

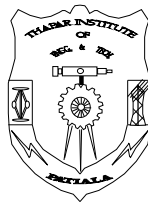
**CONCRETE MIX DESIGN USING
ARTIFICIAL NEURAL NETWORK**

**A
THESIS
Submitted
in partial fulfillment of the requirements
for the award of degree of
MASTER OF ENGINEERING**

**IN
CIVIL ENGINEERING (STRUCTURES)**

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CERTIFICATE

This is to certify that the work presented in thesis entitled, “Concrete mix design using artificial neural network” submitted by Mr. Rishi Garg (Roll no. 8002309) in partial fulfillment of requirements for the award of degree of **MASTERS OF ENGINEERING IN CIVIL (Structures) ENGINEERING** of Thapar Institute of Engineering and Technology, (Deemed University), Patiala, is an authentic record of students own work carried out under our supervision and guidance. The matter presented in the thesis has reached the standards fulfilling the requirements of the regulation for the award of said degree.

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CHAPTER 1

INTRODUCTION

1.1 GENERAL

Concrete is the most widely used construction material because of its flowability in most complicated form i.e. its ability to take any shape while wet, and its strength development characteristics when it hardens. Generally concrete is used to build protective structures, which are subjected to several extreme stress conditions. Concrete is the most widely used construction material manufactured at the site. This composite material is obtained by mixing cement, water and aggregates. Its production involves a number of operations according to prevailing site conditions. The ingredients of widely varying characteristics can be used to produce concrete of acceptable quality. The strength, durability and other characteristics of concrete depend upon the properties of its ingredients, the proportions of the mix, the method of compaction and other controls. The popularity of concrete as a construction material is due to the fact that it is made from commonly available ingredients and can be tailored to functional requirements in a particular situation.

Among the various properties of concrete, its compressive strength is considered to be the most important. However, workability of concrete plays an important role in the mix design. Other factors such as W/C ratio, Fineness modulus of aggregate and specific gravity of cement have their own importance in mix design.

1.2 PROBLEM IDENTIFICATION AND OBJECTIVES

The development of normal concrete i.e. mix design is carried out using certain empirical relationships among design parameters, developed from the past experience. A normal concrete mix of required strength can be achieved after carrying out several trials on the mix proportions.

Artificial neural network (ANN) is a network consisting of several nodes, known as neuron. The connection between these neurons carries weights, which defines the relationship between input and output data. ANN is a technique that can be used for the problems, where no solution algorithm is known. The mix design of concrete can be put under same category of problems. Again, development of concrete, which requires large sets of trial, is a very complex problem in itself. The feature of ANN to establish relationship between input and output data can be used to obtain some kind of relationship between various design parameters of normal as well as high performance concrete. Use of Artificial Neural Network for the development of Concrete mix may reduce the requirement of large number of trials .To develop Artificial neural Network model for concrete mix design, sufficient set of mix proportions with corresponding characteristic strength, water content and fineness modulus of aggregate are required for training of the neural network . Since sufficient data for mix design is not available, mix design data corresponding above mentioned characteristics has been generated experimentally for the training of the ANN.

. Further using this data ANN modeling is done for concrete mix design.

Following are the main objectives of the present study ;

- 1) To obtain data of mix design experimentally.
- 2) Training and testing of ANN model for concrete mix design using data generated in (1)

1.3 SCOPE OF THE WORK

The scope of the present work consists of training and testing of ANN for field of concrete mix design. The present work is limited to normal concrete.

1.4 ORGANISATION OF THE THESIS

The Thesis has been divided into seven Chapter 2 deals with the review of literature. Chapter 3 presents the concrete mix design principles, methods and particularly ACI method which has been used in present study for concrete mix design. Chapter 4 presents the Artificial Neural Network modeling with special emphasis on back propagation learning network and is used in present work. Chapter 5 presents the results and discussions and finally in Chapter 6 conclusions of the study is presented.

CHAPTER 2

LITERATURE REVIEW

This chapter presents the work done by various researchers, for concrete mix design using various analytical techniques. Extensive literature is available on experimental studies for mix design, however very few literature is available on concrete mix design using analytical techniques.

Krishna Raju et. al.(1989) presented the results of a comparative study of different methods of designing concrete mixes. Using ordinary Portland cement, sand and crushed granite aggregates, mixes for concrete of grades M15, M30 and M45 were designed in accordance with Road note no 4, the American Concrete Institute and Murdock's methods. Standard tests were carried out to determine the compressive strength of concrete. The results show that Murdock's method used the minimum cement content for concrete in the low and medium strength ranges, and Road note no 4 method gave economical mixes especially in the high strength range.

Ken W. Day presented the Conad Software system for concrete mix design. The concrete producer, with no special computer expertise can use the Conad software system both to rapidly upgrade the practitioner's technological base and to produce a more economical and consistent concrete. This software system can enable concrete practitioners with limited access to computers to make full use of permission to vary mix proportions. The purpose of utilising

this technology is to reduce concrete variability and to produce a quality product.

Popovics et.al.(1996) described that computerised calculations for concrete proportioning is not a new idea. Nevertheless, with new developments both in concrete technology and in computer science. It is possible to further improve the proportioning software. The novelty of the software is that it is not restricted to the relationships recommended by ACI which are limited to the standard 28-day compressive strengths. The software package was presented for which both the ACI 211.1 procedures can be performed and new strength formulas can be simply established for a given group of concretes. These new strength formulas are valid regardless of the nature and type of the cement used, the class and quantity of the admixtures, type of strength, age, air content, or curing procedure.

