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SEMINAR REPORT ON

ANALYSIS OF DURABILITY OF HIGH PERFORMANCE CONCRETE USING ARTIFICIAL NEURAL NETWORKS

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This is to certify that the seminar report titled as ‘ANALYSIS OF DURABILITY OF HIGH PERFORMANCE CONCRETE USING ARTIFICIAL NEURAL NETWORKS’ has done by SANGEETH AP with Reg no : 20010722 of 3rd year student of CIVIL ENGINEERING under the DIRECTORATE OF TECHNICAL EDUCATION, Government of kerala during the accademic year 2022-2023 under the guidance at Govt. polytechnic college Westhill.

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I.ABSTRACT

This study aims to explore the capability of artificial neural networks (ANN'S) in predicting the durability of high performance concrete, which is depentand on multiple parameters. To achieve this ,an ANN model is developed , which is expressed in terms of chloride ions permeability. The case study also includes verification of the model by carrying out regression equations and comparing it with the trained neural networks. The results indicate that the developed model is reliable and accurate. This study is to highlight the application of ANNs in forecasting complex experimental results in various fields of Civil Engineering

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CHAPTER 1

INTRODUCTION

The essence of high performance concrete (HPC) emphasizes three main characteristics namely active mineral addictive like fly ash, silica fume and super plasticizer apart from three basic ingredients that is ; cement ,aggregate and water in conventional concrete. They have been incorporated to make highly workable high strength and durable concrete. HPC design seems more complicated due to more number of ingredients. Maintaining a low water--binder ratio with adequate workability is more complicated. Traditionally expert civil engineers can produce HPC mix proportions by using empirical results from previous research plus their experience to achieve required performance. But the number of components in the making of concrete has gone up to 10. This makes the empirical methods insufficient as the number of properties to be investigated has gone up as well. Durability is a fundamental property of concrete based on its permeability and it can be explicated by electrical conductivity. If the 6 hour period charge passed of concrete is lower than 1000 coulombs, the concrete is said to possess very highly impermeable and good durability. The permeability of concrete depends on its pore structure, while the electrical conductivity of concrete is determined by both pore structure and chemistry of pore solution. Many research have found out that the microstructure of concrete can be improved and charged passed can be decreased by adding supplementary cementing materials such as fly ash , silica fume and blast furnace slag. Since HPC is a highly heterogeneous material, the modelling of its behaviour is difficult task

CHAPTER 2

DURABILITY OF HIGH PERFOPRMANCE CONCRETE

2.1 HIGH PERFORMANCE CONCRETE

The American Concrete Institute (ACI) defines high-performance concrete as concrete meeting special combinations of performance and uniformity requirements that cannot always be achieved routinely when using conventional constituents and normal mixing, placing and curing practices A high-performance concrete is something which demands much higher performance from concrete as compared to performance expected from routine concrete. The HPC is designed for either strength criterion or durability criterion parameters or both. The strength parameters include compressive strength, modulus of elasticity, shrinkage and creep whereas durability parameters include freeze-thaw, scaling, chloride permeability and abrasion.

Various advantages of using HPC can be categorized into performance benefits and cost and other benefits. The first category include ease of placement and consolidation without affecting strength , long-term mechanical properties , high early strength(20 to 28 mpa at 3 to 12 hours or 1 to 3 days) , toughness , volume stability , longer life in severe environments.The category include less material, fewer beams, reduced maintenance, extended life cycle and aesthetics.High-performance concretes are also more sensitive to changes in constituent material properties than conventional concretes. This means that a greater degree of quality control is required for the successful production of high-performance concrete. By careful selection of raw materials (including chemical/mineral admixtures) & appropriate mix design to achieve the desired performance objectives. Most high-performance concretes have a high cementitious content and a water-cementitious material ratio of 0.40 or less along with superplasticizers to increase its workability.

2.2 FACTORS AFFECTING DURABILITY OF HPC

Concrete durability has been defined by the American Concrete Institute (ACI) as its resistance to weathering action, chemical attack, abrasion and other degradation processes**.** Durability problems of ordinary concrete can be associated with the severity of the of the environment and the use of inappropriate high water/binder ratios. The various factors affecting durability of concrete are seawater exposure, chloride resistance and steel corrosion, resistance to alkali-silica reaction, abrasion resistance, resistance to freezing and thawing, resistance to sulphate attack etc

2.3 PROBLEMS IN PREDICTING THE DURABILITY OF HPC

HPC need to have certain desirable properties to claim good durability against the above mentioned factors. So various additives are included into concrete to make it highly performing in every sense . Some additives for improving cementing and durability characteristics are fly ash, silica fume, slag and calcarious clay/shale, superplasticizers for flowability, water reducers, retarders, accelerators, corrosion inhibitors and polymer or latex modifiers for other purposes. All the above mentioned additives or even some of them when added to ordinary concrete make it a highly heterogenic high performance concrete. Predicting any properties of such a heterogenic compound is a complicated process. Here comes the relevance of artificial neural networks. ANNs with its learning capability can be used for this task.

