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PREDICTING COMPRESSIVE STRENGTH OF CONCRETE CONTAINING TERNARY COMBINATION OF INDUSTRIAL BY-PRODUCTS AS PARTIAL REPLACEMENT OF CEMENT AND FINE AGGREGATES USING ANN AND ANFIS

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Abstract- Compressive strength of concrete is one of the important mechanical properties of the concrete and most essential factor for the quality assurance of concrete. This paper presents three different data-driven models, i.e. Taguchi, artificial neural network (ANN) and ANFIS to predict the compressive strength of concrete containing ternary combinations of industrial by-products as partial replacement of cement and fine aggregates. Cement was partially replaced with fly-ash, ladle furnace slag and copper slag at 10%, 25% and 40% level and fine aggregate was partially replaced by electric arc furnace slag, iron slag and glass powder at 20%, 30% and 40% level. The water to binder ratio was fixed at 0.40, 0.44 and 0.48 and the curing age was fixed at 7, 28 and 90 days. An L9 Taguchi orthogonal array was used to design the experiments for four parameters at three levels giving rise to a total of nine trial experiments for one set of water to binder ratio and curing age. The mix constituents were fed as the input parameters to achieve the compressive strength as the target. Thus a total of 90 datasets are used to develop an ANN and ANFIS models to predict the compressive strength having input and output data obtained from the laboratory experiments. Results show that the ANFIS model provides better accuracy than the ANN model for prediction of the compressive strength of this type of concrete.
Keywords- Concrete; Compressive strength; Industrial by-products; Artificial neural network (ANN); Adaptive neuro-fuzzy inference systems (ANFIS); Taguchi method.

1. INTRODUCTION

Today, concrete is one of the most widely used construction material composed of binding material like cement, fine and coarse aggregates. The construction cost is becoming very high due to the shortage of natural ingredients which provide volume to concrete like sand and aggregates and the high cost of concrete. There is a need for alternate material that matches the properties of cement and natural sand in concrete. This problem can be solved by partial replacing cement and sand with industrial waste. Such waste includes fly ash, ladle furnace slag, copper slag, electric arc furnace slag, iron slag, glass powder and others. The usage of these as partial replacement material reduces the amount of Portland cement and sand needed for concrete. This also reduces both energy and impact of CO2 on the environment and helps in improving the workability and long-term properties of concrete. The utilization of such materials in concrete not only makes it economical but also helps in reducing the disposal problems. These industrial by-products possess sufficient cementitious and pozzolanic properties which make them an excellent alternative material for partial replacement of cement and sand [1-4].Several studies have been reported in the literature that justifies the use of these alternate industrial wastes as replacement of sand and cement. A comprehensive review of literature shows that there have been several studies that report the effect of industrial waste on compressive strength, however many of these industrial by-products have not been used in ternary combinations as partial replacement of cement and sand, but some researchers have used some industrial by-products in binary combinations as partial replacement of cement and sand.

Adolfsson et al. [5] investigated the hydraulic characteristics of ladle furnace slag (LFS) as a substitute for cement for some applications. LFS contains a high content of calcium aluminates and the hydration of different calcium aluminates in water results in the formation of hydrates such as C2AH8, C4AH13, CAH10 and C3AH6 which give strength to the material. Devi et al. [6] have reported that there is an increment in compressive strength of concrete by 27.04% in which sand was replaced by 40% steel slag. Papayianni et al. [7] used high-calcium fly ash and LFS as the binder and electric arc furnace slag (EAF) as aggregate. The produced concrete showed high-strength (>70 MPa) in case of 100% replacement of the coarse and 50% replacement of the fine aggregate by EAF. Chidiac et al. [8] studied the use of glass powder in high strength concrete and

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found that no ASR was detected even with 25% of the cement replaced with waste glass powder. Ducman et al. [9] investigated the feasibility of the refractory concrete production using EAFS as aggregates and the results showed that when slag was heated up to a temperature of 1000 °C, prior to its use for refractory concrete, the final product exhibited mechanical properties which are comparable to concrete with conventional refractory aggregate, e.g. bauxite. Rashad [10] reviewed from the various researchers that the ASR expansion of mortar and concrete specimens containing glass sand can be mitigated by adding 10–30% MK, 20–50% FA, 50–60% slag, 10% SF, 1–2% Ni2CO3, 1% LiNO3 and suitable amount of fibers. The presence of C3S, C2S and C4AF endorse steel slag having cementitious properties. Huang et al. [11] prepared a cementitious material by utilizing phosphogypsum (PG), steel slag (SS), granulated blast-furnace slag (GGBFS) and limestone (LS). The results showed that the 28 days compressive strength of a mixture of 45% PG, 10% SS, 35% GGBFS and 10% LS exceeded 40 MPa and the main hydration products were ettringite and C–S–H gel. Pellegrino et al. [12] found that replacement of fine natural aggregates with EAF slag is feasible at lower substitution ratios (Up to 7%). Thomas [13] reviewed in his paper that ASR damages can be effectively mitigated by using fly ash and other supplementary cementitious materials (SCM's) in concrete. Adaway et al. [14] replaced fine aggregate with glass powder at 15, 20, 25, 30 and 40% level. The compressive strength was found to increase up to a level of 30%, at which point the strength developed was 9% and 6% higher than the control after 7 and 28 days respectively. Kothai et al. [15] found that the compressive strength of the concrete increases and the optimum value was found at a slag replacement proportion of 30% of fine aggregate and after that, any further replacement of slag decreases the compressive strength. Du et al. [16] found that concrete containing up to 100% glass sand obtained similar compressive strength to that of the control after 28 days, with 90-days compressive strength increasing with glass percentage.