Ganju(1996) presented a method of design of trial mixes, enabling the direct computation of ingredients using formulae without the use of any charts or tables. Trial mix design examples given by Mindess and Young, Popovics, and Mehta are recalculated using spreadsheet and Microsoft Excel and compared calculated values with other methods based on ACI and British practice. Improvements to the proposed method are possible by including specification constraints, such as tables in spreadsheet. Spreadsheets are the preferred format for calculations as they can be used interactively.

CHAPTER 3

CONCRETE MIX DESIGN

3.1 GENERAL

The present chapter discusses the conventional method of concrete mix design. The concrete mix design is a process of selecting the suitable ingredients of concrete and determining their most optimum proportions which would produce, as economically as possible, concrete that satisfies the job requirements, i.e. the concrete having a certain minimum compressive strength, the desired workability and durability. In addition to these requirements, the cement content in the mix should be as low as possible to achieve maximum economy. The proportioning of the ingredients of concrete is an important part of concrete technology as it ensures the quality and economy.

3.2 PRINCIPLES OF CONCRETE MIX DESIGN

Proportioning of a concrete mix comprises of determining the relative quantities of materials to be used in production of concrete for a given purpose. The process of selecting proportions of these materials is called "Concrete Mix Design" and should not be misunderstood with structural design. Proportioning may be based on certain data obtained by practical experience and investigations of test results of various ingredients or an empirical data. The process of mix design involves the consideration of properties and costs of ingredients. Requirements of

placing and finishing the fresh concrete and properties of hardened concrete such as strength, durability, and volumetric stability etc.

The main objectives of the concrete mix design can thus be stated as production of concrete, which shall be:

- Satisfying the requirements of fresh concrete (Workability).
- Satisfying the properties of hardened concrete (Strength and durability).
- Most economical for the desired specifications and given materials at a given site.
- Performing most optimally in the given structure under given conditions of environment.

The concrete mix design is based on the principles of

- Workability of fresh concrete.
- Desired strength and durability of hardened concrete which in turn is governed by water-cement ratio law
- Conditions at the site, which helps in deciding workability, strength and durability requirements.

3.3 INGREDIENTS OF CONCRETE MIX

The main ingredients are:

- Cement
- Aggregates
- Water

3.3.1 CEMENT

Cement is most important ingredient of any type of concrete. It determines the strength and other properties of both fresh hardened state of concrete. Selection of type of cement depends upon the specific requirements of concrete. Properties considered in selection of the cement are a) compressive strength at various ages, b) Fineness, c) heat of hydration, d) alkali content, e) C_3A content, f) its compatibility with admixture.

3.3.2 AGGREGATES

Aggregate consists of the largest volume of concrete and can be divided into two categories: 1) coarse aggregate, and 2) fine.

3.3.2.1 Coarse Aggregate (CA)

The coarse aggregate is the strongest component of concrete. Selection of Coarse aggregate depends upon the properties such as crushing strength, durability, modulus of elasticity, maximum size, gradation, shape and surface characteristics, flakiness and elongation indices and presence of deleterious particle.

The maximum size of aggregate is governed by two factors. First, bigger size particles cause concentration of stresses around particles due to differences between elastic moduli of paste and the aggregate, leading to failure of bond between mortar and aggregate. Second, the crushing process, generally, takes place along potential

zone of weakness within the parent rock and thus removes them. So, smaller particles of coarse aggregate fraction are likely to be stronger than larger ones

3.3.2.2 Fine aggregates or Sand

Fine aggregates with rounded particle shape and smooth texture have been found to require less mixing water. Sand having fineness modulus (FM) below 2.5 introduces stickiness into the concrete, making it difficult to compact. Sand with FM of about 3.0 gives best workability and compressive strength. Sand particle should pack to give minimum void ratio, as higher void ratio leads to requirement of more water. Finally, sand should be free from deleterious materials like clay, silt content and chloride contamination etc.

3.3.3 WATER

Water conforming to requirement of IS: 456 has been found to be suitable for producing concrete mix. In concrete mix, the water requirement is reduced to the value required for hydration of cement, as excess water leads to formation of void in hardened cement paste phase of concrete. In general, water fit for drinking is fit for production of concrete.

The various impurities in water such as chloride, sulphate, carbonate, salt, etc. affects the setting/ hardening characteristics of concrete and causes reduction of both initial and final strength. The salt content of

water should also be limited, from point of view of its affect on initial hydration rate of cement, as this may lead to rapid loss of workability on account of higher amount of heat generated.

3.4 DESIGN METHODS

The methods of design followed all over the world are essentially similar, except that each country has its own set of tables and graphs for the calculation of density, water required for workability and strength, etc., based on the type of aggregates and cement available locally. Only minor variations exist in different mix design methods in the process of selecting the mix proportions.

Some of the common mix design methods are :-

- Mix Design According to Indian Standard Recommended guidelines
- ACI Mix Design method
- USBR Mix Design Method
- British Mix Design Method
- Trial And Error Method

In the present work ACI design method has been used for developing mix design data. The ACI design method has been discussed briefly in the following paragraphs.

3.5 ACI method of mix proportioning

The ACI method is based on the fact that for a given maximum size of well-shaped aggregate, the water-content (kg/m^3) determines the workability of mix, i.e. it is largely independent of mix proportions. The

method further assumes that the optimum ratio of the bulk volume of coarse aggregate to the total volume of concrete depends only on the maximum size of aggregate and on the grading of fine aggregate. The optimum volume of coarse aggregate when used with fine aggregate of different fineness moduli is given in Table 3.3. Having determined the maximum size and type of available aggregate, the water content for a specified workability is selected from the Table 3.2 and bulk volume of coarse aggregate from the Table 3.3. The water cement ratio is determined as in other methods to satisfy both strength and durability requirements. The air content in concrete is taken into account for calculating the volume of fine aggregate. The step-in-step procedure adopted for the selection of mix proportions is as follows.