CHAPTER-3

ARTIFICIAL NEURAL NETWORKS

3.1 INTRODUCTION

Artificial neural networks are biologically inspired; that is the development of ANNs is inspired by a desire to understand the human brain and emulate its functioning. Knowledge about the brain's overall operation is so limited that there is little to guide those who would like to emulate it. Hence there is a need to go beyond the current biological knowledge and seek structures that perform useful functions .Within the last decade; the development of ANNs has experienced a huge resurgence due to the development of more sophisticated algorithms and emergence of powerful computation tools.

The idea of artificial neural networks was proposed by Mc. Cullock and Pitts. Since early nineties, ANNs have been successfully used in civil engineering related areas.

3.2 WHAT IS AN ARTIFICIAL NEURAL NETWORK?

An ANN is a massively parallel distributed information processing system that has certain performance characteristics resembling biological neural network of human brain (Haykin, 1994).

A neural Network is an interconnected assembly of simple processing elements, units, nodes or neurons, whose functionality is closely based on the biological neuron. The processing ability of the network is stored in the inter unit connection strengths or weights obtained by a process of adaptation to or learning from, a set of training patterns.

The development of ANNs has been motivated right from its inspection by the recognition that the brain compute in an entirely different way from the conventional digital computer. The human brain is a highly complex, non-linear and parallel computer. It has the capability to perform certain computations like pattern recognition, perception and motor control many times faster than the faster digital computer in existence today.

