Prediction of Compressive Strength of High Performance Concrete and It's Durability

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Abstract- *Neural networks have recently been widely used in some of the human activities in many areas of civil engineering applications. The present study is relating to the models in artificial neural networks (ANN) for predicting compressive strength of cubes and their durability of concrete containing metakaolin with fly ash and silica fume with fly ash have been developed at the age of 3,7,28,56 and 90 days respectively. For purpose of development of these models, training and testing used based on the available experimental results for required number of specimens produced with 7 different mixture proportions were used. The data used in the multilayer feed forward neural networks(FFNN) models are arranged in format of eight input parameters that covers the age of specimen, cement, metakaolin(MK), fly ash(FA), water ,sand, aggregate and super plasticizer and in another set of specimen which contain silica fume (SF) instead of metakaolin(MK). As per these input parameters, FFNN are used to predict the compressive strength and its durability. The training and testing results in the neural network models have shown that neural networks have strong potential for predicting 3,7,28,56 and 90 days compressive strength and its durability which contains metakaolin, silica fume and fly ash at 5% level of significance.*

I. INTRODUCTION

High Performance Concrete is a term used to describe concrete with special properties. HPC was first known to be concrete with high strength for structural purpose. However, advances in concrete technology have generated a new (Super plasticizer, retarders, fly ash, blast furnace slag, silica fume, fumed silica and metakaolin) combined according to a selected mix design, properly mixed, transported, placed, consolidated and cured to give excellent performance, such as high compressive strength, high density, low shrinkage, high modulus of elasticity, low permeability, and good resistance. Also, the concrete must have a durability factor greater than 80 after 300 cycles of freezing and thawing to meet their definition,

The American Concrete Institute (ACI) formed a special committee on HPC in 1992. This committee has taken a broader view of HPC to include performance aspects other than compressive strength in its definition (this definition is similar to an earlier definition proposed by the National Institute of Standards and Technology):

Concrete meeting special performance and uniformity requirements which cannot always be achieved routinely using only conventional constituents and normal mixing, placing and curing practices. These requirements may involve enhancements of the following:

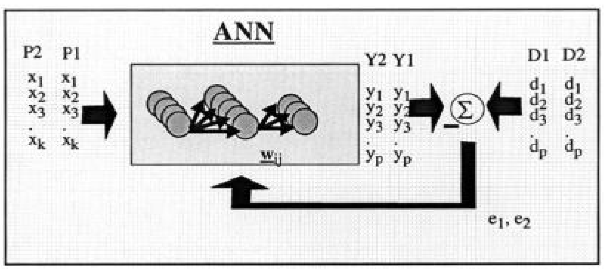
- ✓ Ease of placement and completion without segregation
- ✓ Long-term mechanical properties
- ✓ Early-age strength
- ✓ Toughness
- ✓ Volume stability
- ✓ Long life in severe environments

HPC can be designed to meet special performance requirements with regard to workability, strength and durability. To produce HPC, it is normal/general/necessary to use super plasticizing chemical admixtures in addition to the same ingredients, which are generally used for normal concrete. However, such HPC requires high paste volume, which often leads to excessive shrinkage and large evolution of heat of hydration besides, increase in cost. A partial substitution of cement by mineral admixture such as flyash, silica fume, Metakaolin, fumed silica and ground granulated blast furnace slag (GBS) is usually used. Use of such materials not only improves the properties of fresh concrete but also enhances the durability characteristics. When high strength is required, the use of micro silica becomes imperative, especially in the case of precast structural elements since micro silica achieves early strength even at 12 and 24 hrs. In addition, it improves impermeability, resistance to aggressive fluids, mitigation of alkali-aggregate reaction etc.

II. METHODOLOGY

1. Neural Networks

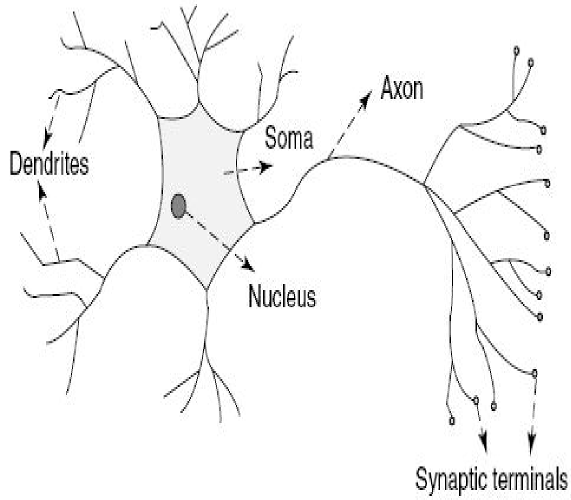
An **artificial neural network (ANN)**, usually called **neural network (NN)**, is a mathematical model or computational model that is inspired by the structure and/or functional aspects of biological neural networks. A neural network consists of an interconnected group of artificial neurons, and it processes information using a connectionist approach to computation. In most cases an ANN is an adaptive system that changes its structure based on external or internal information that flows through the network during the learning phase. Modern neural networks are non-linearstatisticaldata modeling tools. They are usually used to model complex relationships between inputs and outputs or to find patterns in data. An artificial neural network is an interconnected group of nodes, akin to the vast network of neurons in the human brain.



The style of neural computation.

