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PREDICTING THE STRENGTH OF GGBS BASED GEOPOLYMER CONCRETE BY USING ARTIFICIAL NEURAL NETWORKS

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ABSTRACT-The use of secondary binding materials is well accepted because of the several improvements in concrete composites, the overall economy of the structures, and environmental preservation. Blast furnace slag is a non-metallic product consisting essentially of glass containing silicates and alumino-silicate of lime, which is developed simultaneously with iron in a blast furnace or electric pig iron furnace. Granulated slag is obtained by further processing of the molten slag by rapid chilling or quenching with water or steam and air.This paper presents the investigation of the compressive strength of geopolymer concrete. Ground Granulated Blast Furnace Slag (GGBS) is partially incorporated in a mathematical model developed based on the Neural Network (NN) concept for predicting the compressive strength of concrete with GGBS. The strength of concrete was estimated by the neural networks and also compared with the laboratory test results. The study established that Neural Network techniques are effective for predicting the strength of GGBS with the cement concrete depending upon their mix proportions. The application of this technique makes the possibility for the desired strength. Therefore, the use of GGBS as a pozzolanic component should be given priority from technical, economic, and environmental considerations.
Keywords: Ground Granulated Blast Furnace Slag; Compression Strength; Neural Network; Geopolymer Concrete; Molarity

1. INTRODUCTION

The utilization of GGBS is established as a replacement material for cement in concrete and the details of the strength properties are narrated in the literature. The GGBS is in use due to the overall economy in their production as well as their superior performance characteristics in aggressive environments. The lower cement requirement also leads to a reduction in CO_2 generated by the production of cement. Research work suggests that these auxiliary cementitious resources improve many of the performance characteristics of the concrete like strength, workability, permeability, and corrosion resistance. The pozzolanic reaction of GGBS starts at a very early age. The reaction becomes more noticeable at curing ages from 3 to 56 days. The pozzolanic reaction rate is directly proportional to the specific surface area of GGBS. The small variations in the results are primarily depending upon the chemical composition, fineness, and glass content of GGBS. The compressive strength of concrete is generally obtained by testing the concrete specimen after a standard curing period of 28 days in laboratories. A model is developed to predict the strength of concrete varying from with GGBS content of 100%. It was found that the model is giving almost the same values as normal concrete by comparing its regression coefficients. The tested values of early age strength of concrete results in the time delay in forecasting 56 days strength. Moreover, choosing an appropriate neuron network require experience because of the concrete strength which is influenced by many parameters. If the strength prediction is considered as a mapping from influencing factors to the compressive strength, then a mapping model can be formed by using Multi-Layer Feed Forward Neural Networks (MFNN) instead of regression equations. The study of neural networks (NN) was found based on the behavior of the biological nerve cell structure. The processing elements (neurons) in NN are the fundamental elements of the central nervous system and are used to determine the actions to be taken. The MFNN model is one of the most frequently used Artificial Neural Network (ANN) models, whose application is extended in all fields. This paper is aimed to establish a concept for predicting the compressive strength of GGBS mixed concrete at 3,7, 28, and 56 days using the neural network concept [28].