For the last three decades, different modeling methods based on artificial neural networks (ANN) and Adaptive neuro-fuzzy inference systems (ANFIS) have become popular and have been widely used to solve a variety of problems in many areas of science and engineering applications. The compressive strength of concrete can be predicted using the models built with ANN and ANFIS. Raif et al. [17] predicted the mechanical properties of concrete containing GGBFS and CNI using ANN and ANFIS and determined that experimental data can be estimated to a notably close extent via ANN and ANFIS models. Atici [18] predicted the strength of mineral admixture concrete containing blast furnace concrete and fly ash using MRA and ANN and found that ANN is suitable for calculating nonlinear functional relationships, for which classical methods cannot be applied. Chithra et al. [19] constructed models based on artificial neural networks and regression analysis to predict the compressive strength of high-performance concrete containing nano-silica and copper slag as partial replacement of cement and fine aggregate and concluded that ANN models generated better results. Douma et al. [20] predicted compressive strength of self-compacting concrete containing fly ash using fuzzy logic inference system and resulted in the strong potential for predicting the compressive strength. Muthupriya et al. [21] developed artificial neural networks for predicting the compressive strength of concrete containing metakaolin with fly ash and silica fume and found that ANN has a high potential for predicting the compressive strength values of such concrete. Vidivelli et al. [22] presented an ANN-based model to predict the compressive strength of concrete containing industrial by-products and concluded that the artificial neural network (ANN) performed well to predict the compressive strength of high-performance concrete for various curing period. Saridemir [23] developed artificial neural networks and fuzzy logic models for prediction of long-term effects of ground granulated blast furnace slag on compressive strength of concrete and found that ANN and fuzzy logic systems have strong potential for prediction of long-term effects of ground granulated blast furnace slag on compressive strength of concrete. Chopra et al. [24] proposed an ANN model to predict the compressive strength of concrete and found that Levenberg- Marquardt (LM) with tan-sigmoid activation function is best for the prediction of the compressive strength of concrete. Gupta [25] presented the application of artificial neural network to develop a model for predicting 28 days compressive strength of concrete with partial replacement of cement with nano-silica. Topcu et al. [26] developed artificial neural networks and fuzzy logic models for predicting the 7, 28 and 90 days compressive strength of concretes containing high-lime and low-lime fly ashes and found that ANN and fuzzy logic systems have strong potential for predicting the 7, 28 and 90 days compressive strength of concretes containing high-lime and low-lime fly ashes. Naniz et al. [27] developed two Artificial Neural Network (ANN) models for predicting the compressive strength of concrete containing Slag and Silica fume, at the age of 7, 28, 90 and 180 days and found that ANN has strong potential as a powerful tool for predicting 7, 28, 90 and 180 days compressive strength values of concretes containing slag and silica fume.

This study aims to predict the compressive strength of concrete containing industrial by-products in ternary combinations as partial replacement of cement and sand by constructing ANN and ANFIS models. The obtained results of compressive strength tests for both ANN and ANFIS have been compared with predicted results

In this study, cement was partially replaced with fly-ash, ladle furnace slag and copper slag each at 10%, 25% and 40% level and fine aggregate was partially replaced by electric arc furnace slag, iron slag and glass powder each at 20%, 30% and 40% level. The water to binder ratio was fixed at 0.40, 0.44 and 0.48 and the curing age was fixed at 7, 28 and 90 days for each level. There are four factors namely (i) percentage of by-product used as binder, (ii) percentage of by-product used as fine aggregate, (iii) type of replacement material as a binder and (iv) type of replacement material as fine aggregate. Each factor was varied at three levels. Water to binder ratio and curing age was kept constant for all levels. The list of factors and their respective levels are shown in Table 1. As per the concept of experimental design, to obtain a relationship of each factor to compressive strength, each factor must be varied at least two levels. However, it is difficult to establish a mathematical

relationship between only two data points. Thus it was decided to vary each factor at a minimum of three levels. Increasing the number of levels at which each factor is varied would have made the experimental work extremely large. With four factors varied at three levels each, Taguchi L9 orthogonal array was selected for experimentation. An L9 orthogonal array has four columns, and each factor was assigned to of the four columns. L9 allows for 9 trials to be conducted by varying the four factors at three levels each. The experimental test strategy during L9 is given in Table 2.
Using full factorial method the number of experiments comes out to be 729, and to reduce the number of experiments, a standard L9 Taguchi Orthogonal Array (OA) was used. Using this methodology, the total experiments have been reduced to 81 instead of 729 thus considerably saving the time and material.

Table 1: List of factors varied during the experimentation and their levels

Factors		Levels at which varied		
Designation	Type	1	2	3
A	Percentage of by-product to be used as partial replacement of cement	10%	25%	40%
B	Percentage of by-product to be used as partial replacement of fine aggregate	20%	30%	40%
C	Type of replacement material as a binder	Fly ash (FA)	Ladle Furnace Slag (LFS)	Copper Slag (CS)
D	Type of replacement material as Fine aggregate	Electric Arc Furnace Slag (EAFS)	Iron Slag (IS)	Glass Powder (GP)

Table 2: Experimental test strategy

Experiment No	A Percentage of by-product to be used as partial replacement of cement	B Percentage of by-product to be used as partial replacement of fine aggregate	C Type of replacement material as a binder	D Type of replacement material as Fine aggregate	Response
1.	10%	20%	Fly ash	Electric Arc Furnace Slag	For each experiment compressive strength was measured
2.	10%	30%	Ladle Furnace Slag	Iron Slag	
3.	10%	40%	Copper Slag	Glass Powder	
4.	25%	20%	Ladle Furnace Slag	Glass Powder	
5.	25%	30%	Copper slag	Electric Arc Furnace Slag	
6.	25%	40%	Fly ash	Iron Slag	
7.	40%	20%	Copper Slag	Iron Slag	
8.	40%	30%	Fly ash	Glass Powder	
9.	40%	40%	Ladle Furnace Slag	Electric Arc Furnace Slag	

Each of the experimental plans depicted in Table 2 was completed for three sets of curing age (i.e. 7, 28 and 90 days) and three sets of W/B ratio, namely 0.40, 0.44 and 0.48. So in effect, 81 experiments were conducted for this study (9 as depicted above for 3 curing ages and another 3 for W/B ratio).
The compressive strength of concrete is a major and important mechanical property, which is generally obtained by crushing the concrete specimen after a specified curing period. Conventional methods of predicting the compressive strength of concrete are generally based on Abrams water-cement ratio rule. Several studies have shown that the compressive strength of concrete is also influenced by the content of other concrete ingredients such as the use of supplementary cementitious materials (SCM's). During this study, modeling methods based on ANFIS and ANN has been used to predict the compressive strength of concrete consisting of SCM's.

2. MATERIALS

The details of the properties of materials used in the study are presented in the following sections.

2.1. Cement

The cement used in this study was Ordinary Portland Cement of 43 grades conforming to BIS 12269 -1987 [28], with a specific gravity of 3.12.

2.2. Fine and coarse aggregate

The fine aggregate used in this study was river sand and conforming to grading zone II as per BIS 383-1970 [29]. The fine aggregate is characterized by a specific gravity of 2.73, fineness modulus of 2.46 and water absorption of 1.01%. The coarse aggregate conforming to BIS 383-1970 [29] used in this study was crushed stone with an optimum mix of 20 mm and 10 mm size aggregates having a specific gravity of 2.69 and 2.72 respectively. The fine and coarse aggregates were tested as per BIS 2386 Part III-1963 [30].

2.3 Industrial by-products

Total of six industrial by-products were used in this study. Three industrial by-products namely fly ash, ladle furnace slag and copper slag were used as a cement replacement, and the other three industrial by-products namely electric arc furnace slag, iron slag and glass powder was used as the sand replacement. All these industrial by-products were locally procured from the nearby industries. The Energy Dispersive X-ray Spectroscopy (EDS) and Scanning Electron Microscopy (SEM) tests were used to find the chemical composition of these industrial by-products. The physical and chemical properties of these industrial by-products are presented in Table 3.