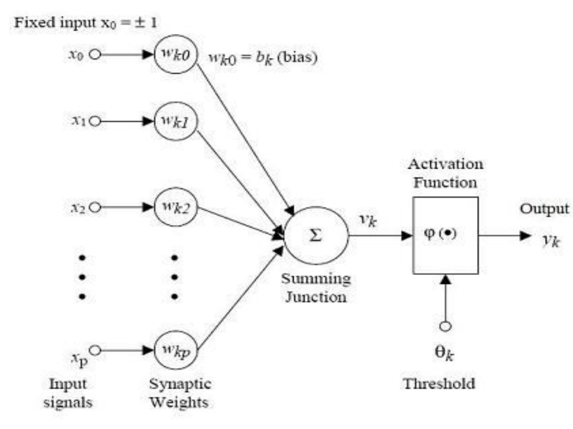
2. The Biological Model

Artificial neural networks born after McCulloc and Pitts introduced a set of simplified neurons in 1943. These neurons were represented as models of biological networks into conceptual components for circuits that could perform computational tasks. The basic model of the artificial neuron is founded upon the functionality of the biological neuron. By definition, “Neurons are basic signaling units of the nervous system of a living being in which each neuron is a discrete cell whose several processes are from its cell body”



Analysis:

Once modeling an artificial functional model from the biological neuron, we must take into account three basic components. First off, the synapses of the biological neuron are modeled as weights. Let’s remember that the synapse of the biological neuron is the one which interconnects the neural network and gives the strength of the connection.. Mathematically, this process is described in the figure



From this model the interval activity of the neuron can be shown to be:

$$v_k = \sum_{j=1}^{p} w_{kj} x_j$$

The output of the neuron, yk, would therefore be the outcome of some activation function on the value of vk.

Activation functions

As mentioned previously, the activation function acts as a squashing function, such that the output of a neuron in a neural network is between certain values (usually 0 and 1, or -1 and 1). In general, there are three types of activation functions, denoted by $\Phi(.)$. First, there is the Threshold Function which takes on a value of 0 if the summed input is less than a certain threshold value (v), and the value 1 if the summed input is greater than or equal to the threshold value.

$$\varphi(v)=\begin{cases}1 & \text{if } v\geq 0\\ 0 & \text{if } v<0\end{cases}$$

Secondly, there is the Piecewise-Linear function. This function again can take on the values of 0 or 1, but can also take on values between that depending on the amplification factor in a certainregion of linear operation.

$$\varphi(v)=\begin{cases}1 & v\geq \frac{1}{2}\\ v & -\frac{1}{2}>v>\frac{1}{2}\\ 0 & v\leq -\frac{1}{2}\end{cases}$$

Thirdly, there is the sigmoid function. This function can range between 0 and 1, but it is also sometimes useful to use the -1 to 1 range. An example of the sigmoid function is the hyperbolic tangent function

$$\varphi(v)=\tanh\left(\frac{v}{2}\right)=\frac{1-\exp(-v)}{1+\exp(-v)}$$

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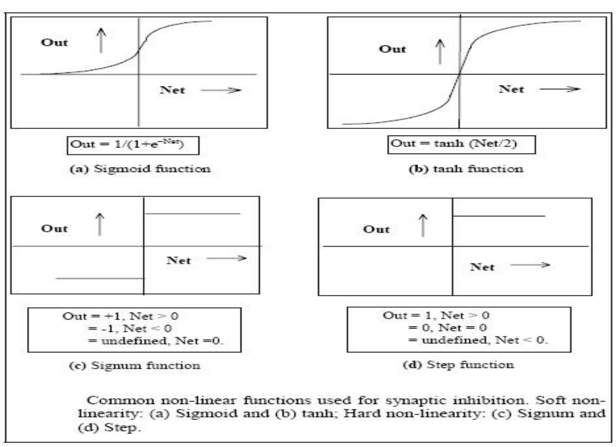
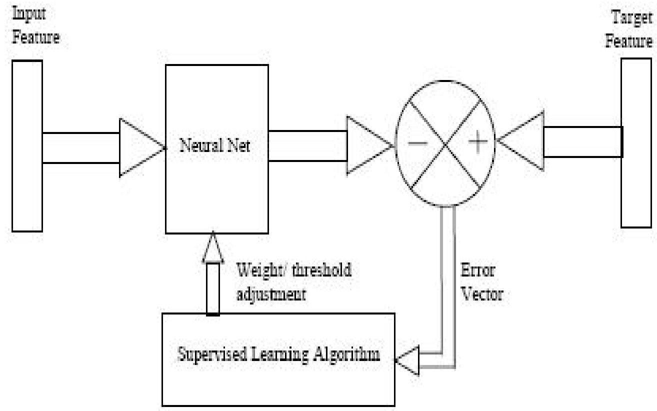


Common non-linear functions used for synaptic inhibition. Soft non-linearity: (a) Sigmoid and (b) tanh; Hard non-linearity: (c) Signum and (d) Step.

Framework for distributed representation



Modifying patterns of connectivity of Neural Networks

Both learning paradigms supervised learning and unsupervised learning result in an adjustment of the weights of the connections between units, according to some modification rule.

The basic idea is that if two units j and k are active simultaneously, their interconnection must be strengthened. If j receives input from k, the simplest version of Hebbian learning prescribes to modify the weight wjk with

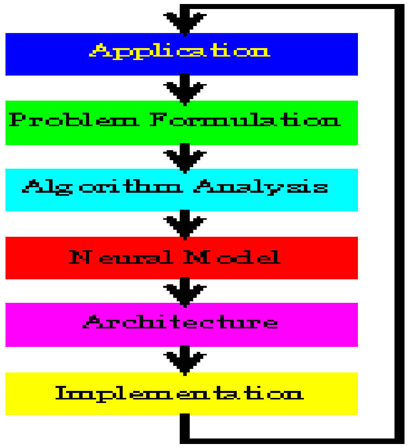
$$\Delta w_{jk}=\gamma y_j y_k,$$

where ϒ is a positive constant of proportionality representing the learning rate. Another common rule uses not the actual activation of unit *k* but the difference between the actual and desired activation for adjusting the weights:

$$\Delta w_{jk}=\gamma y_j(d_k-y_k),$$

in which dk is the desired activation provided by a teacher. This is often called the Widrow-Hoff rule or the delta rule, and will be discussed in the next chapter. Many variants (often very exotic ones) have been published the last few years.