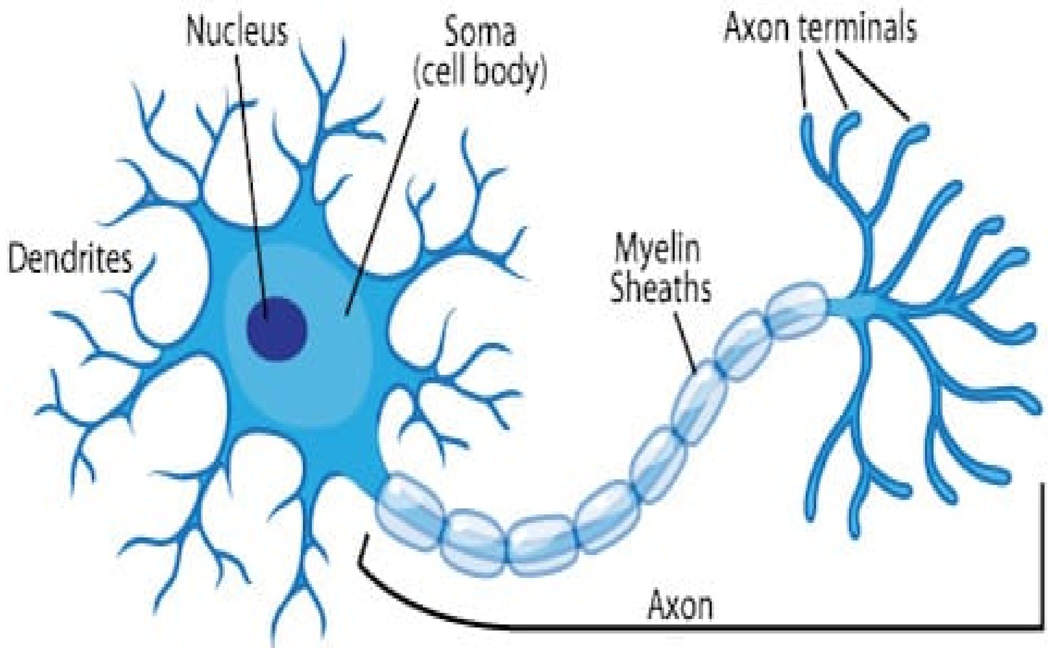
3.3 CHARACTERISTICS OF NEURAL NETWORKS

An ANN resembles the brain in two ways

1. Knowledge is acquired by the network through a learning process

2. Inter neuron connection strength known as synaptic weights are used to store the knowledge.

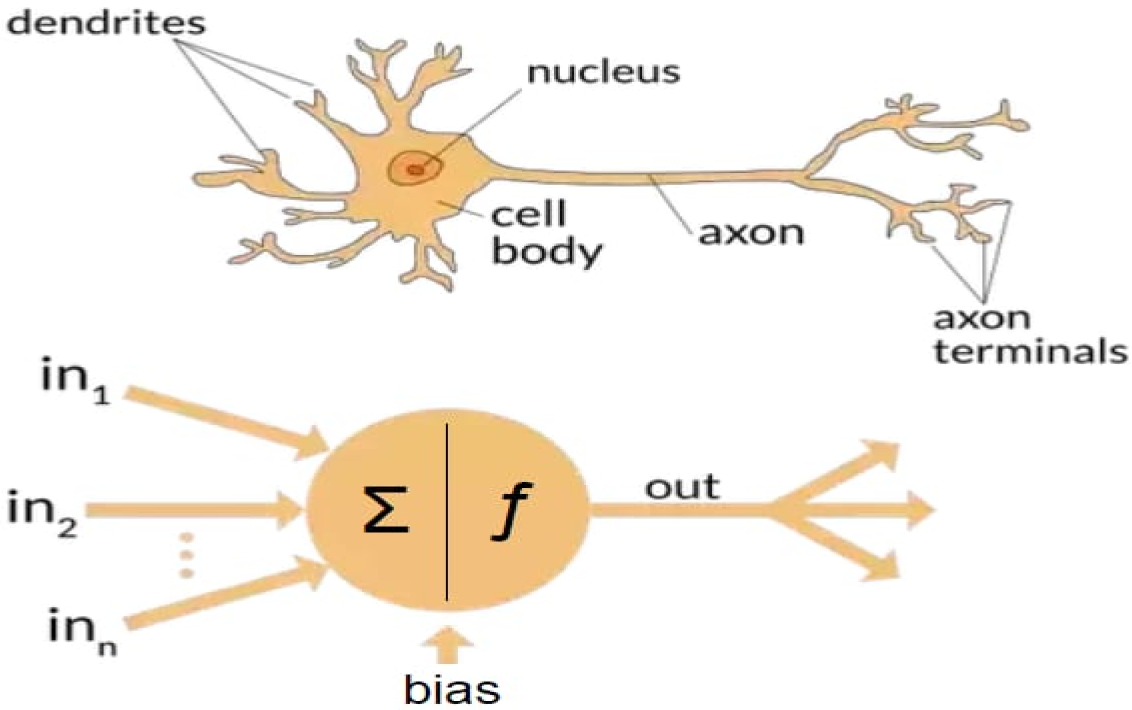
The procedure used to perform the learning process is called a learning algorithm, the function of which is to modify the synaptic weights of the network in an orderly fashion so as to attain a desired design objective.



A Biological Neuron (fig no:1)

3.3 MATHEMATICAL MODEL OF A NEURON

The fundamental building block of an ANN is neuron which is a processing element. A schematic diagram of a typical neuron is shown in fig 2.



A Neuron in ANN (Fig no:2)

The general neuron has a set of n inputs x_i, where the subscript i take values from 1 to n and indicates the source of the input signal. The inputs to the neuron may come from the environment in which it is embedded or output of other neurons depending on the layer that the neuron is located in. Each input x_i is weighted before reaching the main body of the processing element by the connection strength or the weight factor w_i (i.e., x_i is multiplied by w_i). In addition, it has a bias term b, a threshold value that has to be reached or exceeded for the neuron to produce a signal, a non linearity or activation function that acts on the produced signal, to produce the output of the neuron, O. O may constitute the input to other neurons. When the neuron is a part of a network of many neurons, it is referred as a node and the subscript j is needed to distinguish it from other nodes.

3.4 LEARNING IN ANN'S

Among the many interesting properties of a neural network, the property that is of primary significance is the ability of the network to learn from its environment. In the context of neural networks, learning may be defined as follows:

Learning is a process by which the free parameters of a neural network are adapted through a continuing process of stimulation by the environment in which the network is embedded. The type of learning is determined by the manner in which the parameter changes takes place. (Haykin, 1994).

During the process of learning, the network adjusts its parameter, the synaptic weights, in response to an input stimulus so that its actual output response converges to the desired output response. When the actual output response is the same as the desired one, the network has completed the learning phase and has acquired knowledge. As different learning methodologies suit different people, so do different learning techniques suit different artificial neural networks.

3.4.1 Supervised Learning

During the training session of a neural network, an input stimulus is applied that results in an output response. The response is compared with the target response. If the actual response differs from the target response, the neural network generates an error signal, which is then used to calculate the adjustment that should be made to the network synaptic weights so that the actual output matches the target output. In other words, the error is minimized, possibly to zero. The two commonly used learning techniques are the Delta rule and Gradient Descend rule.

The Delta rule is based on the idea of continuous adjustments of the value of the weights such that the difference of the error (delta) between the desired output value and the actual output value of a processing element is reduced. This is also known as the Windrow -Hoff learning rule.

