

“Artificial Neural Network Modeling of Wind Loads on R.C.C Chimneys with Interference Effects”

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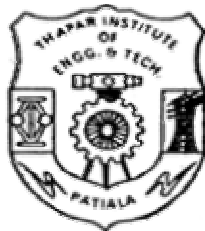
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(With specialization in Structures)

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Date:
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ABSTRACT

In the design of tall chimneys, estimation of exact wind loads is very difficult. Empirical as well as analytical approach proposed by different researchers for the estimation of along wind response of a chimney doesn't give satisfactory results. Codal recommendations are only for the estimation of along wind response. No codal recommendations exist for estimation of across wind response of a chimney in isolated chimney case or in interference due to a chimney situated near the main chimney, which often dominates over wind response.

Wind tunnel testing is the sole alternative resorted because simulation of atmospheric boundary layer and structural modeling is possible only in wind tunnels. Wind tunnel tests become a laborious and time-consuming affair for interference studies.

Artificial Neural Networks (ANNs), because of their capability to map the relationship between the input and output parameters, have been used in the present study, which can predict the along wind and the across wind response of a tall chimneys of different heights with interference effect. ANN modeling has been used to predict the along wind and the across wind response of a tall chimneys of height 83m ,102.3m and 224.24m. In which 102.3 m high chimney is used as test chimney and other two are used for training the network.

The developed ANN networks have been trained with 102.3 m chimney of the experimental data and satisfactory results have been obtained thus reducing the wind tunnel testing upto some extent. The number of patterns in training data set has been determined by plotting scatter diagrams between experimental and ANN predicted values of response in interference condition for different number of training patterns.

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Chapter 1

Introduction

1.1 IMPACT OF WIND LOADS ON STRUCTURES

From the earliest times, designers of buildings and other structures have to a large extent relied on past experience and intuition to design against wind action. The systematic study of wind loading did not begin until about 100 years ago when, prompted by the Tay Bridge disaster in 1879, engineers began to assign quantitative values to the wind loads. At first these were very crudely estimated; it is said that the wind load of 2.7 kN/m^2 used for the design of the Forth Railway Bridge was derived from considerations of the plate glass window near the bridge site which had been broken by gales. Since that time, and particularly within the last 30 years, the methods of estimating the wind loading and of assessing the dynamic effects of wind have been improved and refined, and the data available have been extensively increased. These improvements in our knowledge have to a large extent been made possible by the increased availability of wind tunnels in which tests on models of structures can be carried out, and from studies of the nature and characteristics of atmospheric winds to which structures are subjected. Wind tunnel tests together with studies of the atmospheric winds have become more necessary in recent years because modern tendency to build more slender and more flexible structures make modern constructions more sensitive to the action of wind, and this is particularly with regard to oscillations induced by wind. Recent advances in experimental and statistical techniques have provided an impetus for systematic study of the wind excited motion of tall structures (Sach 1981)

Wind loads essentially cause a dynamic response in a tall slender structure. A number of Wind structure mechanisms are capable of giving rise to dynamic oscillations. The two most Common forms of dynamic excitations of towers and chimneys exposed to wind are

- 1) Buffeting by gusts giving rise to along wind response.
- 2) Vortex induced excitation because of eddy shedding from the downstream face

Analytical formulations developed between 1960 and 1980, for along wind response has sufficiently incorporated the various parameters such that they have found a place in a number of wind loading codes. On the other hand, the across wind forcing mechanisms have proved to be so complex that a closed-form solution, giving due weight age to different across wind mechanisms, is difficult to be formulated and only the semi-analytical approaches, using force-spectra (based on experimental measurements), provide limited guide-lines.

Buffeting and interaction from upstream structures can produce strong changes in the dynamic response of a tall structure. Interference effects, though first pointed out by Harris(1934) and Bailey & Vincent(1943), gained importance only after the collapse of three, out of eight, cooling towers at the Ferry Bridge Power Plant on 1st Nov 1965 (Sachs 1978). The cause was determined to be increased loading on the towers due to the presence of adjacent towers. Since then there is a growing awareness that the wind forces to which tall structures are exposed, may be of a more complex nature in urban environments than usually expected. The characteristics of oncoming flow and wake flow on one hand together with shape, dimensions and dynamic properties of upstream as well as downstream structures on the other, can be viewed as the basic interaction parameters. Till today no analytical approach or even mathematical model based on experimental results is available to predict quantitatively the extent of interference, except for some work towards the application of Neural Networks.

The effects of interference from adjacent structures, existing or proposed are now routinely studied during wind tunnel model testing of tall structures. For a wind tunnel experiment, the two basic important parameters are the proper simulation of atmospheric boundary layer (ABL) characteristics and correct structural modeling. Substantial progress has been made in the field since Jensen in 1958 laid down the 'model law'. Many augmentation devices have been developed and turbulence characteristics have been well defined by many researchers to help in achieving the desired flow conditions for a wind tunnel test. Use of rigid, aero elastic and aerodynamic models can provide a complete picture of the phenomenon to which a structure may be subjected. A well simulated. Wind tunnel test may provide

explanation to the many unanswered questions in the field structural aerodynamics, including complicated fluid-structure interactions.

1.2 IMPACT OF WIND ON CHIMNEYS

Chimneys are tall and slender structures meant for discharging the effluent gases into the atmosphere at a sufficient height to control pollution. Now-a-days the trend is towards constructing taller and taller chimneys. Thus horizontal forces, like wind, find predominance in their design.

The wind-forces acting on a structure are classified into two parts; one in the direction of wind called along wind and other in the perpendicular direction called across wind. The along wind response has two components, namely static and time-varying responses. The analytical approach to compute the along wind response was suggested by Davenport . On the other hand the across-wind response is caused by alternate shedding of vortices on the downstream face of the chimney. The maximum across-wind the resonant condition, i.e. when the shedding-frequency of vortices coincides with the natural frequency of the chimney.

1.3 NEED OF STUDY

Wind tunnel tests give a fair idea of the response or the prototype only if proper modeling of structural system of the chimney, exact simulation of the atmospheric boundary layer (ABL) is achieved. Wind tunnel test are quite tedious and time consuming. The task becomes more difficult for interference studies because the tests have to be performed by placing the interfering chimney model at different locations from the concerned chimney. This gives rise to the need for alternate technique, which can predict the response of the chimney for different locations of the interfering chimney based upon wind tunnel test. In other words a technique is required which if presented with a certain set of input parameters and their corresponding outputs can predict the outputs for the inputs not presented earlier. This technique should be capable of mapping the relationship between the response of the chimney and the parameters affecting the response.

The above is a clear indication towards the need for Artificial Neural Network (ANN) modeling of wind loads because ANNs have the capability to predict the

response of the chimneys based on some limited experimental data. ANNs can map the relationship between input and output parameters if presented with an input and output data set. Therefore the present work has been undertaken to predict the response of chimney in along wind and across wind direction in interference condition based on limited wind tunnel test data. Data used for training and testing of the network is taken from extensive wind tunnel testing carried out by Aggarwal (1996), Sahu (2003) and Singh (2004) on tall chimneys.

1.4 OBJECTIVES

The main objectives of this study are:

1. To predict the along wind response of tall chimneys of different height and diameter with analytical approach taken as per IS 4998-1992 (part 1) and compared with corresponding experimental values.
2. ANN modeling of along wind and across wind response of tall chimneys with interference effects.

1.5 SCOPE OF WORK

The scope of the present work includes developing ANN models for predicting the buffeting factors (It is the ratio of maximum response in interference effect to the maximum response in standalone effect) of tall chimneys in interference effects due to nearby other chimney. In this work chimney 102.3m high (test chimney) has been used for experimental checks with two interfering chimneys 83m and 224m used for training work for different responses i.e. along wind mean, fluctuating, total along wind and across wind responses.

1.6 ORGANIZATION OF THE THESIS

The thesis been divided into 6 chapters.

Chapter 2 presents the literature relevant to the response of tall chimneys in along wind and across wind direction with interference effect. Chapter3 presents the Artificial Neural Modeling has also been discussed .Chapter 4 deals with study of isolated chimneys with analytical approach. Chapter 5 deals with development of

ANN models and comparison of experimental values of buffeting factors of 4 responses with ANN predicted values. Finally, Chapter 6 has conclusions drawn after the study.

Chapter 2

Literature Review

2.1 General

These days, structures are forever getting lighter, taller, longer and more slender, thus calling the need for a more accurate and rational approach which gives a reliable quantitative information of the dynamic effects of wind load. The simple quasi static approach for such slender structures gives rise to larger deflections and forces. Today's building codes require buildings to be designed for the same wind speed in all directions. Requiring the same design in all directions prevents the designer from shaping and orienting the building to minimize the maximum wind, and *or* proportioning the structural system to provide maximum economy. Most skyscrapers being built these days are making use of lighter building materials, high slenderness ratio, and low damping which forces the structure engineer to bother about the dynamic response of building.

2.2 Structural Aerodynamics

The complex problem of flow in urban environment uncertainties of functional relationships between wind induced effects and the flow properties made the job of structure engineer difficult. Therefore initially the wind loads were treated as equivalent static load with an allowance for increase in wind velocity and force with height. Some pioneering works in the area of modeling of natural wind are available from Saunders (1974). The motion of tall buildings, have been observed to occur primarily in three different modes. For a rectangular building, for example, with one face perpendicular to the mean flow, the motion has been observed in the direction of wind flow, i.e. along wind and in a direction perpendicular to the direction of flow i.e. across wind, as well as in torsion mode.

2.3 Alongwind Response Of Chimneys

The along wind response of isolated tall structures can be estimated using basic principles of random vibration theory in conjunction with information on the characteristics of (1) the oncoming flow, and (2) the aerodynamic loads it induces on the structure. The effect of atmospheric turbulence on the response of an elastic structure immersed in turbulent flow was first published by Liepmann in 1952. Using this concept

Davenport developed models representing the turbulent wind flow near the ground (Davenport 1961). These included a height independent expression for the spectrum of longitudinal velocity fluctuations. He further developed the "Gust Factor Approach" for analytical prediction of along wind response of tall structures (Davenport 1967). Davenport emphasized that the fluctuating component of the structural motion can be conveniently divided into one part responding to wind frequency components significantly lower than the structure's natural frequency; And the other part exhibiting a resonant response. The ratio of this 'background response to 'resonant' response depends on the relation between the geometric and dynamic properties of the structure to those of the turbulent natural wind. So in different situations either of these dynamic phenomenon may dominate. Davenport showed how spectral analysis could be used to determine structure's response spectral density (stresses or displacements). This shows the various statistical processes transformed into their spectral components. These phenomena can be represented and analyzed in the following manner. By starting with the 'gusts', represented as velocity spectrum and multiplying this on a frequency basis by the aerodynamic admittance (the transfer function squared), the force (or pressure) spectrum can be determined. From this, by multiplying by the mechanical admittance, the response spectrum is determined. The area under this curve is the variance of displacement (Bendat and Piersol 1986). On the basis of his analysis and experiments, Vickery developed a further refinement of 'Gust Factor Method' (Vickery 1985). These all methods given by Davenport (1967) and Vickery (1982) will be discussed in the proceeding chapter.

Lakshmanan et. al (1993) studied the effects of soil-structure interaction and cracking on the gust response factors have been studied by Lakshmanan et al (1993), and it has been shown that the gust response factors would not be altered if the rotational stiffness of the foundation exceeds $(20 E I_e/h)$ where $E I_e$ is the effective flexural rigidity of the chimney. Cracking can lead to nearly 20% increase in the values of G . The above observation is particularly critical under extreme wind loading conditions as in the case of cyclones.

Srinivas et. al (2004) has studied along wind-response of a tall tapered chimney has been studied using spectral density approach in finite element framework. The wind velocity is considered as stationary zero mean random process superimposed over mean velocity. The power spectral density (PSD) of the response due to along wind component has been obtained using complex frequency response function (CFRS) and the spectral density of the along wind drag, The numerical integration has been carried out in the frequency range of interest to find the response variance, The effect of the taper ratio, mean wind speed and terrain condition on the response of the chimney have been studied.

2.4 Closure

The various approaches to along wind analysis have been presented in the foregoing paragraphs. But various results indicate that in order to carry out a reliable analysis, proper definition of flow characteristics - particularly the correlation between windward and leeward face pressures, and spectra of longitudinal fluctuations and structural properties need to be incorporated. This however requires large amount of full-scale measurement data for prototypes and an accurate estimate/measurement *of* their dynamic structural properties. Only then can a more reliable approach towards prediction *of* dynamic along wind response be developed.

2.5 Across Wind Response

The across wind forcing mechanisms have proved to be so complex that yet there is no generalized analytical method available to calculate across wind response of structures, though it may have a major contribution to the wind forces on the structure. The fluctuating pressure field acting over the side and leeward face is greatly influenced by the wake dynamics, i.e. vortex shedding which renders the applicability of the foregoing theories doubtful. Thus, a lack of convenient transfer function, between the velocity fluctuations in the incident turbulence and the pressure fluctuations with flow separation, has prohibited any acceptable estimation, to date, of the across wind loads on tall structures (Melbourne 1975). Hence, either empirical relations or physical modeling of

fluid structure interaction provides the only variable means of obtaining information on the across wind loads.

2.6 Closure

It is possible to conclude that the across wind motion is a complex phenomenon resulting from interaction of various approach flow parameters and structural characteristics and is amplitude dependent too. Through no closed form solution has been evolved which can treat all parameters and predict across wind forces and motions, empirical expressions based on experiments have been developed and tested. Attempts have been made to develop mode generalized forced spectra through pressure studies and displacement measurements which can predict across wind displacements and accelerations. All these studies form a reasonable state-of-the-art in understanding of the across wind motion and prediction can be made, to a sufficient degree of reliability, within the limitations of similarity of structural environments and characteristics.

2.7 Interference Effects

Interference effects, though first pointed out by Harris(1934) and Bailey & Vincent(1943), gained importance only after the collapse of three, out of eight, cooling towers at the Ferry Bridge Power Plant. The cause was determined to be increased loading on the towers due to the presence of adjacent towers. Since then there is a growing awareness that the wind forces, to which tall structures are exposed may be of a more complex nature in environments, than usually expected. 'The characteristics of oncoming now and wake now on one hand, together with shape, dimensions and dynamic properties of upstream structures on the other can be viewed as the basic interaction parameters.

Krishnaswamy et. al (1975) has studied the effect of aerodynamic interference or oscillatory response of pairs of several identical stack models of different tapers. The study showed that stacks with a taper of 1:50 experience maximum magnification (ratio of the oscillatory amplitude when two models are present to the amplitude when only one model is present), which is about 10 times of the response of isolated stack. They

observed that maximum magnification for all ranges of tapers occurred when the models were separated by a spacing of five times the diameter at two-third's height. Also, the wind direction at all spacing which yielded the maximum magnifications for all the models was about 15 degrees.

Price and Paidoussis (1984) studied the aerodynamic forces acting on groups of two and three circular cylinders when subjected to cross-flow. It was found that the effect of cylinder displacement on the fluid forces for one cylinder in a group of three is very similar to that obtained with one cylinder in a group of two. An attempt to use a superposition principle to determine the fluid forces in the former arrangement from the knowledge of the fluid forces in the latter arrangement, yielded remarkable success range of cylinder spacing in which the work was conducted. i.e. 1.5 to 5.0 cylinder diameters in inflow direction and 0.75 to 2.0 diameters in the cross-flow direction.