- (i) The water-cement ratio is selected from Table 3.1 for the average strength.
- (ii) The maximum size of the coarse aggregate to be used is determined by sieve analysis. The degree of workability is decided depending upon the placing conditions, etc.
- (iii) The water content is selected from Table 3.2 for the desired workability and maximum size of aggregate.
- (iv) The cement content is calculated from the water content and water-cement ratio required for strength and durability.
- (v) The coarse aggregate content is estimated from Table 3.3 for maximum size of aggregate and fineness modulus of sand.

- (vi) The content of fine aggregate is determined by subtracting the sum of absolute volumes of the coarse aggregate, cement, water and entrained air from unit volume of concrete. Trial batches are tested and final proportions are obtained by adjustments.

Table 3.1 Relationship between water-cement ratio and average compressive strength (ACI Manual of Concrete Practice, Part I, 1979).

<i>Compressive Strength at 28-days, Mpa</i>	<i>Water-cement Ratio by Mass</i>	
	<i>Non-air-entrained concrete</i>	<i>Air-entrained concrete</i>
45	0.38	-
40	0.43	-
35	0.48	0.40
30	0.55	0.46
25	0.62	0.53
20	0.70	0.61
15	0.80	0.71

Table 3.2 Approximate water requirements for different slumps and maximum size coarse aggregate (ACI Manual of Concrete Practice, Part I, 1979).

<i>Slump, mm</i>	<i>Mixing water (kg/m³ of concrete) for maximum sizes of aggregate, mm</i>							
	10	12.5	20	25	40	50	70	150
<i>Non-air entrained concrete</i>								
30-50	205	200	185	180	160	155	145	125
80-100	225	215	200	195	175	170	160	140
150-180	240	230	210	205	185	180	170	-
Approx. percentage of entrained air	3.0	2.5	2.0	1.5	1.0	0.5	0.3	0.2
<i>Air-entrained concrete</i>								
30-50	180	175	165	160	145	140	135	120
80-100	200	190	180	175	160	155	150	135
150-180	215	205	190	185	170	165	160	-
Recommended average total air content, per cent	8.0	7.0	6.0	5.0	4.5	4.0	3.5	3.0

Table 3.3 Bulk volume of coarse aggregate (ACI Manual of Concrete Practice, Part I, 1979)

<i>Maximum size of aggregate, mm</i>	<i>Bulk volume of dry-rodded coarse aggregate per unit volume of concrete, for fineness modulus of fine aggregate</i>			
	<i>2.40</i>	<i>2.60</i>	<i>2.80</i>	<i>3.00</i>
10	0.50	0.48	0.46	0.44
12.5	0.59	0.57	0.55	0.53
20	0.66	0.64	0.62	0.60
25	0.71	0.69	0.67	0.65
40	0.76	0.74	0.72	0.70
50	0.78	0.76	0.74	0.72
70	0.81	0.79	0.77	0.75
150	0.87	0.85	0.83	0.81

CHAPTER 4

ARTIFICIAL NEURAL NETWORKS

4.1 GENERAL

Artificial Neural Network (ANN) is a *network of artificial neurons*, an information processing units, is inspired by the way in which human brain performs a particular task or function of interest. A neural network is a computational method inspired by studies of the brain and nervous systems in biological organism. Artificial Neural Network represents highly ideological mathematical models of our present understanding of such complex systems. Artificial Neural Network models have the ability to learn and generalise the problems even when input data contain error or incomplete.

4.2 INTRODUCTION TO ARTIFICIAL NEURAL NETWORK

4.2.1 The Biological Neuron

The human brain is estimated to contain about 10^{11} interconnected neurons. The structure of a biological neuron consists of a central cell body, an axon and a multilayer of dendrites. Fig 4.1a shows the structure of a biological neuron. The output from the cell is transmitted through the axon to synapses where the outputs are increased or decreased depending upon the synaptic weights before passing it to the

next neuron. The dendrites are the points where the input signals are received. The inputs are got from the sensory organs or from other neurons. The signal as they pass through the network creates different levels of activations in the neurons. The identification or recognition depends on the activation levels of the neurons.

4.2.2 The Artificial Neuron

An Artificial Neuron (refer Fig.4.1b) models the behaviour of the biological neuron. Each Artificial neuron receives a set of inputs. Each input is multiplied by weight analogous to synaptic strength. The sum of all weighted inputs determines the degree of firing called the activation level. Notationally if $I_1, \dots, I_i, \dots, I_n$, are the input values and $w_1, \dots, w_{ij}, \dots, w_{nj}$ are synaptic weight values, net_j is the summation (over all the incoming neurons) of the product of the incoming neuron's activation and synaptic weight of connection at the typical j^{th} neuron expressed as $\sum I_i \cdot w_{ij}$. A threshold value ϕ_i is incorporated into the output. Thus we have the resultant.

$$net_j = \sum_{i=1}^n I_i w_{ij} + \phi_i$$

where n is the number of incoming neurons.

Output from j^{th} neuron can be expressed as

$$O_j = g(net_j)$$

g is activation function.

There are several conventionally used choices for the activation function, which is also called as threshold function, transfer function or squashing function. The most commonly used activation functions are Linear Function, Nonlinear Function, Step Function, Sigmoid Function and Hyperbolic Tangent Function. Out of the above mentioned activation functions, Sigmoid Function is very popular. Output of j^{th} neuron using sigmoid function can be written as: -

$$O_j = \frac{1}{1 + \exp(-\text{net}_j)}$$

Sigmoid Function is most commonly used activation function as it is continuous function and it has a very simple derivative that is useful for development of learning algorithms, and also it represents the processing of biological neuron. Fig.4.2 shows the sigmoid function. It can be seen from Fig.4.2 that the output of neuron is low when input is low, and output is high when the input is also sufficiently high.

