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WIND PRESSURE COEFFICIENTS PREDICTION ON DIFFERENT SPAN TO HEIGHT RATIOS DOMES USING ARTIFICIAL NEURAL NETWORKS

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Abstract

Large spans always fascinated architects and engineers. Domes provide an easy and economic method of roofing large areas with minimum material in all forms of space structures. Wind loads have significant proportion of the total load to act on such structures that's why the magnitude and distribution of the resultant pressures must be considered. To overcome this problem, the concept of Artificial Neural Network is adopted to find wind induced pressure coefficients for spherical domes of different span/height ratio. This paper aims to use this neural network application in steel space structures. Here, pressure measurements had been made on a large dome roof model with Computational Fluid Dynamics (CFD) technique and the data generated were used as the training sets to develop artificial neural network models to recognize the input–output patterns.

Keywords: Space structures; Domes; Back-propagation neural network; Computational Fluid Dynamics; Wind pressure coefficients

1. Introduction

Space frame being lightweight, structurally efficient and optimum in material consumption, scores over other structural system [1]. The lightness of the structure is mainly due to the fact that material is distributed spatially in such away that the load transfer mechanism is primarily axial force, either tension or compression, so that in any given element, all the material is fully utilized. In large span roofs, where the self weight of the structure constitutes an important part of the total load; the lightness of the constituent elements largely contributes to the rationality and economy of the entire structure.

Domes provide an easy and economic method of roofing large areas and are used frequently by the designers who realize the advantages and the elegant beauty of this form of construction. Analysis and design of such domes are time consuming since a large number

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of nodes and members are involved [2]. One of the most important criteria to design the dome is to construct with its optimized (minimum) weight considering dead, live and wind load.

Wind is a phenomenon of great complexity because of the many flow situations arising from the interaction of wind with structures. Wind is composed of a multitude of eddies of varying sizes and rotational characteristics carried along in a general stream of air moving relative to the earth's surface. These eddies give wind-its gusty or turbulent character. Large eddies, whose dimensions are comparable with the structure, give rise to well correlated pressures as they envelop the structure. On the other hand, small eddies result in pressures on various parts of a structure that become practically uncorrelated with distance of separation. Therefore, an understanding of the flow of wind around any structure, leading to the accurate prediction of wind pressure and/or force coefficients, is an essential requirement of modern structural design [3]. Long-span and lightweight roofs, such as spherical pneumatic domes, tend to vibrate in strong winds [4]. In other words, wind loads have significant proportion of the total load acting on such structures and so the magnitude and distribution of the resultant pressures must be considered [5].

The magnitude and distribution of pressures on any structure is governed primarily by the pattern of wind flowing around it. Normally, the pressure at a point is expressed in terms of a dimensionless pressure coefficient, C_p, where

$$C_p = p/q \text{ and } q = \tfrac{1}{2}\rho V^2 \tag{1}$$

In which p is the pressure at the point of interest, q is the dynamic pressure (kinetic energy) of the wind, ρ is the density of air and V is the velocity of the approaching flow.

Unfortunately, the majority of codes are only able to provide data relating to the most common types of building and do not provide for unusual or difficult structures with curved surface. In addition to that it was found that majority of codes and technical papers provide the pressure coefficients detail for domes having span/height (S/H) ratio 2 or 3 and that is also for central line only, which is definitely insufficient data for analysis and design of domes. When little information available on the pressure coefficients on these roof forms, it is not easy for structural designer to make an informed decision on the choice of pressure coefficients. There are other sources of pressure coefficients on curved roofs such as research papers and commercial wind tunnel studies, but in general these are not in a form suitable for codification or they lack essential experimental details which are necessary for codification purposes. Thus, developing approximate methods using Artificial Neural Networks (ANNs) to find wind coefficients on structure is found to be very useful.

2. Computational Fluid Dynamics

The research field of Computational Wind Engineering (CWE) is well established today as a powerful tool in wind engineering research. It is now over 25 years since the Computational Fluid Dynamics (CFD) technique was first applied to a problem of wind engineering. In general, CFD is the use of computers and numerical techniques to solve problems involving fluid flow. Application of it was originally introduced for industrial applications [6], but today it has also become a common tool for assessing wind effects on structures [7-8], building ventilation [9] and environmental performance [10]. Thus, in general CFD is ‘‘a very powerful technique’’ in predicting air movement and characteristics [11].