Lakshmana et. al (1987) studied the interference effects on the fluid-induced vibrations of circular cylinder. The experimentation consisted of studying interference effects of single-in-line, rigid body on the transverse vibrations of a spring mounted cylinder. The results of the experiments conducted showed that the interference effects the flow around the test cylinder and on its vibration amplitude depend on the relative dimension ion of the test cylinder and the interfering body and the latter's geometry relative gap spacing, and on the magnitude of the non-dimensional uniform flow velocity. There is a critical combination of non-dimensional velocity, gap spacing and relative dimensions, which gives rise to maximum amplitudes of vibration.

Aggarwal(1996) has studied that interference effect is substantially reduced in the in the interfering chimneys when they are placed beyond 7.5D where D is the diameter of chimney at $2/3^{\text{rd}}$ height.

Sahu (2003) has studied the interference effect which shows the critical direction ,which gives the maximum bending moment at 15 degree orientation from direction of wind flow. The mean component of along wind bending moment is reduced by interference due to shielding effect.

Singh (2004) has studied the interference effect which shows the critical direction, which gives the maximum bending moment at 20 degree to the alignment of two chimneys. The mean component of along wind bending moment is reduced by interference due to shielding effect. Fluctuating component of along wind response increased upto 2.12 times in case of interference with similar chimney.

2.8 Closure

On the basis of the works reviewed above, it can be summarized that: When an upstream structure interferes with another structure, it increases or decreases forces on the downstream structure by modifying the structure of wind in its wake alongwind forces on a downstream structure are reduced due to shielding. This shielding clearly decreases with increase in the separation distance.

The dynamic wind loads due to interference follow a different trend from that of mean loads and the effects are much more severe. The increased turbulence intensity in the wake of an upstream structure tends to increase the dynamic loading on the downstream structure. For large separation distances, the vortices get enough time and space to become well organized before they hit the downstream structure, thus increasing the vertical correlation of wind loading which is responsible for higher dynamic loads. A downstream interfering structure has very little effect on the response of an upstream structure for most locations. However, for locations of close proximity, a channel wide enough is created for the wind flow to converge between the two structures and alter the wake characteristics of the upstream structure resulting in high dynamic loads Bailey & Kwok (1985).

2.9 Artificial Neural Networks (ANN)

Detailed wind tunnel experiments remain the main source of knowledge of interference effects till date. The complex nature of problem and the large amount of variables make it impossible to test all structures under interference situations. The experimental approach adopted has been to minimize the number of model configurations and to keep them simple while searching for limiting conditions. The

generalization of results thus obtained, to various other structural configurations and wind conditions, remains elusive. So ANN technique has been used in this study and various studies done by different researchers in the past has been mentioned below.

Khanduri *et al.* (1995) have demonstrated the ability of NN to be trained to generalize when presented with data examples. They applied neural modeling on wind induced interference effects. After the network was trained to a learning threshold of 0.0001, it was tested using a completely new set of data. Their major achievement is that no single item from this new data set was present in the data used for training the network. Predicted values of interference are compared with experimental values. The maximum error between the experimental Interference Factor and NN predictions is less than 10 % in most cases, increasing upto 13% in a couple of cases. The probable reason for inaccuracy in predictions is the small and narrow training set used.

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.

Gupta (1996) applied ANN for predicting the design along wind and across wind components in stand alone situation as well as for interference with another building. Data used for training and testing and testing of neural network has been obtained from wind tunnel tests carried out by

Kwatra et al (2002) have applied neural networks for determination of wind induced pressures on gable roof. Data was obtained from wind tunnel testing of different models of building. Models of gable roof building were made and the roof area divided into different zones as per the Indian standard code (IS 875-1987, Part-3). Experiments were also conducted to find out the effects of interference from a similar building on the building model. The neural network was trained using the roof slope and location of different zones on the building as input and design wind pressure coefficients on the same as output parameter. The trained network predicts pressure coefficients for different zones on the buildings for roof slopes not covered in the training set. The predicted values of design pressure coefficients have been

compared with actual values (experimental). The main conclusions drawn from their study are that ANN modeling is seen to predict successfully, the pressure coefficient for any slope not covered by the experimental study, based on data from other roof slopes. The maximum error seen in their study is 7%.and within 5% in case of interference study. The major conclusion drawn by them is that ANN modeling reduces the wind tunnel testing for interference studies to almost half.

Singh (2002), has been also used to predict the along wind and across wind response of a tall rectangular building model (1:2:10) in long after body as well as in short after body orientation in isolated building in different flow conditions. ANN modeling has also been done for predicting the buffeting factors for across wind response of a tall rectangular building (1:2:10) in interference condition due to a building of dimension (1:1:10) situated in its vicinity at varying locations.

2.10 Closure:

As per work review in this section, it has been observed that ANN modeling can be used effectively in wind engineering .On the basis above work, it is proposed to apply ANN modeling for interference effects on tall chimneys in the present work.

CHAPTER -3

ARTIFICIAL NEURAL NETWORKS MODELING

3.1 Artificial neural network

The subject of Neural Networks is an offshoot of Artificial Intelligence (AI). It is a very vast field covering disciplines ranging from medicine to microelectronics. According to Judith E. Dayhoff (1990), Neural Networks provide a unique computing architecture whose potential has only begun to be tapped. Used to address problems that are intractable or cumbersome with traditional methods, these new computing architectures inspired by the structure of the brain- are radically different from the computers that are widely used today.

3.2 Definition

According to Eberhart and Dobbins "A Neural Network is an analysis tool that is modeled after the massively parallel structure of the brain: It simulates a highly interconnected, parallel computational structure with many relatively simple individual processing elements, or neurons."

ANN attempts to mimic the human thought process to solve complex multivariate and non-linear problems with incomplete or confusing information. 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 new inputs without training the network on all possible input-output examples. Because of proven capabilities at pattern mapping, classification and optimization even with fuzzy, chaotic or complete information, Neural networks have been successfully used to model experimental data from tasks ranging from the prediction of concrete strength to the hysteretic modeling of steel structures.

3.2.1 Applications Potential

Neural networks have far reaching potential as building blocks in tomorrow's computational world. Neural network applications emphasize areas where they appear to offer a more appropriate approach than traditional computing has. Neural networks offer possibilities for solving problems that require pattern recognition, pattern mapping, dealing with noisy data, pattern completion and systems that learn or adapt during use. Examples of specific areas where these types of problems appear include speech synthesis and recognition, image processing and analysis, sonar and seismic signal classification, and adaptive control.

3.2.2 Biological Basis for Neural Networks

Studies over the past few decades have shed some light on the construction and operation of our brains and nervous systems. The basic building block of the nervous system is the neuron. The major components of a neuron include a central cell body, dendrites, and an axon as shown in Fig 3.1. There are many kinds of neurons and the one shown in Fig 3.1 resembles a motor neuron. The signal flow goes from left to right, from the dendrites, through the cell body, and out through the axon. The signal from the neuron is passed on to another by means of a connection between the axon of the first and a dendrite of the second. This connection is called a synapse.

The human brain is a dense neural network in which the neurons are highly interconnected. The total number of neurons in the human is estimated at 100 billions (DARPA Neural Networks Study, 1988). Each Neuron is connected to perhaps 10,000 other cells, meaning each biological neuron can send impulses that may be received by as many as 10,000 target cells.

3.2.3 Basic Structure of a Neural Network Model

A typical neural network is as shown in the Fig. 3.2. It is a simple three-layered feed forward neural network with each layer consisting of some definite number of neurons or processors. Each layer has a weighted input and output vector.

The first layer is called the input layer. The neurons of this layer perform no computations and serve only as distribution points. The last layer of neurons is called

output layer. It is called so because its output becomes the final network's output. The layer that has been placed in between the input layer and output layer is called hidden layer. There can be more than one hidden layer in a neural network. The neurons in each layer have been connected to the neurons in the other layer through connections. The network function is determined largely by the connections between neurons or processors. Each processor accepts a set of inputs from other processors and computes an output, which is propagated to the connected processors. Fig 3.3 depicts an example of a typical processing unit for an artificial neural network. On the left are the multiple inputs to the processing unit, which is connected to the unit shown at the center. Each interconnection has associated connection strength, given as W_1, W_2, \dots, W_N . The processing unit performs a weighted sum on the inputs and uses a nonlinear threshold function, f , to compute its output. The calculated result is sent along the output connections to the target cells shown at the right. The same output value is sent along all the output connections. Each interconnection between processing units acts as a communication route. Numeric values are passed along these interconnections from one processing unit to another. These values are weighted by connection strength when the target-processing unit uses them computationally. The connection strengths that are associated with each interconnection are adjusted during training to produce the final network.

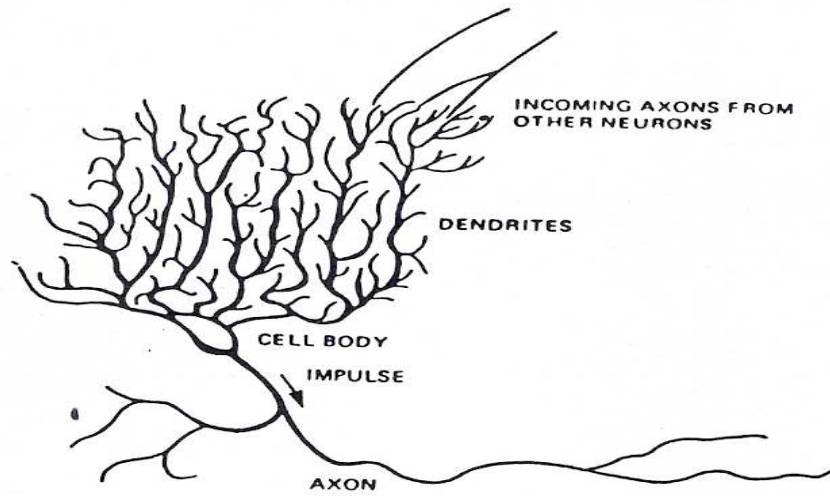


Fig 2.3 Schematic drawing of a biological nerve cell

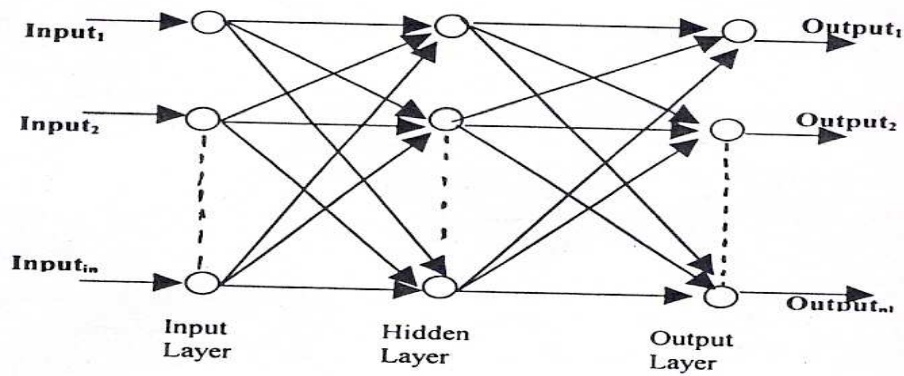


Fig 2.4 A typical Neural Network

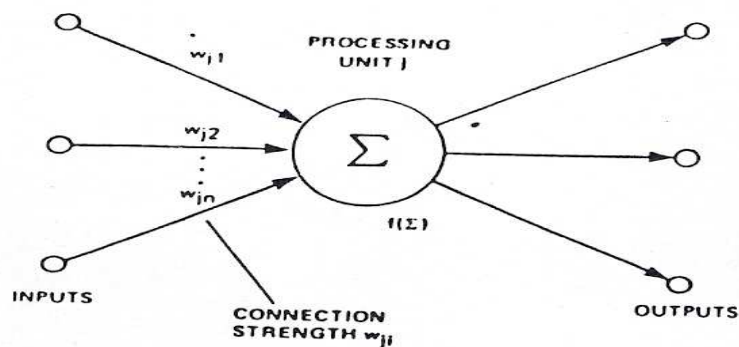


Fig 2.5 Schematic processing unit from an artificial neural network

Networks are trained with available test examples to recognize input patterns and produce appropriate output responses. Each connection is associated with a measure of the strength of the interconnection, called its weight which is used to attenuate the signals. For a given neural architecture it is the weight the connections between the processors which determines the output. Changing the strength or weight of connections with experience (new examples) is a kin to learning the memory of a network being embedded in the strength of the connections. Some neural network applications have fixed interconnection weights; these networks operate by changing activity levels of neurons without changing the weights. Most networks however, undergo a training procedure in which case the network is presented with target answers for each pattern that is input. In some architecture, training is unsupervised- the network adjusts its weights in response to input pattern without the benefit of target answers. In unsupervised learning, the network classifies the input patterns into similarity categories.

3.2.4 Neural Network Characteristics

According to Judith E. Dayhoff (1990), neural networks are not programmed: they learn by example. Typically, a neural network is presented with a training set consisting of a group of examples from which the network can learn. These examples, known as training patterns, are represented as vectors, and can be taken from such sources as images, speech signals, sensor data, robotic arm movements, financial data, and diagnosis information.

The most common training scenario utilizes supervised learning, during which the network is presented with an input pattern together with the target output for that pattern. The target output usually constitutes the correct answer, or correct classification for the input pattern. In response to these paired examples, the neural network adjusts the values of its internal weights. If training is successful, the internal parameters are then adjusted to the point where the network can produce the correct answers in response to each input pattern. Usually the set of training examples is presented many times during training to allow the network to adjust its internal parameters gradually.

Because they learn by example, neural networks have the potential for building computing systems that do not need to be programmed. This reflects a radically different approach to computing compared to traditional methods, which involve the development of computer programs. In a computer program, every step that the computer executes is specified in advance by the programmer, a process that takes time and human resources. The neural network, in contrast, begins with sample inputs and outputs, and learns to provide the correct outputs for each input.

3.2.5 Comparison with Traditional Computer Programs

Fig. (3.4 & 3.5) contrast two different approaches to a pattern classification problem. The task here is to classify picture of a cat, a dog, and a rabbit. Fig. 3.4 illustrates the traditional approach, preprocessing of the image is performed, followed by a human analysis of the data to identify important features. Human resources are then utilized in developing algorithms and programs that make use of those features to identify the cat, dog, and rabbit. The result is a program that may classify the three types of pictures, or three different programs that each recognizes a single picture type. The same program cannot then be used to classify new types of pictures.

Fig. 3.5 illustrates the Neural Network approach. A single neural network is drawn three times in the figure. The network is presented with the picture of the cat as an input, and with the text string "cat" as an output. The weights are readjusted automatically. The same network is then presented with the picture of a dog as an input, and "dog" as an output, and the picture of a rabbit, with "rabbit" as the output. After each presentation the weights are again readjusted automatically. This training procedure is repeated many times. After training the same network can identify all three types of pictures. The same neural network can then be retrained to classify additional picture types, or a completely new set of pictures.

The neural network approach does not require human identification of features, or human development of algorithms and programs that are specific to the classification problem at hand, suggesting that time and human effort can be saved. It

is possible to develop a network that can generalize on the tasks for which it is trained, enabling the network to provide the correct answer when presented with a new input pattern that is different from the inputs in the training set. To develop a neural network that can generalize the training set must include a variety of examples that are good preparation for the generalization task. The training session must be limited in iterations so that no "over learning" takes place. Special considerations in constructing the training set and the training presentations are made to permit effective generalization behavior from a neural network.