4.2.3 The Artificial Neural Network (ANN)

The ANN is a crude imitation of the biological neural network. It consists of several layers of artificial neurons. The first layer is called input layer and the last layer is called output layer. The layers in between the input and output layers are called hidden layer. The layers are connected by weighted pathways.

4.2.4 Types of ANN

Artificial Neural Network models are specified by net topology, node characteristics and training or learning rules. These rules specify an initial set of weights and indicate how weights should be adopted during use of improve performance. A crude classification can be done on the grounds of type input patterns (i.e. either binary inputs or continuous valued inputs). This can further be refined on the basis of types of learning (i.e. supervised on unsupervised). A complete classification of different neural networks is presented in Fig.4.3.

4.2.5 Learning of the ANN

The main phase in neural network is learning. The programming for adjusting the weights is called training and the training can be done either by given weights computed from a set of training data or by automatically adjusting the weights according to some criterion. Learning performance is improved by iteratively updating the weight in the network. The learning of ANN generally classified as:

- (a) **Supervised Learning:** ANN is trained as a set of input-output patterns. The weights are adjusted to minimise the error between network output and actual output.
- (b) **Unsupervised Learning :** In unsupervised training the network adjusts its weights in response to input patterns without the benefit of target answers. In this type of learning network classifies the input patterns into similarity categories.

- (c) Reinforcement Learning : It is a variant of supervised learning in which network attempts to learn the input-output patterns through trial and error with a view to minimise a performance index called the reinforcement signal. The target values are not provided for learning instead of error signal of the output are given to the ANN. This process is analogous to reward or punishment.

4.3 BACK-PROPAGATION LEARNING NETWORK

4.3.1 Introduction

In ANN theory there are many paradigms developed to update synaptic weights. Out of them back-propagation is the most widely used of the neural network paradigms and has been applied successfully in application studies in a broad range of areas. Back-propagation can attack any problem that requires pattern mapping. Given an input pattern, the network produces an associated output pattern. In the present study Back-propagation learning algorithm has been used.

Supervised learning is used in training of Back-propagation learning network. Back-propagation employs three or more layers of processing units. It includes an input layer, hidden layer (atleast one) and an output layer. Input units do not process

information. They simply distribute information to other units. Generally Back-propagation learning algorithm applies two basic steps, (i) feed forward calculation, (ii) error back propagation calculation.

Fig. 4.4 shows the typical multi-layer feed forward Back-Propagation network. A weight is associated with each connection from input to hidden units and from hidden units to output units. Each unit in the input layer is connected to every unit of hidden layer, likewise each unit in the hidden layer is connected to each unit of next hidden layer (if more than one hidden layer is present) or to each unit of output layer.

Bias unit (optional) has been employed to every layer but to output layer. This can be achieved simply by adding a constant input with an appropriate weight. This unit has a constant activation of 1. Each bias unit is connected to all units in the next higher layer, and its weights to them are adjusted like the other weights. The bias units provide a constant term in the weighted sum of the units in the next layer. This some times results in improvement on the convergence properties of the network.

4.3.2 Feed Forward Computation

The input vector representing the pattern to be recognised is incident on the input layer and distributed to subsequent hidden layers and finally to output layer via weighted connections. Each

neuron in the network operates by taking sum of its weighted input and passing the result through a nonlinear activation function.

The net input to the hidden unit j (net_{pj}) is described as :

$$net_{pj} = \sum_{i=1}^n w_{ji} I_i + \psi_j \quad \dots(4.1)$$

w_{ji} - weight from neuron i (source) to node j (destination)

I_i - input value of neuron i

ψ_j - weight from bias unit to neuron j

The output of a hidden unit (H_j) as a function of its net input is given by

$$H_j = g(net_{pj})$$

$$= \frac{1}{1 + \exp(-net_{pj})} \quad \dots(4.2)$$

g = sigmoid function

Net input (net_{pk}) to the each output layer unit and the output (O_{pk}) from each output unit are calculated in analogous manner as described by following equation:

$$net_{pk} = \sum_{k=1}^m w_{kj} H_{pj} + \psi_k \quad \dots(4.3)$$

$$O_{pk} = \frac{1}{1 + \exp(-net_{pk})} \quad \dots(4.4)$$

where w_{kj} = weights from node j to k

Ψ_k = weight from bias unit to node k

The set of calculations that results in obtaining the output state of the network is carried out the same way for training as well testing phase. The test mode just involves presenting input set to input units and calculating the resulting output state in a single forward pass.

4.3.3 Error Back-propagation

Very first thing required to be recognised in the training is the need for a measure of classes of network to an established desired value. This measure is network error. Since network deals with supervised training, desired value is known for the given training set.

For Back-propagation learning algorithm (Rumelhart et al. 1986) an error measure known as the mean square error is used. The mean square error is defined as:

$$E_p = \frac{1}{2} \sum_{j=1}^n (T_{pj} - O_{pj})^2 \quad \dots(4.5)$$

where T_{pj} = target (desired) value of j^{th} output unit for pattern p

O_{pj} = actual output obtained from j^{th} output unit for pattern p .