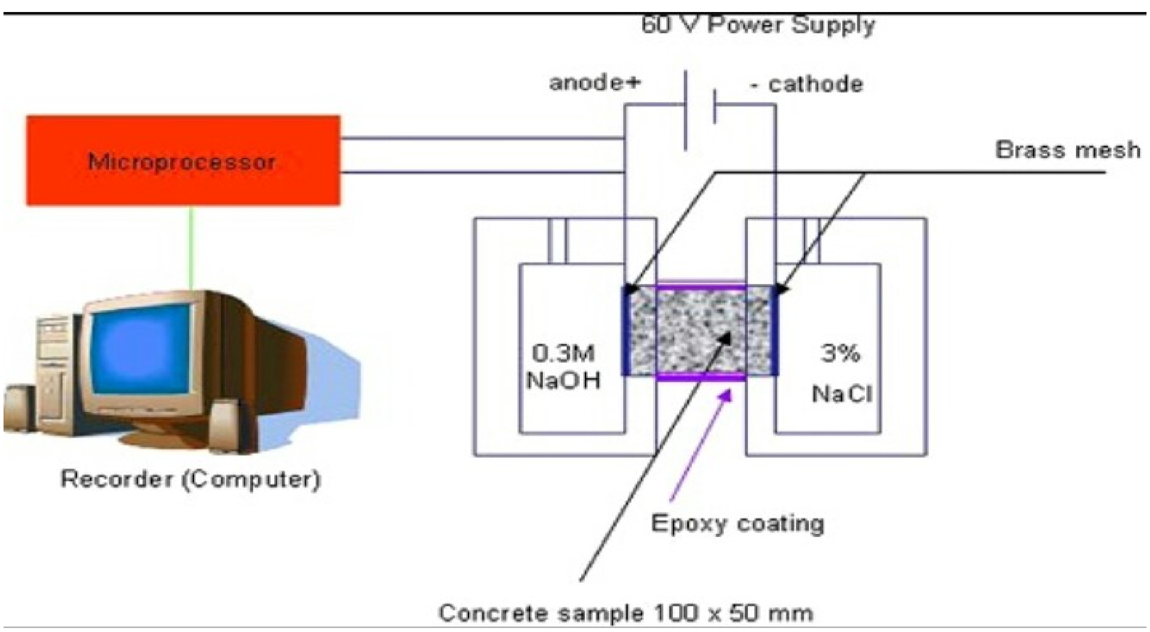
In the Gradient Descend rule, the values of the weights are adjusted by an amount proportional to the first derivative (the gradient) of the error between the desired output value and the actual output value of a processing element, with respect to the value of the weight.

CHAPTER – 4

CASE STUDY

4.1 EXPERIMENTAL PROGRAM AND DATA COLLECTION

The first step in developing the network is to obtain good and reliable training and testing examples. To obtain the data for developing the neural network models, a database of high strength and durable concrete is produced by collecting the data sets from experiments by R.Parichathprechal. combined with data sets from previous researches. The influence of using different pozzolanic materials, cement content, and water-to-binder (*W*/*B*) ratios on the durability of concrete was experimentally investigated by measuring the charge passed of concrete in accordance with ASTM C1202-97. The workability of concrete expressed in terms of slump was kept constant by varying the dosage of superplasticizer based on poly-carboxylic ether (PCE). Two types of pozzolonic material were used, namely pulverized fly ash and a combination of pulverized fly ash and condensed silica fume. The cement materials were varied from 400–550 kg/m^3 with *W*/*B* ranging from 0.3 to 0.4. Control specimens without pozzolanic materials of concrete were also cast and tested for comparison. ASTM C1202-97 Rapid Chloride Permeability Test (RCPT) was used in this experimental program for hardened concrete. The complete RCPT apparatus is illustrated in fig.3



Testing apparatus for rapid chloride permeability test (fig no:3)

This test method covers the determination of the electrical conductance of concrete to provide a rapid indication of its resistance to the penetration of chloride ions. After 28 days' curing, cylindrical specimens of 100 mm diameter and 200 mm length were cut to 50 mm thick on each end. These specimens were saturated in water for 18 ± 2 h until fully saturated and then allowed to surface dry in air for at least 1 h. Next the specimens were placed on suitable silicon and complete coating of all surfaces was ensured.

One side of the cell contained 3.0% NaCl solution and the other 0.3 M NaOH solution. The current (ampere-seconds) was recorded at 30-min intervals during a testing period of 6 h. Based on the charge that passed through the sample, a qualitative rating was made of the concrete's permeability, as shown in *Table 2* in accordance with ASTM C1202-97. A total of 30 mixes were made and the specimens were tested for their charge passed over a duration of 6 h.