In orther to have an integrated understanding on neural networks, we adopt the next perspective, called **top-down**, from application, algorithm to architecture:



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The application domains of neural nets can be roughly divided into the following categories: association, clustering, classifications, pattern completion, regression and generalization, and optimization.

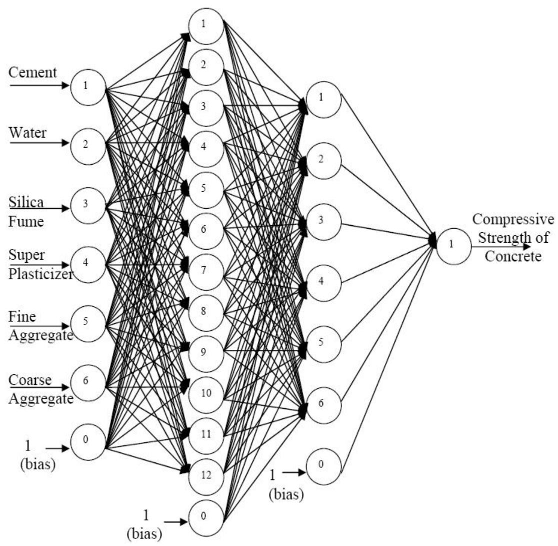

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Fig 1. Architecture of the Developed ANN

Experimental Programme:

The testing process has been carried out for a total 140 data sets. Figure 6exhibits the comparison between predicted compressive strength of concrete againstthe experimental evidence, which highlighted that there is a good agreement betweenthe predicted values and that of experiment data.The results are shown that the artificial neural network was very successful inpredicting of compressive strength of error with MSE of 6.02 percent. Also the ANNpredicts the compressive strength of concrete in testing stage reasonably well the 6-12-6-1 neural models in general performs better than the others and it is able to giveaccurate prediction of compressive strength of concrete. In testing, result showed that,bad output (compressive strength with big error) usually occurred form the bad dataset in range (0-30). One explanation for these results could be that there is aninsufficient amount of training data around this range.The purpose of this experimental investigation is to study the behavior of High Performance Concrete (HPC). In thisinvestigation HPC was manufactured by usual ingredients such as cement, fineaggregate, coarse aggregate, water and mineral admixtures such as SilicaFume (SF),metakaolin and Fly ash at various replacement levels and the Super Plasticizerused was CERAPLAST-300. The water binder ratio (w/b) adopted is 0.30 and 0.32.The concrete used in this investigation was proportioned to target a meanstrength of 60 MPa. Specimens such as cubes, cylinders and prism beams werecast and tested for various mixes viz. seven mixes M1 to M7 are cast with 0%,5%, 7.5% and 10% replacement of SF and another set of specimens with 0%,5%, 7.5% and 10% replacement of SF along with 10% constant replacementof Fly ash and also metakaolin replacement same percentage of silica fume along with a constant replacement of fly ash to study the mechanical properties such as compressive strength, durability tests of concrete and ultimate load of beam and columns at different ages of concrete such as3, 7, 28, 56 and 90 days.

Table1.Compressive strength of concrete mixes with and without mineral admixtures with water bonder ratio of 0.3 at various ages

Age in days	Compressive strength for 0.3 w/b (MPa)												
	NC	SF 5%	SF 7.5%	SF 10%	SF 5% FA 10%	SF 7.5% FA 10%	SF 10% FA 10%	MK 5%	MK 7.5%	MK 10%	MK 5% FA 10%	MK 7.5% FA 10%	MK 10% FA 10%
3	35.67	32	34.33	32.67	33.67	31.33	29	38	41	39.67	29.67	41.33	30.67
7	42.33	40.67	44.67	40.33	42.33	41	39.33	39.33	49.33	43.33	37.67	46.67	43.33
28	54.67	55	61.33	56.33	58.67	57.33	55.33	55.67	59	57.67	56	64	55.67
56	61.33	61.67	69.67	65.67	68.67	68.33	60.33	64.67	66.33	62.67	65.33	67	62
90	66.67	67.67	76.33	71.67	74.33	73.67	67.33	72.33	77.33	71	73.33	80.67	72.33

Table2.Compressive strength of concrete mixes with and without mineral admixtures with water bonder ratio of 0.32 at various ages

Age in days	Compressive strength for 0.32w/b (MPa)												
	NC	SF 5%	SF 7.5%	SF 10%	SF 5% FA 10%	SF 7.5% FA 10%	SF 10% FA 10%	MK 5%	MK 7.5%	MK 10%	MK 5% FA 10%	MK 7.5% FA 10%	MK 10% FA 10%
3	41	42	43	39	38	36.5	34.5	42.4	46	44.5	43	47.5	46.2
7	42.33	40.67	44.67	44.33	42.33	41	39.33	55.35	57.5	56.63	54.5	58.1	54.05
28	61	63	66	60	57	64	63.70	63.70	67	65.20	66	68.50	64.80
56	66	68	73.5	65	64	69	72.5	70.00	72.95	69.00	70.42	74.00	71.50
90	66.67	67.67	76.33	71.67	74.33	73.67	67.33	72.33	77.33	71	73.33	80.67	72.33

MATLAB is a high-performance language for technical computing. It integrates computation, regression, and iterations in an easy-to-use environment where problems and solutions are expressed in familiar mathematical notation. MATLAB was originally written to provide easy access to matrix software developed by the Linear PACKAGE LINPACK projects. MATLAB engines incorporate the LINEAR ALGEBRA PACKAGE (LAPACK) and Basic Linear Algebra Subprograms (BLAS) libraries, embedding the state of the art in software formatrix computation.