3.2.6 The Back- Propagation Model

In this section the back propagation model has been described. Mathematical equations presented by Rumelhart and Mclelland (1986) that describe the network training and operation are discussed here. These equations are divided into two categories: feed forward calculations and error back propagation calculations. The feed for calculations are used both in training mode and in the operation of trained neural network model: back propagation calculations are applied only during training.

3.2.7 Topology and Notations

In Fig. 3.6, a three layer back propagation model is illustrated in detail. Each neuron is represented by a circle and each interconnection, with its associated weight by an arrow. The neurons labeled b are biased neurons. Lower case letters with subscripts represents the attributes of individual neurons or connections. The letter I denotes an input, O an output, W a connection weight, and N the number of nodes in a layer. The subscripts i , j and I refer to the input, hidden and output layers respectively. For example h is the input to an input neuron O_j is the output of hidden layer of neuron and N_i is the number of neurons in i th output layer the subscript k is used for second hidden layer if any. Connection weights require two subscripts that represent the sending and receiving layers. For example the weight of the connection from an input neuron to a hidden neuron is W_{ji} . The receiving neuron layer is the

first subscript and the sending layers the second W_{ji} represents the matrix of weights to the hidden layer from the input layer.

3.2.8 Network Input

As shown in Fig 3.6 inputs are shown into the layer of the network to a layer of processing neurons. The set of N_i inputs is presented to the network simultaneously. These inputs may be a set of raw data, a set of parameters, or whatever we have chosen to represent one single pattern of some kind. The number of neurons in the input layer is decided by the number of input parameters we have in our problem. Normally one neuron is assigned to one input parameter. Each input can take on any value between zero and one.

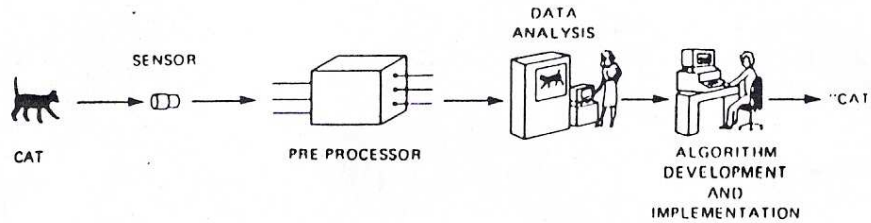
3.2.9 Feed Forward Calculations

The input neurons simply distribute the signal along multiple paths to the hidden layer neurons. The output of each input layer neuron is exactly equal to the input and is in the range 0-1. A weight is associated with each connection to a hidden neuron. Each neuron of the input layer is connected to every neuron of the hidden layer. Similarly each neuron of the hidden layer is connected to every neuron of the output layer. Each connection and all data flow go from left to right in Fig. 3.6. This is called a feed forward network. The way the total input to a neuron is calculated and the way that the neuron calculates its output as a function of its net input are dependent on type of neuron. An additive sigmoid neuron is most commonly used. The signal presented to a hidden layer neuron in the network of Fig. 3.6 due to one single connection is just the output value of the input node (the same as the input of the input node) times the value of the connection weight. The net input to a hidden neuron is calculated as the sum of the values for all connections coming into the neuron as described in Eq (3.1). This includes the input from the biased neuron also, which is assumed to have an output of 1 at all times and is otherwise treated as any other neuron.

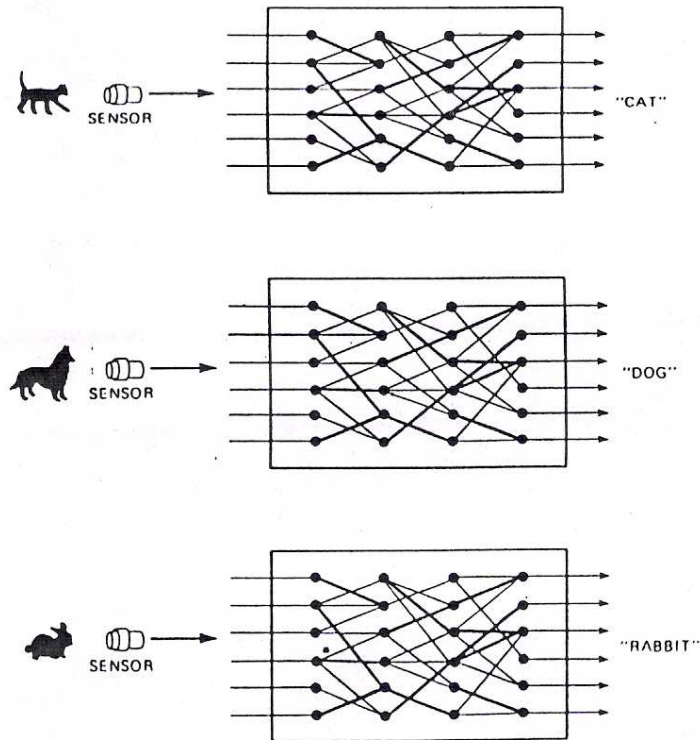
$$\text{Net input}_i = I_i = \sum W_{ji} O_j \dots\dots\dots(3.1)$$

Threshold Function

The output of a hidden neuron as a function of its input is obtained by Threshold function or Squashing function or Nodal function described in Eq. (3.2). There are three types of threshold functions are commonly used which are Hard



**Fig 2.6 Pattern classification by traditional approach
(Adapted from DARPA Neural Network Study, 1988)**



**Fig 2.7 Pattern classification by Neural Network approach
(Adapted from DARPA Neural Network Study, 1988)**

Limiter, Threshold Logic, and Sigmoid function, Hard limiter function has binary states i.e. + 1 and -1. Threshold logic function has a continuous linear variation between 0 and 1. The function in Eq. (3.2) is called as sigmoid function. Fig. 3.7 is an illustration of the general shapes of the three types of threshold functions.

$$\text{Output} = o_i = \frac{1}{1 + \exp(-i)} \quad \dots\dots\dots(3.2)$$

The sigmoid function can be viewed as performing a function similar to an analog electronic amplifier. The gain, or amplification, of the amplifier is analogous to the slope of the line, or the ratio of the change in output for a given change in input. The slope of the function is greatest for total inputs near zero. This serves to mitigate problems caused by possible dominating effects of large input signals. The output, after being put through the sigmoid function is limited to values between 0 and 1. For a net input of zero to the neuron, the output is 0.5. For large negative net input values, the neuron output approaches 0; for large positive values, it approaches 1. The nonlinear nature of this sigmoid transfer function plays an important function in the performance of neural network. Other function can be used as long as they are continuous and possess a derivative at all points. Functions such as the trigonometric sine and the hyperbolic tangent can also be used.

The selection of number of neurons in the hidden layer is more art than science. It can vary widely according to the application and bears a relationship to the number of statically significant figures that exist in the input data. With too few neurons the network does not train at all. With too many neurons, the network becomes robust and takes forever to train and yet does not recognize the new patterns very well. Once the outputs of hidden layer neurons have been calculated, the net input to each output layer neuron is calculated in an analogous manner, as described

by Eq. (3.3). Similarly the output of each layer neuron is calculated as described by Eq. (3.4).

$$\text{Net output} = I_i = \sum w_{ij} o_j \quad \dots\dots\dots(3.3)$$

$$\text{Output} = o_i = \frac{1}{1 + \exp(-I_i)} \quad \dots\dots\dots(3.4)$$

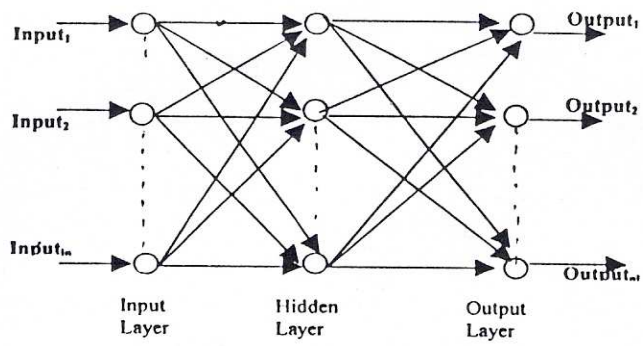


Fig 2.8 A three layered back propagation network

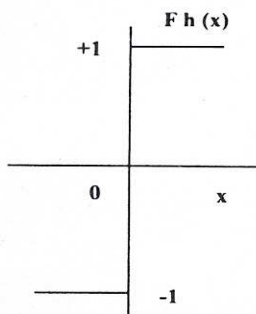


Fig. 2.9 (a) Hard limiter function

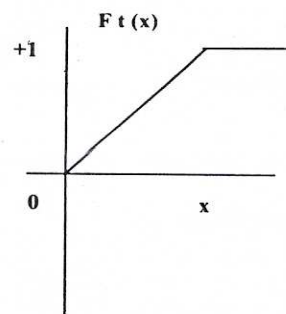


Fig. 2.9 (b) Threshold Function

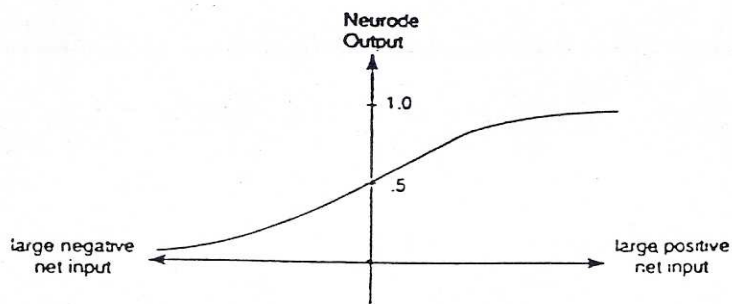


Fig. 2.9 (c) Sigmoid transfer function

Fig 2.9 Illustration of the general shapes of threshold functions

3.2.10 Training of the Network

During the training phase, the feed forward output state calculation is combined with back error propagation and weight adjustment calculations that represent the network's learning, or training. Rumelhart and McClelland (1986) define an error term that depends on the difference between the output value an output neuron is supposed to have, called the target value T_l and the value it actually has as a result of the feed forward calculations O_l . The error term is defined for a given pattern and summed over all output neurons for that pattern. Eq. (3.5) gives the definition of the error. The subscript p denotes what the value is for a given pattern. Error calculation in the back propagation training algorithm is implemented on a neuron by neuron basis over the entire set (epoch) of patterns, rather than on a pattern-by-pattern basis. The error over all the neurons is summed to give a grand total for all neurons and all patterns. The grand total is then divided by the number of patterns, to give an average sum squared error value.

$$E_p = \sum_{l=1}^{p_l} (t_{pl} - o_{pl})^2 \dots\dots\dots(3.5)$$

3.2.11 Estimation of Error for Output Layer Neurons

The goal of the training process is to minimize this average sum squared error over all training patterns. Equation (3.4) gives the output of a neuron in output layer in terms of its input, or $O_l = f(I_l)$. The first derivative of the function $f'(I_l)$ is important in back error propagation. Rumelhart and McClelland (1986) gave a quantity called the error signal represented by δ_l , for output layer neurons and is defined by equation (3.6).

$$\delta_l = f'(I_l)(t_l - O_l) \dots\dots\dots(3.6)$$

For the sigmoid function given by Eq. (3.7) the first derivative is $O_l(1-O_l)$

The final expression for error signal then becomes

$$\delta_l = (t_l - O_l) O_l(1 - O_l). \dots\dots\dots(3.7)$$

This error value has to be back propagated with appropriate weight adjustments. This can be done in two ways. One way is to propagate the error and adjust weights after each training pattern is presented to network; this option is called single pattern

training. The other way is to accumulate the δ 's for each neuron for the entire training set add them, and propagate back the error based on the grand total δ : this is called batch or epoch training. Second option is most commonly used for training a neural network. Rumelhart and McClelland (1986) assumed that weight changes occur only after a complete cycle of patterns. Weights are initialized with random numbers ranging from -0.3 to 0.3. This range for the initial weights has been found by various researchers. Most back propagation neural networks train faster with this range of initial weights than weights of any other range. Lee (1989) has shown that in some instances initializing the weights feeding the output layer to random values between 0.3 and -0.3, while initializing the weights feeding the hidden layer to 0, speeds training

3.2.12 Updating of Weights

δ_l is used to update weights that feed the output layer W_{lj} . First approximation updates the weights as described by the Eq. (3.8)

$$W_{lj} \text{ (new)} = W_{lj} \text{ (old)} + \eta \delta_l O_l \dots\dots\dots(3.8)$$

Here η is defined as learning coefficient. It can be assigned values between 0 and 1. This kind of weight updating gets caught in what are called local energy minima. The error minimization process is analogous to minimizing the energy of the position of a steel ball bearing placed in a bowl shaped surface with a lot of little bumps and ridges in it. Ideally the energy is minimum at the bottom of the bowl. This position is called globally optimal solution. Depending on how much or how little the ball bearing moves at one time, however, it might get caught in some little depression or ridge that it can't get out. This situation is most likely to occur if small value of η is used. This problem is overcome by using the momentum of the ball bearing. Momentum of the ball is taken into account by multiplying the previous weight change by a momentum factor α . The momentum factor can take on values between 0 and 1. Eq. (3.9) is used for updating the weights feeding the output layer in back propagation neural network.

$$W_{ij}(new) = W_{ij}(old) + \eta\delta_i O_i + \alpha[\Delta W_{ij}(old)] \dots\dots\dots(3.9)$$

Here $[\Delta W_{ij}(old)]$ is the previous weight change. It follows from the equation that the new weight is equal to the old weight plus weight change. The weight change consists of δ error signal term and the momentum factor term. The momentum term is the product of the momentum factors and the previous weight change.

3.2.13 Error Term for Hidden Neurons

Error term for hidden layer of neurons cannot be computed directly because the target value for the hidden layer is not known. However Rumelhart and McClelland (1986) showed that the error term for hidden neuron is given by equation Eq. 3.10

$$\delta_h = O_h(1 - O_h) \sum_{l=0}^{n_l} W_{lh} \delta_l \dots\dots\dots(3.10)$$

The weight changes for the connections feeding the hidden layer from the input layer are given by the Eq. 3.11

$$W_{ji}(new) = W_{ji}(old) + \eta\delta_i O_i + \alpha[\Delta W_{ji}(old)] \dots\dots\dots(3.11)$$

Here i take on values from 0 to Ni, the number of input neuron.

3.2.14 Reduction of Root Mean Square Error

Root mean square error of the network is minimized by adjusting the weights. Gradient descent method is used for this. Each weight may be thought of as a N dimension error space. In error space the weights act as independent variables and the shape of the corresponding error surface is determined by error function in combination with training set. The negative gradient of the error function with respect to the weights, thus points in the direction which will most quickly reduce the error function. This can be expressed as

$$\Delta_p W_p \propto -\frac{\partial E_p}{\partial W_p}$$

Where

$$\Delta_p W_p = \text{weight change}$$

E_p = root mean square error

3.2.15 Development of Neural Network

Development of neural network for any kind of problem requires the following prerequisites :

- (i) Development of source code.
- (ii) Selection of suitable input and output parameters in the available data.
- (iii) Training of the network.
- (iv) Testing of the network.

The neural network program has been developed in C language.

3.2.16 Closure

ANN modeling for chimneys have been applied including its interference effects in the present work which is discussed in detail in the subsequent chapters.

Chapter - 4
STUDY OF ISOLATED CHIMNEY

4.1 Analytical Approaches

The along wind response of most of the structures originates almost entirely from the action of the incident turbulence of the longitudinal component of the wind velocity (superimposed on the mean displacement due to the mean drag).their analytical formulations, using spectral approach and spatial correlations to predict the alongwind response of flexible structures has become widely accepted, so that the gust factor approach has found a place in a number of wind loading codes (Davenport 1967).