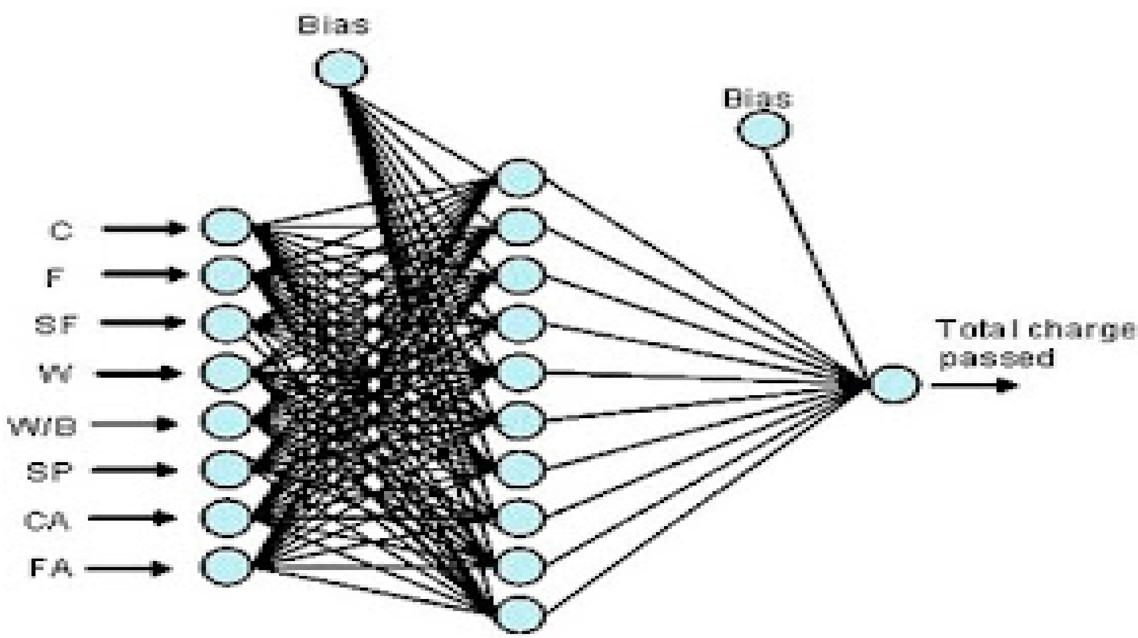
To expand the prediction range of the model built with the experimental data, 56 concrete mixtures and their test results were culled from previous researches .The 28-day compressive strength of all data is in the range of 30–120 MPa. Of these, the ANNs model is developed, trained and tested by using a total of 86 data sets. . The data used in ANNs model are arranged in a format of eight input parameters which include OPC, F, SF, W,SP,CA,FA and W/B ratio. To test the reliability and accuracy of the models, 20% of the 86 data sets were randomly selected as test sets, while the remaining 70 samples were used to train the network. The output of the model is the total charge passed in accordance with ASTM C1202 or AASHTO T277. The input and output of a typical neural network is in the range of 0–1. In this study, x/xmax normalization technique was applied for transforming the input and output values remaining in the range of 0–1.

Components	Data of high strength and durable concrete		
	Min(kg/m^3)	Max(kg/m^3)	Avg(kg/m^3)
OPC	135	611	387
F	0	275	66
SF	0	110	11
W/B	0.21	0.6	0.36
SP	120	220	165
CA	0	17.3	5.7

Table 1.Ranges of components of data sets for chloride ions permeability prediction

4.2 NEURAL NETWORKS FOR MODELLING DURABILITY OF HPC

The electrical conductivity of concrete is determined by both pore structure and the chemistry of the pore solution, which are dependent on the dosage of cement, water, SP, fine aggregate, coarse aggregate and type and dosage of pozzolanic materials. The ANNs model developed in this study has eight neurons inthe input layer, one hidden layer, and an output layer as shown in Fig. 4. The selection of the number of nodes in the hidden layer is the most challenging part in the total network development process. Unfortunately, there are no fixed guidelines available for this purpose and hence this has to be done by the trial-and-error method.



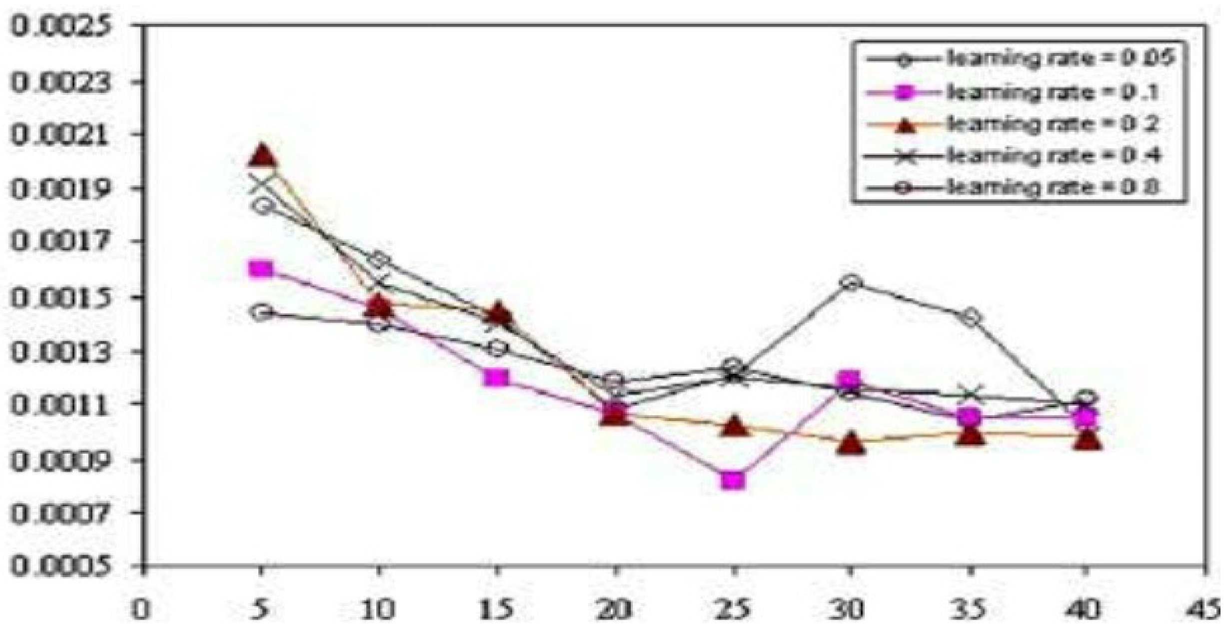
<u>Architecture of neural network for predicting durability of HPC(Fig No:4)</u>

In this study, the neural networks were developed and performed under MATLAB programming. The learning algorithm used in the study was gradient descent with adaptive learning rate back-propagation, a network training function that updates weight and bias values according to gradient descent with adaptive learning rate . The error incurred during the learning process was expressed in terms of mean-squared-error (MSE).