In training phase of Back-propagation learning algorithm, the total error of the network is minimised by adjusting the weights. Gradient descent method is used for this. Each weight may be thought of as a dimension in N -dimensional 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 the 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

$$\Delta_p w_{ji} \propto \frac{-\partial E_p}{\partial w_{ji}} \quad \dots(4.6)$$

Where $\Delta_p w_{ji}$ designates the change in the weight connecting a source neuron i in the layer $L-1$ and a destination neuron, j in layer L (refer Fig. 4.5). Applying chain rule to evaluate $\frac{\partial E_p}{\partial w_{ji}}$

$$\frac{\partial E_p}{\partial w_{ji}} = \frac{\partial E_p}{\partial \text{net}_{pj}} * \frac{\partial \text{net}_{pj}}{\partial w_{ji}}$$

$$\text{net}_{pj} = \sum w_{ji} O_{pi}$$

where O_{pi} is output of all neurons in the $L-1$ layer.

$$\frac{\partial \text{net}_{pj}}{\partial w_{ji}} = \frac{\partial}{\partial w_{ji}} (\sum w_{ji} O_{pi})$$

$$= O_{pi}$$

Hence

$$\frac{\partial E_p}{\partial w_{ji}} = O_{pi} \frac{\partial E_p}{\partial \text{net}_{pj}} \quad \dots(4.7)$$

Defining error signal δ_{pj} as

$$\delta_{pj} = -\frac{\partial E_p}{\partial \text{net}_{pj}} \quad \dots(4.8)$$

Combining 4.7 and 4.8

$$-\frac{\partial E_p}{\partial w_{ji}} = O_{pi} \delta_{pj} \quad \dots(4.9)$$

Putting this value in equation 4.6

$$\Delta_p w_{ji} = \eta O_{pi} \delta_{pj} \quad \dots(4.10)$$

where η is learning rate parameter. The learning rate parameter determines the amounts of weight change will be used for the weight correction.

In order to achieve a useable difference equation that can be used for mathematically δ_{pj} can be found by applying chain rule again, as follow: -

$$\delta_{pj} = -\frac{\partial E_p}{\partial \text{net}_{pj}} = \frac{\partial E_p}{\partial O_{pj}} * \frac{\partial O_{pj}}{\partial \text{net}_{pj}} \quad (4.11)$$

since $O_{pj} = g(\text{net}_{pj})$

$$\frac{\partial O_{pj}}{\partial \text{net}_{pj}} = g'(\text{net}_{pj})$$

(4.12)

To evaluate $\frac{\partial O_{pj}}{\partial \text{net}_{pj}}$, two cases are considered individually

- (i) the destination unit j is an output layer unit
- (ii) the destination unit j is a hidden layer unit

For a destination unit j in the output layer E_p can be directly accessed as a function of O_{pj}

$$\frac{\partial E_p}{\partial O_{pj}} = \frac{\partial \left(\frac{1}{2} \sum (T_{pj} - O_{pj})^2 \right)}{\partial O_{pj}}$$

$$\Rightarrow \frac{\partial E_p}{\partial O_{pj}} = -(T_{pj} - O_{pj})$$

Putting this in 4.11

$$\delta_{pj} = (T_{pj} - O_{pj}) g'(\text{net}_{pj}) \quad \dots(4.13)$$

For a destination unit j in the hidden layer, error function can not be differentiated. So applying chain rule again.

$$\frac{\partial E_p}{\partial O_{pj}} = \sum_k \frac{\partial E_p}{\partial \text{net}_{pk}} \frac{\partial \text{net}_{pk}}{\partial O_{pj}} \quad \dots(4.14)$$

In equation 4.14 the sum (Σ) k is over all units in the $L+1$ layer (Ref. Fig.4.5). Putting the value of net_{pk}

$$\frac{\partial \text{net}_{pk}}{\partial O_{pj}} = \frac{\partial \left(\sum w_{kj} O_{pj} \right)}{\partial O_{pj}}$$

$$= w_{kj}$$

putting this in equation 4.14

$$\frac{\partial E_p}{\partial O_{pj}} = \sum_k \frac{\partial E_p}{\partial \text{net}_{pk}} \cdot w_{kj}$$

$$\frac{\partial E_p}{\partial O_{pj}} = \sum_k \delta_{pk} \cdot w_{kj} \quad \dots(4.15)$$

Now combining equation 4.11, 4.12 and 4.15

$$\delta_{pj} = g'(\text{net}_p) \sum_k \delta_{pk} w_{kj} \quad \dots(4.16)$$

Equation 4.10 provides the difference equation in terms of δ_{pi} . This is valid for both hidden and output layer weights. Equation 4.13 and 4.16 specify δ_{pj} for the output layer and hidden layer weights, respectively. To obtain difference equation suitable for use on digital computer, $f'(\text{net}_{pj})$ is evaluated as follow: -

$$O_{pj} = g(\text{net}_{pj}) = \frac{1}{1 + \exp(-\text{net}_{pj})}$$

$$\frac{\partial O_{pj}}{\partial \text{net}} = g'(\text{net}_{pj}) \left[\frac{1}{1 + \exp(-\text{net}_{pj})} \right] \left[1 - \frac{1}{1 + \exp(-\text{net}_{pj})} \right]$$

$$g'(\text{net}_{pj}) = O_{pj} (1 - O_{pj})$$

To summarise, the difference equation required for Back-propagation training is:

$$\Delta w_{ji} = \eta \delta_{pj} O_{pi} \quad \dots(4.17)$$

where η refers to learning rate parameter; δ_{pj} refers to the error signal at neuron j in the layer $L-1$ (Ref. Fig.4.5) and with the error signal, δ_{pj} , given by

$$\delta_{pj} = (T_{pj} - O_{pj}) O_{pj} (1 - O_{pj}) \text{ for output neurons}$$

$$\delta_{pj} = O_{pj} (1 - O_{pj}) \sum_k \delta_{pk} w_{kj} \text{ for hidden neurons}$$

where, O_{pj} refers to layer L ; O_{pi} refers to layer $L-1$ and δ_{pk} refer to layer $L+1$.