In this study, a multilayered feed forward neural network with a back propagation algorithm was adopted. The nonlinear sigmoid function was used in the hidden layer and the cell outputs at the output layer. As seen in Figs. 2 and 3 two different multilayer artificial neural network architectures namely ANN-I and ANN-II were built. In training and testing of the ANN-I and ANN-II models constituted with two different architectures AS, C, SF,FA,W, CA,S and SP were entered as input of first set and metakaolin used instead of silica fume as another set of inputs ; while f_c value was used as output. In the ANN-I and ANN-II, 140data of experiment results were used for training whereas 65 of these data were employed for testing. In ANN-I model, as seen Fig2; one hidden layer was selected. In the hidden layer 10 neurons were determined due to its minimum absolute percentage error values for training and testing sets. In ANN-II model, as seen Fig. 3; two hidden layers were selected. In the first hidden layer ten neurons and in the second hidden layer ten neurons were determined due to its minimum absolute percentage error values for training and testing sets. In the Fig 4 and 5shows same process as first set of inputs, here metakaolin used instead of silica fume.

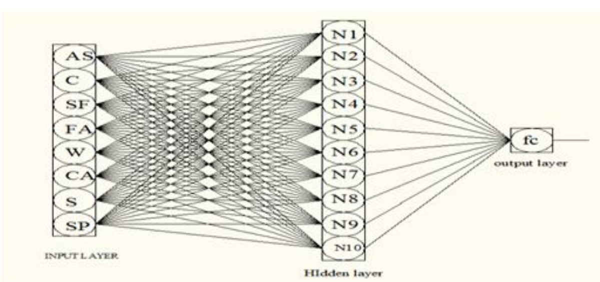

Fig 2. The System Used In the ANN-I Model

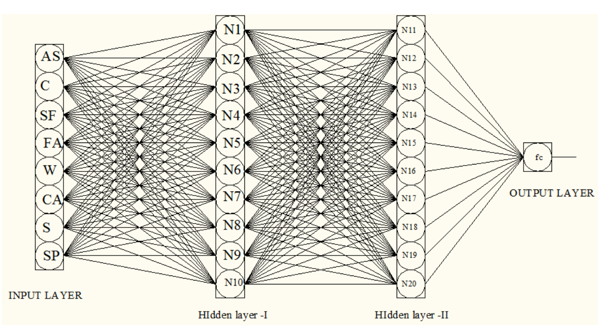

Fig 3. The system used in the ANN-II model.

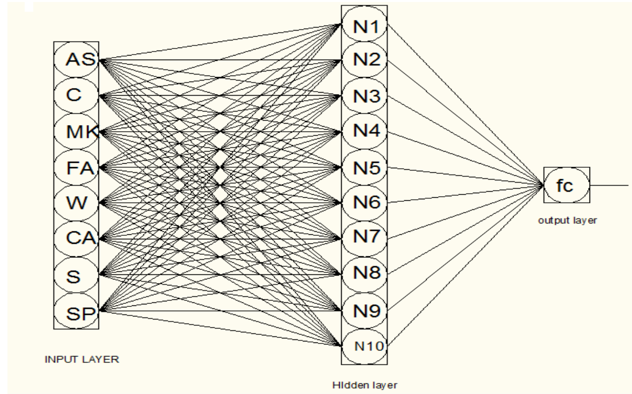

Fig 4. The system used in the ANN-II model

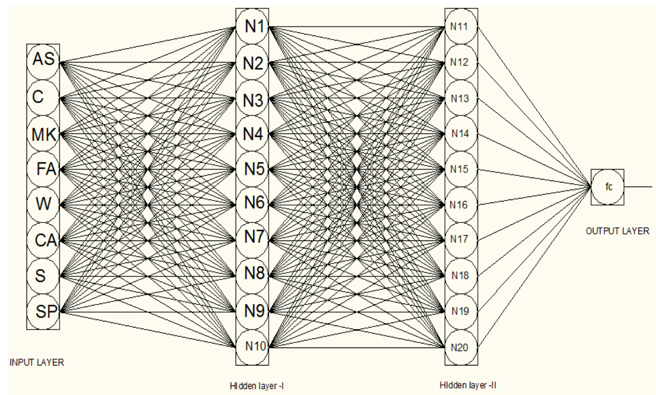

Fig 5. The system used in the ANN-II model

The limit values of input and output variables used in ANN-I and ANN-IImodels of cubes are listed in below Tables

Table3:The input and output quantities used in ANN models for concrete cubes

	Data used in training and testing the models	
Input variables	**Minimum**	**Maximum**
Age of specimen (day)	3	90
Cement (kg/m^3)	457.53	571.91
Silica fume (kg/m^3)&Metakaolin	0	57.16
Fly ash (kg/m^3)	0	57.16
Water (l)	171.47	171.47
Sand (kg/m^3)	566.82	609.72
Aggregate (kg/m^3)	1171.80	1171.80
Super plasticizer(l/m^3)	6.97	17.19
Output variable		
Compressive strength(MPa)for SF	30.8534	75.8197
Compressive strength for Mk	30.6992	79.7649

Table4:The values of parameters used in models for concrete cubes

Parameters	ANN-I	ANN-II
Number of input layer neurons	8	8
Number of hidden layer	1	2
Number of first hidden layer neurons	10	10
Number of second hidden layer neurons	10	10
Number of output layer neurons	1	1
Momentum rate	0.7	0.7
Learning rate	0.3	0.3
Error after learning	0.00100	0.000125
Learning cycle	5000	5000

III. RESULTS AND DISCUSSION

FORMULATION

In this study, the error arose during the training and testing in ANN-I and ANN-II models can be expressed as a root-mean squared (RMS) error and is calculated by Eq. (6.0).

$$\text{RMS}=\sqrt{\frac{1}{p}\sum_i \left|t_i - o_i\right|^2}$$

In addition, the absolute fraction of variance (R^2) and mean absolute percentage error (MAPE) are calculated by Esq. (6.1) and (6.2), respectively.

$$R^2=1-\left(\frac{\sum_i (t_i - o_i)^2}{\sum_i (o_i)^2}\right),$$

$$\text{MAPE}=\left|\left(\frac{t_i - o_i}{o_i}\right)\right|*100$$

Here t is the target value, o is the output value, p is the pattern. In the training and testing of ANN-I and ANN-II models, various experimental data from two different sources are used. In the ANN-I and ANN-II models, 140 data of experiment results were used for training whereas 65 ones were employed for testing.