The relentless demand for concrete in the construction industry increases the potential use of cement. But the production of cement troubles the environment by emitting carbon dioxides which results in the promotion of geopolymer concrete. In geopolymer concrete silica and alumina available in the industrial by-products binds with alkaline activators by the process of polymerization. Last two decades a lot of research carried out in this emerging area identifying mix proportion, 2145 different by-product utilization, alkaline activator ratio, alkaline liquid/cement replacer ratio, different curing methods, etc [11]. The ANNs are computational models that adopt a training mechanism to extract the relationships that link a set of causal input parameters to the resulting conclusions. Once ANNs are trained, they can predict the results for an unknown case (not used in training) if provided with the input parameters alone. In this paper, a model of ANN has been constructed to predict concrete compressive strength and slump using data from different mix designs. The model is validated, tested, and regression analysis has been carried out to evaluate the accuracy of the model. At first, the data has been collected, then preprocessed (reviewing, validating data, standardization, normalization …etc.). And then the model is constructed. ANN offers an alternative to mathematical modeling. The main concept of the neural network is to feed it with input data and target output data, and it will learn the relationship between input and output. Subsequently, the trained network can be used to predict the outcome of other sets of input, where the answer is unknown. For further explanation of ANN, the technique, refer to introductory textbooks on the subject in reference. Using ANN has many advantages which includes solving complex problems for which don't exist any sequential algorithms. Instead, there are only examples of solutions. The ability of the ANN to adapt to changing environments; deterioration of some neurons does not involve a steep deterioration in performance but degrades network performance. The ANNs exhibit opportunity to work with imprecise data; the ability to modify the internal structure to perform the desired action. They generate their own rules of learned examples and are used to model the nonlinear systems. Creating a well-trained ANN led to the removal experimental phase; inexpensive and fast to a slow and expensive program structural analysis. They may be used for real-time applications; the ability to approximate a nonlinear continuous function with the desired degree of accuracy; easily modeled neural networks multivariable systems (a large number of inputs and outputs). Among the disadvantages noted for the ANNs are: that the learning process is complicated because of the difficulty in choosing the training set. Training is lengthy depending on the training method and the training set size and requires very efficient computing means. For training it takes a very large data volume; establishing training base is a difficult operation, it must cover all the search for a satisfactory solution. The ANN has the same weakness as the mathematical model. Because it is also based on empirical data. But the advantage over the mathematical model is that the programmer making the model doesn't have to declare every action of the program. When using ANN applications for problem-solving, it is needed to understand the problem to such a level that relevant parameters can be chosen as input. But when the network is trained, then learning about the problem is achieved by studying the way the network generalizes. In other words, the neural network summarizes the experience hidden in the input-output relationship. The ANN has been called the second-best way to do just about anything. The best way is of course to attain a full understanding of the problem and then find the right formula or optimum algorithm for the problem. However, this may not always be possible, and it leaves plenty of problems to be solved by the second-best approach .The basic architecture of artificial neural network (ANN) is of multi-layered perceptron type comprising three layers. These are the input, hidden, and output layers. The hidden layer is tan-sigmoid in nature and the output layer is pure in nature. Each of the aforesaid layers, irrespective of the input layer, in this study is characterized by a weight matrix and an output vector. The optimum results in this ANN were obtained with 6 inputs, 30 tan-sigmoid hidden neurons, and 1 linear neuron in the output layer. The efficacy of ANN depends primarily on the feature set, network architecture, and a suitable algorithm. Therefore, this design of ANN was trained using the Levenberg-Marquardt algorithm, which has a minimum performance with mean square error (MSE), by the gradient of the performance function. Network generalization improvisation and overfitting in this study were avoided by randomly dividing the input data as 70%, 15%, and 15% for training, validation, and testing purposes respectively. The weights of the input and hidden layer from the first training session were reutilized in further training iterations, to improve training with less time consumption in the process. These iterations were carried out until optimum regression values were obtained. Finally, performance plots, regression plots, error histograms, and training states were generated. Comparison graphs were also generated to test the efficiency of the network .[28]

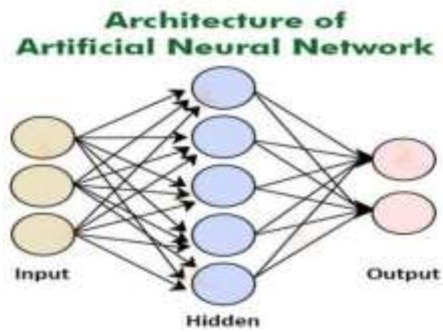

Fig.1 : Architecture of ANN
Source : https://techvidvan.com/tutorials/artificial-neural-network

The current research focuses mainly on predicting the compression strength of GGBS-based geopolymer concrete based on Artificial Neural Networks (ANN).