CFD Basics

CFD model is based on the concept of dividing the solution domain into sub-zones. Then, for each zone, the mass, momentum, and energy (if problem is non-isothermal) conservation equations are solved, and utilized the processing power of computers. This helps to perform calculations more easily and, in comparison with natural ventilation mathematical models, gives more detailed results. CFD codes are used to predict airflow rate, air velocity-temperature, and airflow patterns inside-around buildings. Many software based on CFD codes have been developed like, Ansys-CFX, Fluent, Phoenics.

Following are the governing equations for computational fluid engineering.

Mass:

$$\frac{d\rho}{dt}+\frac{d(\rho u)}{dt}+\frac{d(\rho v)}{dt}+\frac{d(\rho w)}{dt}=0 \tag{2}$$

Momentum (in x direction) :

$$\frac{\partial(\rho u)}{\partial t}+\frac{\partial(\rho uu)}{\partial x}+\frac{\partial(\rho vu)}{\partial y}+\frac{\partial(\rho wu)}{\partial z}=-\frac{\partial p}{\partial x}+\mu\nabla^2 u+other\ forces \tag{3}$$

Where

ρ = density of fluid (air),

u, v, w = Velocity of air in x, y and z direction, respectively.

p = pressure,

μ = dynamic viscosity,

∇^2 is the *Laplacian* operator.

A complete CFD analysis consists of:

- *Pre-processing*;
- *Solving*;
- *Post-processing.*

This study has focused on the “solving” process, but this is of little use without preprocessing and post-processing programs. Commercial CFD vendors often supplement their flow solvers with *grid-generation* and *flow-visualization* tools. These are specialist areas in their own right, with much money and effort devoted to developing “user-friendly” interfaces to make CFD generally accessible and to facilitate its application to complex flows.

In the last few years, an intensive work has been done using CFD. However, in some studies the work is not only limited to the use of CFD modeling, but also to compare the experimental testing results to check validity. Comparisons of CFD results with wind tunnel tests have shown good agreement [12]. CFD performs the unique role in the possibility of bringing down the costs and turn-around times in the design and development of wind induced structures.

Wind-induced pressure distributions on large roof structures depend on several factors such as incident wind direction, turbulence characteristics, upstream terrain; roof shapes configurations and surrounding condition, etc. Under similar flow conditions, the flow pattern around a building strongly depends on incident wind direction and roof shape configurations.

CFD for large domes

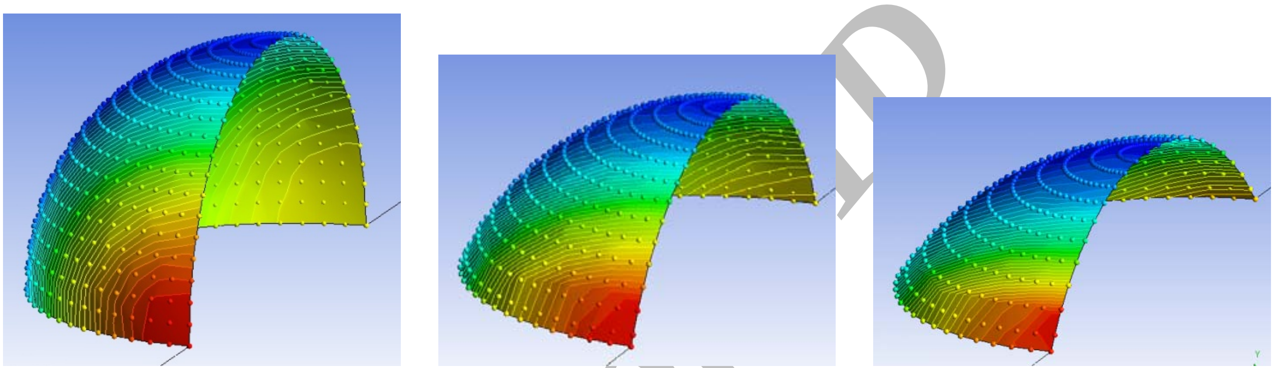
The computational wind tunnel analysis and neural network prediction for dome structures had been attempted as per following steps:

1) Create a computational wind tunnel to simulate the surrounding environment, (pre-processing)
2) Apply wind flow to the dome structures, (solving)
3) Obtain the structural pressure loading due to the wind flow, (post-processing)
4) Find corresponding pressure at every 5^0 in horizontally and vertically in longitude and latitude direction respectively.
5) Get pressure coefficients (C_P) from different pressure values.
6) Prepare data set for neural network training.
7) Train neural network for the same.

