PREDICTION OF COMPRESSIVE STRENGTH OF SINTERED FLY ASH AGGREGATE CONCRETE USING ARTIFICIAL NEURAL NETWORKING

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In this study, a high strength-lightweight concrete of 50 MPa compressive strength was developed using an artificial neural network through MatLab programming. For the structural application of lightweight concrete, density and strength are more crucial. According to IS 456-2000, the concrete used for structural elements such as beams, columns, and slabs must have a minimum compressive strength of 20 MPa. Historically, additional materials like silica fume and fly ash were utilized to partially substitute cement. Nowadays, fly ash is processed systematically into pelletized aggregates and heated to temperatures up to 1500 degrees Celsius and is used as aggregates in lightweight concrete adding to sustainability. A high-strength lightweight concrete was modeled using neural networks, and its compressive strength was validated using laboratory measurements. A total of 57 data sets were used to construct this mix, which was based on earlier research.

Keywords: *Lightweight Concrete, sintered fly ash aggregate, MATLAB, Neural Networking*

1. Introduction

Sintered fly ash aggregate is an artificial aggregate made by burning pulverized coal in electric generation power plant waste. A combination of cement, lime, and bentonite with fly ash was previously studied to evaluate the performance of aggregate in concrete production [1]. The compressive strength of concrete containing sintered fly ash aggregates varies from 27 – 74 MPa after 28 days and its fresh density varies from 1651 – 2017 kg/m^3. It is possible to make structural concrete using sintered fly ash aggregate as it possesses sufficient strength and durability properties at a satisfactory level [2]. The sintered fly ash aggregates in concrete influenced the strength of the concrete due to its pozzolanic activity [3]. The lightweight concrete produced using sintered fly ash aggregates shows a similar characteristic of normal concrete and is also good in durability [4, 8].

The Artificial Neural Network (ANN) is widely used to predict the compressive strength of the concrete by researchers and academicians [5, 6]. The cement, fine aggregate, coarse aggregate, water content, water to cement ratio, superplasticizer, fresh density, and slump values are varied and is used as input for the ANN model to predict the compressive strength of concrete. The powder material, natural fine aggregates, and natural coarse aggregates can be varied to find the strength characteristics of concrete using ANN after the network is trained properly [7].

The study aims to create an ANN model to predict the compressive strength of concrete containing sintered fly ash aggregates at 28 days based on the previous experimental data. For this purpose, a computer program was developed using the MATLAB interface. Finally, concrete compressive strength of 50 MPa was predicted from the created networking and verified with the laboratory tested values.

2.Artificial neural networking

ANN is biologically related to the sensing process of the human brain. It consists of large numbers of sensing processing units known as neurons. A simple artificial neural model is shown in Figure 1.

The X1, X2 & X3 are the inputs applied to the neuron. Whereas W1, W2 & W3 are the weights of the corresponding inputs and b is the bias. Based on the ANN analysis, the output of the neuron is given by Equation 1.

$u = \sum_{a=0}^{n} x_a w_a - b$ & v = f (u) [Equation 1]

Each neuron was connected with an activation link, and it had an activation function to determine the output. There are many kinds of activation functions available. In general, non-linear activation such as the sigmoidal step will be used. The ANN data are usually trained by experience. Therefore, when an unknown input is applied to the network it can be generalized from experience and it will produce a new set of results [9].

In this study, to determine the 28 days compressive strength of sintered fly ash lightweight aggregate concrete, the input parameters considered were cement, fine aggregate, sintered fly ash aggregate, water/cement (w/c) ratio, silica fume, fly ash and dosage of superplasticizer. The compressive strength of concrete was the output parameter of the created model. A multi-layer feed-forward neural network was used. A data set with 55 data samples were obtained from the experimental studies available in the past literature. These data were normalized by dividing the maximum values.

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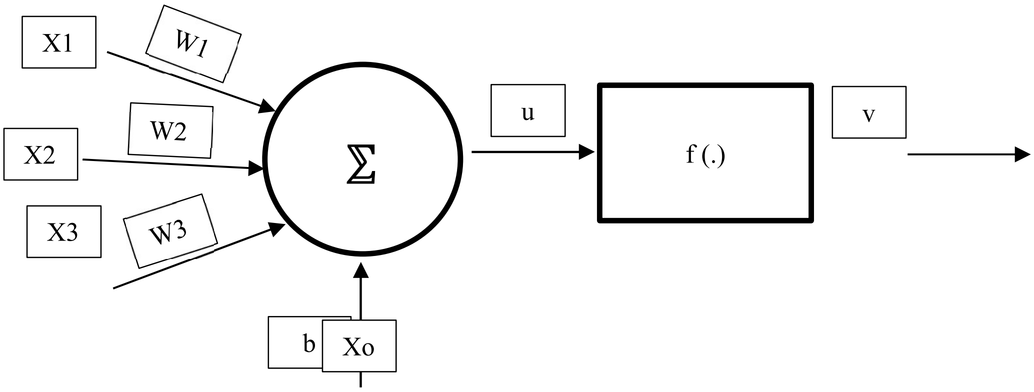

Fig. 1 - Artificial neuron model.