2.LITERATURE REVIEW

Emad S. Bakhoum et al. (2023) stated that the artificial neural networks (ANN) technique and multiple linear regression (MLR) are used to develop models that can predict the compressive strength of concrete including cement kiln dust and fly ash.Using artificial inelegance applications in construction industry can open the door for development of more innovative approaches that contribute to sustainable construction. Most studies have emphasized increasing the number of samples to enhance ANN training and reduce prediction error. Consequently, samples were developed during training and more than one training model was conducted. Therefore, artificial neural networks can be taught in order to obtain the lowest percentage of error prediction based on trial and error.

Musa Adamu et al. (2023) reported that the ANN model is utilized to simulate the mechanical characteristics of concrete incorporating crumb rubber, nanosilica, and fly ash, including splitting tensile, compressive strength, elastic modulus, and flexural strength. The dataset for the modeling was obtained from the experimental results. The ANN model demonstrate more robust and accurate prediction skill in estimating the mechanical properties. Sensitivity analysis is utilized to optimize the ANN model's parameters, and compressive strength, a fundamental mechanical characteristic of concrete, is used to determine whether there is a linear or nonlinear relationships among an input parameters and targeted parameters. The outcome suggests that the most important factor in predicting strength is curing age. During the training phase, the proposed ANN model showed relatively low errors. The mean MoD values predicted values for Fc, Fs, Ff and Ec were −0.28%, 0.14%, 0.87% and 1.17%, respectively, which are near to the zero line. Overall, the ANN model predicted the strength with great accuracy.

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Dina A. Emarah (2022) determined that three machine learning approaches (ANN, DNN, and ResNet) were used to predict models for the C–S of FA-GPC in this work. Based on the 860 datasets from previous studies and the simulation of the FA-GPC's C–S, the following conclusion main finding are: . Geopolymer concrete made from FA can help with sustainable development because it doesn't use cement and instead uses industrial ash or a by-product as a binder. This means that less carbon dioxide is released into the air.

Yaswanth Kuppusamy et al. (2022) determined that the best individual outputs were "tacked-together" from the best five ANN models and were also analyzed, achieving accuracy up to 88%. It is suggested that when these seven mix-design influencing factors are involved, then ANN [2:16:25:7] can be used to predict the mix which can be cross-verified with GDX-ANN [7:14:2] to ensure accuracy and, due to the few mix trials required, help design the SHGC with lower costs, less time, and fewer materials.

3.METHODOLOGY

Procedure for implementation of ANN for predicting the Compression Strength

Data Collection

At the age of 28 days, 55 datasets were collected from previous GGBS/FA-GPC, and references are cited in this paper. There is a wealth of information on geopolymer concrete with various curing settings, specimen ages, and base source materials in the literature. On the other hand, the authors of this work utilize the measured compressive strength after 28 days of curing at room temperature. Those publications employed GGBS and fly ash (FA) as base source materials to manufacture the geopolymer concrete. The authors could incorporate additional datasets in the created models since the models required eleven input parameters. For example, if the mix proportions and any other model parameters of the investigation were not supplied, such studies were disregarded. Table 1 shows the dataset ranges, including all significant parameters and the observed compressive strength of GGBS/FA-GPC at 28 days.