After a number of trials as shows in Fig. 5, the best network architecture and parameters that minimize the MSE error of training data were selected as follows:

• 8 input units;

- 1 hidden layer;
- 25 hidden units;
- 1 output unit;
- Activation function = sigmoidal function;
- Learning rate = 0.1
- Learning cycles = 10,000.



Selection of number of neuron in hidden layer for training sets with various learning rate

(fig no:5)

4.3 RESULTS AND DISCUSSION

4.3.1 ANNs Model Analysis.

The results indicate that the proposed ANNs model is successful in learning the relationship between the different input and the output parameters .The statistical parameters of the training and testing sets are shown in Table 2. All of the statistical values in Table3 demonstrate that the proposed ANNs model is suitable and can help predict the total charge passed close to the experimental values.

Table 2. Chloride ion penetrating based on charge passed

Charge passed (coulombs)	Chloride ion penetrability
>40000	High
2000-4000	Moderate
1000-2000	Low
100-1000	Very low
<100	Negligible

Table 3 .Statistical parameters of neural networks and regression model

Statical Parameter	Linear Regression model	
	Training set	Testingset
MSE	.089	.0144
MAPE(%)	52.88	33.02
R^2	.9141	.3260

Statical Parameter	Non linear regression model	
	Training set	Testing set
MSE	.0039	.0476
MAPE(%)	34.75	62.59
R^2	.9647	.8968

To compare with statistical techniques, the seven input parameters, namely *C*, *F*, SF, *W*, SP, CA, and FA, are remodeled with linear and nonlinear regression techniques. In this research, SPSS version 10 was applied to determine the best fit of linear and nonlinear regression. For the observation of the performance of the classical statistical method, linear regression was employed to characterize mapping among seven input parameters and total charge passed of concrete the result of multiple regression analysis is given as

In addition, the second trial for the characterization of mapping among input parameters was made by using nonlinear multiple regression analysis. Various different nonlinear equations were tried and the best equation was determined by considering related R^2 and scatter plots between measured and calculated results.

Table 3 shows the statistical parameters of ANNs and regression models. It can be seen that the ANNs model gives a higher degree of accuracy than the regression techniques. Furthermore, Fig. 5 and Fig. 6 verify that the ANNs model is the most accurate of the three compared paradigms for estimating the chloride ions permeability of high performance concrete.

4.3.2 Influence of Relevant Materials on Chloride Ions

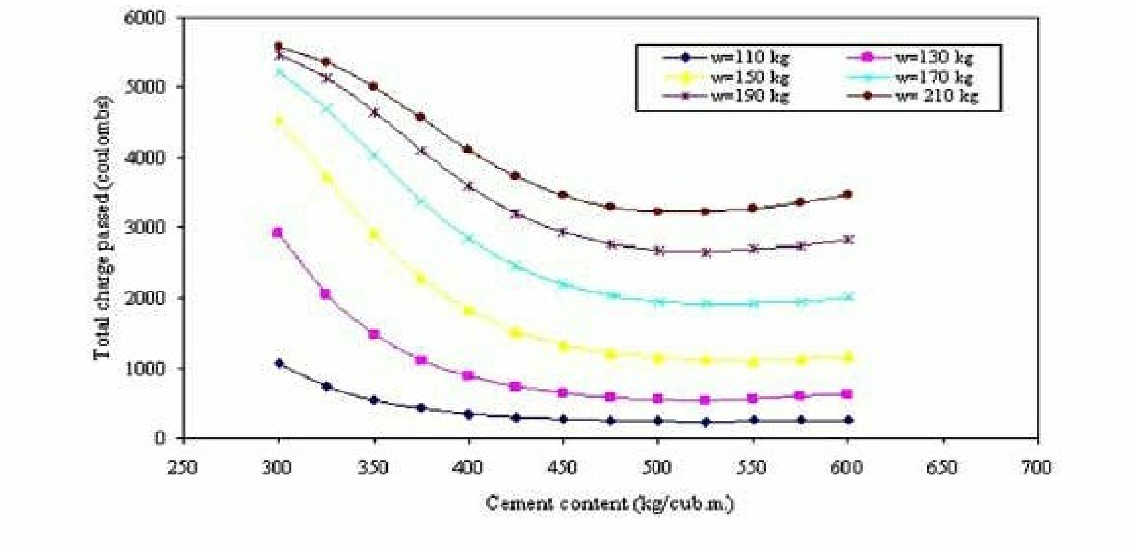
The ANNs model was trained and tested on cases reflecting a wide range of concrete mix proportions, validated on independent test data, and compared with the models from regression techniques. The results show that the ANNs model is the most accurate among the three compared paradigms for estimating the total charge passed of HPC. Although there are eight input parameters in the model, it is more meaningful to investigate the influence of water and cement contents, water–binder ratio (*W*/*B*), fly ash-binder ratio (*F*/*B*), and silica fume-binder ratio (SF/*B*) the on durability of HPC. The binder is a cementitous material, that is, cement plus fly ash and silica fume. The range of each variable is shown as follows:

- The cement content was varied from 300 to 600 kg/m^3.
- The water content was varied from 110 to 200 kg/m^3.
- The water to binder ratio was varied from 0.25 to 0.5.
- The fly ash-binder ratio (*F*/*B*) was varied from 0% to 50%, and binder content was kept constant at 450 kg/m^3.
- The silica fume content was varied from 0% to 15%, and binder content was kept constant at 450 kg/m^3.

All other components or ratios were kept constant: SP contents were kept constant at 1% of binder; the fine aggregate to coarse aggregate ratio by weight was kept at 0.67; entrapped air was kept at 1.00%; and the volume of concrete was 1.000 m^3.

Influence of Cement And Water Content

FigNo:8 illustrates the variations in total charge passed with increasing cement content at various levels of water content which is produced by using the trained neural networks developed in this study. For concrete having cement content of 300–450 kg/m^3, the higher the cement content, the lower the total charge passed, and for concrete having cement content of 450–600 kg/m^3, an increase in cement content results in a slight decrease of the total charge passed. As shown in Fig.8, it was also found that the optimum cement content for design of HPC in terms of chloride penetration resistance ranged from 450 to 500 kg/m^3.



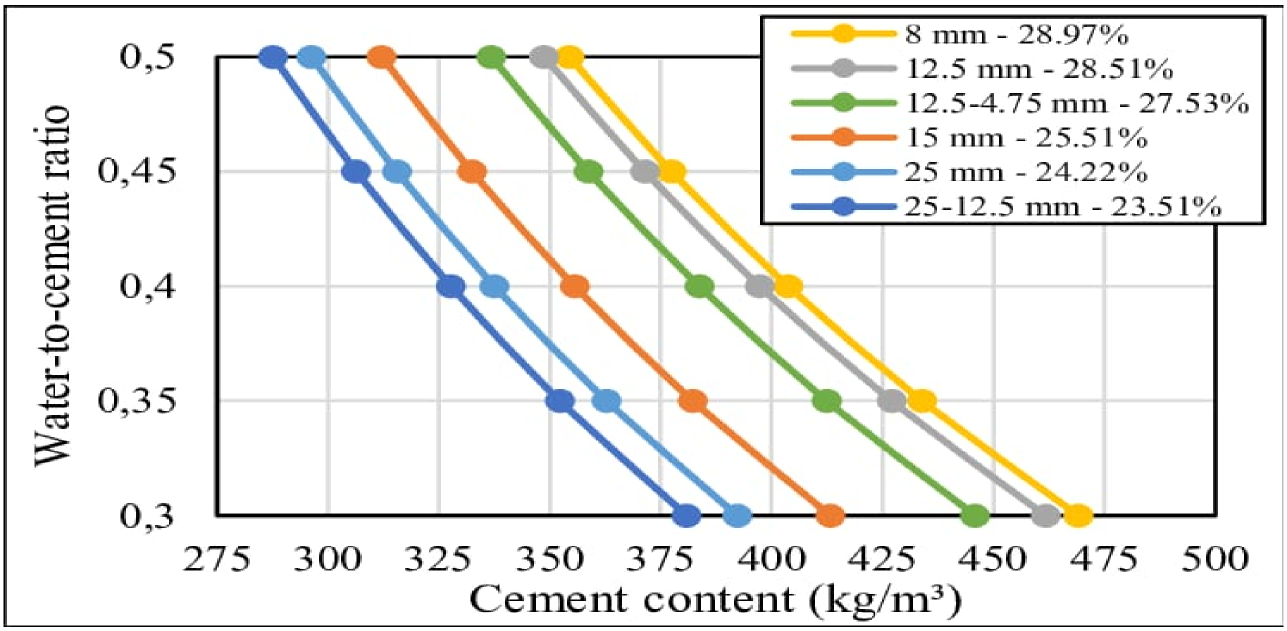
Influence of cement content on total charge passed at various levels of water content

(Fig no:6)

According to ASTM C1202, for water content of concrete greater than 150 kg/m^3, the chloride ion penetrability of concrete containing any level of cement content can be classified in the level of low to high, and for water content of concrete lower than 150 kg/m^3, it can be classified in the level of negligible to low. Furthermore, it is of interest to note that the charge passed of concrete was found to decrease with decreasing water content.

