Prediction of Strength of High Volume Fly ash Concrete Using Artificial Neural Networks

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Abstract. The purpose of this research project is to evaluate the strength and durability of concrete that has been prepared using groundwater and treated water. Concrete's strength is evaluated using a variety of strength metrics, including split tensile strength, bond strength, and compression test results. By evaluating the corrosion in the steel reinforcement, the durability of the concrete is examined. This experiment also sought to predict strength using artificial neural networks. In this study, we aim to use artificial neural networks (ANN) to predict the values of compressive strength of 28 days, 56 days and 90 days, 100 hours half-cell potential and water absorption,. The main goal is to anticipate compressive strength. Regarding laboratory outcomes, the ANN model's output yields both positive and negative variations. The range of the positive variances is 3.44 % to 8.22 %. The negative variances are between 2.02% and 11.35% of the total. The outputs of the ANN model may be used to calculate the 28-day, 56-day, 90-day, water absorption of concrete in hardened state, 100 hours half-cell potential from properties of fresh concrete and 3-day compressive strength. Since the outcomes are good, the ANN prediction model can be adopted as a reference to forecast the strength properties of concrete three days after the concrete has started to be laid.

Keywords: ANN, Strength, Durability, High volume Fly ash, concrete

1 Introduction

A variety of components, including both fresh and hardened concrete, can affect the compressive strength of concrete. The primary factor used to calculate the compressive strength of concrete is its strength following a 28-day curing period. The concrete test sample is inspected after curing period, and the findings are used to as-

K. R. Madhavi et al. (eds.), *Proceedings of the International Conference on Computational Innovations and Emerging Trends (ICCIET 2024)*, Advances in Computer Science Research 112,
https://doi.org/10.2991/978-94-6463-471-6_19

sess the sample's stiffness and quality. It takes a lot of time to wait 28 days when the concrete's quality needs to be guaranteed. In concrete research, the Artificial Neural Network (ANN) model has been widely utilised to estimate the compressive strength of concrete.[1-2]

Due to the laborious nature of formulating the mathematical relationships between the qualities of the material, new concrete, and hardened concrete, using sophisticated artificial intelligence software at this time may be the best course of action. In this study, the software artificial neural network (ANN) is chosen and its predictive power for 28 days as well as the compressive strength at various ages is attempted.[3-4]

Conventional methods for anticipating concrete's 28-day compressive strength rely on statistical analysis, with numerous regression equations established to address this prediction challenge. Concrete compressive strength may be predicted accurately using an Artificial Neural Network (ANN). To describe the load-deflection curve, the researchers developed a neural network-based identification of material model characteristics. A unique approach for identifying material model parameters was presented. This approach combines stochastic nonlinear analysis with an artificial neural network.[5-8]

Researchers used an ANN using a range of coefficients of learning rate values to evaluate the prediction of the initial setting time of self-compacting concrete. To predict the characteristics of long-standing strengths of steel fibre reinforced concrete (SFRC) comprising fly-ash, researchers employed an ANN. Aimed at the purpose of examining the structural properties of SFRC with fly-ash, an ANN model was created. Researchers investigated how well an ANN could predict the strength and density of concrete that contains silica fume.[9] Rresearchers looked at the concrete's 28-day compressive strength forecast on the third day Using an artificial neural network.[10]

Objective of the study:

To evaluate the strength characteristics of concrete is made with different percentages of fly ash and silica fume. Fly ash varies from 10 to 60% of fly ash with 20% silica fume. to assess how long-lasting concrete constructed with various fly ash percentages and fly ash and silica fume combinations—such as 10%, 20%, 30%, 40%, 50%, and 60% of fly ash combined with 20% silica fume and without silica fume will last. This paper attempts to forecast the compressive strength after 28 days utilizing material and new concrete parameters, as well as a mathematical model. The ANN was used to evaluate the reinforcement's strength and potential level of corrosion in a concrete specimen.

2 Materials and Method

The materials used in the manufacture of concrete are evaluate in the lab in accordance with the mandated norms stated by the relevant IS requirements. The quality of two types of waters used in this work was examined by collecting and testing samples in cleaned polythene bottles using the techniques outlined in IS 3025 - 1983. A target strength of 28.25 N/mm^2 was established, and the nearest rounded figure of 30 N/mm2 was used as the needed strength. The mix proportion was designed for this strength, and the control mix has come. In six phases, cement is replaced with fly ash at percentages of 10, 20, 30, 40, 50, and 60. The other control mix contains 20% silica fume instead of cement. To substitute cement further, 20% silica fume is applied together with fly ash components. The specimens are cast to these 14 mix requirements.