Table-1: Data Collection

S. No	Source	GGBS	Fly Ash	Coarse Agg.	Fine Agg.	Sodium Hydroxide	Sodium Silicate	Compression Strength	Split Tensile Strength	Flexural Strength
1	[7]	260	440	1090.8	500	69	171	78.88	-	-
2	[7]	300	252	838.8	770	69	171	41.5	-	-
3	[7]	200	400	1201	647	69	171	31.96	-	-
4	[7]	300	400	1201	647	69	171	57.5	-	-
5	[7]	400	400	1201	647	69	171	66.6	-	-
6	[8]	409	205	1293	554	41	102	60	-	-
7	[9]	150	300	1058	742.7	51.43	129	41	-	-
8	[10]	409	0	1293	554	41	102	46.23	-	-
9	[10]	306	102.2	1293	554	41	102	46.23	-	-
10	[10]	204.5	204.5	1293	554	41	102	60.23	-	-
11	[12]	0	390	1092	585	67	167	53	-	-
12	[13]	150	300	1048	742.7	51.43	129	36.9	-	-
13	[14]	0	409	1294	554	40.89	102.22	69.2	3.25	8.28
14	[15]	158	237	1277	547	52	129	54	-	-
15	[16]	39.43	354.8	1293.6	554.4	45.06	112.65	49	2.96	-
16	[16]	78.86	315.4	1293.6	554.4	45.06	112.65	15.74	3.25	-
17	[16]	118.2	276.0	1293.6	554.4	45.06	112.65	78.88	3.72	-
19	[16]	197.1	197.1	1293.6	554.4	41	103	31.62	-	-
20	[17]	550	0	962	503	71	177	35.6	-	-
21	[18]	414	0	1136	600	53	133	48.04	-	-
22	[19]	168	420	1084	617.2	42	105	72	-	-
23	[20]	0	408	1201	660	41	103	28.56	-	-
24	[21]	192	347	1204	602	66.2	166	26.5	-	-
25	[22]	0	350	1250	650	41	103	27.53	2.54	1.29
26	[23]	0	410	1044	530.6	67	117	34.7	2.73	1.33

27	[24]	48	432	1090	590	69	171	70.8	4.4	-
28	[24]	96	384	1090	590	69	171	23.4	4.9	-
29	[24]	144	336	1090	590	69	171	29.52	5.4	-
30	[24]	192	288	1090	590	69	171	32.86	2.41	3.21
31	[24]	240	240	1090	590	69	171	35.73	3.28	3.6
32	[25]	204	408	1290	549	41	102	46.6	-	--
33	[26]	367.2	0	1294	554	41	103	45.55	4.37	4.68
34	[26]	326.4	39	1294	554	41	103	33.22	1.92	2.4
35	[26]	285.6	78	1294	554	41	103	23.46	5.94	5.97
36	[26]	408	0	1294	554	41	103	27.54	-	-
37	[26]	244.8	117	1294	554	41	103	29.5	2.38	-
38	[27]	409	0	1293	554	41	102	58.6	3.54	5.76
39	[29]	0	350	1081	483	40	100	36.93	4.04	3.65
40	[29]	35	315	108	483	40	100	39.23	4.36	3.83
41	[29]	70	280	1081	483	40	100	21.45	4.69	3.86
42	[29]	105	245	1081	483	40	100	34.32	4.94	4.01
43	[29]	140	210	1081	483	40	100	42.48	3.15	3.58
44	[29]	175	175	1081	483	40	100	16.6	3.91	4.16
45	[30]	400	400	1209	651	45.7	114.3	40	-	-
46	[31]	40	360	1209	651	45.7	114.3	27.3	2.07	1.17
47	[31]	80	320	1209	651	45.7	114.3	40.5	2.35	1.23
48	[31]	40	360	1217	655	40	100	49.3	3.1	-
49	[31]	80	320	1217	655	40	100	60.4	3.8	-
50	[32]	415	0	1039	784	46	71	40.02	-	-
51	[32]	350	350	1200	645	41	103	57.5	-	-
52	[32]	414	414	1091	588	104	138	44	-	-
53	[33]	80	400	1222	658	56	113	47	-	-
54	[34]	0	394	1293.4	554.4	45.1	112.6	38	2.62	-
55	[35]	350	450	1343	575	52.5	131	30.57	-	-
56	M1	414	0	1134	660	53.2	133	61.67	3.74	6.2
57	M2	414	0	1134	660	53.2	133	65.29	4.05	6.27
58	M3	414	0	1134	660	53.2	133	68.34	4.52	6.32
59	M4	414	0	1134	660	53.2	133	70.20	4.65	6.45
60	M5	414	0	1134	660	53.2	133	73.82	5.02	6.54