The predicted high performance concrete results of ANN-I and ANN-II for compressive strength of cubes, also input values and experimental results with testing results obtained from ANN-I and ANN-II models. In the below figures shows the comparison of experimental results with predicted results of ANN.

Table5:Testing data sets for comparison of experimental results with testing results predicted from models (0.3w/b)

Data used in models construction								Compressive strength (MPa)			
AS(day)	C (kg/m³)	SF (kg/m³)	FA (kg/m³)	W (kg/m³)	CA (kg/m³)	S (kg/m³)	SP (l/m³)	Experimental results	ANN-I	ANN-II	% Error
3	571.19	0	0	171.47	1171.8	609.72	6.97	35.67	37.1806	35.6700	-4.23493
3	543.31	28.58	0	171.47	1171.8	599.81	8.83	32	35.1726	32.0000	-9.91438
3	529.01	42.87	0	171.47	1171.8	594.58	9.23	34.33	36.5486	38.1858	-6.46257
3	514.72	57.16	0	171.47	1171.8	589.35	9.75	32.67	32.3999	32.6700	0.826752
3	486.12	28.58	57.16	171.47	1171.8	577.28	16.72	33.67	33.1987	33.6700	1.399762
3	471.82	42.87	57.16	171.47	1171.8	572.05	17.19	31.33	32.7407	31.3300	-4.50271
3	457.53	57.16	57.16	171.47	1171.8	566.82	17.19	29	30.6062	29.0000	-5.53862
7	571.19	0	0	171.47	1171.8	609.72	6.97	42.33	40.5497	42.3300	4.205764
7	543.31	28.58	0	171.47	1171.8	599.81	8.83	40.67	39.9614	38.0635	1.742316
7	529.01	42.87	0	171.47	1171.8	594.58	9.23	44.67	42.1719	44.6700	5.592344
7	514.72	57.16	0	171.47	1171.8	589.35	9.75	40.33	38.2956	38.7379	5.044384
7	486.12	28.58	57.16	171.47	1171.8	577.28	16.72	42.33	38.2867	42.3300	9.551854
7	471.82	42.87	57.16	171.47	1171.8	572.05	17.19	41	38.2146	40.7288	6.793659
7	457.53	57.16	57.16	171.47	1171.8	566.82	17.19	39.33	36.1621	39.3300	8.054666
28	571.19	0	0	171.47	1171.8	609.72	6.97	54.67	55.3674	54.6700	-1.27565
28	543.31	28.58	0	171.47	1171.8	599.81	8.83	55	57.9681	55.0000	-5.39655
28	529.01	42.87	0	171.47	1171.8	594.58	9.23	61.33	61.8237	61.3300	-0.80499
28	514.72	57.16	0	171.47	1171.8	589.35	9.75	56.33	55.8945	54.2256	0.773123
28	486.12	28.58	57.16	171.47	1171.8	577.28	16.72	58.67	59.8254	58.6700	-1.96932
28	471.82	42.87	57.16	171.47	1171.8	572.05	17.19	57.33	58.0191	57.3300	-1.20199
28	457.53	57.16	57.16	171.47	1171.8	566.82	17.19	55.33	55.0602	55.3300	0.48762
56	571.19	0	0	171.47	1171.8	609.72	6.97	61.33	61.2641	61.3300	0.107451
56	543.31	28.58	0	171.47	1171.8	599.81	8.83	61.67	62.4786	67.8248	-1.31117
56	529.01	42.87	0	171.47	1171.8	594.58	9.23	69.67	68.4972	69.6700	1.683364
56	514.72	57.16	0	171.47	1171.8	589.35	9.75	65.67	65.6221	62.0506	0.07294
56	486.12	28.58	57.16	171.47	1171.8	577.28	16.72	68.67	67.1433	68.6700	2.223242
56	471.82	42.87	57.16	171.47	1171.8	572.05	17.19	68.33	61.2353	67.5019	10.38299
56	457.53	57.16	57.16	171.47	1171.8	566.82	17.19	60.33	60.8411	60.3300	-0.84717
90	571.19	0	0	171.47	1171.8	609.72	6.97	66.67	66.5322	66.6700	0.20669
90	543.31	28.58	0	171.47	1171.8	599.81	8.83	67.67	67.9173	67.6700	-0.36545
90	529.01	42.87	0	171.47	1171.8	594.58	9.23	76.33	71.4487	76.3300	6.394995
90	514.72	57.16	0	171.47	1171.8	589.35	9.75	71.67	72.0549	71.6700	-0.53704
90	486.12	28.58	57.16	171.47	1171.8	577.28	16.72	74.33	74.3562	78.7473	-0.03525
90	471.82	42.87	57.16	171.47	1171.8	572.05	17.19	73.67	73.4628	76.8461	0.281254
90	457.53	57.16	57.16	171.47	1171.8	566.82	17.19	67.33	75.5732	67.3300	-12.243

Table 6:Testing data sets for comparison of experimental results with testing results predicted from models (0.3w/b)