4.3.3.1 Selection of Learning Rate Parameter

The learning rate determines what amount of calculated error sensitivity to weight change will be used for weight correction. Its value varies between 0.0 and 1.0. The best value of learning rate depends on the characteristics of the error surface i.e. a plot of E versus w_{ji} . If surface changes rapidly, the gradient calculated on local information will give a poor indication of the true 'right path'. In this case, a smaller rate is desirable. On the other hand, if the surface is relatively smooth, a large learning rate will speed convergence. A general rule might be to use such a value of learning rate parameter that it may not cause the system to oscillate and thereby slow or prevent the network convergence.

4.3.3.2 Momentum Constant

In practice a momentum term is frequently added to equation 4.17 as an aid to more rapid convergence in certain problem domain. The momentum takes into account the effect of past weight change. The momentum constant, β , determines the emphasis to place on this term. Momentum has the effect of smoothing the error surface in weight space by filtering out adjusted in the presence of momentum by:

$$\Delta w_{ji}(n+1) = \eta (\delta_{pj} O_{pi}) + \beta \Delta w_{ji} n \quad \dots(4.18)$$

4.3.3.3 Pattern Presentation and Weight Adjustment

There are two ways of pattern presentation and weight adjustment of the network:

- (i) One way involves propagating the error back and adjusting weight after each training pattern is presented. This is called *single pattern training*.
- (ii) Another way is *Epoch training*. One full presentation of all patterns in the training set is termed an epoch. Error is back propagated based on total network error δ . This is used in the present study for training neural network.

4.3.3.4 Selection of Initial Weights

Initial weights are taken as 'small' random number over some range. It is found a range between -0.3 to $+0.3$ speeds training (Lee 1989). When the weights associated with a neuron grow sufficiently large, the neuron operates in the region with in which the activation function approaches limits (in the case of sigmoid function 1 or 0). With this derivative of activation function will be extremely small. Referring to equations 4.10, 4.13, and 4.16 it is evident that when derivation of activation function approaches zero the weight adjustment made through back-propagation also approaches zero, which results in ineffective training.

4.3.3.5 Problem of Local Minima

Sometimes during the training of the network, it could be trapped in local minima rather than proceeding towards global minima for the error function. This can be avoided either by changing the learning parameter or by changing the number of hidden units.

4.3.3.6 Normalisation of the Training Data Set

Normalisation of the training data set is required before presenting it to the network for its learning, so that it satisfies the activation function range. Normalisation is also necessary if there is a wide difference between the range of features values. Normalisation process enhances the learning speed of the network and it avoids the possibility of early network saturation. In the present study normalisation of each variable present in the training data set is done separately, by dividing it with the maximum value for the each variable.

CHAPTER-5

RESULTS & DISCUSSIONS

5.1 EXPERIMENTAL PROGRAM

In the present study concrete mix design has been done by ACI design method. Locally available sands of fineness modulus 2.4 and 2.6 are used. Coarse aggregates of 10mm and 20mm are used in the ratio of 50:50 and 67:33 of total volume. Ambuja Cement of 53 grade is used . The detailed calculations are given in Appendix A. For each mix proportion nine cubes of 150 mm size were casted in the laboratory and tested in Automatic Compression Testing Machine (ACTM) for 7,14and 28 days. Concrete mix proportioning and its compressive strength are given in Table 5.1 and are discussed in the following paragraphs.

TABLE 5.1 CONCRETE MIX PROPORTIONING AND ITS COMPRESSIVE STRENGTH

MIX RATIO	W/C RATIO	WATER Kg	FINENESS MODULUS	COARSE AGGREGATE RATIO (10mm,20 mm)	7 DAYS (N/mm²)	14 DAYS (N/mm²)	28 DAYS (N/mm²)

1:49:2.28	0.40	185	2.4	1:1	22.22	28.08	32.17
1:1.56:2.21	0.40	185	2.6	1:1	27.68	32.71	38.4
1:1.4:2.22	0.40	190	2.4	1:1	24.66	26.68	29.88
1:1.47:2.15	0.40	190	2.6	1:1	27.35	28.68	35.88
1:1.49:2.23	0.40	185	2.4	2:1	24.75	27.66	29.77
1:1.56:2.21	0.40	185	2.6	2:1	27.42	34.95	39.37
1:1.4:2.22	0.40	190	2.4	2:1	23.15	29.51	31.48
1:1.47:2.15	0.40	190	2.6	2:1	23.55	32.40	34.86
1:1.62:2.4	0.42	185	2.4	1:1	18.04	26.17	24.64
1:1.68:2.32	0.42	185	2.6	1:1	19.86	28.91	27.68
1:1.51:2.33	0.42	190	2.4	1:1	24.33	30.6	30.66
1:1.69:2.26	0.42	190	2.6	1:1	26.15	32.62	34.2
1:1.62:2.4	0.42	185	2.4	2:1	19.90	27.22	27.82
1:1.68:2.32	0.42	185	2.6	2:1	25.73	30.51	32.55
1:1.51:2.33	0.42	190	2.4	2:1	26.02	35.35	37.4
1:1.69:2.26	0.42	190	2.6	2:1	27.82	37.6	39.22
1:1.74:2.51	0.44	185	2.4	1:1	17.55	21.95	24.77
1:1.82:2.43	0.44	185	2.6	1:1	20.64	22.46	26.95
1:1.63:2.45	0.44	190	2.4	1:1	23.77	27.11	34.68
1:1.72:2.37	0.44	190	2.6	1:1	27.35	31.71	34.68
1:1.74:2.51	0.44	185	2.4	2:1	20.0	21.53	25.97
1:1.82:2.43	0.44	185	2.6	2:1	22.8	28.42	34.8
1:1.63:2.45	0.44	190	2.4	2:1	24.6	29.88	31.35
1:1.72:2.37	0.44	190	2.6	2:1	26.0	36.48	38.86