Configuring the Data Set

Caluclating the Column Distribution of Compression Strength, Split Tensile Strength and Flexural Strength

Figure 2 shows the histogram for the variable compression strength.The abscissa represents the centers of the containers, and the ordinate represents their corresponding frequencies.The maximum frequency is 17.0732% (7 samples), which corresponds to the bin with a center of 36.627. The minimum frequency is 2.43902% (1 samples), which corresponds to the bin with a center of 65.237.Figure 3 shows the histogram for the variable split tensile strength.The abscissa represents the centers of the containers, and the ordinate represents their corresponding frequencies.The maximum frequency is 39.6552% (23 samples), which corresponds to the bin with a center of 0.297.Figure 4 shows the histogram for the variable flexural strength.The abscissa represents the centers of the containers, and the ordinate represents their corresponding frequencies.The maximum frequency is 58.6207% (34 samples), which corresponds to the bin with a center of 0.414. The minimum frequency is 0% (0 samples), which corresponds to the bin with a center of 7.038.

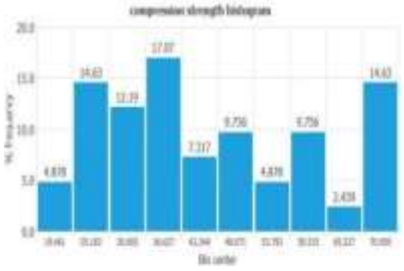

Fig.2 : Compression Strength Distribution

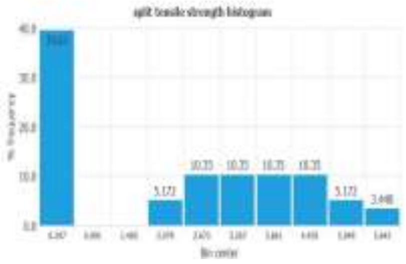

Fig.3: Split Tensile Strength Distribution

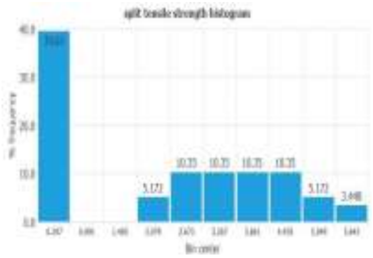

Fig.4: Flexural Strength Distribution

Modelling

Input and Output Parameters

The number of inputs is 6 and outputs is 3.The following table 2 depicts the name of the inputs and outputs from the neural network.

Scaling layer,Percepton layer and unscaling layer(Hidden layers) in Modelling

The size of the scaling layer is 6, the number of inputs.

The most important layers of a neural network are the perceptron layers (also called dense layers). Indeed, they allow the neural network to learn.The number of perceptron layers in the neural network is 2.The following table 3 depicts the size of each layer and its corresponding activation function.

Table-2: Input and Output parameters

Input Parameters	Output Parameters
GGBS	Compression Strength
Fly Ash	Split Tensile Strength
Fine Aggregate	Flexural Strength
Coarse Aggregate	
Sodium Hydroxide	
Sodium Silicate	

Table-3: Size of Percepton Layer

	Inputs Number	Neurons Number	Activation Function
1	6	3	Hyperbolic Tangent
2	3	3	Linear

The size of the unscaling layer is 3, the number of outputs.Table 4 shows the values used for scaling the inputs and unscaling the outputs. They include the minimum, maximum, mean, and standard deviation.