Dome with span of 30 m and span/height ratio 2 is considered for this study. An artificial uniform wind flow with a velocity of 44 m/s (as per IS: 875 (Part 3) wind load) [13] had been applied to the entrance of the tunnel. The wind tunnel used for this simulation is of size 21D x 8D x 8D where D is the diameter of the dome, which in our case is 30 m. To avoid the complexity of model the researchers take only half portion of spherical surface (see Figure 1). To find out correct variation authors tried different models with different conditions. The main models are of isothermal with shear stress transport and k-ε having different turbulence such as 1%, 5% and 10% with isothermal effect. ANSYS CFX 10 software which can numerically solve the two basic conservation equations of mass and momentum in an iterative manner, has been used. From this model pressure coefficients were obtained.

For the same span/height ratio the coefficients of pressures were compared with the IS: 875 (part- 3) wind load coefficients. IS-code gives pressure coefficient values at every 15^0 along the centre line. Accordingly authors had taken same points for coefficients of pressure, to check the value for simulated models. The values were taken from the best suited model i.e. shear stress transport with 5% turbulence with isothermal features. The study proves that the CFD models gives nearly best results for wind loading on domes.

As the model with S/H ratio of 2 matches with IS code values, the researchers tried other two ratios 3 and 4. The same procedure had been carried out for other two ratios. In order to train the network over the entire region of dome, the large database had been formed. The database was covered by taking pressure coefficient values with the variation of θ (*theta*) and φ (*fi*). *Theta* is angle measured vertically with respect to the vertical axis of the dome to the ring beam and *fi* is angle measured horizontally with respect to wind direction. The interval was kept common as 5^0 in both *theta* and *fi*. For span/height ratio 2, 3 and 4, pressure and pressure coefficient values were taken respectively at 703, 555 and 444 points respectively (see Figure 1(a), (b), (c)). The need of above data is to prepare data set to train neural network and to find out pressure coefficients on domes.



(a) (b) (c)

Figure 1. Contour diagram for wind pressure and point under consideration for C_P values for dome having span/height ratio 2, 3 and 4

3. Artificial Neural Networks

Artificial Neural Networks (ANNs) are, by definition, interconnected networks of processing elements that have the ability to be trained to map a given input into the desired output [14]. ANNs possess some distinctive properties not found in conventional computational models. Traditional computing models are based on predefined rules (equations, formulas, etc.) that clearly specify the problem. The program follows an explicit step-by-step procedure to compute desired outputs. This is feasible when the rules defining the problem are known in advance. In most cases however, there are only observational data of the problem, while the underlying rules relating the input variables to the output variables are either unknown or extremely difficult to discover. Under there circumstances, ANNs exhibit their superiorities over conventional computational techniques.

ANNs are composed of any interconnected processing units. Each processing units keeps some information locally, is able to perform some simple computations, and can have many inputs but can send only one output. The ANNs have the capability to respond to input stimuli and produce the corresponding response, and to adapt to the changing environment by learning from experience. Garrett [15] has given an interesting engineering definition of the ANN as: “An ANN is a computational mechanism from one multivariate space of information to another, given a set of data representing that mapping.”

Back-propagation neural networks

The most widely used paradigm of ANNs is Back-Propagation Neural network (BPNN), which belongs to the family of Multi Layer Perceptron (MLP) network [16]. BPNN is made of at least three layers of nodes: i) An input layer that receives input values, ii) An output layer that reports the final answer(s) and iii) one or more hidden layers between the input and output layers . The neighboring layers are fully interconnected by weights. A typical back propagation neural network is shown in Figure 2. Here, the notation BPNN *n-m-h-o* is used as a label for a net with *n* input variables, *o* output variables and two hidden layers with *m* and *h* neurons in the first and second hidden layers, respectively. Layers are fully interconnected, as shown by arrows.