Table 3: Physical properties and Chemical composition of by-products used as a Binder and fine aggregate

Binder						Fine Aggregate					
Copper Slag		Ladle Furnace Slag		Fly-ash		Glass Powder		Electric Arc Furnace Slag		Iron Slag	
Fineness (% retained at 90µm)	85	Fineness (% retained at 90µm)	20	Fineness (% retained at 90µm)	0	Fineness Modulus	1.5	Fineness Modulus	1.6	Fineness Modulus	1.63
Specific gravity	3.91	Specific gravity	3.35	Specific gravity	2.35	Specific gravity	2.61	Specific gravity	2.93	Specific gravity	3.35
CaO	1.12	CaO	51.33	CaO	0.89	CaO	3.89	CaO	29.92	CaO	0.85
SiO_2	12.27	SiO_2	13.98	SiO_2	49.65	SiO_2	53.42	SiO_2	4.33	SiO_2	30.33
Al_2O_3	1.65	Al_2O_3	6.21	Al_2O_3	35.52	Al_2O_3	2.11	Al_2O_3	24.09	Al_2O_3	12.40
FeO	76.66	MgO	1.61	FeO	6.72	MgO	1.86	MgO	13.45	MgO	0.75
CuO	0.83	CuO	1.31	CuO	2.43	CO_2	5.77	CO_2	17.46	CO_2	34.95
SO_3	0.73	SO_3	4.09	SO_3	---	K_2O	7.41	$\sum TiO_2 + SO_3 + MnO + Cr_2O_3$	---	TiO_2	0.60
K_2O	0.28	K_2O	---	K_2O	1.09	Na_2O	6.32	PiO_2	10.76	MnO	9.67
ZnO	2.23	ZnO	---	ZnO	2.14	PbO	15.84				
CO_2	4.23	CO_2	21.46	TiO_2	1.55	CuO	3.38				

2.4. Superplasticizer

The superplasticizer used in the current study was polycarboxylate based, i.e. Auramix 400 which conforms to BIS 9103-1999 [31]. Auramix 400 is a high-performance superplasticizer intended for applications where high water reduction and long workability retention are required. The properties of the superplasticizer used are presented in the table. 4.

Table 4: Properties of Superplasticizer

S. No.	Characteristics	Value
1.	Appearance	Light yellow coloured liquid
2.	pH	Minimum 6.0
3.	Volumetric mass@ 20 0C	g/litre

3. DATA COLLECTION

The experimental methodology was designed as per Taguchi's L9 orthogonal array. The cement was replaced with fly ash, ladle furnace slag and copper slag at 10%, 25% and 40% level. The sand was replaced with electric arc furnace slag, iron slag and glass powder at 20%, 30% and 40% level. The mix was designed for water to binder ratio of 0.40, 0.44 and 0.48 as per

BIS 10262-1982 [32]. Thus 27 concrete mixtures relating to each of the nine experiments listed in Table 2 were prepared. Additionally, three more mixes representing a control mix with no replacement were also made for comparison as given in Table 5 to Table 7. Potable water was used for making concrete. All the concrete mixtures were prepared with good supervision and were cured adequately for curing ages of 7, 28, and 90 days. The raw data for model generation includes (i) water/binder ratio (W/B), (ii) Curing period (CP) (iii) Cement content (C), (iv) type of binder as replacement of cement (RC), (v) Replaced binder % content (RCP), (vi) Sand content(S), (vii) type of fine aggregate as replacement of sand (RS), (viii) Replaced fine aggregate % content (RSP) and (ix) Dose of superplasticizer(SP). The coarse aggregate content (CA) and water content (W) were kept constant for all the concrete mixes. The response parameter is the experimental compressive strength (CST), whereas, the output obtained is designated as predicted compressive strength (PCS).

Table 5: Concrete Mix Design Proportion Using specific gravity of by-products for Water /Binder Ratio = 0.40

Exp. No	Binder (Kg/m³)			Fine Aggregate (kg/m³)			Superplasticizer (l/m3)	Compressive Strength (MPa)		
	Cement	Replacement Material	Amount	FA	Replacement Material	Amount		7 days	28 days	90 days
1.	393.75	FA	32.95	522.67	EAFS	140.24	1.97	41.5	53.76	72.05
2.	393.75	LFS	46.97	457.33	IS	240.51	2.95	39.82	50.32	64.35
3.	393.75	CS	54.83	392	GP	249.85	3.93	30.8	46.2	51.18
4.	328.12	LFS	117.44	522.67	GP	124.92	3.28	27.5	39.6	44.55
5.	328.12	CS	137.07	457.33	EAF	210.36	3.28	29.81	40.92	46.2
6.	328.12	FA	82.38	392	IS	320.68	3.28	31.24	49.94	66.33
7.	262.5	CS	219.31	522.67	IS	160.33	1.31	21.12	31.21	36.22
8.	262.5	FA	131.81	457.33	GP	187.39	2.62	29.77	49.14	64.9
9.	262.5	LFS	187.9	392	EAF	280.47	5.24	25.85	30.88	39.38
Control Mix										
	437.5	-	0	653.34	-	0	0	39.8	51.05	55.64

Table 6: Concrete Mix Design Proportion Using specific gravity of by-products for Water /Binder Ratio = 0.44

Exp. No	Binder (Kg/m³)			Fine Aggregate (kg/m³)			Superplasticizer (l/m3)	Compressive Strength (MPa)		
	Cement	Replacement Material	Amount	FA	Replacement Material	Amount		7 days	28 days	90 days
1.	360	FA	30.13	543.14	EAF	145.73	0.9	30.97	47.83	61.33
2.	360	LFS	42.95	475.25	IS	249.93	2.16	31	45.68	56.21
3.	360	CS	50.13	407.36	GP	259.63	2.7	29.83	40.79	48.11
4.	300	LFS	107.37	543.14	GP	129.82	2.25	26.94	37.14	43.45
5.	300	CS	125.32	475.25	EAF	218.6	2.25	28.82	37.62	45.34
6.	300	FA	75.32	407.36	IS	333.24	1.5	30.42	46.6	60.35
7.	240	CS	200.51	543.14	IS	166.62	0.72	19.58	27.03	33.81
8.	240	FA	120.52	475.25	GP	194.73	1.2	25.74	37.95	51.62
9.	240	LFS	171.8	407.36	EAF	291.47	4.8	23.96	28.08	36.74
Control Mix										
	400	-	0	678.93	-	0	0	30.5	45.13	47.2

Table 7: Concrete Mix Design Proportion Using specific gravity of by-products for Water /Binder Ratio = 0.48

Exp. No	Binder (Kg/m³)			Fine Aggregate (kg/m³)			Superplasticizer (l/m3)	Compressive Strength (MPa)		
	Cement	Replacement Material	Amount	FA	Replacement Material	Amount		7 days	28 days	90 days
1.	333.75	FA	27.93	560.98	EAF	150.52	0.33	28.6	46.05	57.09
2.	333.75	LFS	39.82	490.86	IS	258.14	1.66	28.38	45.02	55.96