Table-4: Descriptive analysis of Data Base Parameters in hidden layers (scaling and unscaling layer)

Statistical Parameters	Input Parameters(scaling layer)						Output Parameters(unscaling layer)		
	GGBS	Fly Ash	Coarse Aggregates	Fine Aggregates	Sodium Silicate	Sodiu Hydroxide	Compression Strength	Split Tensile Strength	Flexural Strength
Minimum	0	0	108	483	40	71	15.74	0	0
Maximum	550	440	1294	784	104	177	78.88	2.14545	1.67482
Mean	208.262	242.457	1158	592.116	51.4858	124.193	45.2354	2.14545	1.67482
Deviation	150.581	152.424	173.465	71.1936	13.1579	27.8403	16.2646	1.92592	2.38059
Scalar	Mean Standard Deviation								

Network Architecture

The next figure depicts a graphical representation of the network architecture.It contains the following layers:
Scaling layer with 6 neurons (yellow).Perceptron layer with 3 neurons (blue).Perceptron layer with 3 neurons (blue).Unscaling layer with 3 neurons (red).Bounding layer with 3 neurons (purple).

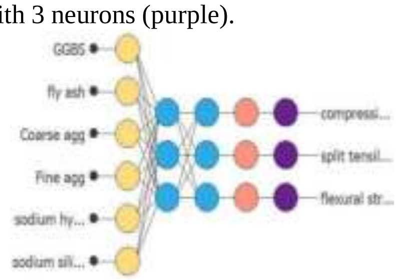

Fig.5: Network Architecture

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Model Selection

Model selection algorithms are in charge of finding a neural network with a topology that optimizes the error on new data. There are two different types of algorithms for model selection.Neurons selection algorithms and input selection algorithms.Neurons selection algorithms are used to find the optimal number of hidden neurons in the network.Inputs selection algorithms are responsible for finding the optimal subset of input variables.Neuron selection algorithm starts with a minimum number of neurons and adds a given number in each iteration.In input selection algorithm method, the inputs are added progressively based on their correlations with targets.

	Description	Value
Minimum neurons	Minimum number of hidden perceptrons to be evaluated.	1
Maximum neurons	Maximum number of hidden perceptrons to be evaluated.	10
Step	Number of hidden perceptrons added in each iteration.	1
Trials number	Number of trials for each neural network.	3
Selection loss goal	Goal value for the selection error.	0
Maximum selection failures	Maximum number of iterations at which the selection error increases.	100
Maximum iterations number	Maximum number of iterations to perform the algorithm.	1000
Maximum time	Maximum time for the neurons selection algorithm.	3600

Fig.6: Neuron Selection Algoritm

	Description	Value
Trials number	Number of trials for each neural network.	3
Selection error goal	Goal value for the selection error.	0
Maximum selection failures	Maximum number of iterations at which the selection error increases.	100
Maximum inputs number	Maximum number of inputs in the neural network.	6
Minimum correlations	Minimum value for the correlations to be considered.	0
Maximum correlation	Maximum value for the correlations to be considered.	1
Maximum iterations number	Maximum number of iterations to perform the algorithm.	1000
Maximum time	Maximum time for the inputs selection algorithm.	3600

Fig.7: Input Selection Algorithm

Testing Analysis

The purpose of testing is to compare the outputs from the neural network against targets in an independent set (the testing instances). Testing methods are subject to the project type (approximation or classification).If all the testing metrics are considered, the neural network can move to the so-called deployment phase. Note also that the results of testing depend very much on the problem at hand, and some numbers might be right for one application but bad for another.The goodness-of-fit analysis is a method to test the performance of a model in approximation applications, it describes how well it fits a set of observations.The determination of Coefficient of the goodness-of-fit parameters for the output compression strength,split tensile strength and flexural strength are 0.14780892, 0.1834182 and 0.012341451.