A feed forward operation, represented the flow of information is from left to right, as shown in Figure 2. Initially a random weight is assigned to each connection. These weights are then adjusted as the learning progress. The next step in the feed forward operation is to calculate the input of each hidden neurode.

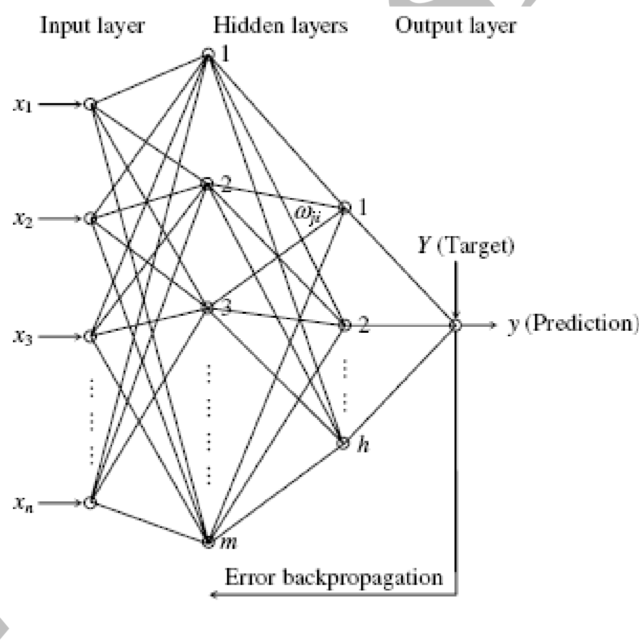


Figure 2. A typical back propagation neural network

The value of input to hidden layers is calculated as:

$$I_h = \sum (W_i * P_i) \tag{4}$$

Where

I_h is the value of input to the hidden layer neurons

W_i is the network interconnecting weights from the input to the hidden layer

P_i is the value of the input variables in the output layer

At this point, an activation function is called to calculate the output value from the hidden neurons to output neurons. Once the output of the hidden neurons is calculated, the activation function is again called to calculate the network output. The network output is an estimate prediction of the target output using the input patterns and the associated network weights. At his stage, the network error was calculated, which is the difference between the target output Y and the network prediction y, as:

$$E = (Y - y) \tag{5}$$

This error is then back propagated to the system to adjust the interconnecting weights for each layer. The repeated process of back-propagation of network error and adjusting the interconnecting weights are continued for many iterations (epochs) until the network error is reduced to an acceptable level. Once this has been achieved, training is considered to be completed, the inter-node link weights are registered and kept unchanged and the network is considered ready to handle new problems.

Before using the network, it needs to be adequately trained using a carefully selected and large set of solved examples (i.e. sets of given input and output values) that effectively cover the range of variables likely to be encountered. The network uses these examples to adjust the weights of its inter-node links so that the error in the output is minimized.

Neural networks in structural engineering

In the last decade, a wide range of research had been carried out and many papers published in using neural networks for doing analysis and design of structures. Hajela and Berke applied the neural networks in analysis of structural mechanics [17]. Jenkins used the neural networks method as an approximation approach for structural analysis [18], and Adeli and Park applied the counterpropagation nets in structural engineering [19]. The use of ANN increases then in typical areas of structural engineering such as El-Kassas E. M. A. used neural networks in cold-formed steel design [20], Hadi Muhammad adopted neural networks applications in optimizing concrete structures [21]. Further, Cladera A. used ANN in shear design procedure for reinforced concrete beams (normal and high strength) without and with stirrups [22, 23] and Adikary B. used ANN for the prediction of shear capacity of steel plate strengthened RC beams [24]. In addition to concrete structures, ANN also used in analysis and design of steel structures. Kaveh A. [25] and Keyvani S. [26] applied Backpropagation neural networks in double layer grids and Kaveh A. also used ANN in analysis and design of Domes [2]. In wind engineering application, Fu J. Y. [27, 28] used ANN applications in prediction of wind pressures on large flat and gymnasium roofs.

ANNs have many inputs and outputs and allow nonlinearity in the transfer function of the neurons; therefore they can be used to solve multivariate and nonlinear modeling problems, such as some wind engineering problems. For this research paper the set of *theta* and *fi* values with coefficients of pressure values are considered as data set.