4.2 Analytical Estimation Of Response

To predict the analytical estimation for along wind for different height of chimneys this Devanport approach has therefore been adopted by various world codes in different forms whose basis is as follows:

Consider a slender stack of circular cross-section, idealized as a continuous system. Tile stack is subjected to drag wind force, $F(z,t)$ per unit height. On ignoring the contributions of the air mass acceleration to the total force, this may be written as

$$F(z,t) = \frac{1}{2} \rho C_D(z) D(z) \{U(z,t) - x(z,t)\}^2 \quad (4.1)$$

Where $x(z,t)$ is the along-wind displacement response of stack at height z and time t . $C_D(z)$ and $D(z)$ are the local drag coefficient and diameter respectively at height z . Taking $X(z,t)=X(z)+x(z,t)$, $U(z,t)=U(z)+u(z,t)$ and ignoring the second order terms, equation (4.1) becomes:

$$F(z,t) = \frac{1}{2} \rho C_D(z) D(z) \{U^2(z,t) + 2U(z)u(z,t)\} - 2U(z)x(z,t) \quad (4.2)$$

Hence, the mean component, $F(z)$ is

$$F(z) = \frac{1}{2} \rho C_D(z) D(z) U^2(z) \quad (4.3)$$

and the fluctuating component $\hat{f}(z,t)$ becomes:

$$\hat{f}(z,t) = f(z,t) - \rho C_D(z)D(z)U(z)x(z,t) \quad (4.4)$$

$$\text{with } f(z,t) = \rho C_D(z)D(z)U(z)u(z,t) \quad (4.5)$$

The equation of motion for the continuous system may be written as

$$m(z)x(z,t) + C(z)x(z,t) + EI(z)x''''(z,t) - GA(z)x''(z,t) = F(z,t) \quad (4.6)$$

where, $m(z)$, $c(z)$, $EI(z)$, $GA(z)$ respectively represent the mass, damping, flexural rigidity, shear rigidity per unit height at height z . On decomposing $X(z,t)$ and $F(z,t)$ into static (mean) and dynamic (fluctuating) parts, eqn.(4.6) leads to the following two equations

$$m(z)x(z,t) + C(z)x(z,t) + EI(z)x''''(z,t) - GA(z)x''(z,t) = f(z,t) \quad (4.7)$$

$$\text{and } EI(z)x''''(z,t) - GA(z)x''(z,t) = F(z) \quad (4.8)$$

Equation (2.6) may alternatively be written as

$$m(z)x(z,t) + \{C(z) + \rho C_D(z)D(z)U(z)\}x(z,t) + EI(z)x''''(z,t) - GA(z)x''(z,t) = f(z,t) \quad (4.9)$$

Expanding $x(z,t)$ in terms of normal coordinates, i.e.,

$$x(z,t) = \sum_i \psi_i(z)q_i(t) \quad (4.10)$$

Substituting in equation (4.11), multiplying both sides by $\psi_j(z)$, by taking the integral of both sides for the entire height of stack, and on using the modal orthogonally relationships, we get the decoupled equation of motion in the i th mode as:

$$M_i q_i + C_i q_i + K_i q_i = F_i \quad i=1,2,3.. \quad (4.11)$$

Where

$$M_i = \int_0^H m(z)\psi_i^2(z)dz \quad (4.12)$$

$$C_i = \int_0^H \{C(z) + \rho C_D(z)D(z)U(z)\} \psi_i^2(z)dz = 4\pi\varepsilon_i M_i n_i \quad (4.13)$$

$$K_i = \int_0^H EI(z)\psi_i''''(z)\psi_i(z)dz = \int_0^H GA(z)\psi_i''(z)\psi_i(z)dz = 4\pi M_i n_i \quad (4.14)$$

$$F_i = \int_0^H f(z,t)\psi_i(z)dz = \rho \int_0^H C_D(z)D(z)U(z)u(z,t)\psi_i(z)dz \quad (4.15)$$

are respectively the modal mass, damping, stiffness and forces in the i th mode. Also, ε_i and n_i represent the damping and frequency of this mode. In equation (4.11), coupling between different modal equations has been assumed to be weak and thus ignored. Also, the modal damping ratio ε_i is equal to $[(\varepsilon_i)_{str} + (\varepsilon_i)_{aero}]$ where $(\varepsilon_i)_{str}$ is due to the damping inherent in the structure and $(\varepsilon_i)_{aero}$ is the aerodynamic damping. The latter may be computed as

$$(\varepsilon_i)_{aero} = \frac{\int_0^H \rho [C_D(z) D(z) U(z) \psi_i^2(z) dz]}{4\pi M_i n_i} \quad (4.16)$$

In case of a uniform prismatic structure in uniform flow, where $U_r = \frac{U}{n_i D}$ and $M_r = \frac{m}{\rho D^2}$ are the dimensionless velocity and mass respectively,

$$(\varepsilon_i)_{aero} = \frac{C_D}{4\pi} \frac{U_r}{M_r} \quad (4.17)$$

This relationship may be used for a rapid and approximate assessment of aerodynamic damping and thus decide whether detailed calculations may be necessary or not using eqn. (4.18) (Vickery 1995).

Further, using the spectral approach, the r.m.s value of the fluctuating component of wind, $\sigma_x(z)$ can be calculated. Expected largest peak displacement at height z of the chimney, $X_{peak}(z,t)$ can be written as $X(z)$ plus the expected largest peak value of $x(z,t)$ - a process of duration T . Since the largest peak of the random process can be related to its r.m.s value through a peak factor, it can be written as $X_{peak}(z, t) = X(z) + g_f \sigma_x(z)$ where g_f is the peak factor for the expected response in time duration T . In other words, $X_{peak}(z,t)$ may be evaluated by multiplying $X(z)$ with a factor G where,

$$G = 1 + g_f r [B + SE / \varepsilon_i]^{0.5} \quad (4.18)$$

is the gust factor with which the multiplication of mean response leads to the peak total

response.

In eqn.(4.18), B is the background excitation factor, which is a measure of the slowly varying component of the fluctuating wind load. S is the size reduction factor and is also called the gust energy factor. E is a measure of the available energy in the wind flow at the natural frequency of the structure. The values of the damping ratio in the fundamental mode, i.e. ε_i are 0.01 for welded steel stacks, 0.02 for the bolted steel stacks and 0.016 for the reinforced concrete stacks (IS:875(Part-3)-1987). Further B and SE/ε_i account for the resonant and non-resonant parts respectively of the total response.

For large number of peaks, Davenport (1964) has shown that the peak factor, g_f is given

$$g_f = \sqrt{2 \ln vT} + \frac{0.577}{\sqrt{2 \ln vT}} \quad (4.19)$$

Where

$$vT = \frac{n_i}{[1 + B\varepsilon_i/SE]^{0.5}} \quad (4.20)$$

is the expected rate of positive zero crossings in the process.

Vickery Approach (1985) have used to calculate the gust factor, G provided the parameters B,S, E, r are known. Vickery (1985) has assumed the following model for wind characteristic

- Mean Velocity profile: $U(z) = U(H)(z/H)^{0.17}$ (4.21)

- Turbulence Intensity: $(J' \sigma_x(z)/U(z) = 0.311 - 0.089 \ln(z))$ (4.22)

- Velocity fluctuation spectrum: $\frac{nS_u(z, n)}{\sigma_u^2(z)} = \frac{4nL_{ux}(z)/U(z)}{[1 + 70.8(nL_{ux}(z)/U(z))^2]^{5/6}}$ (4.23)

- Integral Length Scale: $L_{ux} = 30(z)^{0.35}$ (4.24)

Also, a reasonable mode shape for the fundamental mode of vibration, and

$C_D(z) \cong C_D(H)$ was assumed. Based on this he has given a simplified expression for

$$B = [1 + (H / 265)^{0.63}]^{-0.88} \quad (4.25)$$

$$S = [1 + 5.78(n_i / U_{10}^{1.14} H^{0.98})]^{-0.88} \quad (4.26)$$

$$E = \frac{123(n_i U_{10}) H^{0.21}}{[1 + (330 n_i / U_{10})^2 H^{0.42}]^{0.83}} \quad (4.27)$$

$$r = 0.622 - 0.178 \log_{10} H \quad (4.28)$$

where U_{10} = hourly mean wind speed in m/sec at 10m from G.L

f_1 = natural frequency of the chimney

The expression for G as in equation (4.18), besides being independent of z, has been derived for displacement response assuming the contribution of higher modes to the mean and rms response to be negligibly small.

The along wind load per unit height at any height z on a chimney shall be calculated from the equation:

$$F_z = F_{zm} + F_{zf} \quad (4.29)$$

Where F_{zm} is the wind load in N/m height due to HMW at height z and is given by:

$$F_{zm} = p_z \cdot C_D \cdot dz \quad (4.30)$$

$$F_{zf} = 3 \cdot (G-1) / H^2 \cdot (z/H) \int_0^H F_{zm} z dz \quad (4.31)$$

Where p_z = design pressure at height z, due to HMW is obtained as $0.6V^2 z$ (N/m²)

The procedures for estimating the alongwind responses are given in above equations(4.18 to 4.31). These above equations are used in making program in C language and MS excel worksheet which gives more accurate results and it also reduces the time consumption and easy to workout the results.

In this chapter there are three isolated chimneys with different heights i.e. 83m,102.3m and 224.24m shown in tables 4.1 to 4.3 which are analyzed by computer programs C language and M.S excel sheet and thus compared with experimental values which are drawn by researchers from wind tunnel testing. For all the prototype chimneys are

discretised as a line like structure and various structural properties were lumped at predecided nodal points. The prototype chimneys are of M-25 grade with modulus of elasticity 32000 N/mm². The various aerodynamic parameters require for the analysis have been taken as per IS: 4998-1992 (part-1) i.e in case of 102.3 m chimney a basic wind speed which of 27m/sec (3-sec gust) and value of $\alpha = .18$, in case of 83m chimney basic wind speed of 42m/sec value of $\alpha = .135$, and in case of 224.24m chimney a basic wind speed of 51m/sec value of $\alpha = .14$,,all at the height of 10m as specified by IS:875-1987 (part-3) for terrain category 2 & 3 respectively taken. The results obtained are compared with predicted values obtained from experiments which were done by the researchers.

4.3 Calculations of along wind of different heights of chimneys

The results of 102.3m, 83m and 224.24m chimneys given in tabular form are as follows:

Table 4.1

Calculations For 102.3m height chimney

Height (m)	Mean Velocity (m/s)	Diameter (at X) (m)	Shear force (KN)	Moment (KN-m)
0	27	11.8	86.848	45713.11
10.23	27	11.093	45.4919	37831.47
20.46	27	10.386	60.3771	30498.49
30.69	27	9.679	70.73869	23761.73
40.92	27	8.972	78.83916	17728.6
51.15	27	8.265	85.42342	12481.33
61.38	27	7.558	90.87525	8036.406
71.61	27	6.851	95.42517	4598.733
81.84	27	6.144	99.22564	2064.062
92.07	27	5.437	102.3843	520.5775
102.3	27	4.730	104.9811	0

Table 4.2 Calculations For 83m height chimney

Height (m)	Mean Velocity (m/s)	Diameter (at X) (m)	Shear force (KN)	Moment (KN-m)
0	42	0.3	309.4	17189
9.9	42	8.09	306.0	14134
28	42	7.34	283.6	8841.4
56	42	6.05	189.0	2451.0
83	42	4.79	265.2	0

Table 4.3 Calculation For 224.24m height chimney

Height (m)	Mean Velocity (m/s)	Diameter (at X)(m)	Shear force (KN)	Moment (KN-m)
0	51	5.21	26.22	289095.07
14.24	51	20.00	26.80	130712.51
34.24	51	18.59	29.69	74820.05
54.24	51	17.19	30.09	60260.45
94.24	51	14.38	28.11	35600.89
144.24	51	10.86	23.13	29716.72
164.24	51	9.46	20.67	14826.76
184.24	51	8.05	18.00	6582.36
204.24	51	6.63	15.17	1577.71
214.24	51	5.94	13.70	486.5308
224.24	51	5.24	12.19	0

4.4 Comparison of experimental and analytical values of isolated chimney

The above results are calculated by computer programming and now these results are compared with experimental values which are taken from wind tunnel tests which were done by Aggarwal (1996), Sahu(2003)and Singh (2004).

These comparisons are shown below in tabular form :

Table 4.4 Comparison of experimental and analytical values of isolated chimney

Total Height (m)	Distributed height from base (m)	Experimental moment (kN m)	Analytical moment (kN m)
102.3	0	25690	45713.11
	51.15	7990	12481.33
83	0	9840	17189
	56	1550	2451.0
224.24	0	170840.0	289095.07
	144.24	19320	29716.72

From above comparisons it can be concluded that the along wind response for isolated structure obtained analytically using above method tends to estimate response in which analytical values are higher than experimental values for different chimneys (approx. 40%). This has been found to be more for the chimney of greater height. From above comparisons we calculated the percentage error between experimental and analytical values with different heights as shown below in the table. The percentage errors are different heights are nearly 40% as calculated below.

Table 4.5 Comparison of percentage errors

Total Height (m)	Percentage Error (%age)
102.3	39.89
83	39.75
224.24	37.94

4.5 Closure:

The comparison of analytical and experimental values once again lays emphasis on the extent of study required for proper evaluation of response. The mechanisms behind the behavior still need much to be understood.

Chapter 5

ANN MODELING OF WIND LOADS ON TALL CHIMNEYS

5.1 Need Of ANN Modeling

As discussed in chapter 2, the wind induced responses, both along wind and across wind of rectangular tall chimneys are functions of many parameters like geometric and dynamic characteristic of the chimney as well as the turbulence characteristics of the approach flow. The turbulence parameters of approach flow are Intensity of Turbulence (I_u) and Scale of turbulence (L_u) on the response respectively. The flow approaching towards a tall chimney inherits the combined effect of the wake of obstacles it has overcome. These may be natural features like forests, hills, etc. and also man made structures both low and high rise structures. A few analytical approaches are available for the estimation of wind induced responses of tall chimneys in along wind and across wind directions for stand alone or isolated chimney condition. IS code has provision for along wind response but for estimating across wind response wind tunnel testing has been advised. Further no provision for interference due to some other chimney situated in the vicinity of main chimney has been given in the code. From the literature review on interference effects in tall chimneys, it is beyond any doubt that wind loads get modified when another chimney is situated near the main chimney. These estimates can only be verified by prototype measurements and in the absence of a sufficiently large number of field data; wind tunnel tests provide a viable alternative. To economize on the effort of cumbersome wind tunnel testing there is a need to explore ways of predicting wind loads from a comparatively reduced test programme.

Large number of wind tunnel tests has been performed by various researchers Aggarwal (1996), Sahu(2003)and Singh(2004), both for isolated chimney case as well as for interference due to some other chimney situated in the vicinity of main chimney, but they have not been able to generalize their findings i.e. predicting the response of any type of building subjected to any kind of flow condition. Moreover, wind tunnel tests though give a viable alternative but the work is very much laborious and tedious as it involves modeling the chimney geometry as well as flow conditions. Researchers

performed extensive wind tunnel tests for studying the along wind and across wind response of a tall chimney in isolated chimney condition as well as in interference condition. In their work they have concluded that buffeting factors for the response of the test chimney because of interference due to a chimney situated in its vicinity is a function of too many parameters. These parameters are geometry and orientation of the interfering chimney, distance of the interfering chimney from the test chimney, flow conditions etc. The problem becomes very much complicated when the two or more chimneys are situated in the vicinity of the main chimney.