3.	333.75	CS	46.47	420.74	GP	267.13	1.66	26.48	39.82	45.98
4.	278.12	LFS	99.54	560.98	GP	133.56	1.39	21.48	30.23	38.5
5.	278.12	CS	116.18	490.86	EAF	225.78	1.39	22.3	33.96	41.09
6.	278.12	FA	69.83	420.74	IS	344.19	0.69	22.73	39.08	56.77
7.	222.5	CS	185.9	560.98	IS	172.1	0.44	16.06	23.76	31.1
8.	222.5	FA	111.73	490.86	GP	200.35	1.1	21.78	31.82	44.73
9.	222.5	LFS	159.27	420.74	EAF	301.04	4.44	17.16	24.11	32.45
Control Mix										
	370.83	-	0	701.23	-	0	0	27.00	42.06	46.2

3.1. Testing method

The compressive strength was tested on cubes of sides 150 mm in accordance with BIS 516-1959 [33]. The compressive strength was determined for curing ages of 7, 28, and 90 days. For each mixture, three specimens were tested. The testing was carried out on the specimen in wet condition using Compression Testing Machine of 5000 kN capacity. The cubes were placed on the machine such that the load was applied to the opposite sides of the cube as cast. The loading was increased continuously at a rate of 140 kg/cm2/min, and the maximum load that can be sustained by the specimen was noted. The maximum load divided by the cross-sectional area of the specimen gave the compressive strength. For each mixture, the average of the three samples was considered to be the compressive strength of the particular mix at a specified curing age. The variations between the three specimens did not exceed ±15 %.

Compressive strength was measured at 7, 28 and 90 curing days and as shown in the last three columns of Tables 5 to 7 above.

4. MODELLING

To obtain a generalized structure, the compressive strength results presented in Table 8 were modelled using ANN and ANFIS. For each model, the input and output parameters were varied.

4.1. Artificial Neural Network (ANN) Model

Neural networks are very sophisticated modelling techniques capable of modelling extremely complex functions. The true power and advantage of neural networks lie in their ability to represent both linear and nonlinear relationships and in their ability to learn these relationships directly from the data being modelled. These networks learn by example. The user of neural networks gathers representative data and then invokes training algorithms to learn the structure of the data automatically. Artificial Neural Network consists of many simple elements called neurons. The neurons interact with each other using weighted connection similar to biological neurons. Inputs to the artificial neural net are multiplied by corresponding weights. All the weighted inputs are then segregated and then subjected to nonlinear filtering to determine the state or active level of neurons. The ANN consists of three groups, or layers of units: a layer of "input" units also called input layer is connected to a layer of "hidden" units also called hidden layer, which is further connected to a layer of "output" units also called output layer, as represented in Fig. 1.

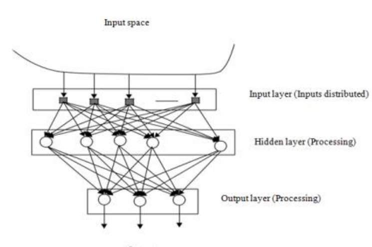

Figure1: Artificial neural network

4.1.1. Architecture of neural networks

There are several algorithms which can be implemented in Artificial Neural Network Modelling. Among the various algorithms available, Levenberg–Marquardt backpropagation (LMBP) algorithm is the most commonly used training algorithm due to its speed and robustness Kermani et al. [34]. Hence, in this paper, Levenberg–Marquardt backpropagation (LMBP) algorithm has been adopted to synthesize Artificial Neural Network models. This algorithm uses the layered feed-forward networks, in which, the neurons are arranged in layers, signals are sent forward, and errors are propagated backwards (Fig. 2.). The number of iterations required by the neural network model to converge is termed as the epoch. It is an indication of the number of times the weights were reinitialized until a satisfactory model with the highest possible correlation, was obtained with minimum error.

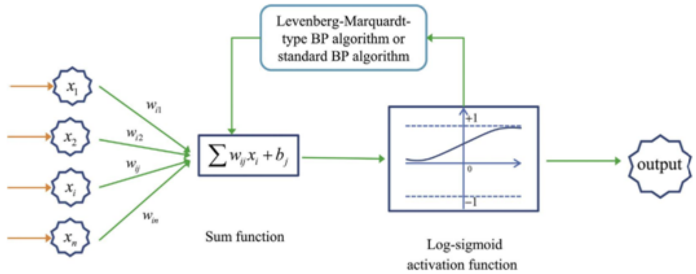

Figure2: Architecture of typical ANN. A typical ANN with input, sum function, log-sigmoid activation function, and output

4.1.2. Neural network model structure and parameters

The neural network model has been developed using Neural Network Toolbox in MATLAB software. The model is generated with nine neurons in the input layer and 20 neurons in the hidden layer and one neuron in the output layer as shown in Fig. 3.

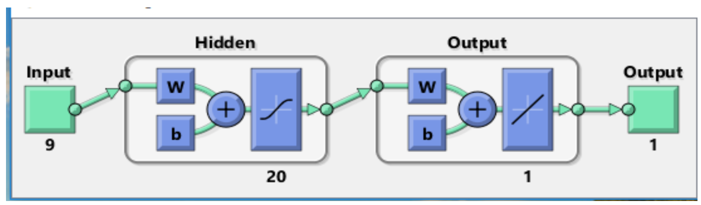

Figure3: A multi-layer tansig-purelin network with nine input neurons, one output neuron, and one hidden layer of twenty neurons

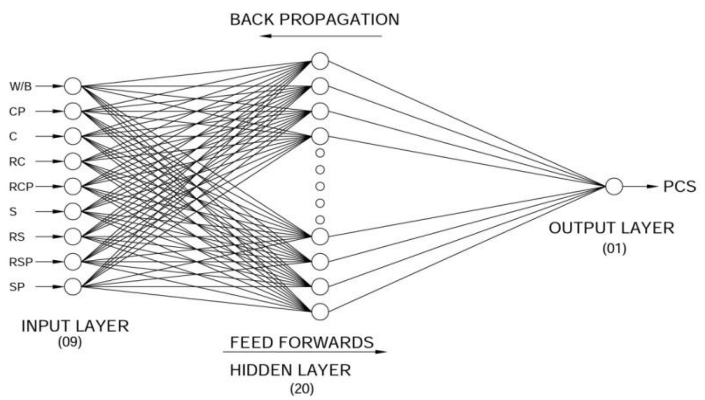

Figure4: Configuration of the FFBP neural network for the concrete on the response compressive strength

The neurons of adjacent layers are completely interconnected with each other by weights. The output layer neurons produce the network output as a prediction of compressive strength. The configuration of the Feed Forward Back Propagation (FFBP) neural network for the concrete on the response compressive strength has been shown in fig. 4. Among the total data, approximately 70% of the data has been considered for training. Out of the remaining 30% data, 15% each has been considered for testing and validation respectively. In training, adjustments of weights of each parameter take place, such that the variation between actual and predicted values is minimized. A non-linear sigmoidal function is used as the transfer function. The learning behaviour of the FFBP neural network model and performance results of the FFBP algorithm, developed for the model of compressive strength is shown in the fig. 7 and fig. 8.