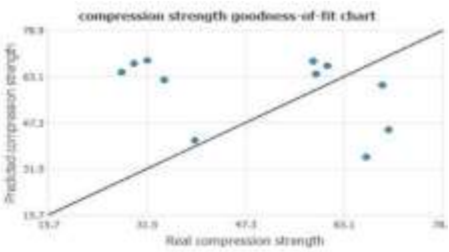

Fig.6: Compression Strength

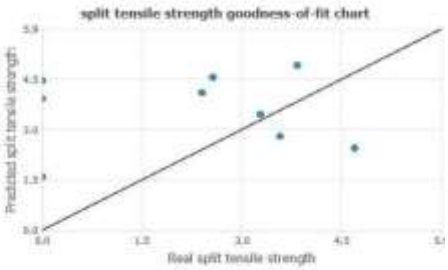

Fig.7: Split Tensile Strength

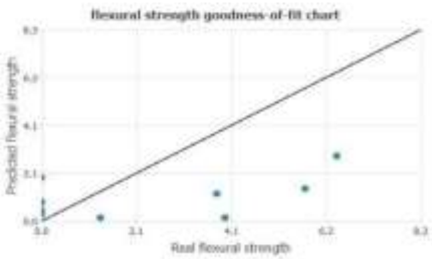

Fig.8: Flexural Strength

4.EXPERIMENTAL STUDY

Materials

Ground Granulated Blast furnace Slag

Ground Granulated blast furnace slag (GGBS) is a by-product of iron manufacturing industries. This GGBS was formed in the form of slag in the blast furnace unit, raw materials like limestone, iron ore, and coke were fed into the blast furnace at 1500^{0}C at the bottom of the furnace molten iron was formed and above that, a layer of is formed and that slag was removed from the furnace rapidly cooled after that it was ground up to required fineness now GGBS was formed. GGBS that was used in this experimental study formed JSW cement which was available in 50 kg bags. A sample of GGBS was shown in Figure-9. The physical propertyof GGBS that was used in this study were shown in Table 5.

Fine Aggregates

Sand is used as a fine aggregate in mortars and concrete. River Sand for Building Materials. As a finely aggregated material, natural river sand is the favoured option. River Sand is a result of millions of years of natural rock weathering. The river beds are mined. Sand is a granular material that consists of finely divided particles of rock and mineral. The scale is finer than gravel and grosser than silt. Sand may also refer to soil or soil type textural classes, i.e., soil containing by mass more than 85 percent sand particles.

Table-5. Physical properties of GGBS.

S. No	Name of the Test		Test Results
1.	Standard Consistency		33
2.	Setting time of cement in minutes Initial Setting time Final Setting time		 24 170
3.	Specific Gravity		2.92
4.	Fineness of Cement		1.2
5.	Compressive Strength	3 days	36.67
		7 days	47.87
		28 days	58.05

I.S. Sieve (mm)	Percentage passing through I.S. Sieve	
10	100	Fineness modulus = 2.7 Specific Gravity = 2.64 Bulk Density = 1625 kg/m^3 Bulking of sand = 23% Silt content = 0.25%
4.75	98.8	
2.36	95.8	
1.18	63.6	
600 micron	44.8	
300 micron	15.8	
150 micron	5.6	
Zone	II as per IS 383	

Table-6. Physical properties of Fine Aggregate

Coarse Aggregate

Aggregates are the world's most polluted content. Aggregates are parts of construction materials such as concrete and asphalt concrete, and the resulting construction material is reinforced by the aggregate. Grow aggregates of more than 0.19 inches are particles with a diameter varying from 0.375 to 1.5 inches. The crushed granite of size 10 mm was locally available for the cement mix used in this experimental work. So IS 383:1970 andIS 2386:1963 work has been done.