Each piece of concrete was cast using a combination of groundwater and purified water. Measurements and records are made of the new concrete's properties, including temperature, slump, and density. Cube, beam, and cylinder specimens were used for the compressive, flexural, bond, and split tensile strength tests on hardened concrete, respectively. Tests for Young's modulus were conducted on hardened specimens. Concrete that has hardened was subjected to strength tests at 28, 56, and 90 days of age. Experiments on water absorption and half-cell potential were used to assess the concrete's resistance to corrosion.

A model based on artificial neural networks (ANN) was created to calculate compressive strength at 28, 56, and 90 days, 100 hours half-cell potential value, water absorption, by taking the properties of materials, fresh concrete, and 3 days compressive strength as parameters. This model accepts parameters for both purified water and ground-water. This model can also predict strength and durability. This study work can be utilized as a reference to forecast the structural properties like strength and durability differences between the concrete created utilising ground-water and purified water.

3 Preparation of ANN model

The ANN model was created by taking the value of half-cell and compressive strength as outputs by taking different parameters as input variables which are mentioned below.

I. Cement content
II. Fly-ash (FA)
III. Silica fumes (SF)
IV. Fine aggregate content (FAg)
V. Coarse aggregate content (CAg)
VI. Water content
VII. Super plasticizer content
VIII. TDS of water
IX. Slump value
X. Density of concrete
XI. 3 days compressive strength

The quantities of inputs are determined by the quantity of material used, regular tests on material and concrete, and strength tests on samples aged three days. Tables 1 summarise the various values of the input variables. The correctness of the input data is critical since artificial neural network operations are quite delicate. The expected out puts are compressive strength of 28, 56 and 90 days and water absorption and 100 hours half-cell potential value.

Table 1. The Input variables

S.No	Cement Kg	FA kg	SF kg	Fag kg	CAg kg	Water L	SPL	TDS mg/L	Slump mm	Density kg/m^3	3days Comp Strength N/mm^2
1	380	0	0	711	1283	160	5.7	730	32	2374	38.03
2	342	38	0	711	1283	160	5.7	730	30	2373	26.03
3	304	76	0	711	1283	160	5.7	730	32	2372	23.94
4	266	114	0	711	1283	160	5.7	730	33	2371	21.94
5	228	152	0	711	1283	160	5.7	730	34	2370	12.33
6	190	190	0	711	1283	160	5.7	730	36	2369	11.56
7	152	228	0	711	1283	160	5.7	730	38	2368	1.08
8	304	0	76	711	1283	160	5.7	730	30	2370	22.93
9	266	38	76	711	1283	160	5.7	730	31	2369	17.75
10	228	76	76	711	1283	160	5.7	730	30	2368	15.26
11	190	114	76	711	1283	160	5.7	730	29	2367	14.18
12	152	152	76	711	1283	160	5.7	730	30	2366	13.51
13	114	190	76	711	1283	160	5.7	730	32	2365	12.99
14	76	228	76	711	1283	160	5.7	730	31	2364	3.2
15	380	0	0	711	1283	160	5.7	4060	32	2374	19.47
16	342	38	0	711	1283	160	5.7	4060	30	2373	19.2
17	304	76	0	711	1283	160	5.7	4060	32	2372	18.4
18	266	114	0	711	1283	160	5.7	4060	33	2371	16.36
19	228	152	0	711	1283	160	5.7	4060	34	2370	10.56
20	190	190	0	711	1283	160	5.7	4060	36	2369	8.76
21	152	228	0	711	1283	160	5.7	4060	38	2368	3.72
22	304	0	76	711	1283	160	5.7	4060	30	2370	17.18
23	266	38	76	711	1283	160	5.7	4060	31	2369	11.26
24	228	76	76	711	1283	160	5.7	4060	30	2368	11.14
25	190	114	76	711	1283	160	5.7	4060	29	2367	10.58
26	152	152	76	711	1283	160	5.7	4060	30	2366	9.71
27	114	190	76	711	1283	160	5.7	4060	32	2365	9.54
28	76	228	76	711	1283	160	5.7	4060	31	2364	3.96

Table 1 summarizes the varied values of the intended output variables. The goal output matrix of the ANN model is 28 x 5. Rows 1–14 contain data from the concrete made with treated water. The data for the groundwater-prepared concrete are entered in rows 15 through 28.