To minimize the mean squared error (MSE) of the training data, the values of various parameters selected in the neural network model are as under:-

Number of input layer units=9

Number of hidden layers=1

Number of hidden layer units=20

Number of output layer units=1

Momentum rate =0.9

Learning rate= 0.3

Error after learning= 0.001

The comparison of the Experimental/Target and predicted compressive strength versus all data samples and their correlation for training, validation, testing is shown in fig. 5 and fig. 6 respectively.

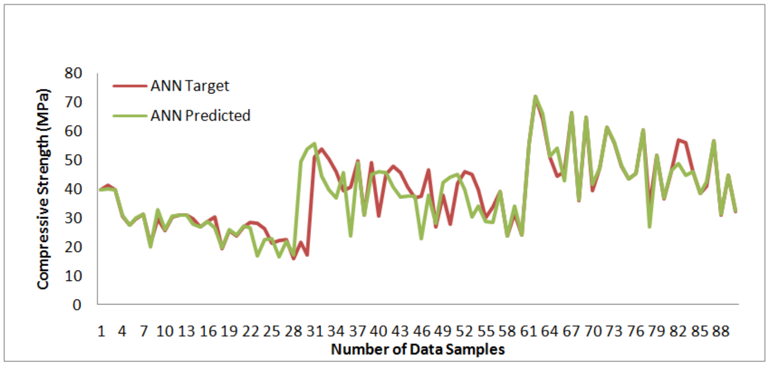

Figure5: The comparison of the Experimental/Target and predicted compressive strength versus all data samples for ANN modelling

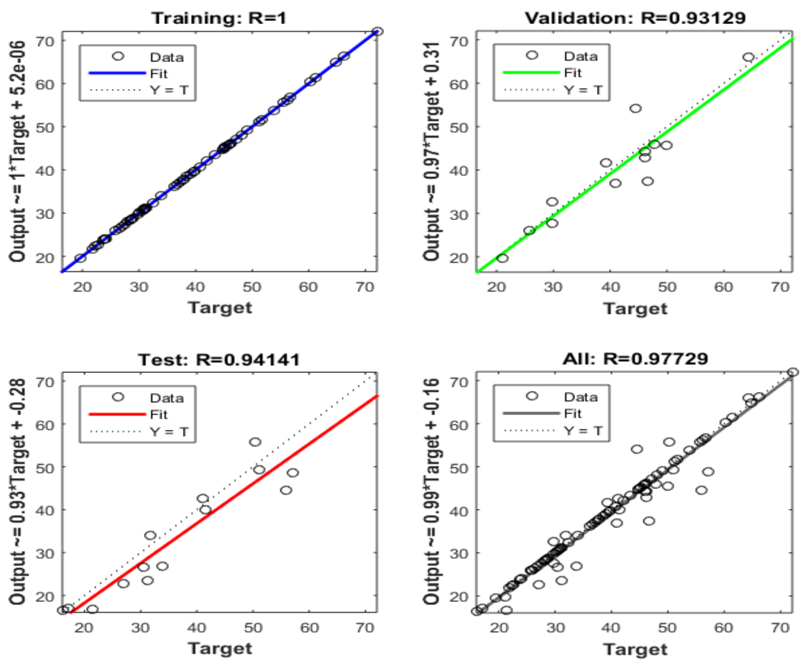

Figure6: The correlation between the experimental values and the FFBP-ANN predicted values of compressive strength for training, validation, testing and overall.

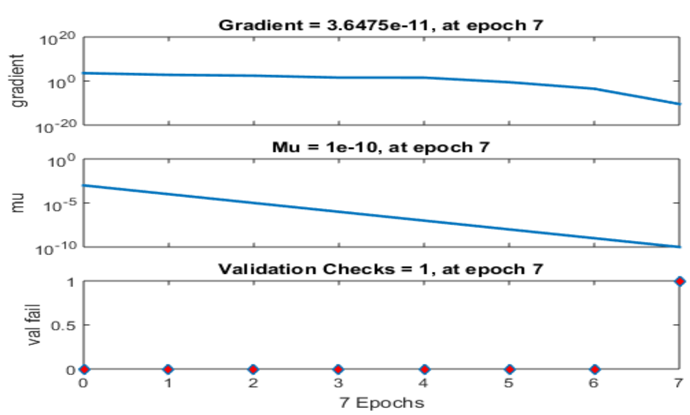

Figure7: Learning behaviour of the FFBP neural network model

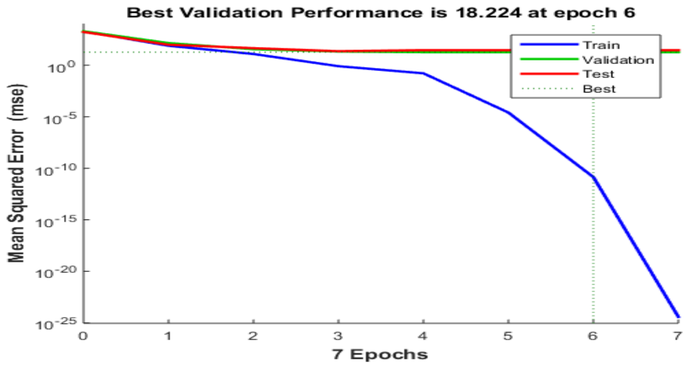

Figure8: The performance results of the FFBP algorithm developed for the model of compressive strength.

4.2. Adaptive Neuro-Fuzzy Inferencing Systems (ANFIS) Model

The adaptive neuro-fuzzy inference system was first introduced by Jang [35]. ANFIS incorporates the human-like reasoning style of fuzzy inference systems (FIS) by the use of input-output sets and a set of IF-THEN fuzzy rules. FIShas a structured knowledge where each fuzzy rule describes a local behaviour of the system. However, it lacks the adaptability to deal with a changing external environment. Therefore neural network learning concepts have been incorporated in FIS, resulting in ANFIS. In the network, the basic learning algorithm, the back propagation, aims to minimize the prediction error. For the reasons above, in ANFIS, both the learning capabilities of a neural network and reasoning capabilities of fuzzy logic are combined. Yuan et al. [36]

The architecture of ANFIS with two input variables is shown in Fig. 9 and the fuzzy-reasoning mechanism illustrates as follows:

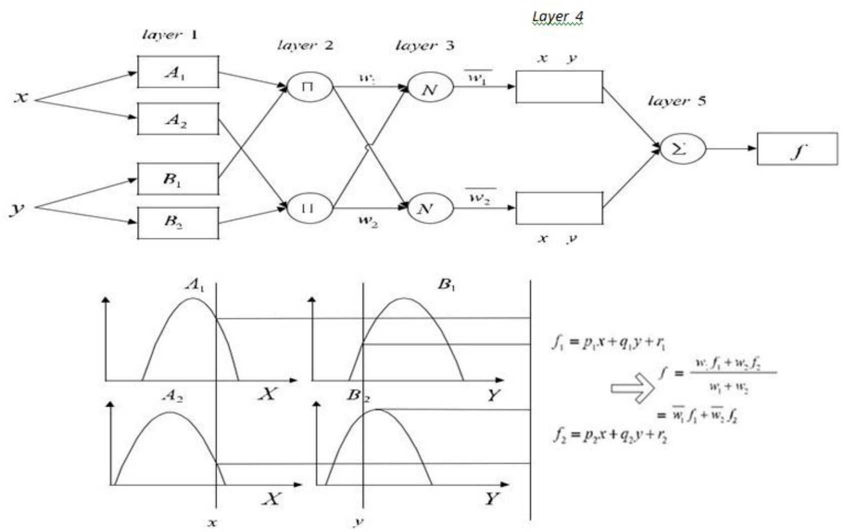

Figure9: Architecture of ANFIS and Fuzzy-reasoning scheme of ANFIS.

Rule 1: IF x is A1 and y is B1, THEN f1 = p1 + q1 + r1.

Rule 2: IF x is A2 and y is B2, THEN f2 = p2 + q2 + r2.

The function of each layer is described subsequently:

Layer 1

The first layer of this architecture is the fuzzy layer. Each node of this layer makes the membership grade of a fuzzy set. Every node in this layer is an adaptive node with a node function.

Oi1 = μAi (x)

The where x is the input to node i and Ai is the linguistic label associated with this node function. Premise parameters change the shape of the membership function.

Layer 2

Every node in this layer is a circle node labeled Π, representing the firing strength of each rule, which multiplies the incoming signals and sends the products out, i.e. Π-norm operation.

Oi2 = μAi(x) x μBi(y), i = 1, 2

Layer 3

Every node in this layer is a circle node labeled N, representing the normalized firing strength of each rule. The ith node calculated the ratio of the ith rule’s firing weight to the sum of all rule’s firing weights:

$Oi3 = \overline{wi} = \frac{wi}{w1+w2}$, i = 1, 2

The outputs of this layer are called normalized firing strengths.

Layer 4

Every node in this layer is an adaptive node with a node function, indicating the contribution of the ith rule towards the overall output.

$Oi4 = \overline{wi}\ fi = \overline{wi}\,(pix + qiy + ri)$, i = 1,2

Where $\overline{wi}$ is the output of layer 3, and (pix + qiy + ri) is the parameter set.

Layer 5

The signal node in this layer is a circle node labeled ∑, indicating the overall output as the summation of all incoming signals calculated, i.e.

$Oi5 = \sum \overline{wi}\ fi = \frac{\sum wifi}{\sum wi}$

There were five layers in this model, including input, input membership function, rule, the output membership function and output. The data set used in the ANFIS model was the first sets of data.

MATLAB R2005a with adaptive neural-fuzzy inference system toolbox was employed. Subtractive clustering method was used to build the model using the MATLAB ANFIS toolbox as it was easy to generate an input-output rule model and without an exponential explosion. The comparison of the Experimental and predicted compressive strength for all data, test data and training data samples for ANFIS modelling have been shown in fig. 10 to fig. 12 respectively. The correlation between the experimental values and the predicted values by ANFIS of compressive strength for training, testing and overall data is shown in fig. 13.

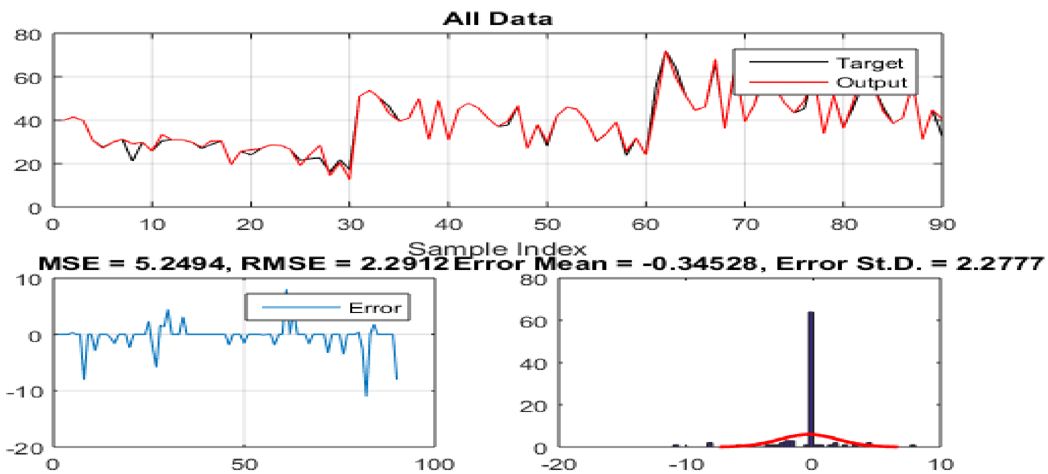

Figure10: The comparison of the Experimental and predicted compressive strength for all data samples for ANFIS modelling.

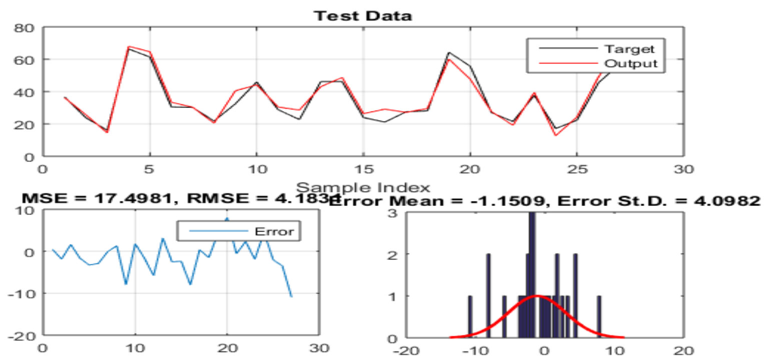

Figure11: The comparison of the Experimental and predicted compressive strength for test data samples for ANFIS modelling

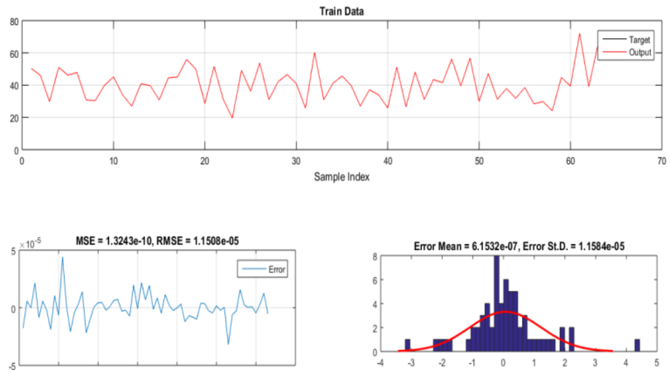

Figure12: The comparison of the Experimental and predicted compressive strength for training data samples for ANFIS modelling.

