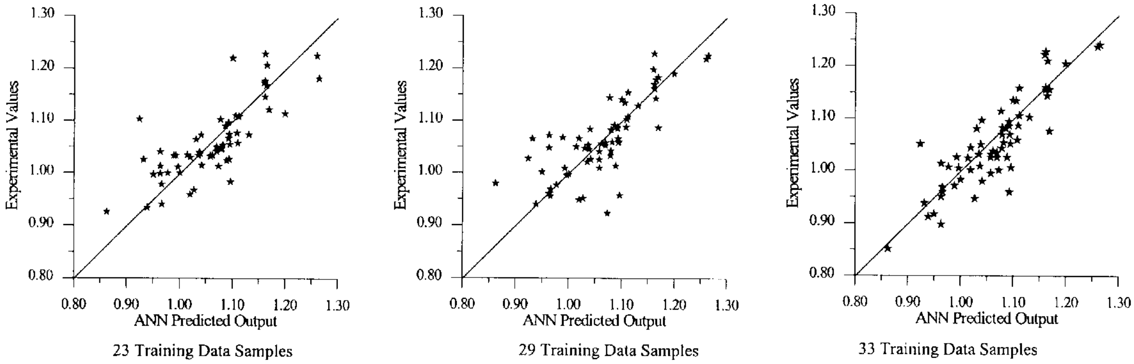


Fig. 7 Correlation plots between experimental and ANN predicted values for Zone 1 with different training data samples

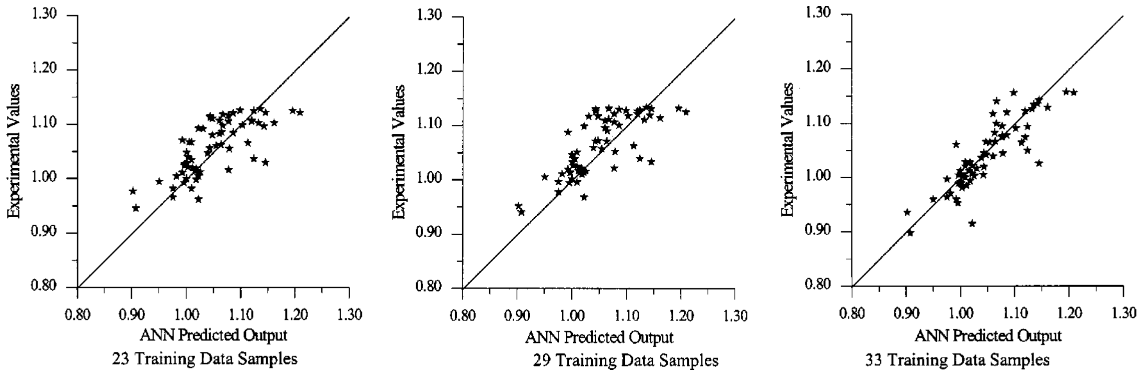


Fig. 8 Correlation plots between experimental and ANN predicted values for Zone 4 with different training data samples