1:1.87:2.65	0.46	185	2.4	1:1	18.97	22.02	23.84
1:1.94:2.45	0.46	185	2.6	1:1	19.22	25.55	28.55
1:1.76:2.56	0.46	190	2.4	1:1	22.33	25.82	25.97
1:1.84:2.48	0.46	190	2.6	1:1	23.48	26.42	28.97
1:1.87:2.65	0.46	185	2.4	2:1	18.62	24.24	25.33
1:1.94:2.45	0.46	185	2.6	2:1	19.64	26.42	28.97
1:1.76:2.56	0.46	190	2.4	2:1	19.98	26.75	29.32
1:1.84:2.48	0.46	190	2.6	2:1	26.2	29.13	34.6
1:1.99:2.74	0.48	185	2.4	1:1	14.44	19.06	23.06
1:2.07:2.65	0.48	185	2.6	1:1	20.8	24.75	31.95
1:1.88:2.67	0.48	190	2.4	1:1	16.11	21.77	26.84
1:1.96:2.58	0.48	190	2.6	1:1	20.4	22.73	32.55
1:1.99:2.74	0.48	185	2.4	2:1	14.08	17.91	19.53
1:2.07:2.65	0.48	185	2.6	2:1	26.0	29.77	27.64
1:1.88:2.67	0.48	190	2.4	2:1	15.71	18.57	25.57
1:1.96:2.58	0.48	190	2.6	2:1	17.66	23.88	28.57
1:2.11:2.85	0.50	185	2.4	1:1	13.91	17.93	21.82
1:2.2:2.76	0.50	185	2.6	1:1	21.60	21.82	24.88
1:2.0:2.78	0.50	190	2.4	1:1	16.11	21.77	26.84
1:2.08:2.69	0.50	190	2.6	1:1	20.4	22.73	32.55
1:2.11:2.85	0.50	185	2.4	2:1	14.08	17.91	19.53
1:2.2:2.76	0.50	185	2.6	2:1	26.0	29.77	27.64
1:2.0:2.78	0.50	190	2.4	2:1	15.71	18.57	25.57
1:2.08:2.69	0.50	190	2.6	2:1	17.66	23.88	28.57
1:2.24:2.97	0.52	185	2.4	1:1	15.08	20.26	24.84
1:2.32:2.87	0.52	185	2.6	1:1	17.13	23.0	28.0
1:2.12:2.89	0.52	190	2.4	1:1	17.82	23.2	25.0
1:2.21:2.80	0.52	190	2.6	1:1	24.31	27.57	28.9
1:2.24:2.97	0.52	185	2.4	2:1	13.84	17.8	25.6
1:2.32:2.87	0.52	185	2.6	2:1	15.66	20.4	29.3
1:2.12:2.89	0.52	190	2.4	2:1	16.91	20.13	25.97
1:2.21:2.80	0.52	190	2.6	2:1	19.57	29.46	29.77

5.2 RESULTS and DISCUSSIONS

5.2 Effect of Fineness Modulus

Fineness Modulus has less effect on the compressive strength. For the Fineness Modulus of 2.4, the increase of compressive strength is not so high as compared to the Fineness Modulus of 2.6 for example when w/c ratio is 0.4, water content 185 kg/m³, 10mm and 20mm coarse aggregate ratio (50:50), at FM 2.4, the compressive strength at 7, 14 & 28 days is 22.22 N/mm², 28.08 & 31.17 N/mm², respectively and the corresponding values at FM 2.6 are 27.68 N/mm², 32.71 N/mm² & 38.4 N/mm² (refer Table 5.1) The rate of increase of strength is 35 % for FM 2.4 and 38% FM 2.6.

Out of the two FM used, the strength of concrete with FM 2.4 is more affected by the change in w/c ratio. For FM 2.6 the 28 days compressive strength (185 kg/m³ water content and 50:50 ratio of 20 & 10 mm Coarse aggregate used) varies from 28.4 N/mm² to 28 N/mm² when w/c ratio changed from 0.4 to 0.52. The corresponding values at FM 2.4 are 32.17 N/mm² & 24.84 N/mm² This can be seen by comparing figures 5.1 and 5.3. From fig 5.5 to 5.8 it is observed that for same water cement ratio, compressive strength at FM 2.6 is higher than at FM 2.4 and it also increases with increase in CA ratio from (67:33) to (50:50). It is also observed that for 185 kg of water content 28 days compressive strength is almost same for FM 2.4 and FM 2.6 (Fig. 5.15 to 5.17). Similar results were obtained for 190 kg of water.

5.3 Effect of the size of coarse aggregate

The strength of concrete by using 20 mm & 10 mm size aggregate in the ratio (67:33) is higher than the strength by using the ratio of 50:50. The effect is more pronounced at lower w/c ratio. From fig 5.1 it is clear that for coarse aggregate size ratio (67:33) the 7, 14, 28 days strength is more than the coarse aggregate ratio (50:50). Pattern remains the same for FM 2.6 & FM 2.4 (ref. fig. 5.3 & 5.4). Figures 5.9 and 5.10 shows that for FM 2.6 , compressive strength significantly increase with increase in percentage of coarse aggregate ratio whereas for fineness modulus 2.4 compressive strength increases upto 14 days and then it starts decreasing with increase in percentage of coarse aggregate.