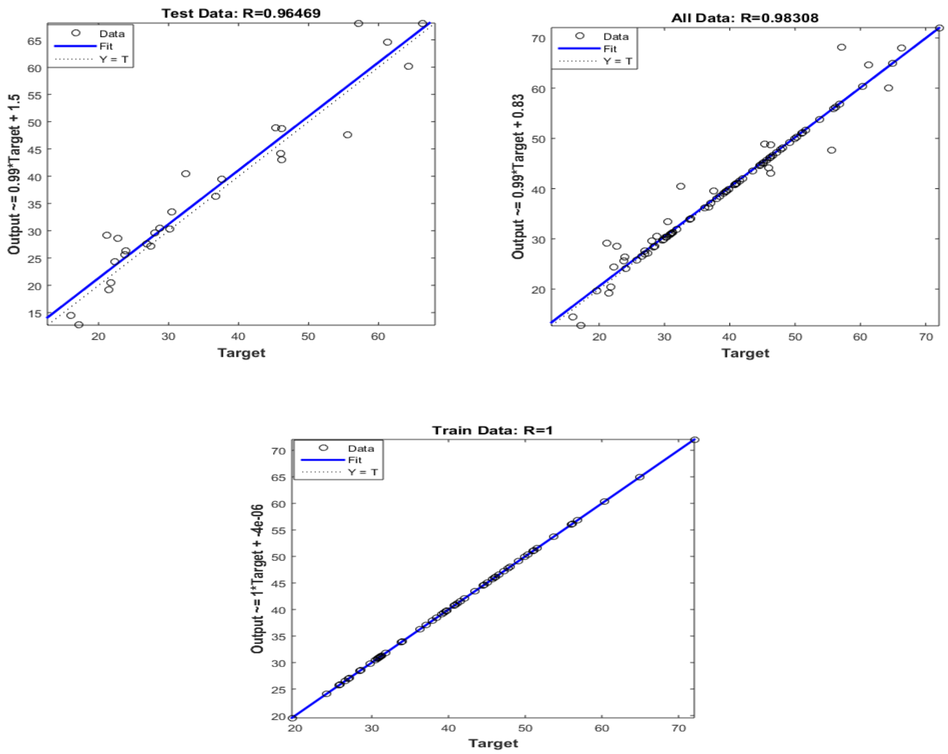

Figure13: The correlation between the experimental values and the ANFIS predicted values of compressive strength for training, testing and overall data.

Table 8: Predicted compressive strength by ANN and ANFIS Models

S. No.	Concrete mix Design as depicted in Table 5 to 7	Curing Age (Days)	W/B Ratio	Compressive Strength Experimental Values (MPa)	Predicted Compressive Strength by ANN Model (MPa)	Predicted Compressive Strength by ANFIS Model (MPa)
1.	1	7	0.40	41.5	39.98956648	41.49999613
2.	2	7	0.40	39.82	39.81999951	39.82000425
3.	3	7	0.40	30.8	30.8000026	30.79999696
4.	4	7	0.40	27.5	27.50000225	27.12873173
5.	5	7	0.40	29.81	29.8100016	29.80999746
6.	6	7	0.40	31.24	31.23999867	31.24000215
7.	7	7	0.40	21.12	19.75438658	29.16179349
8.	8	7	0.40	29.77	32.69187834	29.77000004

9.	9	7	0.40	25.85	25.85000054	25.85000016
10.	Control	7	0.40	39.8	39.79999595	39.80000469
11.	1	7	0.44	30.97	30.96999984	30.97000205
12.	2	7	0.44	31	30.99999952	30.99998052
13.	3	7	0.44	29.83	27.70792374	29.82999822
14.	4	7	0.44	26.94	26.94000062	27.55248073
15.	5	7	0.44	28.82	28.82000061	30.45885392
16.	6	7	0.44	30.42	26.59476457	30.4200188
17.	7	7	0.44	19.58	19.5799996	19.57999882
18.	8	7	0.44	25.74	25.97503398	25.73997815
19.	9	7	0.44	23.96	23.95999993	26.33263902
20.	Control	7	0.44	30.5	30.49999884	33.41261392
21.	1	7	0.48	28.6	26.47999808	28.59999569
22.	2	7	0.48	28.38	16.67181009	28.37998411
23.	3	7	0.48	26.48	22.30000001	26.48001205
24.	4	7	0.48	21.48	22.72999882	19.14868068
25.	5	7	0.48	22.3	16.45369367	24.33765098
26.	6	7	0.48	22.73	21.77999989	28.55074418
27.	7	7	0.48	16.06	17.04653735	14.4415056
28.	8	7	0.48	21.78	49.33806339	20.47791822
29.	9	7	0.48	17.16	53.75999719	12.69583832
30.	Control	7	0.48	27	26.9999997	26.99998849
31.	1	28	0.40	53.76	44.2793771	53.76000289
32.	2	28	0.40	50.32	39.60000196	50.3200175
33.	3	28	0.40	46.2	36.96174996	43.03396048
34.	4	28	0.40	39.6	45.59084331	39.60000262
35.	5	28	0.40	40.92	23.55458413	40.92000093
36.	6	28	0.40	49.94	49.13999944	49.93999909
37.	7	28	0.40	31.21	30.88000032	31.20999964
38.	8	28	0.40	49.14	45.13000014	49.13999366
39.	9	28	0.40	30.88	45.91569217	30.88000231
40.	Control	28	0.40	51.05	55.72857915	51.04997835
41.	1	28	0.44	47.83	40.78999855	47.82999415
42.	2	28	0.44	45.68	37.14000067	45.67999143
43.	3	28	0.44	40.79	37.62000027	40.7900207
44.	4	28	0.44	37.14	37.46512768	37.13999775
45.	5	28	0.44	37.62	22.69438435	39.52500224
46.	6	28	0.44	46.6	37.94999909	46.59998026
47.	7	28	0.44	27.03	28.0799995	27.02999856
48.	8	28	0.44	37.95	42.05999931	37.95003201
49.	9	28	0.44	28.08	44.19696111	29.61307114
50.	Control	28	0.44	45.13	45.67999687	45.13000651
51.	1	28	0.48	46.05	39.81999792	46.04999408
52.	2	28	0.48	45.02	30.23000056	45.02002183
53.	3	28	0.48	39.82	33.96000029	39.81998935
54.	4	28	0.48	30.23	28.59999952	30.33379373
55.	5	28	0.48	33.96	28.37999762	33.9600024
56.	6	28	0.48	39.08	39.07999692	39.07998729
57.	7	28	0.48	23.76	23.7599997	25.63011707
58.	8	28	0.48	31.82	34.05520274	31.82000591
59.	9	28	0.48	24.11	24.11000099	24.10999968
60.	Control	28	0.48	42.06	45.01999758	42.06000725
61.	1	90	0.40	72.05	72.04999026	72.04999705
62.	2	90	0.40	64.35	66.02375885	60.08588752
63.	3	90	0.40	51.18	51.17999939	51.17999667
64.	4	90	0.40	44.55	54.17909038	44.54998601
65.	5	90	0.40	46.2	42.8833483	46.20000851