4. BPNN Prediction for Pressure Coefficients on Domes

The main objective of this study is to check the variation of pressure and thus pressure coefficient along the curved surface of the domes and train neural network for same. The well-establish back-propagation learning algorithm is adopted to train the network. Two alternative networks, Neural Network–1 (NN-1) and Neural Network–2 (NN-2) are considered.

In the first case NN-1, the program requires the following input data:

1. As span of 30 m and span/height ratio 2 is constant, only *theta* and *fi* angles are selected for the input. The output is pressure coefficients at corresponding points of domes. The above developed CFD database is used to train a neural network. So, the processing elements (PEs) in input layer were two and in output layer was one. Please see Figure 3(a).
2. All the above 703 data of C_P are divided into three groups, 563 data for training, (80% of total data), 70 for cross validation (10% of total data) and 70 for testing (10% of total data). Above data are randomized by randomized function. The need of this function is to give data to the neural nets in random way, so mapping from input to output variables to minimize the error between the network response and the target output with satisfactory results are achieved.
3. The networks are selected with both one and two hidden layers. An additional second hidden layer can be considered between the first hidden layer and the output layer to allow smoother mappings possible. The PEs in first hidden layer and second hidden layer are varied from 4 to 10 as shown in Table 1.
4. Multi layer perceptron in combination of delta bar delta learning rule with both sigmoid and tangent hyperbolic functions are taken for the process of training.
5. The error tolerance, which is set to 0.0001 for training set and cross validation set in this study, and is defined according to mean squared error (MSE). The maximum number of training cycles or epochs, which is chosen as 50,000 to achieved the specified error tolerance. Once this number is attained the program is terminated even if the error tolerance is not met.

In this paper *Neurosolutions* is employed for training and testing of our structure. The program *Neurosolutions* is capable of representing useful information in the process of training. Once it is trained, the network is capable of generalization and is able to approximate the solution to unseen problems.

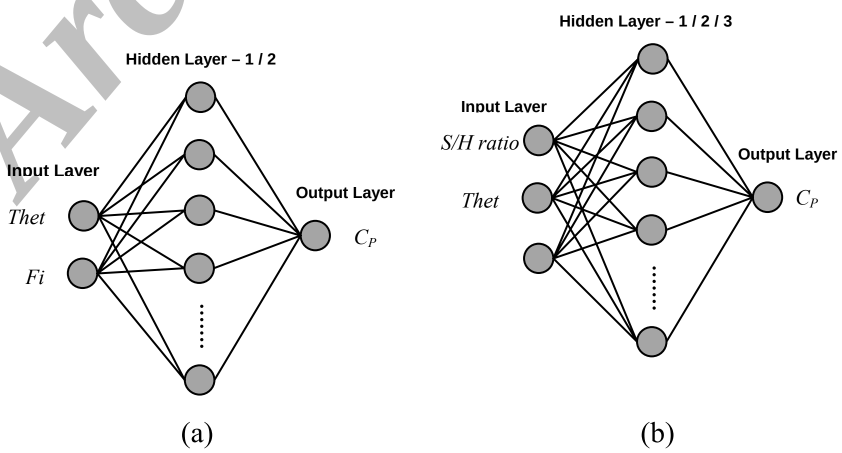


Figure 3. Model NN –1 and NN–2

For the second case NN 2, the program requires the following input data:

1) Here, span/height ratio (i.e. 2, 3 and 4), *theta* and *fi* angles are selected for the input. The output is pressure coefficients at corresponding points of domes. So, the processing elements (PEs) in input layer were three and in output layer was one. Please see Figure 3(b).
2) For S/H ratio 2, 703 data, for ratio 3, 555 data and for ratio 4, 444 data are considered for training. All above 1702 data are divided into three groups, 80% for training, 10% for cross validation and 10% for testing. Above data are randomized by randomized function.
3) The networks are selected with one, two and three hidden layers. The PEs in hidden layer is varied from 6 to 14 as shown in Table 1.
4) Multi layer perceptron in combination of delta bar delta learning rule with tangent hyperbolic functions are taken for the process of training.
5) The error tolerance and maximum number of epochs are taken same as NN – 1for network termination.