In the present study Artificial Neural Networks (ANNs) have been used for finding the along wind and across wind responses on tall chimney in interference due to a single chimney condition. ANNs can map the relationship between the input parameters and the corresponding output parameter. 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 normalization, makes it an attractive proposition for knowledge acquisition for problems where there is no acceptable theory or empirical generalization theory or empirical generalization at the present.

5.2 ANN Modeling for Interference Due to a Single Chimney

Data on interference studies has also been taken from wind tunnel tests carried out for interference due to a single chimney by Abhishek(1996), Singh(2004), and Sahu(2003). In their work authors have studied the variation of buffeting factors for the along wind and across wind responses of the test chimney in whose periphery another chimney is situated. The variation has been presented in the form of buffeting factors for along wind and across wind responses of the test chimney in different conditions.

After analyzing their work it is concluded that the buffeting factors for the response of test chimney(Fig.1) depend on number of factors which are as follows

- i) Dimensions of the prototype chimney i.e height, diameter, shell thickness
- ii) Dimensions of the interfering chimney i.e height, diameter, shell thickness
- iii) Distance from dia. of the interfering chimney from $2/3^{\text{rd}}$ height
- iii) Buffeting factors of interfering chimney with different positions(0,15 and 30 degrees).

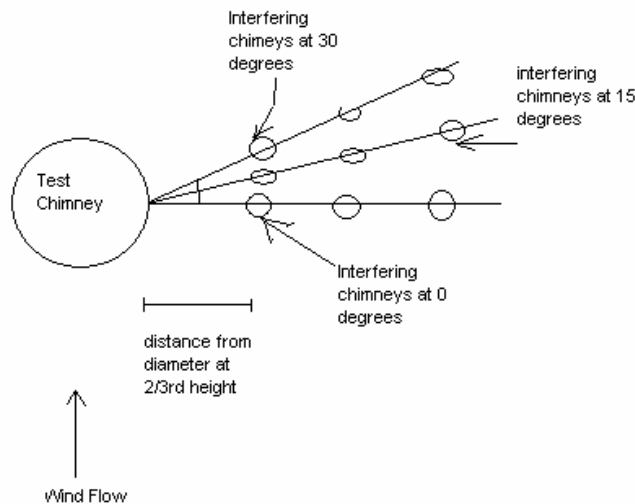


Fig:1 shows different positions of interfering chimneys w.r.t test chimney.

As per above findings five neurons have been selected for ANN modeling of chimney for interference effects as input layer which are given below representing each input parameter:

1. Distance of diameter from 2/3rd height.
2. Different positions (0,15 and 30 degrees)
3. Diameter of chimney.
4. Thickness of shell of chimney
5. Total height of chimney.

One neuron has been selected in the output layer (i.e buffeting factors) representing the chimney. The network has been used for training consists of two hidden layers with an input layer and output layer. Each hidden layer consists of 25 neurons each. Non linear sigmoid function has been used as activation.

Output layer has one neuron, which represents the buffeting factors of the chimney in along wind, or across wind direction as the case may be. In all, four types of responses are estimated using ANN which lead to need for development of four neural networks. These responses are given below:

- i) Along wind mean response.(ALM)
- ii) Along wind fluctuating response.(ALF)
- iii) Total along wind response.(ALT)
- iv) Across wind response. (ACW)

All the input and output data have been normalized by maximum value(which is termed as normalizing factor) for each parameter, so that the values remain between 0 to 1. The output of the network is obtained in the form of normalized output, which is then converted to actual values by multiplying each value, by corresponding normalizing factor as used for preparing the training set. The initial weights have been set as random number between the range -0.3 to 0.3.

5.2.1 Selection of Learning Rate Parameter and momentum Factor

The learning rate parameter (η) and momentum factor(α) are kept .15 and .85 respectively. Training of the network is carried out till the root mean square error of the network is reduced to 0.0002. The training was done in steps of 10000 iterations. First step of iteration was performed with the initial random weights assigned to connections. Subsequent steps of iterations started with the weights achieved obtained after first step.

5.2.2 Selection of Training Data Set

Selection of training data set is a very important step in chimneys. Any neural network is efficient only if is able to predict the output values for input parameters for which it was not trained. For finding out the minimum numbers of patterns are required for successful training of the network a study has been conducted. For this study it has been assumed that the training is successful if percentage errors between experimental and ANN values for all patterns are less than 10%. In this work three different heights of chimneys are taken i.e. 102.3m, 83m and 224.24 m. Two chimneys 83m and 224.24 are used for training of neural networks and one chimney called test chimney which is 102.3 m high, used for testing the experimental data for different responses.

In all four responses, two chimneys 83m and 224.24m has been chosen for training the network as shown in tables 5.1 to 5.4 and Fig.5.1 to 5.4. The locations of the interfering chimneys corresponding to 83m and 224.24m patterns with 39 patterns after

training of neural networks are shown in tables 5.1 to 5.4. Scatter diagrams have been plotted between experimental and ANN values with different number of training data samples. First four diagrams show the checking of training data is with less percentage error (below 10%) Fig. 5.1 to 5.4.

Table 5.1

Along wind mean response of 83m and 224.24m heights after training the data

Patterns	Exp Values	ANN values
1.	0.73913	0.740534
2.	0.913043	0.917722
3.	0.782609	0.784494
4.	0.652174	0.685197
5.	0.73913	0.741834
6.	0.608696	0.618254
7.	0.782609	0.698645
8.	0.695652	0.704878
9.	0.478261	0.487737
10.	0.608696	0.688065
11.	0.730435	0.728128
12.	0.478261	0.483285
13.	0.652174	0.627411
14.	0.695652	0.700728
15.	0.434783	0.439997
16.	0.604348	0.614727
17.	0.434783	0.438637
18.	0.434783	0.436716
19.	0.478261	0.481652
20.	0.391304	0.395587
21.	0.421739	0.425768
22.	0.826087	0.832605
23.	0.869565	0.877425
24.	0.782609	0.787215
25.	0.913043	0.90372
26.	0.921739	0.902891
27.	0.826087	0.829177
28.	0.913043	0.922268
29.	0.895652	0.920492
30.	0.521739	0.532715
31.	0.652174	0.65746
32.	1	0.978371
33.	0.434783	0.441211
34.	0.565217	0.56906
35.	0.656522	0.660361

36.	0.565217	0.568189
37.	0.478261	0.482455
38.	0.608696	0.609916
39.	0.478261	0.483072

Table 5.2

Along wind fluctuating response of 83m and 224.24m heights after training the data

Patterns	Exp values	ANN values
1	0.24	0.242678
2	0.32	0.325828
3	0.536	0.546799
4	0.4	0.404665
5	0.864	0.861211
6	0.84	0.838866
7	0.48	0.479806
8	0.88	0.89312
9	0.68	0.689167
10	0.52	0.524517
11	0.84	0.835734
12	0.84	0.832703
13	0.536	0.539432
14	0.76	0.766271
15	0.832	0.841652
16	0.56	0.560107
17	0.784	0.779977
18	0.8	0.798772
19	0.32	0.325681
20	0.424	0.426883
21	0.592	0.600081
22	0.576	0.568668
23	0.592	0.605956
24	0.984	0.971353
25	0.544	0.560066
26	0.64	0.616893
27	0.96	0.979397
28	0.68	0.674965

29	0.68	0.703952
30	0.952	0.974408
31	0.736	0.739415
32	0.848	0.831254
33	1	0.953342
34	0.664	0.664768
35	0.832	0.840696
36	0.88	0.940999
37	0.616	0.619616
38	0.824	0.826974
39	0.96	0.932828

Table 5.3

Total along wind response of 83m and 224.24m heights after training the data

Patterns	Exp. Values	ANN values
1	0.511628	0.501544
2	0.730233	0.730556
3	0.47907	0.479632
4	0.418605	0.451603
5	0.84186	0.843186
6	0.651163	0.651467
7	0.465116	0.42831
8	0.846512	0.84627
9	0.44186	0.442585
10	0.376744	0.394265
11	0.646512	0.646921
12	0.502326	0.50243
13	0.372093	0.369838
14	0.553488	0.554023
15	0.534884	0.534956
16	0.372093	0.373302
17	0.511628	0.511754
18	0.511628	0.511806
19	0.534884	0.55269
20	1	0.99081
21	0.623256	0.637431
22	0.572093	0.516812
23	0.613953	0.615325
24	0.627907	0.589816
25	0.44186	0.509201
26	0.590698	0.590475
27	0.534884	0.55974
28	0.55814	0.528786
29	0.627907	0.629005
30	0.530233	0.540095

31	0.604651	0.60755
32	0.665116	0.664763
33	0.534884	0.512209
34	0.534884	0.534937
35	0.469767	0.47107
36	0.488372	0.505709
37	0.427907	0.428042
38	0.451163	0.45056
39	0.511628	0.508355

Table 5.4

Across wind response of 83m and 224.24m heights after training the data

Patterns	Exp values	ANN values
1	0.677273	0.675486
2	0.522727	0.52461
3	0.454545	0.45379
4	0.613636	0.622934
5	0.768182	0.763567
6	0.590909	0.591189
7	0.636364	0.60269
8	0.65	0.65412
9	0.490909	0.49279
10	0.55	0.589667
11	0.581818	0.58421
12	0.5	0.496683
13	0.618182	0.596697
14	0.5	0.492688
15	0.386364	0.390256
16	0.595455	0.602863
17	0.504545	0.508119
18	0.431818	0.430245
19	0.404545	0.40691
20	0.404545	0.408315
21	0.5	0.504923
22	0.568182	0.563204
23	0.590909	0.569091
24	0.772727	0.763511
25	0.681818	0.696398
26	0.659091	0.684185
27	0.681818	0.688664
28	0.795455	0.780628

29	0.672727	0.666784
30	0.440909	0.435122
31	0.604545	0.606811
32	0.454545	0.453626
33	0.377273	0.383184
34	0.545455	0.543303
35	0.431818	0.436781
36	0.377273	0.369192
37	0.363636	0.365448
38	0.386364	0.380958
39	0.340909	0.345497

Scatter diagram of along wind mean response of 83m and 224.24 heights after training

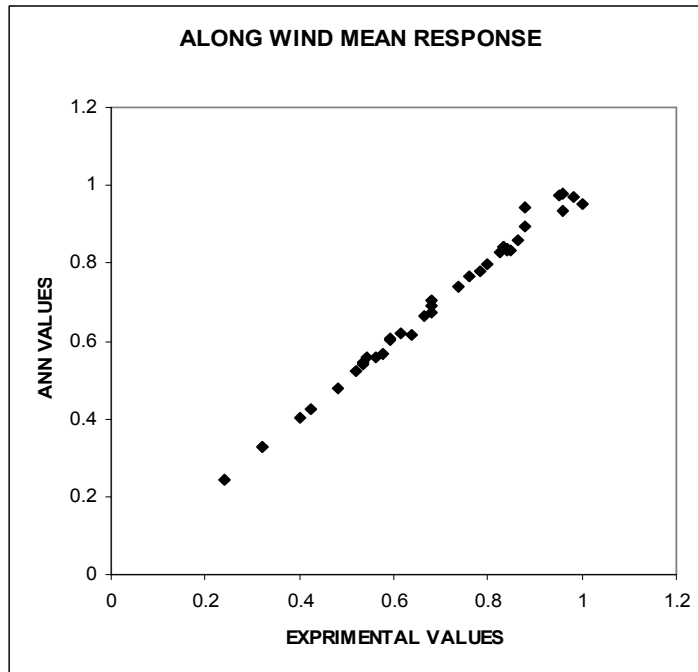


Fig-5.1

Scatter diagram of along wind Fluctuating response of 83m and 224.24 heights after training

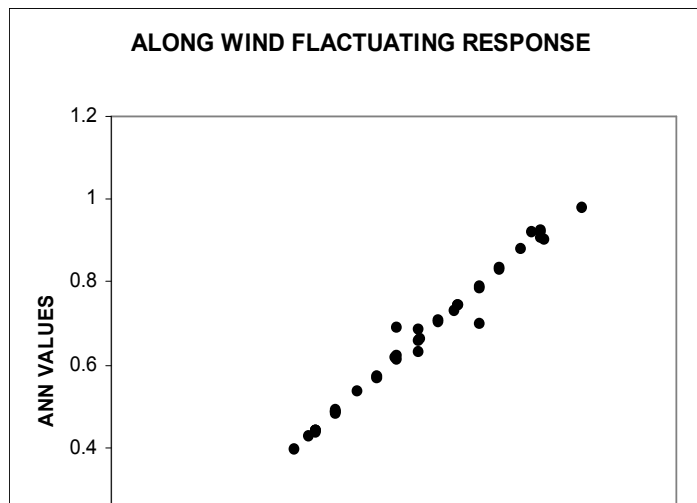


Fig.-5.2

Scatter diagram of along wind Fluctuating response of 83m and 224.24 heights after training

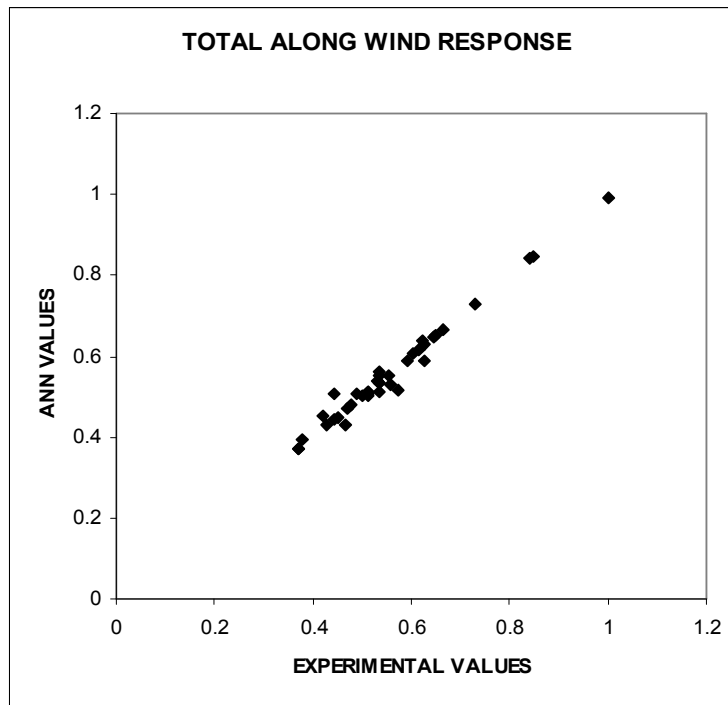


Fig.-5.3

Scatter diagram of along wind Fluctuating response of 83m and 224.24 heights after training