66.	6	90	0.40	66.33	66.32999296	68.01360399
67.	7	90	0.40	36.22	36.21999815	36.2199927
68.	8	90	0.40	64.9	64.89999546	64.90000517
69.	9	90	0.40	39.38	41.57957803	39.38000457
70.	Control	90	0.40	55.64	55.63998864	47.62513745
71.	1	90	0.44	61.33	61.32999251	64.60448713
72.	2	90	0.44	56.21	56.20999608	56.20999636
73.	3	90	0.44	48.11	48.11000041	48.11000698
74.	4	90	0.44	43.45	43.44999889	43.45000999
75.	5	90	0.44	45.34	45.33999886	48.8551834
76.	6	90	0.44	60.35	60.34999224	60.3499932
77.	7	90	0.44	33.81	26.9446058	33.80995568
78.	8	90	0.44	51.62	51.61999539	51.61999544
79.	9	90	0.44	36.74	36.7399989	36.28834618
80.	Control	90	0.44	47.2	47.199988	47.20000225
81.	1	90	0.48	57.09	48.7066843	68.07460176
82.	2	90	0.48	55.96	44.62857681	55.9600099
83.	3	90	0.48	45.98	45.97999881	44.17953859
84.	4	90	0.48	38.5	38.49999848	38.5000029
85.	5	90	0.48	41.09	42.6567015	41.09000139
86.	6	90	0.48	56.77	56.76999122	56.77000444
87.	7	90	0.48	31.1	31.09999824	31.10000814
88.	8	90	0.48	44.73	44.72999568	44.72999902
89.	9	90	0.48	32.45	32.44999742	40.47576797
90.	Control	90	0.48	46.2	46.19999185	48.72752419

5. RESULTS AND DISCUSSION

Five indices were determined to evaluate the performance of the ANN and ANFIS models in predicting compressive strength. These indices are the root mean squared error (RMSE), determination coefficients (R^2), Mean absolute percentage error (MAPE), Integral absolute error (IAE) and mean absolute error (MAE) between the predicted and experimental results which are computed using the equations given in the table. 9.

Where t and o are the target and the predicted value of the network respectively, and n is the total number of patterns and $\bar{t}$ is the average of the target values.

Table 9: Statistical values of proposed models

S. No.	Performance indices	Formula	ANN	ANFIS
1	RMSE	RMSE = $\sqrt{\frac{1}{n}\sum_{i=1}^{n}(ti-oi)^2}$	7.17	2.2911
2	R^2	$R^2 = 1-\frac{\sum_{i=1}^{n}(ti-oi)^2}{\sum_{i=1}^{n}(ti-\bar{t}i)^2}$	0.659	0.9652
3	MAPE	MAPE = $\frac{1}{n}\left[\frac{\sum_{i=1}^{n}\lvert ti-oi\rvert}{\sum_{i=1}^{n} ti}\times 100\right]$	0.1047%	0.02755%
4	IAE	IAE = $\frac{\sum_{i=1}^{n}\left[(ti-oi)^2\right]^{1/2}}{\sum_{i=1}^{n} ti}\times 100$	1.946%	0.6219%
5	MAE	MAE = $\frac{1}{n}\left[\sum_{i=1}^{n}\lvert ti-oi\rvert\right]$	3.661	0.9627

The correlation coefficient (R) obtained for training, testing, validation and overall data for the ANN and ANFIS models is presented in Table.10.

Table 10: The values of the correlation coefficient (R)

Model	Training	Testing	Validation	Overall
ANN	1	0.94141	0.93129	0.97729
ANFIS	1	0.96469	-	0.98308

The ANN and ANFIS models developed in the present study were used to predict the compressive strength of concrete containing industrial by-products. The comparisons between the predicted values and actual results for the training, testing and all datasets of each model are shown in fig. 4 and fig. 9 to fig. 11. It can be seen that the predicted values of the training

and testing sets in the constructed ANN and ANFIS models are very close to the target values, demonstrating that these models could successfully learn the nonlinear relationship between the input and output variables. Therefore, both models show good potential for predicting the compressive strength of concrete containing industrial by-products.
The correlation coefficient (R) obtained for training, testing, validation and overall data for the ANN and ANFIS models is presented in Table. 10. From this table, we see that the overall value of the correlation factor (R) for the ANN model is 0.97729 and for the ANFIS model is 0.98308, which is better and closer to one. It shows that the prediction of the compressive strength is better by the ANFIS model than the ANN model.
The performance indices of the ANN and ANFIS models for both the training and testing sets, including RMSE, MAPE, R2, IAE and MAE are given in Table. 9. Therefore a prediction is considered better when RMSE, MAPE, and IAE is closer to zero and R^2 is closer to one. From the performance indices shown in Table 9, it is seen that the ANFIS model showed better results than the ANN model.

6. CONCLUSIONS

The main goal of the present study is to design and develop ANN and ANFIS models for predicting the compressive strength of concrete containing ternary combinations of industrial by-products as partial replacement of cement and fine aggregates.
The following conclusions were drawn from this study:
The neural network and ANFIS models could predict the compressive strength of concrete containing industrial by-products with satisfactory performance owing to their distributed and parallel computing nature.
The predicted values from the ANFIS model proved highly accurate. Moreover, the comparison of the performance indices showed that the ANFIS model provided better results than the ANN model.
In general, the proposed ANN and ANFIS models have high applicability and reliability with respect to predicting the compressive strength of concrete containing industrial by-products as partial replacement of cement and sand.

7. NOTATIONS

The following notations are used in the present paper.
ANFIS: Adaptive neuro-fuzzy inferencing systems
ANN: Artificial neural network
ASR: Alkali-silica reaction
BIS: Bureau of Indian standards
CA: Coarse aggregate
CC: Cement content
CO2: Carbon dioxide
CP: Curing period
CS: Copper Slag
EAF: Electric arc furnace slag
EDS: Energy dispersive spectroscopy
FA: Fly ash
FFBP: Feed forward back propagation
FIS: Fuzzy inference systems
GGBFS: Granulated blast-furnace slag
GP: Glass powder
IS: Iron Slag
IAE: Integral absolute error
LFS: ladle furnace slag
LM: Levenberg- marquardt
LMBP: Levenberg–marquardt backpropagation
LS: Limestone
MAE: Mean absolute error
MAPE: Mean absolute percentage error
MK: Metakaolin
MSE: Mean squared error
OA: Orthogonal array
PCS: Predicted compressive strength
PG: Phosphogypsum
RC: Replacement of cement
RMSE: Root means squared error
RS: Replacement of sand
SCM: Supplementary cementitious materials
SEM: Scanning electron microscopy
SF: Silica Fume

SS: Steel Slag

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