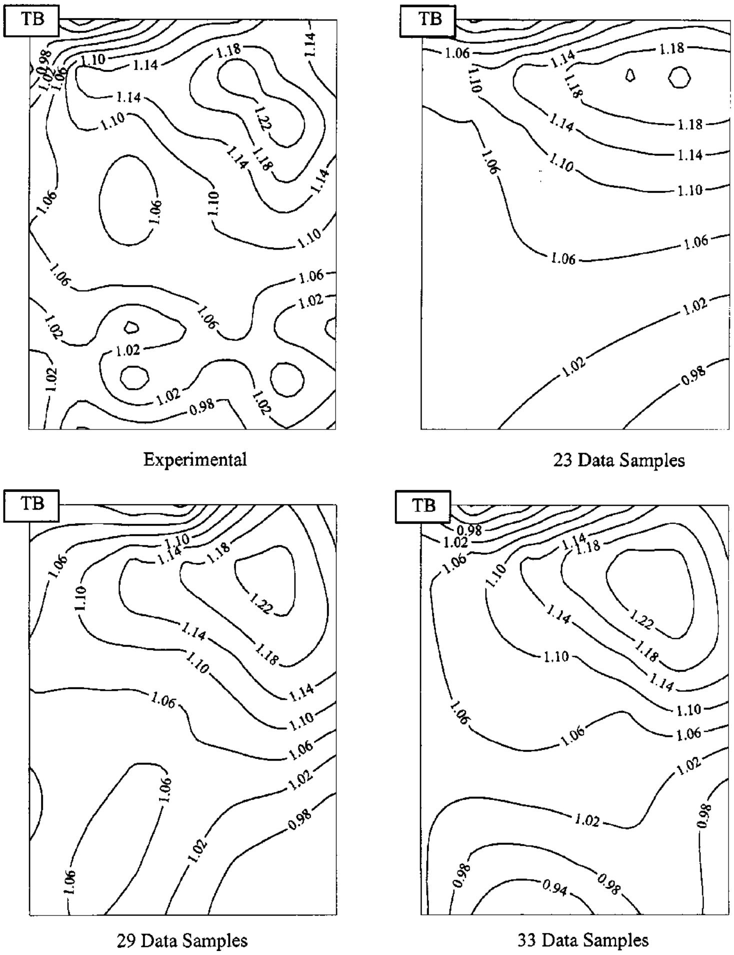


Fig. 9 Comparison of contours of interference factor for *Cpq* predicted by ANN (with different training data samples) and by experimental values for Zone 1

difference between the predicted values and experimental values reduces. Contours of predicted values of IF for *Cpq* for zone 1 and zone 4 for different training data samples have been plotted and compared with corresponding experimental values in Figs. 9 and 10. Contour plots of predicted values of IF for *Cpq* show that as the number of samples in the training set is increased from 23 to 29 the contour patterns approach closer to that of the experimentally obtained values. Further as the samples in the training set is increased to 33 the contours of the predicted values of IF for *Cpq* for zone 1 and zone 4 are found to be in close agreement with the contours of the same obtained experimentally.

Results of this study leads to conclusion that 33 samples are sufficient for training of the neural network. The predicted values of IF for *Cpq* for the positions of interfering building not covered in the training data set lie within the variation of 5%. Thus, these 33 positions of interfering building have been selected for training of the neural network for other zones of the building roof as well.

For each zone of the building roof, training of neural network is performed separately with the selected training data set as discussed earlier. Predictions of the values of IF for *Cpq* for each zone

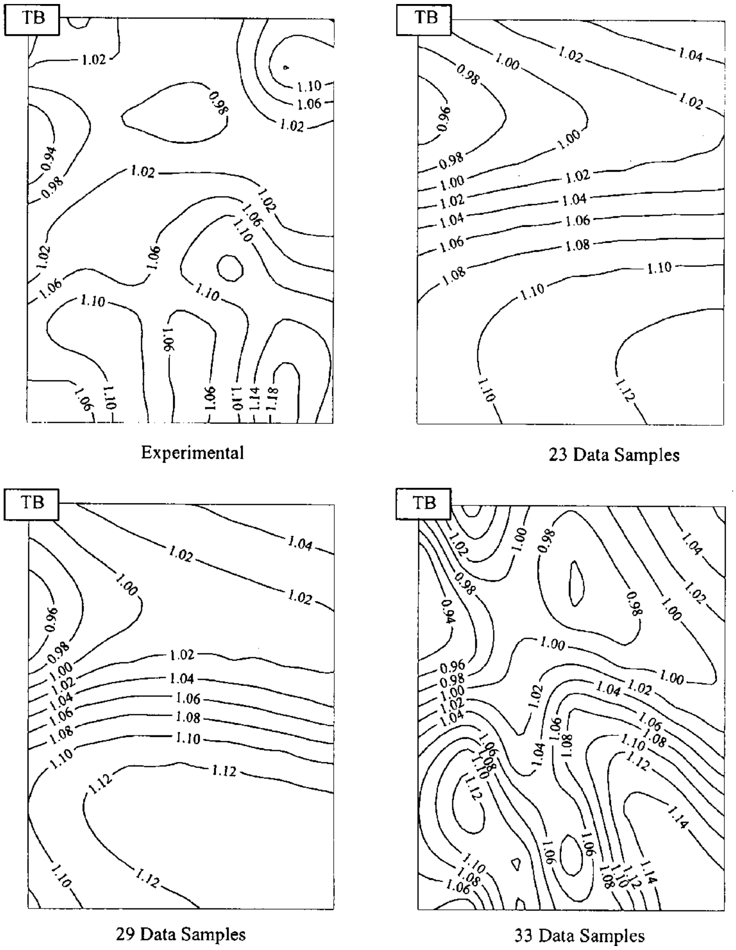


Fig. 10 Comparison of contours of interference factor for *Cpq* predicted by ANN (with different training data samples) and by experimental values for Zone 4