Table 1

Data used for neural networking [11 – 28]

Input (kg/m^3)							Target (MPa)
cement	**silica Fume**	**fly ash**	**fine aggregate**	**sintered fly ash aggregate**	**w/c**	**Super-plasticizer**	**compressive strength**
272.6	0	0	526.8	908.4	0.35	0	29.03
358.6	0	0	693.1	732.6	0.35	0	30
430.3	0	0	831.7	586.1	0.35	0	32
440	0	0	793	598	0.4	0	45.4
440	0	0	793	598	0.4	0	41
440	0	0	793	598	0.4	0	40.5
440	0	0	793	598	0.4	0	54.8
440	0	0	793	598	0.4	0	43.6
500	0	0	917.8	532.3	0.35	0	48.1
500	0	0	662.9	705.8	0.35	0	48.1
500	0	0	407.9	879.4	0.35	0	45
500	50	0	333	528	0.55	6	51
410	0	0	720	706	0.44	0	30
400	0	0	310	350	0.45	0	41.2
400	24	0	307	350	0.48	0	38.5
400	0	120	304	350	0.53	0	37.1
400	0	0	297	350	0.64	0	33.9
350	0	0	315	350	0.55	0	37.3
300	0	0	328	350	0.65	0	30.6
300	0	27	326	350	0.69	0	28.3
300	0	45	324	350	0.76	0	27.7
300	0	90	319	350	0.93	0	26.3
550	0	0	624	727	0.35	8.25	47
495	55	0	614	715	0.35	11	55
400	0	0	651	759	0.55	0	34
360	55	0	645	752	0.55	1	44
385	0	165	789	504	0.3	6.1	44.51
330	0	141	825	528	0.35	4.2	43.22
289	0	123	852	544	0.4	2.9	39.85
257	0	109	874	558	0.45	1.5	37.7
231	0	99	890	568	0.5	0.7	34.78
550	55	180.2	0	966.8	0.32	11	64.8
298	0	0	632	802	0.69	0	27.5
394	0	0	652	826	0.44	5.91	61.9
548	55	0	633	567	0.29	6.7	53.5
549	55	0	634	580	0.29	6.7	55.8
450	0	0	787	561	0.42	2.25	44
225	0	154	787	561	0.42	1.89	34
295.5	29.5	0	418.3	524	0.72	3	36
500	50	0	333	528	0.5	6	51
390	0	167	775	408	0.37	4.2	37
370	0	0	895	570	0.54	0	38.5
450	0	0	314	350	0.35	3.15	47.8
400	0	0	310	350	0.45	2.8	41.2
400	24	0	307	350	0.45	2.8	38.5
400	0	60	304	350	0.45	2.8	37.1
400	0	120	297	350	0.45	2.8	33.9

350	0	0	315	350	0.55	3.15	37.3
550	55	180	536.6	415.2	0.347	11	70.2
400	0`	0	360	250	0.45	2.8	41.9
400	0	0	335	300	0.45	2.8	41.3
400	0	0	285	400	0.45	2.8	41.5
353	35.3	0	499	625	0.79	3.5	35
280	28	0	570	700	0.7	3	38
536	53.6	0	357	567	0.55	6.5	50
480	48	0	345	726	0.42	5.5	49.5
300	40	300	162	766	0.64	1.95	66.75

Table 2

Maximum and minimum values from the data sets

Input	**Minimum (kg/m^3)**	**Maximum (kg/m^3)**
Cement	225	550
Silica fume	0	55
Fly ash	0	300
Fine aggregate	0	917.8
Sintered fly ash aggregate	250	966.8
Water/ Cement	0.29	0.93
Superplasticizer	0	11
Target	**Minimum (MPa)**	**Maximum (MPa)**
Compressive strength	26.3	70.2

The data used for the neural networking is shown in Table 1. The maximum and minimum values used in this training data are shown in Table 2.