Data used in models construction								Compressive strength (MPa)			
AS(day)	C (kg/m³)	MK (kg/m³)	FA (kg/m³)	W (kg/m³)	CA (kg/m³)	S (kg/m³)	SP (l/m³)	Experimental results	ANN-I	ANN-II	% Error
3	571.19	0	0	171.47	1171.8	609.72	6.97	31.67	34.7699	44.9089	-9.78813
3	543.31	28.58	0	171.47	1171.8	599.81	8.83	38	36.1983	48.5502	4.741316
3	529.01	42.87	0	171.47	1171.8	594.58	9.23	41	42.6622	49.7599	-4.05415
3	514.72	57.16	0	171.47	1171.8	589.35	9.75	39.67	40.2548	44.8524	-1.47416
3	486.12	28.58	57.16	171.47	1171.8	577.28	16.72	29.67	30.6992	31.9423	-3.46882
3	471.82	42.87	57.16	171.47	1171.8	572.05	17.19	41.33	39.5046	49.6930	4.416647
3	457.53	57.16	57.16	171.47	1171.8	566.82	17.19	30.67	35.1654	64.2075	-14.6573
7	571.19	0	0	171.47	1171.8	609.72	6.97	42.33	38.5616	47.7150	8.902433
7	543.31	28.58	0	171.47	1171.8	599.81	8.83	39.33	39.4298	50.9818	-0.25375
7	529.01	42.87	0	171.47	1171.8	594.58	9.23	49.33	45.7944	51.9690	7.167241
7	514.72	57.16	0	171.47	1171.8	589.35	9.75	43.33	43.3153	47.7649	0.033926
7	486.12	28.58	57.16	171.47	1171.8	577.28	16.72	37.67	35.4088	35.8681	6.002655
7	471.82	42.87	57.16	171.47	1171.8	572.05	17.19	46.67	44.9872	53.2351	3.605742
7	457.53	57.16	57.16	171.47	1171.8	566.82	17.19	43.33	41.0843	66.6270	5.182783
28	571.19	0	0	171.47	1171.8	609.72	6.97	54.67	55.6254	57.4813	-1.74758
28	543.31	28.58	0	171.47	1171.8	599.81	8.83	55.67	56.5992	62.7938	-1.66912
28	529.01	42.87	0	171.47	1171.8	594.58	9.23	59	61.4769	61.5164	-4.19814
28	514.72	57.16	0	171.47	1171.8	589.35	9.75	57.67	56.8890	57.4781	1.354257
28	486.12	28.58	57.16	171.47	1171.8	577.28	16.72	56	57.6097	54.5571	-2.87446
28	471.82	42.87	57.16	171.47	1171.8	572.05	17.19	64	66.7489	68.0191	-4.29516
28	457.53	57.16	57.16	171.47	1171.8	566.82	17.19	55.67	52.6241	64.0402	4.638191
56	571.19	0	0	171.47	1171.8	609.72	6.97	61.33	61.5902	61.9474	-0.42426
56	543.31	28.58	0	171.47	1171.8	599.81	8.83	64.67	63.6546	72.8006	1.570125
56	529.01	42.87	0	171.47	1171.8	594.58	9.23	66.33	66.4007	67.8888	-0.10659
56	514.72	57.16	0	171.47	1171.8	589.35	9.75	62.67	57.5247	61.7325	8.210148
56	486.12	28.58	57.16	171.47	1171.8	577.28	16.72	65.33	59.6996	71.5947	8.618399
56	471.82	42.87	57.16	171.47	1171.8	572.05	17.19	67	66.5104	74.7460	0.730746
56	457.53	57.16	57.16	171.47	1171.8	566.82	17.19	62	63.4232	72.2025	-2.29548
90	571.19	0	0	171.47	1171.8	609.72	6.97	66.67	66.3562	72.0829	0.470676
90	543.31	28.58	0	171.47	1171.8	599.81	8.83	72.33	72.5650	70.3067	-0.3249
90	529.01	42.87	0	171.47	1171.8	594.58	9.23	77.33	77.8410	73.1089	-0.6608
90	514.72	57.16	0	171.47	1171.8	589.35	9.75	71	70.8850	69.9708	0.161972
90	486.12	28.58	57.16	171.47	1171.8	577.28	16.72	73.33	72.9947	70.1241	0.457248
90	471.82	42.87	57.16	171.47	1171.8	572.05	17.19	80.67	80.5015	72.0714	0.208876
90	457.53	57.16	57.16	171.47	1171.8	566.82	17.19	72.33	79.7649	74.6988	-0.1027

Table 7 Testing data sets for comparison of experimental results with testing results predicted from models (0.32w/b)