5.4 Effect of water cement ratio

Variations of compressive strength by changing the water cement ratio have been plotted in figures 5.15 to 5.18. It has been observed that as the water cement ratio increases, compressive strength decreases irrespective of the amount of cement, fineness modulus or the ratio of aggregate used. From figs. 5.15, 16, 17 & 18 it is observe that compressive strength at lower w/c ratio is higher than at higher w/c ratio.

5.5 ANN MODELLING OF CONCRETE MIX DESIGN

ANN can map the relationship between the input parameters and the corresponding output parameters. The ability of the neural network approach is

to train a given data set, and on that basis, to predict missing data and also to achieve possible normalisation, makes it an attractive proposition for knowledge acquisition for problems where there is no acceptable theory. In the present study Back Propagation Neural Network was used for finding out the ratio of fine aggregate and coarse aggregate. All the input and output data have been normalised by maximum value (which is termed as normalising factor) for each parameter so that the values remain between 0 to +1. The output of the network is obtained in the form of normalised output which is then converted to actual values by multiplying each value by corresponding normalising factor as used for preparing the training set. The initial weights have been set as random number between the range of -0.3 to $+0.3$

5.5.1 SELECTION OF LEARNING RATE PARAMETER & MOMENTUM CONSTANT

The learning rate parameter and momentum coefficient were kept constant throughout the training of the network. The learning rate parameter and momentum constant are kept 0.15 and 0.75 respectively

5.5.2 ARCHITECTURE OF NETWORK

Architecture of the network has been selected by trial and error to minimise the error and to obtain speedy convergence. The network used for the training of the data consists of two hidden layers with an input

and output layer. An input layer has five neurons representing input parameters which are i) 28 days compressive strength ii) Fineness Modulus iii) Coarse Aggregate ratio iv) Water content and v) Water cement ratio. Output layer has two neurons which represent i) Fine aggregate mix proportion ii) Coarse aggregate mix proportion. Each hidden layer consists of thirty neurons. Non linear sigmoid function has been used as activation function.

5.5.3 SELECTION OF TRAINING DATA SET

Selection of training data set for the training of the network is the most important step. In preparing the training data set different conditions have to be considered which include the size of the network, learning rate parameter and momentum coefficient. Increasing the number of pattern increases the potential level of accuracy that can be achieved by the network. A large number of training patterns however can sometimes overwhelm training algorithm. Consequently, there is no guarantee adding more patterns leads to improved solutions. All values of water content, fineness modulus, coarse aggregate ratio and 28 days compressive strength corresponding to water cement ratio 0.42, 0.44, 0.46, 0.48 and 0.50 have been taken for the training of the network whereas all the values of water content, fineness modulus and 28 days compressive strength corresponding to water cement ratio 0.40 and 0.52

have been taken for prediction. The mean square error between target output and network output has been reduced to 0.0005.

5.5.4 TESTING OF THE NETWORK

The variations of water content, fineness modulus, coarse aggregate ratio and 28 days compressive strength for each water cement ratio have been trained as data set. The network output values of fine aggregate mix proportion and coarse aggregate mix for water cement ratio of 0.40 and 0.52 have been considered for testing of the network. The network output values have been plotted in figures 5.19 to 5.22 in the form of bar chart and their corresponding experimental values are also being plotted. These results confirm that neural network has been trained properly as all the output given by the network are within 2% error.

5.5.5 COMPARISON OF PREDICTED AND EXPERIMENTAL VALUES

The predicted values of mix proportions for water cement ratio 0.42 and 0.50 (as these data were not included in the training data set) for all data set have been plotted in figures 5.23 to 5.26. Their corresponding experimental value is also being plotted. The predicted values of fine aggregate and coarse aggregate have been found in close agreement with the experimental values. The maximum error obtained in the predicted values of mix proportion is 5%. Training has been done by taking w/c ratio, water content, fineness modulus, ratio of coarse aggregate and 28

days compressive strength of concrete as input and proportioning of concrete ingredients at output. These results are plotted in the graphs from 5.19 to 5.26 and discussed below :

In figure 5.19 and 5.20 experimental results of fine aggregate with fineness modulus 0.4 and 0.52 were compared with ANN results and it is found that results were almost same. From figures 5.21 and 5.22 it is observed that for coarse aggregates also experimental and ANN results match with each other.

In figure 5.23 experimental and ANN results match with each other except for 10 number data set, this may be because of faulty experimental observation or poor workmanship etc. In figure 5.24 experimental and ANN results match with each other.

In figure 5.25 it is observed that prediction of the coarse aggregate is exact and the experimental and ANN results are almost identical. From figure 5.26 it is observed that prediction of coarse aggregate at fineness modulus 0.5 is 98 percent accurate and thus we can easily predict the coarse as well as fine aggregate.

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APPENDIX A

W/C ratio	= 0.4
Water	= 190 Kg/m ³
F.M of sand	= 2.4
Cement content	= 190/0.4 = 475 Kg/m ³
Bulk weight of coarse aggregate	= 0.66
Mass of coarse aggregate	= 0.66 * 1600 = 1056 Kg/m ³
Volume of cement	= 475/3.15*1000 = 0.158 m ³
Volume of water	= 190/1000 = 0.19 m ³
Volume of coarse aggregate	= 1056/2.64*1000 = 0.4 m ³
Total volume	= (0.158 + 0.19 + 0.4)= 0.74 m ³
Volume of fine aggregate required	= 1.00 – 0.74 = 0.26 m ³
Mass of fine aggregate	= 0.26 x 2.64 x 1000 = 665 Kg/m ³
Proportions	= 1:1.4 : 2.223

CONCLUSIONS

APPENDIX A

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FIGURES

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