NETWORK ARCHITECTURE

The NF tool was used for the ANN model because of its excellent accuracy at approximating comparable functions with a large number of input data sets. There are three layers in a neural network. They consist of three layers: input, concealed, and output. The model in this study has been trained using 28 hidden neurons. 80% is the allotted train ratio. A 10% weight is given to both test ratio and validity.

INPUT: The inputs are the qualities of the new concrete and the concrete substance. The arrangement of the input variables shown in Table is designed to work with the format of ANN input. The updated matrix measures 11 by 28 inches. It has eleven criteria for twenty-eight combinations made with groundwater and treated water. For the input data, a new M-file is produced and saved with a txt extension. Every material and fresh concrete attribute of the different mixes is represented in each column of the input matrix.

TARGETED OUTPUT: The strength, absorption, cell potential, and 28-day, 56-day, and 90-day values of all 28 mixtures that were discovered during the testing are organised in a 5 by 28 matrix and stored in a new M-file with the extension. The ANN model must be trained in order to produce the desired output, which is this new M-file. The model's validity is demonstrated by contrasting the intended output results with the compressive strength, absorption, cell potential, and strength values of the corresponding mixtures. Either there should be very little difference between these two numbers, or they should be equal.

NEURAL FITTING TOOL: The neural fitting tool (NFT) uses a feed forward neural network with two layers to solve an input-output fitting issue. Neural network mappings between sets of numerical input data and objectives are involved in fitting difficulties. NFT evaluates neural network performance using regression analysis and mean square error.

DATA SELECTION : By clicking on the input and target boxes, the workspace's M-files for the input and intended output are chosen and imported into the programme.

VALIDATION AND TEST DATA: Now, a percentage is used to determine which samples will be used for training, validation, and testing. Eighty percent of the labour is devoted to teaching, ten percent to validation, and ten percent to testing. Within the allotted training %, training will be modified. Network generalisation is measured by validation, and training will end if generalisation becomes unsatisfactory. An unbiased gauge of network performance both during and after training is provided by testing.

NETWORK SIZE: Here, the number of neurons in the network's hidden layer is chosen to fix the size of the network. 28 hidden neurons are chosen. The training process must be redone from this stage with a different number of neurons if the network does not function effectively. This has to be done again till the desired outcome is obtained. In order to establish the network size in this study, 11 inputs per sample, 28 hidden layers and 5 output layers are allocated.

TRAIN NETWORK: It is done to train the network to fit the input and the objectives. In trainlm back propagation, training has been conducted. When the improvement in generalisation ceases, training automatically ends. An rise in mean squared error indicates this. The mean squared error (MSE) between the input and the targets is calculated. It is beneficial to have lower MSE values. Zero indicates the absence of mistake. R values quantify how closely targets and output are correlated. An R value of one indicates a stronger correlation between the intended and NFT outputs. Eighty percent of the samples have been used for the training.

The results showed an MSE of 0.0016 and a R value of 0.099. The fact that training has an MSE very less and a R of 1 indicates that it has received the best results. This demonstrates that testing has produced the greatest results, as seen by the extremely low MSE and R value of 1. Ten percent of the samples were used for the validation. This demonstrates that validation has produced the greatest results, with an extremely low MSE and an R value of 1.By changing the number of neurons, the training has been conducted across a large number of trails.

The final trial yielded the best outcome.

Seven epochs were used to generalise the training. Figure 1 displays the total training status. In Figure 2, the performance plot is displayed.