Data used in models construction								Compressive strength (MPa)			
AS (day)	C (kg/m³)	SF (kg/m³)	FA (kg/m³)	W (kg/m³)	CA (kg/m³)	S (kg/m³)	SP (l/m³)	Experimental results	ANN-I	ANN-II	% Error
3	571.19	0	0	182.90	1171.8	609.72	6.97	41	39.8121	40.9077	2.897317
3	543.31	28.58	0	182.90	1171.8	599.81	8.83	42	40.9684	41.9668	2.45619
3	529.01	42.87	0	182.90	1171.8	594.58	9.23	43	48.5766	40.2898	-12.9688
3	514.72	57.16	0	182.90	1171.8	589.35	9.75	39	41.1020	39.0706	-5.38974
3	486.12	28.58	57.16	182.90	1171.8	577.28	16.72	38	41.3959	38.0398	-8.93658
3	471.82	42.87	57.16	182.90	1171.8	572.05	17.19	36.5	41.0693	36.4176	-12.5186
3	457.53	57.16	57.16	182.90	1171.8	566.82	17.19	34.5	39.5496	34.1566	-14.6365
7	571.19	0	0	182.90	1171.8	609.72	6.97	42.33	41.1472	43.3135	2.794236
7	543.31	28.58	0	182.90	1171.8	599.81	8.83	40.67	42.3729	44.7696	-4.18712
7	529.01	42.87	0	182.90	1171.8	594.58	9.23	44.67	49.3674	44.6781	-10.5158
7	514.72	57.16	0	182.90	1171.8	589.35	9.75	44.33	42.2562	44.3331	4.678096
7	486.12	28.58	57.16	182.90	1171.8	577.28	16.72	42.33	46.1976	38.9734	-9.13678
7	471.82	42.87	57.16	182.90	1171.8	572.05	17.19	41	45.8415	41.5603	-11.8085
7	457.53	57.16	57.16	182.90	1171.8	566.82	17.19	39.33	44.2249	40.7892	-12.4457
28	571.19	0	0	182.90	1171.8	609.72	6.97	61	59.7935	60.4818	1.977869
28	543.31	28.58	0	182.90	1171.8	599.81	8.83	63	60.8687	63.0685	3.383016
28	529.01	42.87	0	182.90	1171.8	594.58	9.23	66	66.0386	67.5261	-0.05848
28	514.72	57.16	0	182.90	1171.8	589.35	9.75	60	61.2055	63.6606	-2.00917
28	486.12	28.58	57.16	182.90	1171.8	577.28	16.72	57	61.8216	49.9294	-8.45895
28	471.82	42.87	57.16	182.90	1171.8	572.05	17.19	64	61.7973	63.3652	3.441719
28	457.53	57.16	57.16	182.90	1171.8	566.82	17.19	67	61.9203	66.2662	7.581642
56	571.19	0	0	182.90	1171.8	609.72	6.97	66	70.6058	65.9877	-6.97848
56	543.31	28.58	0	182.90	1171.8	599.81	8.83	68	67.5857	72.5078	0.609265
56	529.01	42.87	0	182.90	1171.8	594.58	9.23	73.5	73.2627	76.5833	0.322857
56	514.72	57.16	0	182.90	1171.8	589.35	9.75	65	71.3565	64.9618	-9.77923
56	486.12	28.58	57.16	182.90	1171.8	577.28	16.72	64	69.7872	63.9073	-9.0425
56	471.82	42.87	57.16	182.90	1171.8	572.05	17.19	69	69.9256	69.4009	-1.34145
56	457.53	57.16	57.16	182.90	1171.8	566.82	17.19	72.5	70.0845	72.2466	3.331724
90	571.19	0	0	182.90	1171.8	609.72	6.97	66.67	67.3017	66.8701	-0.9475
90	543.31	28.58	0	182.90	1171.8	599.81	8.83	67.67	70.8083	66.9610	-4.63765
90	529.01	42.87	0	182.90	1171.8	594.58	9.23	76.33	76.0160	75.8728	0.411372
90	514.72	57.16	0	182.90	1171.8	589.35	9.75	71.67	73.3761	71.5011	-2.38049
90	486.12	28.58	57.16	182.90	1171.8	577.28	16.72	74.33	73.6580	68.8911	0.904076
90	471.82	42.87	57.16	182.90	1171.8	572.05	17.19	73.67	73.6901	73.0228	-0.02728
90	457.53	57.16	57.16	182.90	1171.8	566.82	17.19	67.33	73.2255	72.0396	-8.75613

Table8 Testing data sets for comparison of experimental results with testing results predicted from models (0.32w/b)

Data used in models construction								Compressive strength (MPa)			
AS (day)	C (kg/m³)	MK (kg/m³)	FA (kg/m³)	W (kg/m³)	CA (kg/m³)	S (kg/m³)	SP (l/m³)	Experimental results	ANN-I	ANN-II	% Error
3	571.19	0	0	182.90	1171.8	609.72	6.97	41	39.5607	38.5920	3.510488
3	543.31	28.58	0	182.90	1171.8	599.81	8.83	42.4	48.9336	45.8287	-15.4094
3	529.01	42.87	0	182.90	1171.8	594.58	9.23	46	50.8648	49.4082	-10.5757
3	514.72	57.16	0	182.90	1171.8	589.35	9.75	44.5	44.8786	40.6819	-0.85079
3	486.12	28.58	57.16	182.90	1171.8	577.28	16.72	43	43.9120	44.7331	-2.12093
3	471.82	42.87	57.16	182.90	1171.8	572.05	17.19	47.5	50.3154	44.5809	-5.92716
3	457.53	57.16	57.16	182.90	1171.8	566.82	17.19	46.2	48.4570	45.5674	-4.88528
7	571.19	0	0	182.90	1171.8	609.72	6.97	42.33	43.1016	41.9701	-1.82282
7	543.31	28.58	0	182.90	1171.8	599.81	8.83	55.35	52.6207	48.9622	4.930985
7	529.01	42.87	0	182.90	1171.8	594.58	9.23	57.5	54.8136	53.0566	4.672
7	514.72	57.16	0	182.90	1171.8	589.35	9.75	56.63	47.8480	46.0619	15.50768
7	486.12	28.58	57.16	182.90	1171.8	577.28	16.72	54.5	46.6720	49.2148	14.3633
7	471.82	42.87	57.16	182.90	1171.8	572.05	17.19	58.1	53.8550	48.2915	7.306368