Table 1. Architecture and results of NN–1 network for testing data

Model name	**PEs in each layer**				**Transfer function**	**Mean squared error**	**Correlation coefficient**
	Input layer	**First hidden layer**	**Second hidden layer**	**Output layer**			
M4 ct	2	4	-	1	Tanh	0.00220	0.9968
M6 ct	2	6	-	1	Tanh	0.00168	0.9976
M8 ct	2	8	-	1	Tanh	0.00161	0.9977
M10 ct	2	10	-	1	Tanh	0.00135	0.9980
M4 cs	2	4	-	1	Sigmoid	0.00262	0.9962
M6 cs	2	6	-	1	Sigmoid	0.00181	0.9974
M8 cs	2	8	-	1	Sigmoid	0.00228	0.9967
M10 cs	2	10	-	1	Sigmoid	0.00238	0.9965
M4 4ct	2	4	4	1	Tanh	0.00143	0.9979
M6 6ct	2	6	6	1	Tanh	0.00126	0.9982
M8 8ct	2	8	8	1	Tanh	0.00126	0.9982
M10 10ct	2	10	10	1	Tanh	0.00124	0.9983
M4 4cs	2	4	4	1	Sigmoid	0.00198	0.9971
M6 6cs	2	6	6	1	Sigmoid	0.00193	0.9972
M8 8cs	2	8	8	1	Sigmoid	0.00217	0.9969
M10 10cs	2	10	10	1	Sigmoid	0.00224	0.9968