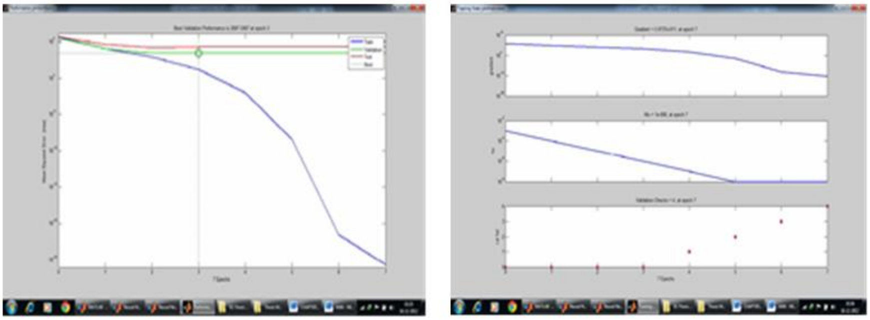

Fig.1. Training of the network & Regression plot of the training network

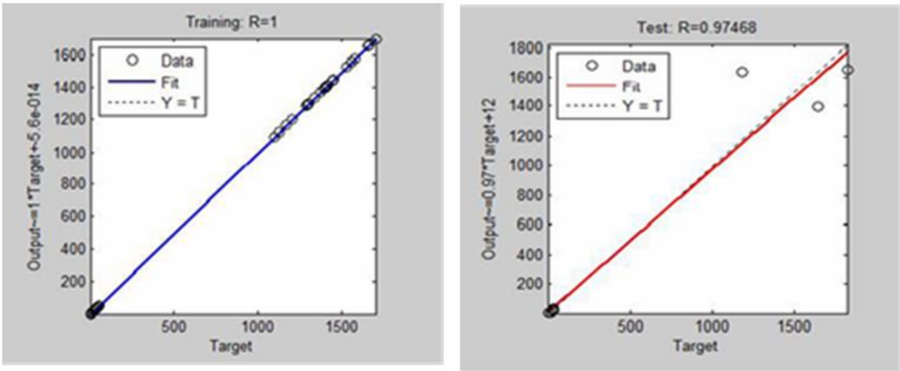

Fig2. Regression :training & testing

The link between the training result and the desired goal is quantified by R. R value is measured for training, testing and validation processes. Until the R value approaches 1, iterations have been carried out. It was found that R values for all have all hit their maximum and are less than one after seven epochs. This demonstrates that there is a strong link between the intended and actual output.

Table 2. Laboratory results

Mix ID	Laboratory results				
	28-day-strength (N/mm^2)	Water Abs-%	56-day-strength (N/mm^2)	90-day-strength (N/mm^2)	Cell potential(-mV)
CONTW	45.6	0.719	55.07	56.98	1330
10FATW	42.3	0.602	46.56	59.8	1399
20FATW	42.8	0.705	46.7	47.45	1666
CON20SFTW	42.65	0.428	48.5	54.26	1485
10FA20SFTW	39.16	0.329	41.6	41.44	1497
20FA20SFTW	38.67	0.367	39.82	41.64	1520
CONGW	44.6	0.570	43. 8	44.64	1851
10FAGW	38.7	1.41	39.03	41.33	1774
20FAGW	35.4	1.217	35.57	40.57	1778
CON20SFGW	45.76	1.469	46.47	48.67	1749
10FA20SFGW	35.7	0.783	36.8	37. 8	1223
20FA20SF GW	29.9	0.847	41.55	43.25	1487

The neural network training produced good results, and the data was preserved. To display the necessary outputs, the display option is recommended. The source block parameter window's constant value box contains the different inputs. After saving the input data, the programme is executed. The simulink window's display box displays the output value.

VALIDATION OF ANN MODELS

The data was saved and the neural network training yielded good results. Simulink diagrams are designed to use the trained network to achieve its goal by supplying different inputs and obtaining matching outputs. The show option is advised in order to display the required results. To construct the required Simulink diagram, the network's Simulink library browser option is selected.

4 Results and Discussions

In this study, an artificial neural network (ANN) is used to forecast the compressive strength after 28 days, water absorption, 56 days, 90 days, and 100 hours half-cell potential value. The main goal here is to anticipate compressive strength. However, there are a number of material, fresh concrete, and hardened concrete qualities that affect the compressive strength of concrete. Testing of the concrete sample requires 28 days. The stiffness and quality of concrete are determined by the compression test

results. It takes a lot of time to wait 28 days when the concrete's quality needs to be guaranteed.
In order to forecast strength and durability characteristics like absorption of water and half-cell potential value, the programme ANN is chosen and used in this study. Here, an ANN model has been developed to forecast the values of half-cell potential, water absorption, and compressive strength after 28, 56, and 90 days. The specimens created independently using purified water and water from ground the same area, with the mixes specified before in this study, are used to verify the validity of the model. The characteristics of hardened concrete as well as the half-cell potential values are determined and documented for samples that are left for 28, 56, and 90 days.

Regarding laboratory outcomes, the ANN model's output yields both positive and negative variations. Positive outcomes are indicated by values higher than the laboratory findings, while bad outcomes are indicated by values higher than the laboratory results. The 28-day compressive strength maximum positive variation is 3.26 N/mm^2, or 7.12% of the variance from the mix CON20SFGW. The 28-day compressive strength shows a maximum negative fluctuation of 1.8 N/mm^2, or 6.02% variance from the mix 20FA20SFGW.