are made through trained network for all positions of interfering building. Correlation between the ANN predicted values and experimental values of IF for *Cpq* for different zones of the roof have been studied. Predicted values of *Cpq* for most of the cases are found to be very close with the corresponding experimental values. For local pressure zones the predicted values of IFs for *Cpq* for some positions of interfering building are found to be deviating from the experimental values. Whereas for other than local pressure zones, ANN predicted values and experimental values of IFs for *Cpq* are observed to be in matching closely for all positions of interfering building. Contours of predicted values of IF for *Cpq* for different zones of the roof have been presented in Fig. 11. The contours of IFs for *Cpq* predicted by ANN follow a similar pattern as that of experimental values. Moreover the contours of predicted values of *Cpq* show a generalised trend of variations, as ANN predictions attempt to map all the cases of input-output. It can be concluded by the results of these

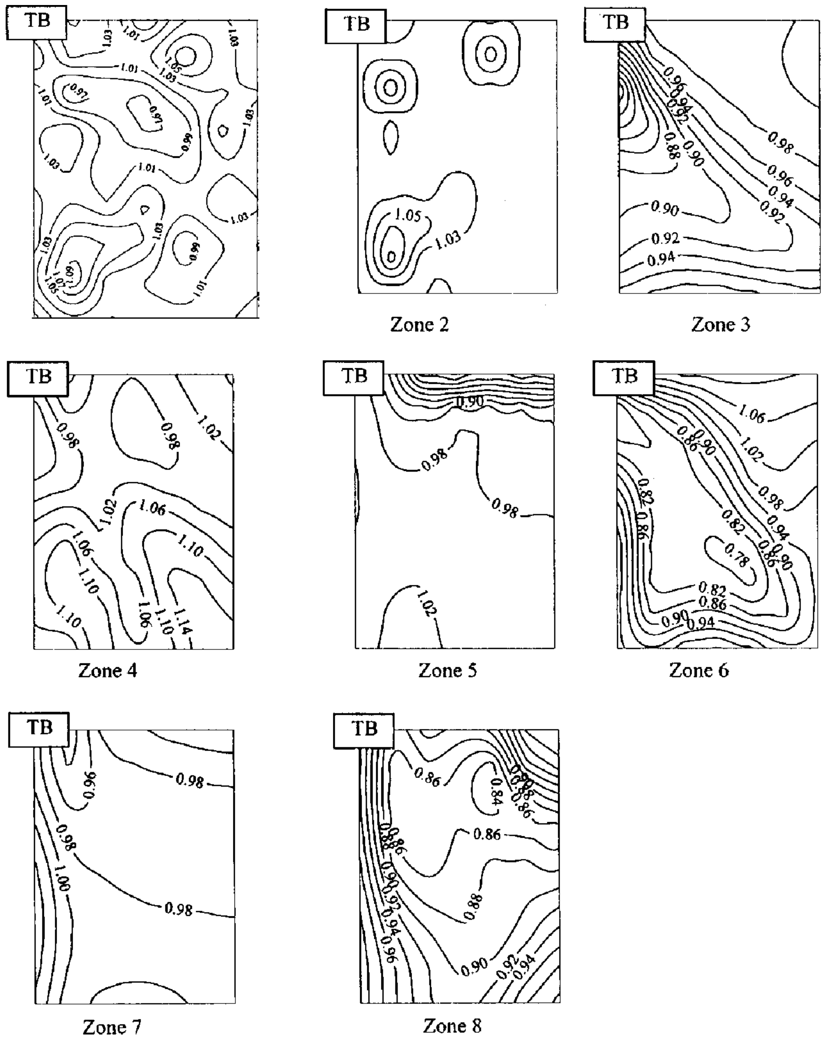
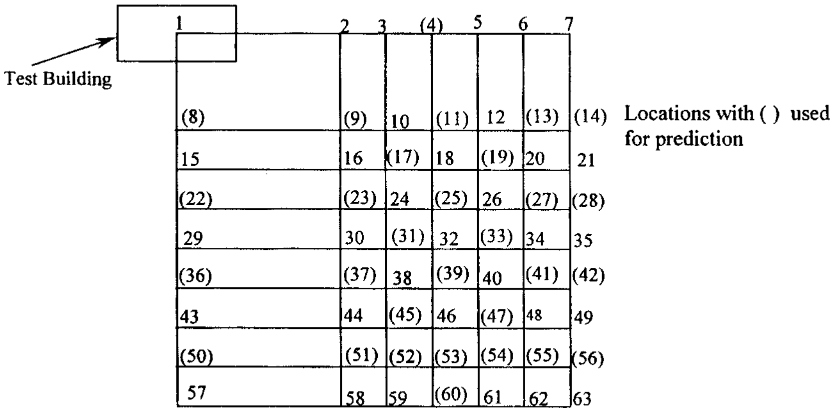