7	457.53	57.16	57.16	182.90	1171.8	566.82	17.19	54.05	51.3431	47.8876	5.008141
28	571.19	0	0	182.90	1171.8	609.72	6.97	61	59.7119	56.6797	2.111639
28	543.31	28.58	0	182.90	1171.8	599.81	8.83	63.7	65.1722	60.2211	-2.31115
28	529.01	42.87	0	182.90	1171.8	594.58	9.23	67	66.5070	65.4213	0.735821
28	514.72	57.16	0	182.90	1171.8	589.35	9.75	65.2	62.2260	63.3655	4.56135
28	486.12	28.58	57.16	182.90	1171.8	577.28	16.72	66	59.9868	67.1228	9.110909
28	471.82	42.87	57.16	182.90	1171.8	572.05	17.19	68.5	67.3223	65.6470	1.71927
28	457.53	57.16	57.16	182.90	1171.8	566.82	17.19	64.8	64.5692	59.1054	0.356173
56	571.19	0	0	182.90	1171.8	609.72	6.97	66	66.5495	67.4413	-0.83258
56	543.31	28.58	0	182.90	1171.8	599.81	8.83	70	71.0091	68.4202	-1.44157
56	529.01	42.87	0	182.90	1171.8	594.58	9.23	72.95	74.2301	74.1683	-1.75476
56	514.72	57.16	0	182.90	1171.8	589.35	9.75	69	74.5866	72.0435	-8.09652
56	486.12	28.58	57.16	182.90	1171.8	577.28	16.72	70.42	71.5630	68.4062	-1.62312
56	471.82	42.87	57.16	182.90	1171.8	572.05	17.19	74	72.5775	70.8677	1.922297
56	457.53	57.16	57.16	182.90	1171.8	566.82	17.19	71.5	71.9113	71.9234	-0.57524
90	571.19	0	0	182.90	1171.8	609.72	6.97	66.67	66.7330	66.4152	-0.0945
90	543.31	28.58	0	182.90	1171.8	599.81	8.83	72.33	70.4433	69.8030	2.608461
90	529.01	42.87	0	182.90	1171.8	594.58	9.23	77.33	71.7324	74.5534	7.238588
90	514.72	57.16	0	182.90	1171.8	589.35	9.75	71	72.5326	72.0904	-2.15859
90	486.12	28.58	57.16	182.90	1171.8	577.28	16.72	73.33	74.8022	73.2528	-2.00764
90	471.82	42.87	57.16	182.90	1171.8	572.05	17.19	80.67	79.2472	67.9087	1.763729
90	457.53	57.16	57.16	182.90	1171.8	566.82	17.19	72.33	85.9765	67.8394	-18.867

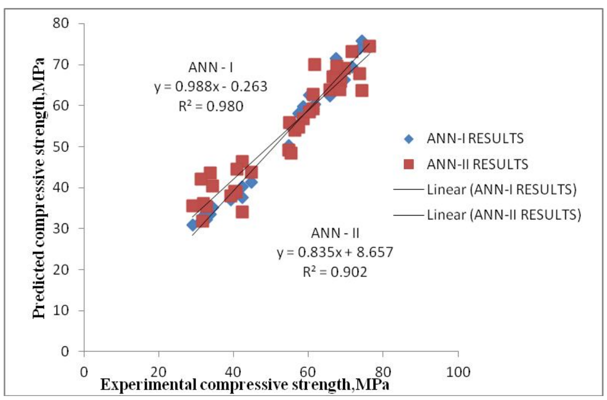

Fig. 6.Comparison of f_c experimental results with predicted results

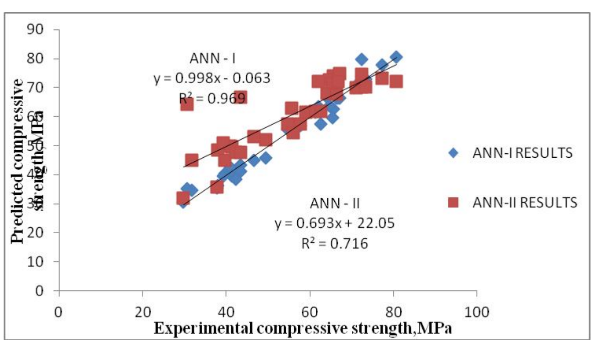

Fig..7.Comparison of f_c experimental results with predicted results

All results, obtained from experimental studies and predicted by using the training and testing results of ANN I and ANN II models, for 3, 7, 28, 56, and 90 days f_c were given in Figs. 6 and 7, respectively.The testing results obtained from ANN-I and ANN-II models were given in Tables. As it is visible in Figs. 6 and 7. The values obtained from the training and testing in ANN-I and ANN-II models are very closer to the experimental results.

The performance of the ANN models for compressive strength of cubes fc,is shown in Figs. 6 to 7, respectively. The statistical values for all the station such as RMS, R^2 and MAPE, both training and testing, are given in Table 9 While the statistical values of RMS, R^2 and MAPE from training in the ANN-I model were found as 2.1422, 99.12% and 1.8514%, respectively, these values were found in testing as 2.2551, 99.01% and 0.4287%, respectively. Similarly, while the statistical values of RMS, R^2 and MAPE from training in the ANN-II model were found as 4.4043, 99.65% and 3.7135%, respectively, these values were found in testing as 4.7382, 94.99% and 3.3920%, respectively. The best value of R^2 is 99.65% for training set in the ANN-II model. The minimum value of R^2 is 99.01% for testing set in the ANN-I model. All of the statistical values in Table 9 show that the proposed ANN-I and ANN-II models are suitable and predict the 3, 7, 28, 56, and 90 days fc values very close to the experimental values.

Table.9. The f_c statistical values of proposed ANN-I and ANN-II models for SF&FA(0.3w/b)

Statistical parameters	ANN-I		ANN-II	
	Training set	Testing set	Training set	Testing set
RMS	2.1422	2.2551	4.4043	4.7382
R^2	0.9912	0.9901	0.9965	0.9459
MAPE(%)	1.8514	0.4287	3.7135	3.3920

IV. CONCLUSION

Artificial neural networks are capable of learning and generalizing from examples and experiences. This makes artificial neural networks a powerful tool for solving some of the complicated civil engineering problems. In this study, using these beneficial properties of artificial neural networks in order to predict the 3, 7, 14, 28, 56, and 90 compressive strength of concretes containing metakaolin and silica fume along with fly ash without attempting any experiments were developed with two different multilayer artificial neural network architectures namely ANN-I and ANN-II. In the two models developed in ANN method, a multilayered feed forward neural network with a back propagation algorithm was used. In ANN-I model, one hidden layer was selected. In the hidden layer 10 neurons were determined.

In ANN-II model, two hidden layers were selected. As a result, compressive strength of concretes containing metakaolin and silica fume can be predicted in the multilayer feed forward artificial neural networks models without attempting any experiments in a quite short period of time with tiny error rates.

The obtained conclusions have demonstrated that multilayer feed forward artificial neural networks are practicable methods for predicting compressive strength values of concretes containing metkaolin and silica fume.

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