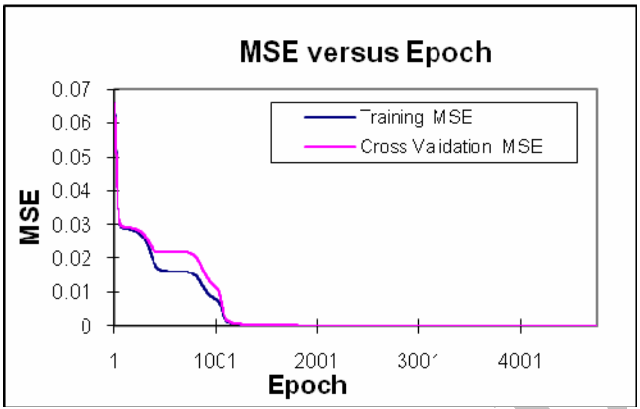


Figure 4. Training of M10 10ct model

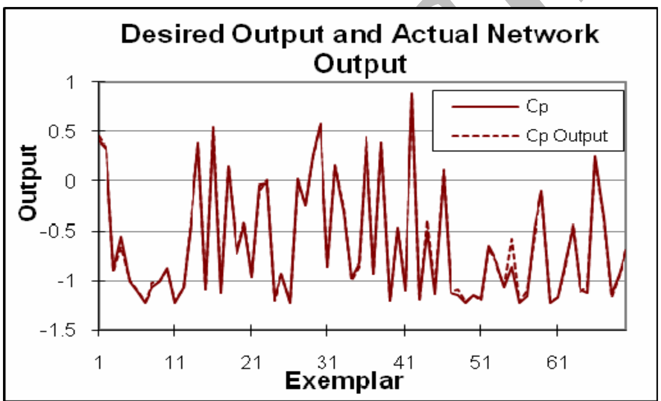


Figure 5. Testing of M10 10ct model

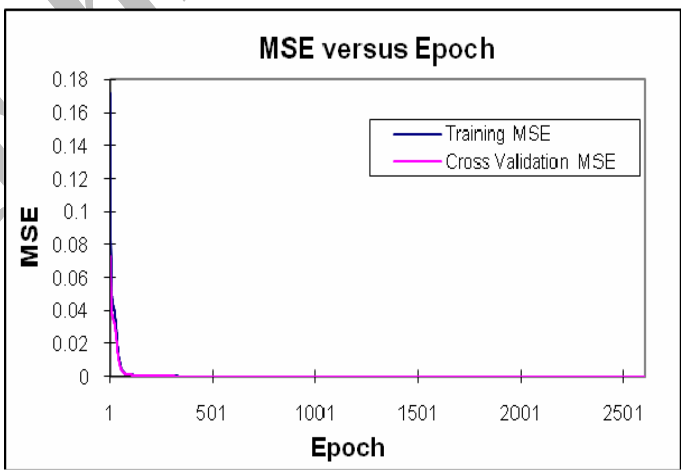


Figure 6. Training of m14-3ct model

Table 2. Architecture and results of NN-2 network for testing data

Model name	Model notation	PEs in each layer					Transfer function	Mean squared error	Correlation coefficient
		Input layer	First hidden layer	Second hidden layer	Third hidden layer	Output layer			
m6 ct	3-6-1	3	6	-	-	1	Tanh	0.00167	0.9971
m10 ct	3-10-1	3	10	-	-	1	Tanh	0.00077	0.9986
m14 ct	3-14-1	3	14	-	-	1	Tanh	0.00074	0.9987
m6-2ct	3-6-6-1	3	6	6	-	1	Tanh	0.00043	0.9992
m10-2ct	3-10-10-1	3	10	10	-	1	Tanh	0.00030	0.9994
m14-2ct	3-14-14-1	3	14	14	-	1	Tanh	0.00030	0.9994
m6-3ct	3-6-6-6-1	3	6	6	6	1	Tanh	0.00040	0.9993
m10-3ct	3-10-10-10-1	3	10	10	10	1	Tanh	0.00034	0.9994
m14-3ct	3-14-14-14-1	3	14	14	14	1	Tanh	0.00031	0.9995

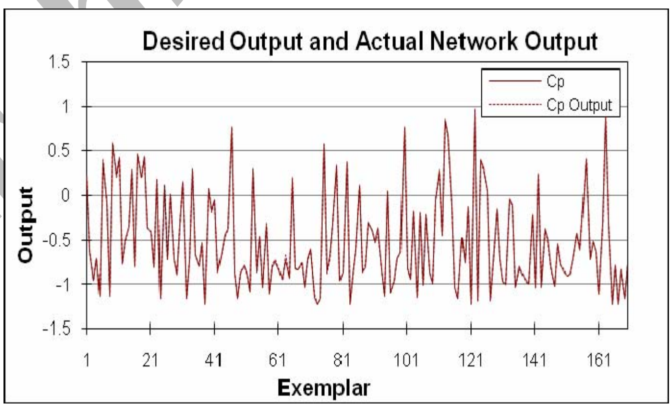


Figure 7. Testing of m14-3ct model

5. Results

A successful attempt was made to apply a backpropagation neural network to the prediction of pressure coefficient on a large hemispherical roof. The results of NN–1 and NN – 2 networks with different model configuration are shown in Table 1 and 2. The best models are shown with bold figures. In addition to that, the training and testing of the best models were presented in Figures 4 to 7 respectively. Using tanh activation function and almost 10 nodes in two hidden layer the correlation factors approached to **0.9983** and **0.9995** for NN–1 and NN–2, respectively.

6. Discussions and Concluding Remarks

The results presented in this paper indicate that the developed BPNN models were capable of generalizing the complex, multivariate nonlinear functional relationships among a number of variables such as wind induced pressure and positions of pressure taps, etc, so that they are able to predict wind-induced pressures on the large dome structures with good accuracy for any combination of these variables.

Backpropagation networks using *Neurosolutions* software has perfectly evaluated wind pressure coefficients data. The results show that ANNs have strong potential as a feasible tool for predicting the C_P values at any point on the dome roof. Even NN – 2 network models where more span/height ratios are considered gives good result compare to NN – 1. Based on CFD study and ANN study the following results and conclusions can be drawn for the present work:

1) The neural network reacts negatively to reducing the size of the training set.
2) At least six nodes should be used per hidden layer in order to maintain a high accuracy for the network predictions.
3) Two hidden layers models show mainly the difference in terms of time required for learning and little significant difference in terms of accuracy, than one hidden layer.
4) Increasing the number of hidden layers in the network is not justifiable because of the resulting slow speed of network training and operation and the subsequent very slight change in network accuracy level.
5) By considering above two points network with two hidden layer and with ten neurons nearly give best results.
6) Changes in the transfer function results in effects on the network accuracy but no consistent trend could be identified.

Above study shows comparisons of the prediction results by the ANN approaches and those from the CFD analysis are made to examine the performance of the ANN models. It demonstrate that the ANN approaches can successfully predict the pressures on the entire surfaces of the large dome roof on the basis of computational fluid dynamics data.

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