The backpropagation learning algorithm is used in a feed-forward, single hidden layer neural network. The selection of neurons was based on the ANN model developed by Harun Tanyildizi [10].

3. Results obtained from ANN

The artificial neural networking was carried out using MAT lab software. The data sets used in this study were taken from the literature and were divided into two data sets (input and target). These data sets were trained using Levenberg- Marquard backpropagation method. The created Architecture in the MAT Lab is shown in Figure 2. Of the total data sets, 39 were used for training and the remaining 16 were used for validation and testing.

The training was based on the R^2 values. The predicted trained data sets are shown in Figure 4. In this trained new data set, the overall R^2 was 0.94767. Henceforth the accuracy was 94 %. From this result, it can be understood that the network created is capable of providing augmented results. With the help of the developed network, the input values corresponding to the output values can be generated. Figure 3 depicts the trained R^2 values obtained from the best data set.

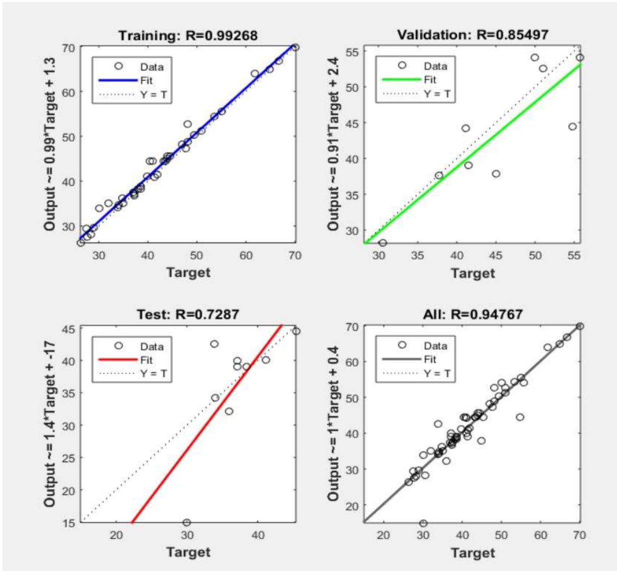

Fig. 3 - Trained R^2 values

The aim of the analysis was to develop a concrete of high strength having a compressive strength of 50 MPa. To develop 50 MPa strength, the input parameters like cement, silica fume, fly ash, fine aggregate, sintered fly ash aggregate, water/ cement ratio, and superplasticizer were given as input and its corresponding output obtained was a compressive strength of 56.70 MPa and it was clearly shown in the command window of the neural networking software. The given input values and the predicted output values are shown in Table 3.

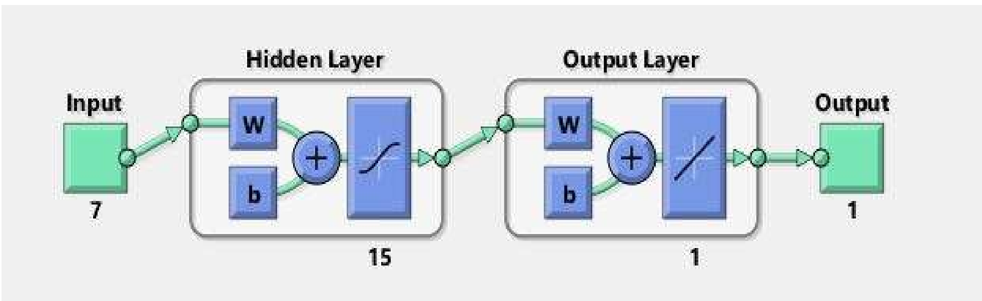

Fig. 2 - Architecture from the MAT LAB

Table 3

Input and Output Values in MAT LAB

Cement (kg/m^3)	silica Fume (kg/m^3)	fly ash (kg/m^3)	fine aggregate (kg/m^3)	sintered fly ash aggregate (kg/m^3)	w/c	super plasticizer (kg/m^3)	compressive strength (MPa)
400	50	200	600	500	0.30	6	56.70

Table 4

Grading of fine aggregate

Sl.No	IS Sieve (mm)	Weight Retained (gms)	Percentage weight Retained (gms)	Cumulative % weight Retained	% passing
1	4.75	25	2.5	2.5	97.5
2	2.36	44	4.4	6.9	93.1
3	1.18	104	10.4	17.3	82.7
4	0.60	258	25.8	43.1	56.9
5	0.30	443	44.3	87.4	12.6
6	0.15	126	12.6	100	0