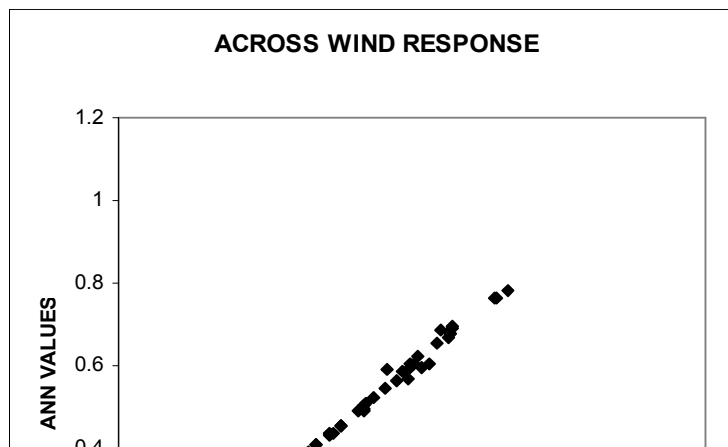
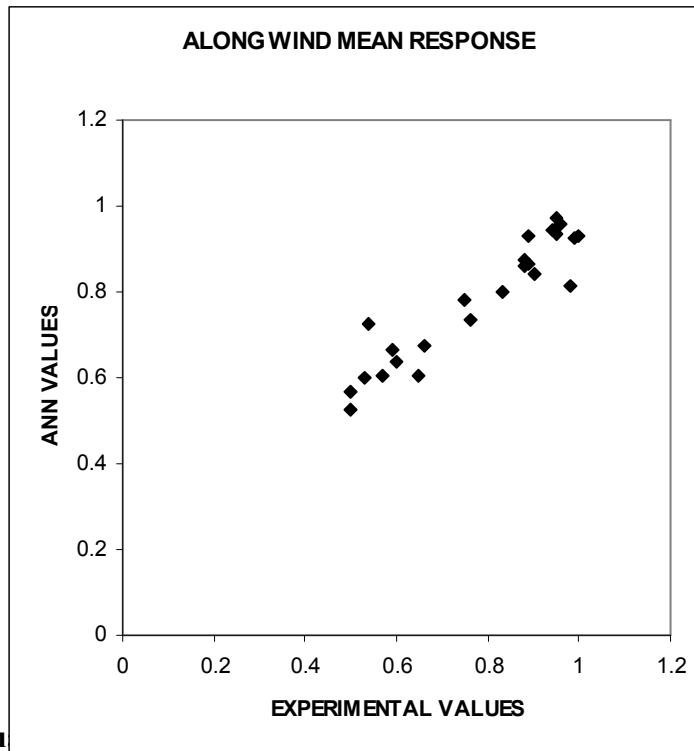


Fig.-5.4

For the four responses of interference effects, the experimental data of 102.3m chimney (test chimney) available consist 24 patterns as shown in tables 5.5 to 5.8 and Fig.5.5 to 5.8. The locations of the interfering chimney corresponding to 24 patterns after training the data are shown in Table 5.5 to 5.8. Scatter diagrams have been plotted between experimental and ANN values with different number of training of experimental data samples. Other four diagrams show the checking of training of experimental data is with less percentage error (below 10%) Fig. 5.5 to 5.8

Table and Fig. 5.5
Along wind mean response of 102.3m height (test chimney) after training the network

Patterns	Distance	Exp values	ANN values
1	21.32	0.5	0.526786
2	21.32	0.65	0.602742
3	21.32	0.88	0.873772
4	28.2048	0.5	0.565708
5	28.2048	0.75	0.781006
6	28.2048	0.95	0.971352
7	35.3899	0.53	0.601791
8	35.3899	0.76	0.735181
9	35.3899	0.96	0.958755
10	42.4599	0.54	0.726847
11	42.4599	0.83	0.801748
12	42.4599	0.94	0.945913
13	49.5399	0.57	0.603757
14	49.5399	0.88	0.858193
15	49.5399	0.95	0.935907
16	56.6199	0.59	0.665621
17	56.6199	0.89	0.863152
18	56.6199	0.89	0.929576
19	63.7	0.6	0.63511
20	63.7	0.9	0.841943
21	63.7	0.99	0.926656
22	77.85	0.66	0.673445
23	77.85	0.98	0.812494
24	77.85	1	0.928232



Along wind fluctuation is used as input for training the network

Patterns	Distance	Exp values	ANN values
1	21.32	1.8899997	1.8681405
2	21.32	1.9999995	1.992122
3	21.32	1.8500004	1.8332058
4	28.31005	1.9000001	1.9429135
5	28.31005	1.980001	1.9488268
6	28.31005	1.7799999	1.7560477
7	35.38995	1.8899997	1.8622249
8	35.38995	1.9200009	1.9483921
9	35.38995	1.7099994	1.7024462
10	42.45998	1.7199998	1.7209152
11	42.45998	1.8899997	1.8654035
12	42.45998	1.6499993	1.6236896
13	49.53998	1.6900009	1.6763136
14	49.53998	1.750001	1.7541571
15	49.53998	1.5499999	1.5578176
16	56.61999	1.6700001	1.6241404
17	56.61999	1.699999	1.6759548
18	56.61999	1.5100006	1.4936752
19	63.7	1.520001	1.5647314
20	63.7	1.6200004	1.6239932
21	63.7	1.4600009	1.4408557
22	77.85	1.4799994	1.4555895

23	77.85	1.5399995	1.5296035
24	77.85	1.4500005	1.4443678

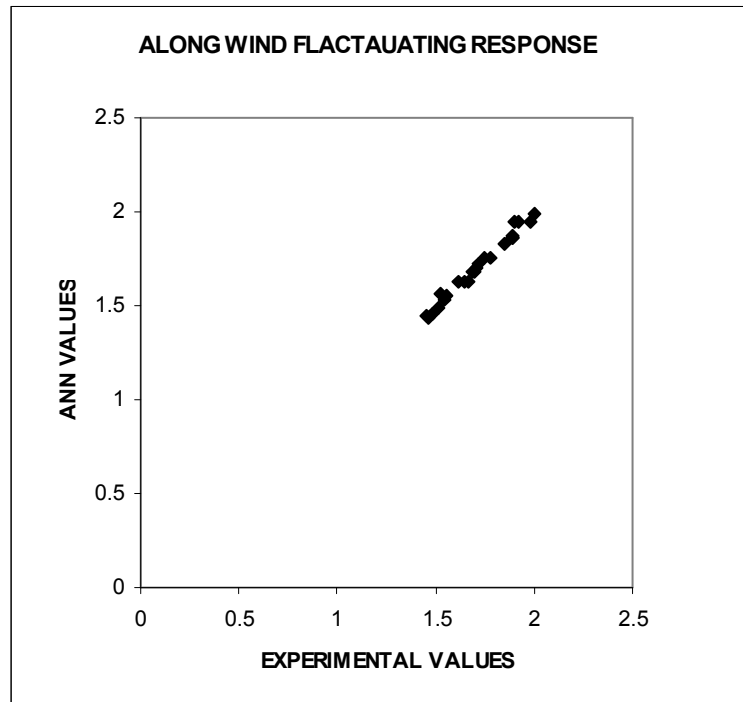


Table and Fig. 5.7

Total along wind response of 102.3m height (test chimney) after training the network

Patterns	Distance	Exp values	ANN values
1	21.32	1.140001	0.998188
2	21.32	1.36	1.5187278
3	21.32	1.4	1.4204104
4	28.310048	1.129999	1.0234344
5	28.310048	1.379999	1.3793497
6	28.310048	1.390001	1.3039965
7	35.389952	1.12	1.1131211
8	35.389952	1.319999	1.4798364
9	35.389952	1.35	1.180722
10	42.459976	1.12	1.0719556
11	42.459976	1.3	1.4809415
12	42.459976	1.319999	1.1141795
13	49.539984	1.1	1.0931224
14	49.539984	1.28	1.340697
15	49.539984	1.29	1.1824907
16	56.619992	1.11	1.269704
17	56.619992	1.249999	1.1209391
18	56.619992	1.270001	1.236699
19	63.7	1.069999	1.0907402

20	63.7	0.956575	0.9789488
21	63.7	0.975341	0.9634537
22	77.850032	0.999999	0.9854066
23	77.850032	1.200001	1.1000956
24	77.850032	1.22	1.24569

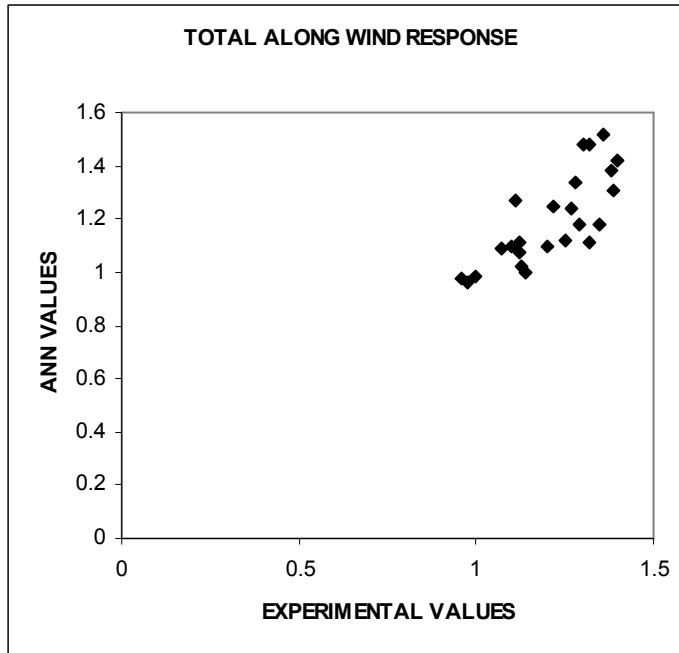
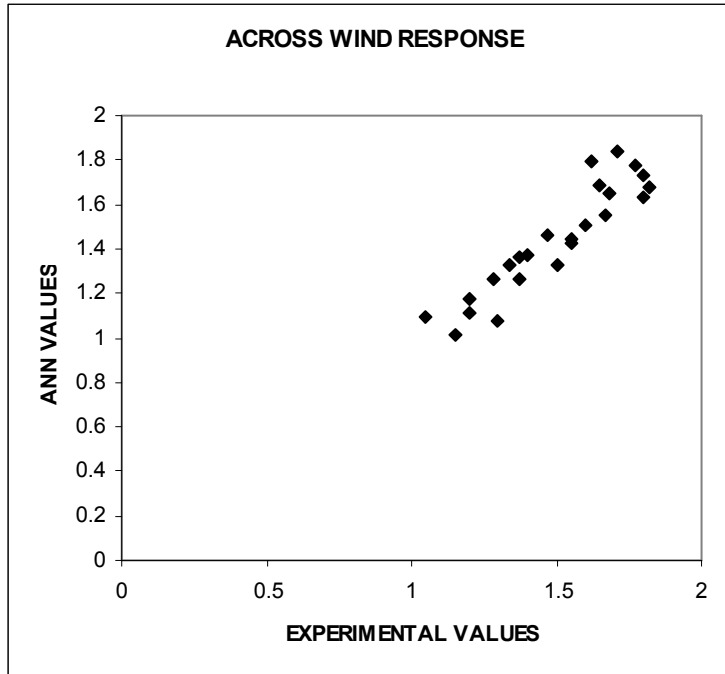


Table and Fig. 5.6

Across wind mean response of 102.3m height (test chimney) after training the network

Patterns	Distance	Exp. Values	ANN values
1	21.32	1.5	1.3271962
2	21.32	1.8	1.729086
3	21.32	1.8200006	1.6781666
4	28.31005	1.8000004	1.633324
5	28.31005	1.67	1.5548654
6	28.31005	1.05	1.0924056
7	35.38995	1.769999	1.7732748
8	35.38995	1.5500008	1.444366
9	35.38995	1.65	1.689998
10	42.45998	1.6799992	1.65462
11	42.45998	1.2000004	1.1759792
12	42.45998	1.6200008	1.7920528
13	49.53998	1.549999	1.4301254
14	49.53998	1.2999994	1.072588
15	49.53998	1.7100006	1.8344138
16	56.61999	1.4000008	1.3701534
17	56.61999	1.6000006	1.5101498
18	56.61999	1.3699994	1.3606026
19	63.7	1.2799996	1.2625976
20	63.7	1.4700004	1.45865

21	63.7	1.3699994	1.2639334
22	77.85003	1.1499994	1.0114434
23	77.85003	1.2	1.109874
24	77.85003	1.3400002	1.3236932



Patterns in testing and training for different responses.

Sr. no	Type of response	Number of patterns for training 83m and 224.24m height	Number of patterns for testing (EXP.)of 102.3m height	Total Patterns for 0,15 and 30 degrees
1	NALM	39	24	24
2	NALF	39	24	24
3	NALT	39	24	24
4	NACW	39	24	24

5.3 Comparison of ANN predictions with Experimental values for interference effect.

The network performance has been checked by checking the output of the network for the same data set as used for the training of the network. The output values of the network for this data has been found to be in close agreement with the target values

(Aggarwal (1996), Sahu(2000) and Darmendra(2002)) of the same. These results ensure successful training of the network. The values of four types of various buffeting factors for various positions have been predicted by ANN. Alternate patterns were selected for training. The predicted values of buffeting factors are compared with the experimental values. The continuous curve is for ANN predicted values while dotted curve is for experimental values. The maximum error in majority of cases is less than 10% of the experimental values except for couple of cases in which the maximum error rises to 15%. The possible reason for this may be because of noisy data.

5.3.1 Normalized Along Wind Mean Response

Table and Fig. 5.9 a, b, c presents the comparison of experimental values and ANN values for the response (NALM). These comparisons have been done for three different positions as shown in tables given below. The experimental data available on 102.3m test chimney was for different values of increasing distance from dia. at 2/3rd height. Combining all the data of 102.3m height of chimney patterns which are divided into three sets at different positions 0,15 and 30 degrees (see table 5.9). Out of this only 83m and 224.24m patterns were included in the training data set because the minimum number of patterns that are required for predicting good results has been found for 102.3m chimney. But prediction has been done for all height patterns.

It can be observed from the Fig-5.9 a, b, c that the curves for experimental results and that for ANN predicted results are almost overlapping each other except few points. The curves for ANN predicted results are smoother than the experimental results.

However for points where the curves are not overlapping the maximum average percentage error is less than 15%. The max average percentage error has been found is 6.36% for 0 degree, 5.06% for 15 degree and 2.7% for 30 degree .

Table 5.9
Comparisons of Along wind mean wind between Exp. Values and ANN values of
Test chimney at positions (0, 15,30 degrees)102.3 m height

Patterns	Distance from dia. at 2/3rd Height	Exp. Values	ANN values
1	21.32	0.5	0.526786
2	28.2048	0.5	0.565708
3	35.3899	0.53	0.601791
4	42.4599	0.54	0.726847
5	49.5399	0.57	0.603757
6	56.6199	0.59	0.665621
7	63.7	0.6	0.63511
8	77.85	0.66	0.673445

(a)

Patterns	Distance from dia. at 2/3rd Height	Exp. Values	ANN values
1	21.32	0.65	0.602742
2	28.2048	0.75	0.781006
3	35.3899	0.76	0.735181
4	42.4599	0.83	0.801748
5	49.5399	0.88	0.858193
6	56.6199	0.89	0.863152
7	63.7	0.9	0.841943
8	77.85	0.98	0.812494

(B)

Patterns	Distance from dia. at 2/3rd Height	Exp. Values	ANN values
1	21.32	0.88	0.873772
2	28.2048	0.95	0.971352
3	35.3899	0.96	0.958755
4	42.4599	0.94	0.945913
5	49.5399	0.95	0.935907
6	56.6199	0.89	0.929576
7	63.7	0.99	0.926656
8	77.85	1	0.928232

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5.3.2 Normalized Along Wind Fluctuating Response

Table and Fig. 5.10 a, b, c present the comparison of experimental values and ANN values for the response (NALM). These comparisons have been done for three different positions. The experimental data available on 102.3m chimney was for different values of increasing distance from dia. at 2/3rd height. Combining all the data of 102.3m height of chimney patterns which are divided into three sets at different positions 0,15 and 30 degrees (see table 5.10) . Out of this only 83m and 224.24m patterns were included in the training data set because the minimum number of patterns that are required for predicting good results has been found for 102.3m chimney. But prediction has been done for all height patterns.