- **Influence of Percent Replacement of Fly Ash And Water–Binder Ratio**

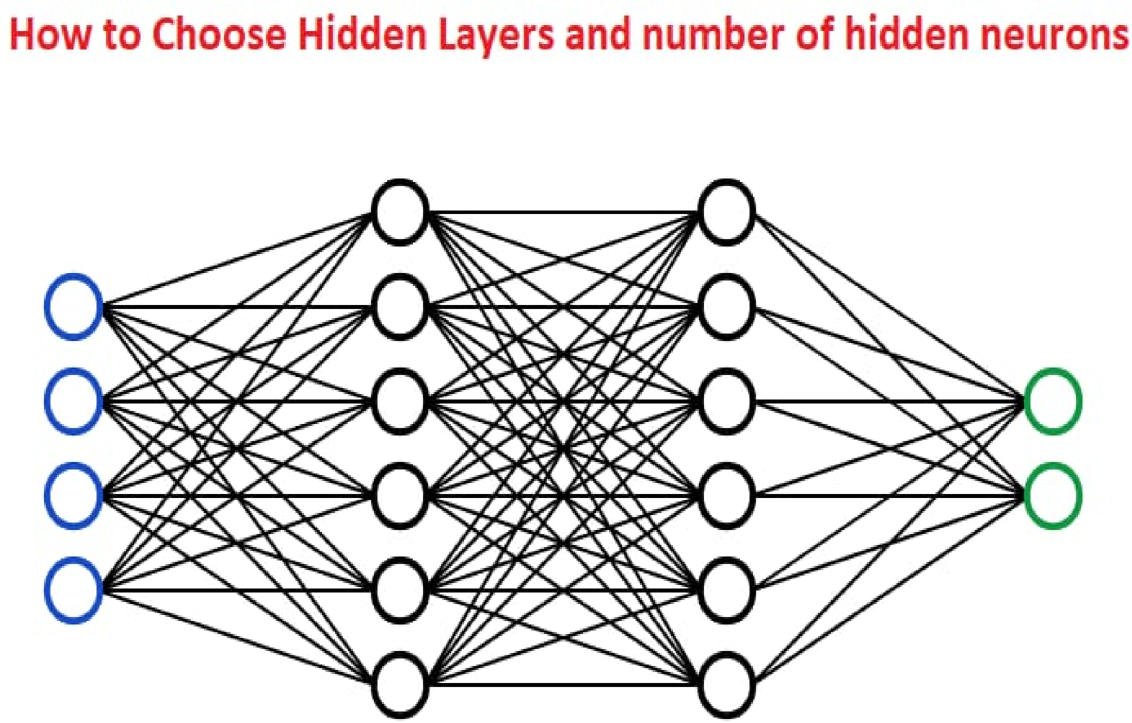
Fig. 9 shows the variations in the total charge passed for HPC when increasing fly ash at different levels of *W*/*B*, produced by using the trained neural network developed in this study. The relative charge passed means the percentage of total charge passed of concrete containing fly ash to total charge passed of concrete without fly ash. At a low level of *W*/*B* ratio (*W*/*B* = 0.25–0.4), the relative charge passed significantly decreases when the replacement of fly ash is greater than 20%, and the chloride ions penetrability of concrete containing any level of fly ash replacement can be classified at the level of negligible to low. However, at a higher level of *W*/*B* ratio (*W*/*B* = 0.45–0.5), the reduction in relative charge passed is proportional to the increase in percent replacement of fly ash, and the chloride ions penetrability of concrete containing any level of fly ash replacement can be classified in the level of low to high.



Influence of percent replacement of fly ash on relative charge passed. (Fig No: 7)

- **Influence Of Percent Replacement Of Silica Fume And Water–Binder Ratio**

FigNo:10 shows the variations in the total charge passed for HPC with increasing silica fume at different levels of *W*/*B*, produced by using the trained neural networks developed in this study. The relative charge passed means the percentage of total charge passed of concrete containing silica fume to total charge passed of concrete without silica fume. At a low level of *W*/*B* ratio (*W*/*B* = 0.25–0.35), the chloride ions penetrability of concrete containing any replacement of silica fume can be classified at the level of negligible to very low (0–1000 C). However, at a higher level of *W*/*B* ratio (*W*/*B* = 0.4-0.5), the chloride ions penetrability of concrete containing any replacement of silica fume can be classified at the level of very low to high (500–5000 C). For any level of water–binder ratio, when replacing cement with at least 5% of silica fume, the chloride ions penetrability of concrete can be classified at the level of negligible to very low. Furthermore, it can be summarized that an increase in silica fume content results in significantly reducing the chloride ions penetrability to a higher degree when compared with the fly ash results. It can be pointed out that silica fume is a very fine particle and has higher chemical reactivity compared to cement and fly ash.



Choosing number of hidden layers and number of hidden neuron in neural networks

(Fig no:8)

CHAPTER – 5

CONCLUSIONS

The following conclusions were drawn from the above case study :

· The statistical test results indicate that the models are reliable, accurate, and illustrate how ANNs can be used to efficiently predict the durability of HPC.

Based on the simulated total charge passed model built using trained neural networks, the optimum content of various ingredients of HPC were obtained.

Although the capability of the proposed network is limited to the data located within the available range of training data in the database, the available range of the system could be easily expanded by retraining the neural networks with additional data from trial mixes.

The capability of ANNs to predict complicated computations has been explored in the casestudy. This feature of ANNs can be extended to various fields of Civil Engineering to solve the problem of result forecasting

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