Table 2 displayed the results of the laboratory. Table 3 displayed the ANN's output values. Table 4 displayed the variations between the ANN output and the test data. Table 5 displayed the percentage difference between the ANN output and the test results.

Table 3. ANN Output

Mix	**Output of ANN model**				
	28-day-Comp-strength (N/mm^2)	**Water Abs-%**	**56-day-Comp-strength (N/mm^2)**	**90-day-Comp strength (N/mm^2)**	**Cell potential (-mV)**
CONTW	43.06	0.749	54.07	54.98	1333
10FATW	41.69	0.606	45.56	59.51	1411
20FATW	40.63	0.785	45.7	46.45	1686
CON20SFTW	43.19	0.388	50.4	56.26	1455
10FA20SFTW	40.36	0.309	41.99	45.44	1483
20FA20SFTW	37.73	0.38	38.12	38.64	1531
CONGW	44.78	0.575	45.46	45.64	1853
10FAGW	38.9	1.298	39.53	42.53	1769
20FAGW	36.2	1.117	36.57	39.57	1770
CON20SFGW	42.5	1.469	44.87	46.87	1749
10FA20SFGW	35.8	0.773	37.88	38.78	1198
20FA20SF GW	31.7	0.827	42.45	45.45	1587

Table 4. Comparison

ID	Compressive strength (N/mm²)			Water Abs-%	Cell potential (-mV)
	28-day	56-day	90-day		
1	2.54	1	2	-0.03	-3
2	0.61	1	0.29	-0.004	-12
3	2.17	1	1	-0.08	-20
4	-0.54	-1.9	-2	0.04	30
5	-1.2	-0.39	-4	0.02	14
6	0.94	1.7	3	-0.013	-11
7	-0.18	-1.66	-1	-0.005	-2
8	-0.2	-0.5	-1.2	0.112	5
9	-0.8	-1	1	0.1	8
10	3.26	1.60	1.80	-0.10	-14.00
11	-0.1	-1.08	-0.98	0.01	25
12	-1.8	-0.9	-2.2	0.02	-100

The water absorption's maximum positive fluctuation is 0.1, which explains 8.22% of the difference from the mix 20FAGW. The water absorption's greatest negative fluctuation is 0.08, which explains 11.35% of the variance from the mix 20FATW. The 56-day compressive strength maximum positive variation is 1.60 N/mm^2.The 56-day compressive strength maximum negative variation is 1.9 N/mm^2. In terms of 90-day compressive strength, the highest positive variation is 2 N/mm2, or 3.51% of the deviation from the mix CONTW. The 90-day compressive strength maximum negative variation is 2.2 N/mm^2.

Table 5. Percentage Variance

ID	Compressive strength (N/mm²)			Water Abs-%	Cell potential (-mV)
	28-day	56-day	90-day		
1	5.57	1.82	3.51	-4.17	-0.23
2	1.44	2.15	0.48	-0.66	-0.86
3	5.07	2.14	2.11	-11.35	-1.20
4	-1.27	-3.92	-3.69	9.35	2.02
5	-3.06	-0.94	-9.65	6.08	0.94
6	2.43	4.27	7.20	-3.54	-0.72
7	-0.40	-3.79	-2.24	-0.88	-0.11
8	-0.52	-1.28	-2.90	7.94	0.28
9	-2.26	-2.81	2.46	8.22	0.45
10	7.12	3.44	3.70	-7.30	-0.81
11	-0.28	-2.93	-2.59	1.28	2.04
12	-6.02	-2.17	-5.09	2.36	-6.72

The half-cell potential's maximum positive fluctuation in units of (-mV) is 100, which explains 67.2% of the variation from the mix 20FA20SFGW.

5 Conclusion

In this study, artificial neural networks are applied to predict the values of strengths of 3-different ages along with half-cell potential of 100-hours and water absorption. The main goal is to anticipate compressive strength. Regarding laboratory outcomes, the ANN model's output yields both positive and negative variations. Values above the laboratory findings indicate positive outcomes. The range of the positive variances is 3.44 percent to 8.22 percent. The negative variances are between 2.02% and 11.35% of the total. Compressive strength may all be determined using the results of the ANN model. Since the outcomes are good, the ANN model can be adopted as a reference to forecast the concrete's strength three days after the concrete has started to be laid. Every concrete result demonstrates the impact of groundwater.

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