It can be observed from the Fig.-5.10 a, b, c that the curves for experimental results and that for ANN predicted results are almost overlapping each other

except few points. The curves for ANN predicted results are smoother than the experimental results. However for points where the curves are not overlapping the maximum average percentage error is less than 15%. The max average percentage error has been found is 2.7% for 0 degree, 1.6% for 15 degree and 1.5% for 30 degree.

Table 5.10
Comparisons of Along wind fluctuating between Exp. Values and ANN values of
Test chimney at positions (0, 15,30 degrees)102.3 m height

Patterns	Distance from dia. at 2/3rd Height	Exp. Values	ANN values
1	21.32	1.89	1.8681405
2	28.31005	1.9	1.9429135
3	35.38995	1.89	1.8622249
4	42.45998	1.72	1.7209152
5	49.53998	1.690001	1.6763136
6	56.61999	1.67	1.6241404
7	63.7	1.520001	1.5647314

8	77.85003	1.479999	1.4555895
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(a)

Patterns	Distance from dia. at 2/3 rd Height	Exp. Values	ANN values
1	21.32	2	1.992122
2	28.31005	1.980001	1.948827
3	35.38995	1.920001	1.948392
4	42.45998	1.89	1.865404
5	49.53998	1.750001	1.754157
6	56.61999	1.699999	1.675955
7	63.7	1.62	1.623993
8	77.85003	1.54	1.529604

(B)

Patterns	Distance from dia. at 2/3 rd Height	Exp. Values	ANN values
1	21.32	1.8500004	1.8332058
2	28.310048	1.7799999	1.7560477
3	35.389952	1.7099994	1.7024462
4	42.459976	1.6499993	1.6236896
5	49.539984	1.5499999	1.5578176
6	56.619992	1.5100006	1.4936752
7	63.7	1.4600009	1.4408557
8	77.850032	1.4500005	1.4443678

5.3.3 Normalized Total along Wind Response

Table and Fig. 5.11 a, b, c present the comparison of experimental values and ANN values for the response (NALM). These comparisons have been done for three different positions. The experimental data available on 102.3m chimney was for different values of increasing distance from dia. at 2/3rd height. Combining all the data of 102.3m height of chimney patterns which are divided into three sets at different positions 0,15 and 30 degrees(see table 5.11). Out of this only 83m and 224.24m patterns were included in the training data set because the minimum number of patterns that are required for

predicting good results has been found for 102.3m chimney. But prediction has been done for all height patterns.

It can be observed from the Fig-5.11 a, b, c that the curves for experimental results and that for ANN predicted results are almost overlapping each other except few points. The curves for ANN predicted results are smoother than the experimental results. However for points where the curves are not overlapping the maximum percentage error is less than 20%. The max average percentage error has been found is 6.3% for 0 degree, 10.11% for 15 degree and 8.2% for 30 degree .

Table 5.11
Comparisons of total along wind between Exp. Values and ANN values of Test chimney at positions (0, 15,30 degrees)102.3 m height

Patterns	Distance from dia. at 2/3rd Height	Exp. Values	ANN values
1	21.32	1.140001	0.998188
2	28.31005	1.129999	1.0234344

3	35.38995	1.12	1.1131211
4	42.45998	1.12	1.0719556
5	49.53998	1.1	1.0931224
6	56.61999	1.11	1.269704
7	63.7	1.069999	1.0907402
8	77.85003	0.999999	0.9854066

(a)

Patterns	Distance from dia. at 2/3rd Height	Exp. Values	ANN values
1	21.32	1.3599997	1.51872775
2	28.31005	1.379999	1.3793497
3	35.38995	1.31999895	1.4798364
4	42.45998	1.29999965	1.4809415
5	49.53998	1.28000035	1.340697
6	56.61999	1.24999925	1.12093905
7	63.7	0.956575	0.97894875
8	77.85003	1.200001	1.1000956

(b)

Patterns	Distance from dia. at 2/3rd Height	Exp. Values	ANN values
1	21.32	1.40000045	1.4204104
2	28.31005	1.3900008	1.3039965
3	35.38995	1.35000005	1.180722
4	42.45998	1.31999895	1.1141795
5	49.53998	1.29	1.1824907
6	56.61999	1.2700007	1.236699
7	63.7	0.9753409	0.9634537
8	77.85003	1.2200003	1.24569

5.3.4 Normalized Across Wind Response

Table and graph 5.12 a,b,c presents the comparison of experimental values and ANN values for the response (NALM). These comparisons have been done for three different positions. The experimental data available on 102.3m chimney was for different values of increasing distance from dia. at 2/3rd height. Combining all the data of 102.3m height of chimney patterns which are divided into three sets at different positions 0,15

and 30 degrees(see table 5.12). Out of this only 83m and224.24m patterns were included in the training data set because the minimum number of patterns that are required for predicting good results has been found for 102.3m chimney. But prediction has been done for all height patterns.

It can be observed from the Fig-5.12 a, b, c that the curves for experimental results and that for ANN predicted results are almost overlapping each other except few points. The curves for ANN predicted results are smoother than the experimental results. However for points where the curves are not overlapping the maximum average percentage error is less than 20%. The max average percentage error has been found is 8.4% for 0 degree, 9.18% for 15 degree and 8.15% for 30 degree .

Table 5.12

**Comparisons of Across wind between Exp. Values and ANN values of Test chimney
at positions (0, 15,30 degrees)102.3 m height**

Patterns	Distance from dia. at 2/3rd Height	Exp. Values	ANN values
1	21.32	1.5	1.3271962
2	28.31005	1.8	1.633324
3	35.38995	1.769999	1.7732748
4	42.45998	1.679999	1.65462
5	49.53998	1.549999	1.4301254
6	56.61999	1.400001	1.3701534
7	63.7	1.28	1.2625976
8	77.85003	1.149999	1.0114434

(a)

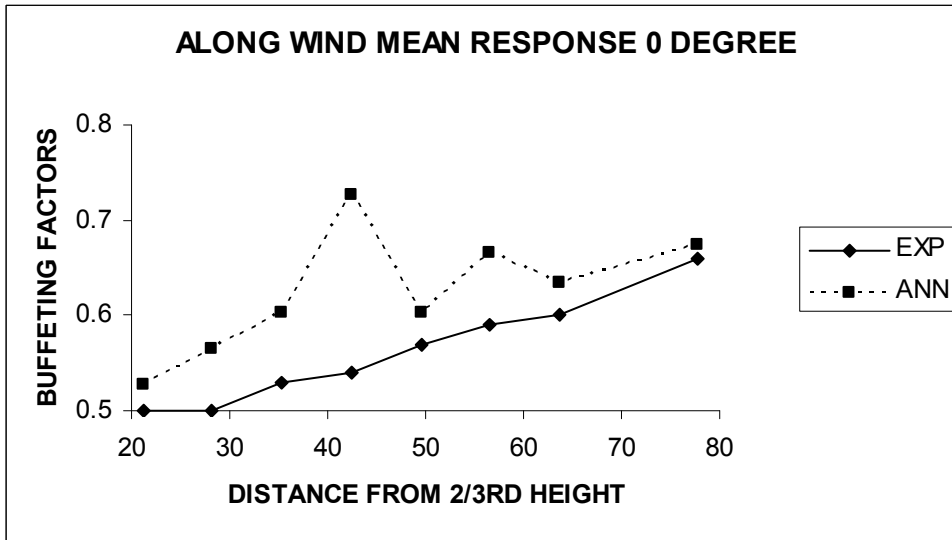
Patterns	Distance from dia. at 2/3rd Height	Exp. Values	ANN values
1	21.32	1.8	1.729086
2	28.31005	1.67	1.5548654
3	35.38995	1.5500008	1.444366
4	42.45998	1.2000004	1.1759792
5	49.53998	1.2999994	1.072588
6	56.61999	1.6000006	1.5101498
7	63.7	1.4700004	1.45865
8	77.85003	1.2	1.109874

(b)

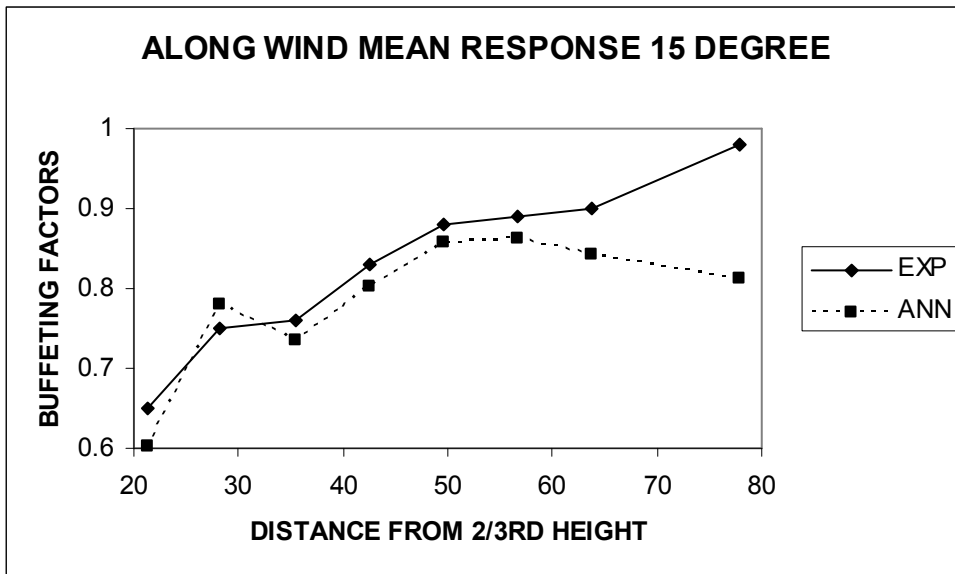
Patterns	Distance from dia. at 2/3rd Height	Exp. Values	ANN values
1	21.32	1.8200006	1.678167
2	28.31005	1.05	1.092406
3	35.38995	1.65	1.689998
4	42.45998	1.6200008	1.792053
5	49.53998	1.7100006	1.834414
6	56.61999	1.3699994	1.360603
7	63.7	1.3699994	1.263933
8	77.85003	1.3400002	1.323693

Fig 5.9 a,b,c

Comparisons of Along wind mean between Exp. Values and ANN values of Test chimney at positions (0, 15 degrees)102.3 m height

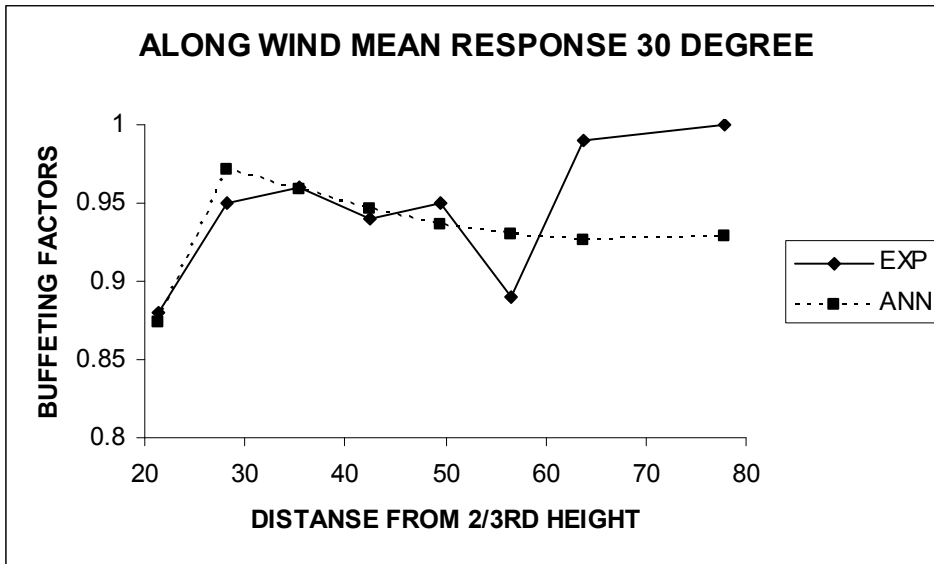


(a)



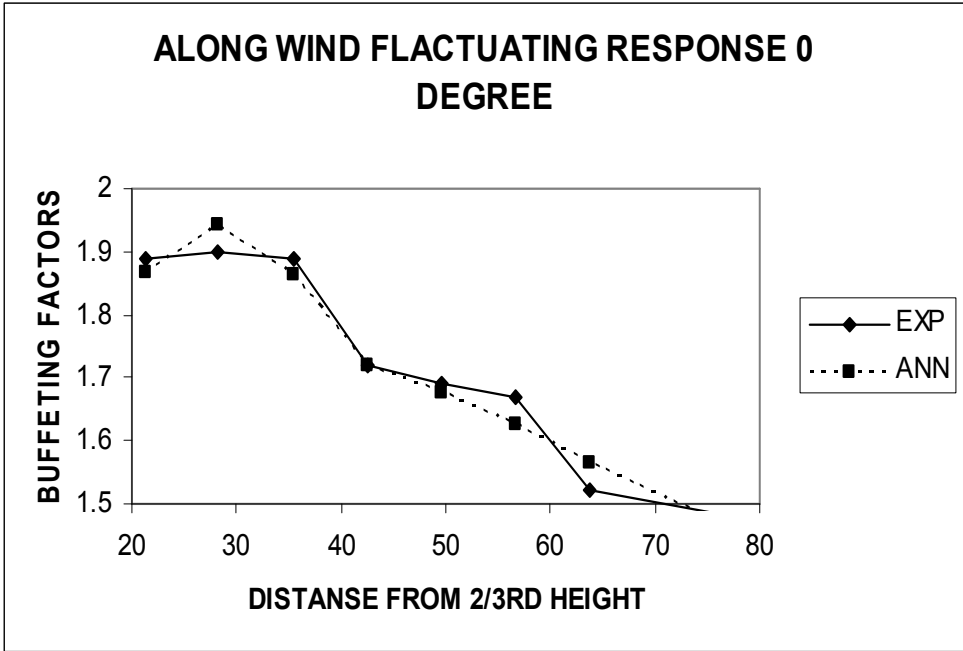
(b)

Comparisons of Along wind mean between Exp. Values and ANN values of Test chimney at positions (30 degree)102.3 m height