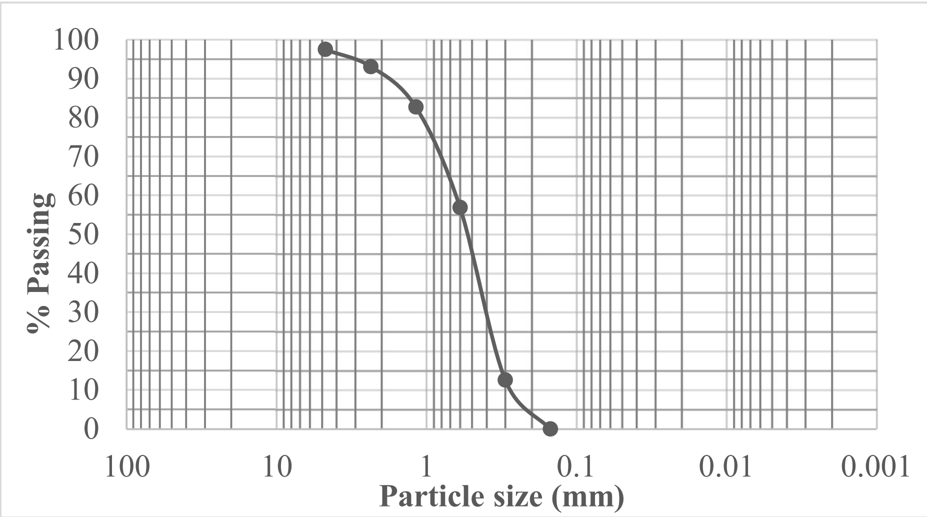

Fig. 4 - Particle size distribution curve for fine aggregate

This prediction was verified experimentally by casting 3 no's of concrete cubes of size 100 mm. These concrete cubes were cured in normal water for 28 days. The compressive strength was evaluated mechanically through a Universal Testing Machine.

4.Experimental evaluation and discussion of test results

4.1.Material properties

To verify the compressive strength of the high-strength sintered fly ash lightweight concrete, the following materials were used.

4.1.1.Cement

Ordinary Portland Cement of 53 Grade Ultratech cement was used. The specific gravity of cement was 3.08 and its fineness was 7 %.

4.1.2.Silica Fume

The silica fume used for concrete was supplied by Aastra chemicals, Chennai, Tamil Nadu, India. The silica fume was found to have a specific gravity of 2.21.

4.1.3.Fly ash

The fly ash used for the concrete was obtained locally from the Dindigul region and its specific gravity was found to be 2.1.

4.1.4.Fine aggregate

The fine aggregate used in this experimental programme was locally procured. It was tested for various physical properties in accordance with IS 2386 (Part 3) -1963. Fine aggregate was natural sand conforming to Zone II of IS 383-1970 passing through a 4.75 mm size sieve. The specific gravity and fineness modulus is found to be 2.64 and 2.54. The grading of fine aggregate is given in Table 4 and the particle size distribution curve is shown in Figure 4.

4.1.5.Sintered fly ash aggregate

Sintered fly ash aggregate used in this investigation was bought from GBC India limited, Gujarat. Sintered fly ash aggregates passing

Table 5

Physical properties of sintered fly ash aggregate

Sl.No	Property	Value
1	Specific gravity	1.4
2	Fineness modulus	2.91
3	Bulk density (Loose)	830 kg/m^3
4	Water absorption	16.8 %

through a 12.5 mm sieve and retained in a 4.75 mm sieve were used in this investigation. The specific gravity, fineness modulus, and bulk density of the procured sintered fly ash aggregate are presented in Table 5. Sieve analysis was performed according to IS 383-1970 and the results are presented in Table 6. The particle size distribution curve for the sintered fly ash aggregates is shown in Figure 5.

Table 6

Grading of Sintered fly ash aggregate

Sl.No	IS Sieve (mm)	Weight Retained (gms)	Percentage weight Retained (gms)	Cumulative % weight Retained	% passing
1	20	0	0	0	100
2	16	47	4.7	4.7	95.3
3	12.5	202	20.2	24.9	75.1
4	10	378	37.8	62.7	37.3
5	4.75	362	36.2	98.9	1.1
6	PAN	11	1.1	100	0