Fig. 11 Contours of interference factor for *Cpq* predicted by ANN for different zones due to change in position single interfering building

Table 1 Comparison of interference factors predicted by ANN and by linear interpolation

Locations of Inetrfering building	Zone 1			Zone 4		
	Experimental	ANN Predicted	Linear Interpolation	Experimental	ANN Predicted	Linear Interpolation
4	1.072	1.000	1.05	1.003	0.981	0.99
8	0.923	1.050	1.02	1.022	0.914	0.97
9	1.168	1.076	1.04	1.009	1.028	1.01
11	1.165	1.21	1.16	0.990	0.959	0.99
13	1.16	1.23	1.22	1.145	1.029	1.04
14	1.099	1.13	1.17	1.124	1.050	1.04
17	1.076	1.114	1.13	0.975	0.996	0.99
19	1.159	1.22	1.10	0.982	0.971	0.99
22	1.019	1.044	1.06	0.900	0.933	0.96
23	1.079	1.08	1.08	0.995	0.953	1.00
25	1.09	1.09	1.10	1.016	1.010	1.01
27	1.198	1.20	1.17	0.996	0.989	1.01
28	1.11	1.158	1.14	0.996	1.000	1.01
31	1.03	1.08	1.08	1.042	1.000	1.04
33	1.107	1.06	1.10	1.110	1.064	1.06
36	1.03	1.03	1.04	0.992	1.060	1.06
37	1.078	1.04	1.06	1.060	1.180	1.07
39	1.09	1.05	1.06	1.102	1.090	1.07
41	1.068	1.025	1.06	1.070	1.096	1.10
42	1.057	1.00	1.03	1.060	1.040	1.07
45	0.963	1.01	1.03	1.120	1.070	1.08
47	1.088	1.03	1.02	1.070	1.140	1.12
50	1.05	1.03	0.98	1.060	1.067	1.07
51	0.988	0.97	0.98	1.060	1.099	1.09
52	1.09	0.96	0.98	1.120	1.120	1.10
53	1.04	0.98	0.98	1.040	1.019	1.09
54	0.977	1.00	0.99	1.085	1.077	1.11
55	1.095	1.00	1.00	1.195	1.158	1.15
56	1.026	0.95	0.96	1.136	1.134	1.13
60	0.95	0.92	0.94	1.047	1.066	1.10



comparisons that almost 50% reduction in the experimental work can be achieved by using the neural network modelling for interference studies on low buildings. As a further exercise, the ANN predicted values have also been compared with the values obtained from linear interpolation as presented in Table 1. It is observed that the linear interpolation also gives close prediction.

6. Conclusions

The main conclusions drawn from this study are summarised below :

1. Artificial Neural Network Modelling is seen to predict successfully, the pressure coefficient for any roof slope not covered by the experimental study, based on data from other roof slopes. The maximum error seen in this study is 7%.
2. ANN modelling trained on the discrete interference results, can predict design pressure coefficients for different zones of the roof for a more generalised interference situation. The results have been found to be within 5% of the measured values.
3. ANN modelling reduces the wind tunnel testing for interference studies to almost half.

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