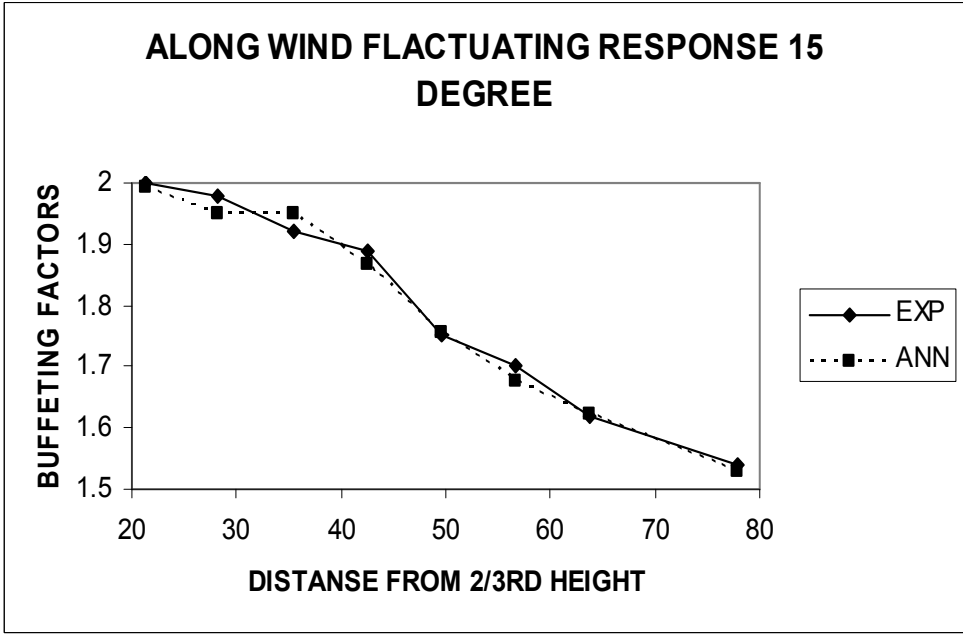


(c)

Fig. 5.10 a,b,c
Comparisons of Along wind fluctuating between Exp. Values and ANN values of
Test chimney at positions (0, 15 degrees)102.3 m height

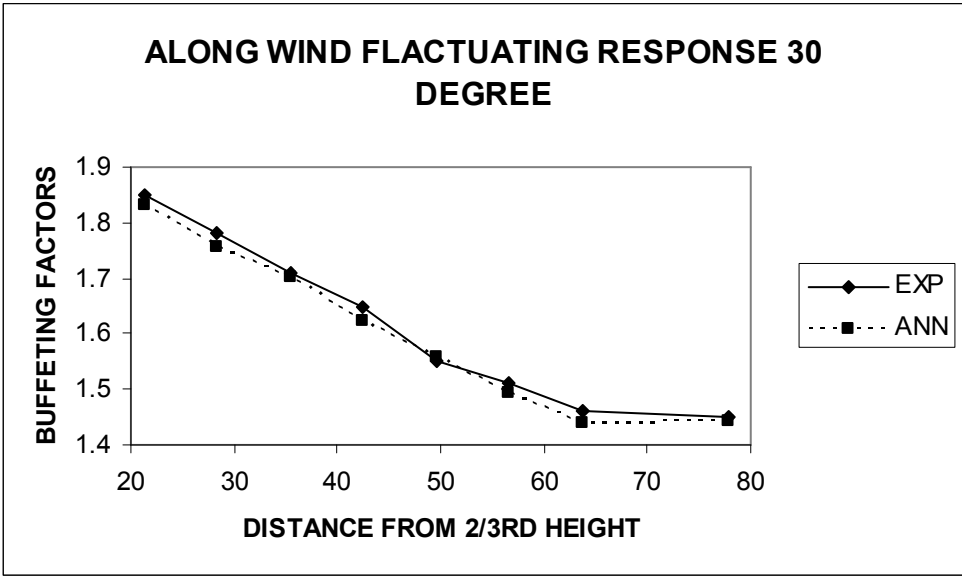


(a)



(b)

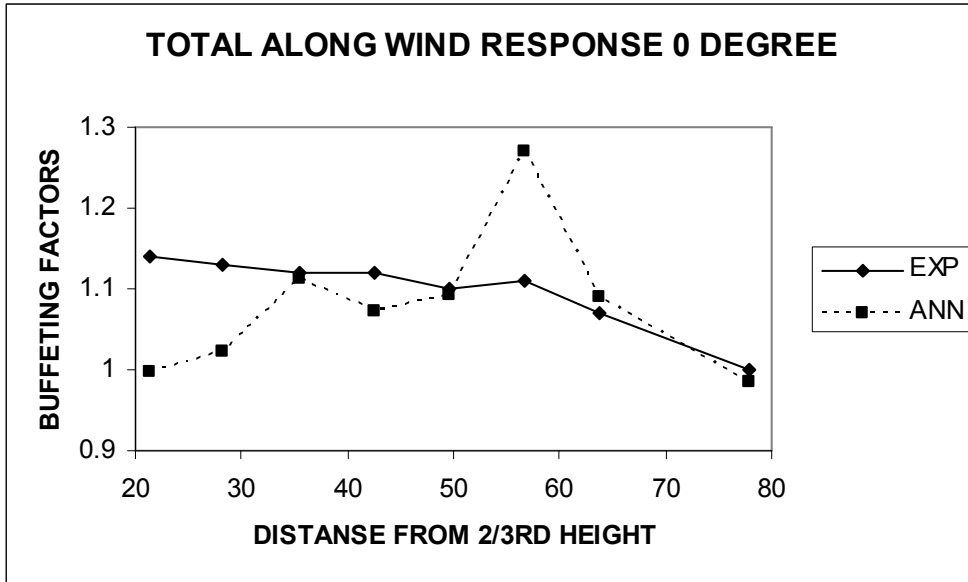
Comparisons of Along wind fluctuating between Exp. Values and ANN values of
Test chimney at positions (30 degree)102.3 m height



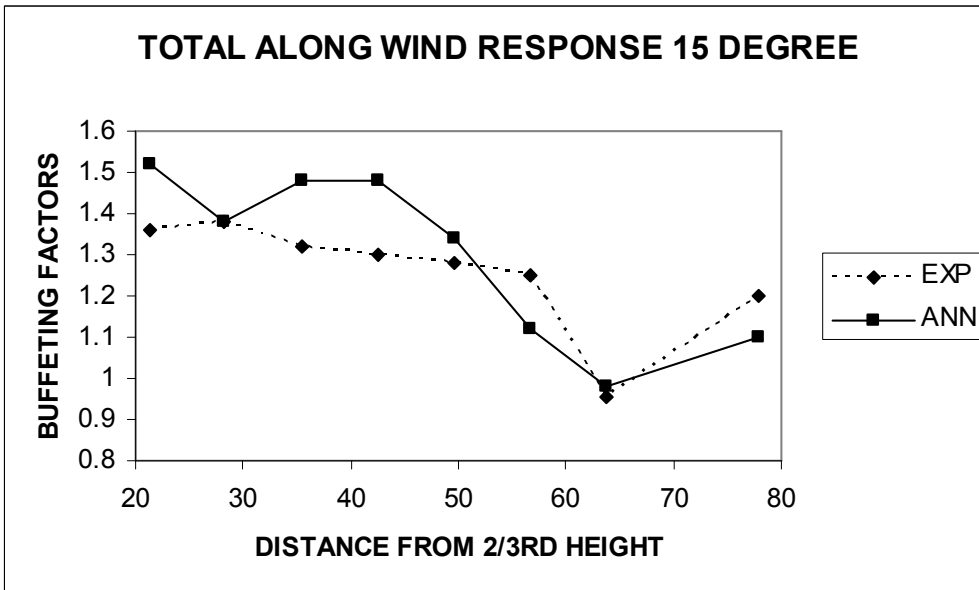
(c)

Fig. 5.11 a,b,c

Comparisons of Total along wind between Exp. Values and ANN values of Test chimney at positions (0, 15 degrees)102.3 m height

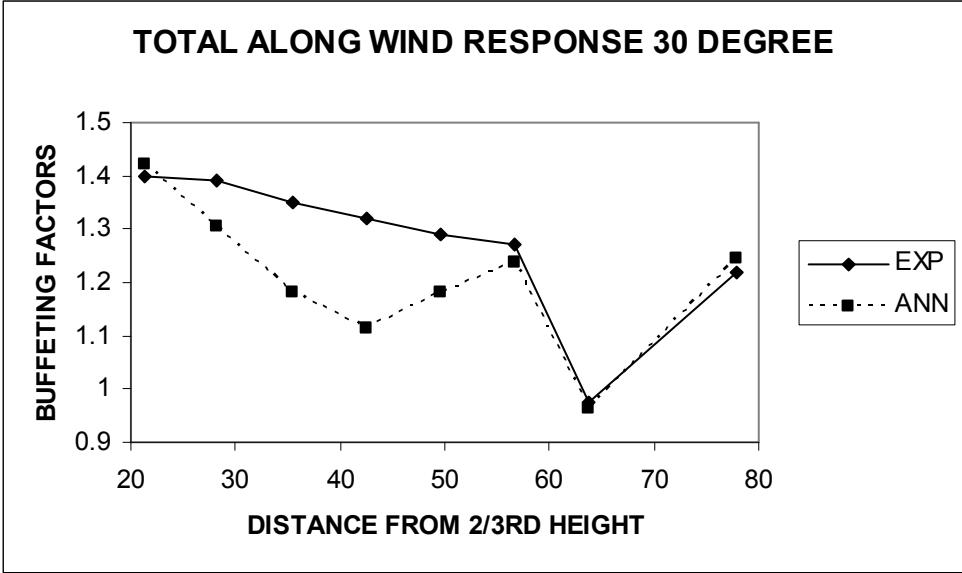


(a)



(b)

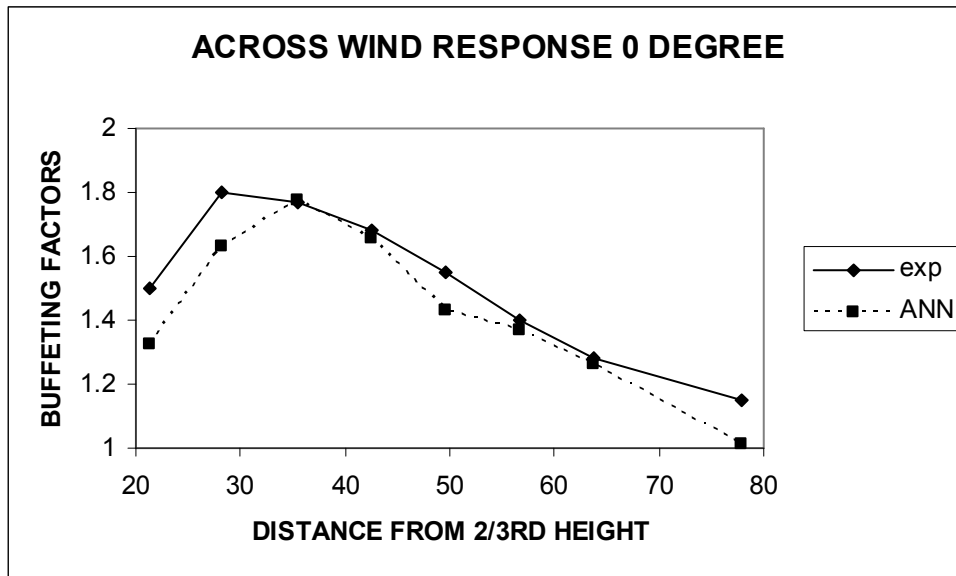
Comparisons of Total along wind between Exp. Values and ANN values of Test chimney at positions (30 degree)102.3 m height

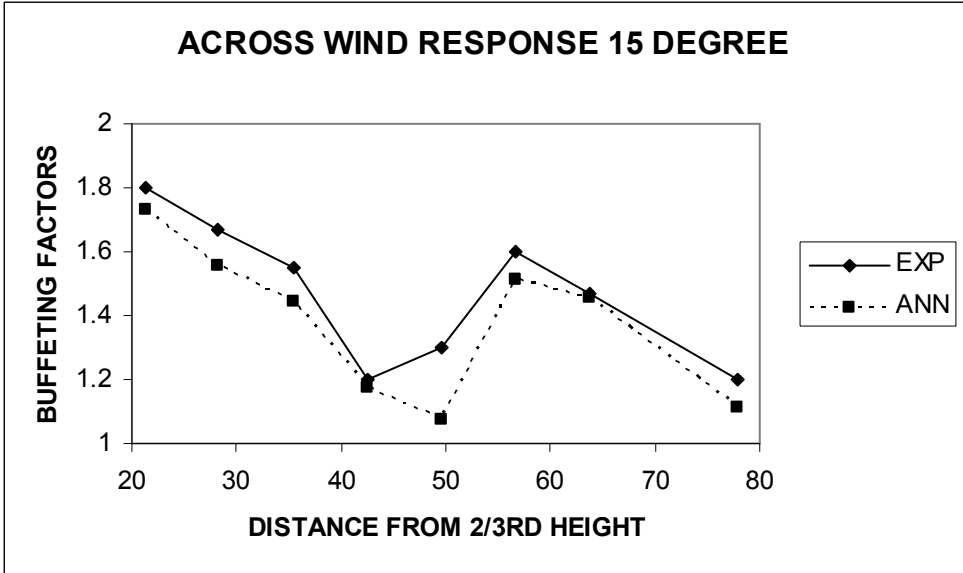


(c)

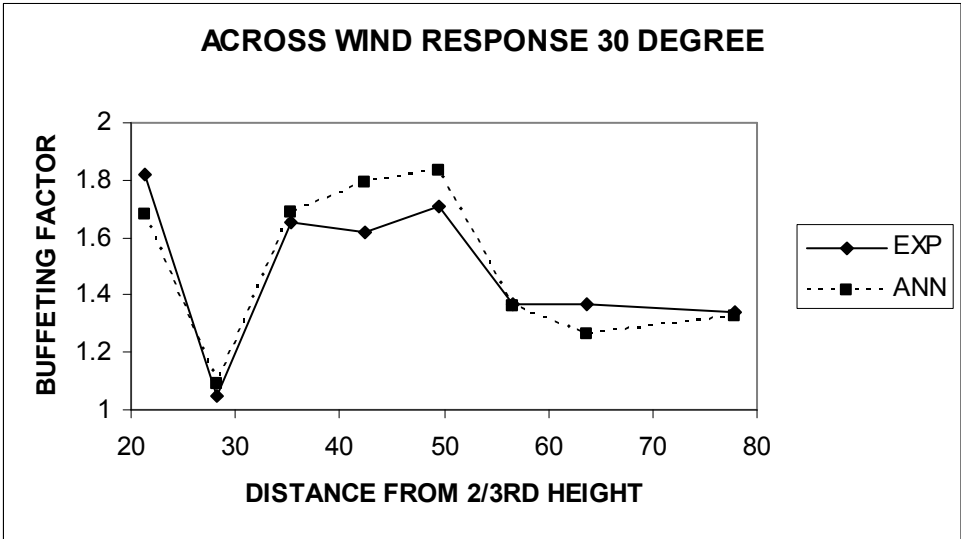
Fig. 5.12 a, b, c

Comparisons of Across wind between Exp. Values and ANN values of Test chimney
at positions (0, 15 degrees)102.3 m height





Comparisons of Across wind between Exp. Values and ANN values of Test chimney at positions (30 degrees)102.3 m height



(c)

CONCLUSIONS

1. The along wind response for isolated structure obtained analytically using IS code method tends to estimate response in which analytical values are 40% higher than experiential values for different chimneys. From the above results it is concluded that as the height of chimney increases, the response of along wind also increases.
2. Use of ANN reduced the number of wind tunnel tests significantly. For the along wind and across wind responses of interference chimney case the total patterns available for 102.3m test chimney are 24. Only 83m and 224.24m chimneys (39 patterns) were used for training of the network. Wind tunnel testing is reduced upto 40-45% if large amount of data on chimneys are present.
3. The curves for experimental and ANN predicted values of various responses of the test chimneys are almost overlapping each other which indicates close agreement between ANN predicted values and experimental values of the responses of the chimney model. The maximum error between all type of responses are below 10%.

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