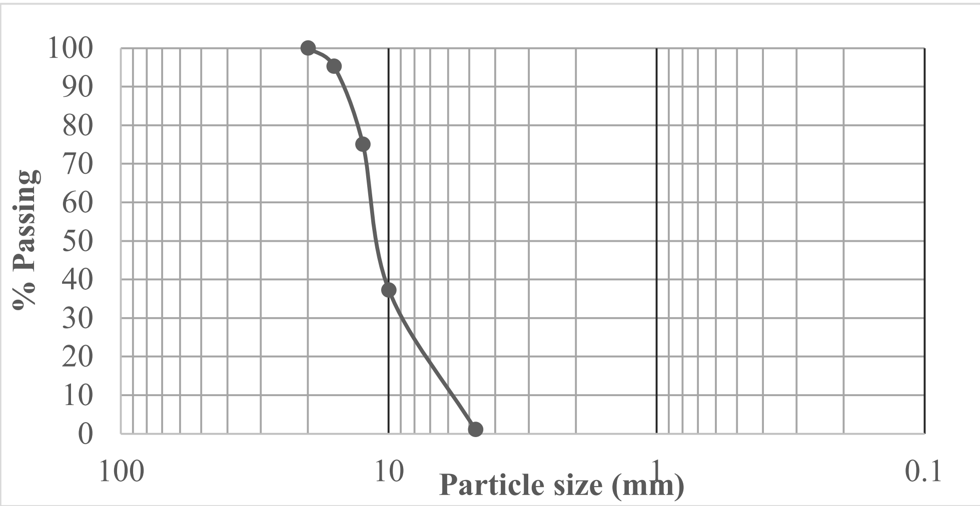

Fig. 5 - Particle size distribution curve for sintered fly ash aggregate

4.1.6. Water

The available water in the laboratory premises was used for mixing, casting, and curing the specimens. The pH of the water was in-between 6 and 7.

4.1.7. Superplasticizer

Conplast SP430, a sulphonated naphthalene polymers-based superplasticizer is used. It is chloride free. The physical properties of the superplasticizer as determined from experiments are shown in Table 7.

Table 7

Physical properties of superplasticizer

Sl. No	Property	Value
1	Colour	Brown
2	Specific Gravity	1.22

4.2. Casting the specimens

The concrete cubes were cast using the laboratory drum mixer of 30 liters capacity. Before starting the mixing process, the materials used to produce the concrete were weighed properly using the laboratory weighing machine. The sintered fly ash aggregates have a higher water absorption nature. To adjust the excess water absorption during mixing, casting, and curing; the sintered fly ash aggregates were pre-soaked in water for 30 minutes before casting. Figure 6 & Figure 7 shows the casting and curing of concrete cubes.

Fig. 6 - Casting of concrete cubes

Fig. 7 - Curing of concrete cubes

4.3. Compressive strength test

To classify the type of concrete based on strength, the compressive strength of concrete cubes is one of the best evaluations (IS 456:2000). This compressive strength test was conducted in accordance with IS 516 and the calculated strength was based on the below formula.

$$\text{Compressive strength } (\sigma_c) = \frac{Crusing\ value\ of\ the\ cube}{load\ acting\ area}\ MPa \qquad \text{[Equation 2]}$$

Figure 8 shows the typical compressive strength test on a concrete cube using a 200 kN compressive testing machine conducted at the strength of materials laboratory.

Fig. 8 - Typical testing method for Compressive strength on concrete cubes

4.4. Compressive strength results and discussion

The tested compressive strength of the cube specimens' is shown in Table 8. The results show that the average compressive strength value is 55 MPa. It indicates that the concrete cast based on the developed neural network was more accurate, and in the future, it can be used for structural evaluations such as flexural strength, shear strength, impact studies, etc.,

Table 8

Compressive strength Results

Specimen	Dry Weight of the cube (kg)	Load at failure (KN)	Stress (MPa)
1	2025	55	55
2	2038	54	54
3	2042	56	56
Average	2035	55	55

5. Conclusions

The following were the conclusions drawn from the above investigation,

- A high-strength lightweight sintered fly ash aggregate concrete was successfully developed using artificial neural networking.
- Even though the model created through an artificial neural network provides the best data for the concrete mix; it needs to be verified experimentally.
- The neural network predicted a fair result; it was not based on the material properties of concrete.
- The Levenberg- Marquard backpropagation method was found to be the most appropriate tool in MatLab for modeling to find the compressive strength of concrete.
- The compressive strength obtained from the best-trained data set is used for the verification of the developed network.
- The predicted compressive strength was only for the short term (28 days) and not for the long term (56 days and later). The long-term compressive strength in the will be higher, due to its pozzolanic additives such as silica fume and fly ash.

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