Table-7: Physical properties of coarse aggregate 10mm

Sieve size (mm)	10 mm	
	Requirement as per IS:383-1970	Percentage Passing
12.5	100%	100%
10	85-100%	94.62%
4.75	0-20%	15.40%
2.36	0-5%	2.89%
Specific gravity		2.7
Water absorption %		0.35%
Aggregate Impact Value		12.67%
Bulk Density (kg/m3)		1663
Flakiness		14%
Elongation		15%

Alkaline Activator solution

The Alkaline activator was the second most component in the geopolymer concrete. The main aim of this activator is to react with the GGBS and make it a binder, without this activator solution GGBS cannot behave as binders. The source material like GGBS contains silicon and aluminium in rich quantity and now the alkaline solution will react with silicon and aluminium to form a binder. Generally, the alkaline activator solutions were based mainly on sodium. Sodium Hydroxide and Sodium Silicate are the commonly used alkaline activators in geopolymerisation .

Mix Design of Geopolymer Concrete

It was known that there is no particular code for the design of geopolymer concrete mix. And due to this reason, the mixed design of geopolymer concrete was taken from past literature; it was observed that the overall density of geopolymer concrete made with GGBS was similar to conventional concrete which was around 2400 kg/m^3. The total percentage of combined aggregates was 75% of the total mass of geopolymer concrete and this was similar to normal concrete made with ordinary Portland cement. And the percentage of fine aggregate from the combined aggregate percentage was 37%. The maximum size of coarse aggregate that was used in this experimental investigation was 10mm aggregate. The reason for using 10mm aggregates was to fill the voids in the concrete which cannot be filled by 20mm aggregates. As the density of geopolymer concrete was known from this the GGBS and alkaline activator solution combined mass was determined. And also the ratio of alkaline liquid to cementitious material was assumed to be 0.45 and now the quantity of GGBS was determined and also the quantity of alkaline activator solution was determined. After the addition of the alkaline activator solution, geopolymerisation will start. In this experimental study, the concentration of sodium hydroxide for the preparation of the alkaline activator solution was 8 to 16 molarity. The ratio of sodium hydroxide and sodium silicate was taken as 1:2.5 for all molarities.

Materials	Quantity kg/m^3
GGBS	413.8
Fine Aggregates	660
Coarse Aggregates	1136
NaOH	53.2
Na_2SiO_3	133

Table-9: Mix Design

NaOH Molarity (M)	Masses of NaOH Pellets dissolved in 1L of distilled water (g)	Masses of NaOH: Na_2SiO_3 the ratio of 1:2.5 (g)
8M	320 grams	112 grams
10M	400 grams	116 grams
12M	480 grams	120 grams
14M	560 grams	124 grams
16M	640 grams	128 grams

Table-10: Mix proportion of NaOH: Na_2SiO_3

5.RESULTS & DISCUSSIONS

Neural Network Outputs

A neural network produces a set of outputs for each set of inputs applied.

The following table shows the input values and their corresponding output values.The input variables are GGBS, fly ash, Coarse agg, Fine agg, sodium hydroxide and sodiumsilicate, and the output variable is compression strength.

	Value
GGBS	208.262
fly ash	242.457
Coarse agg	1158
Fine agg	592.116
sodium hydroxide	51.4858
sodium silicate	124.793
compression strength	50.575047
split tensile strength	2.387079
flexural strength	1.487904

Fig.10: Outputs

Compressive Strength Test Results

The compressor power was performed on 3, 7, 28, 56 days on cement concrete molarity cube of M40 .The results of the experiments increased geopolymer concrete compressive strength, and for 3, 7, 28, 56 days the geopolymer concrete had a compressive strength higher than M40 concrete, as shown in Table 8 . The compressive strength of geopolymer concrete for 3, 7, 28, 56 days of testing was double the strength of grade M40 concrete, raising the strength of geopolymers produced with different molarities with an increase in compressive strength of geopolymer concrete in 8M and 10M – 0.017% for 3, 7, 28, 56 days. 10M and 12M –0.031% for 3, 7, 28, 56 days. 12M and 14M – 0.033% for 3, 7, 28, 56 days. 14M and 16M – 0.151% for 3, 7,, 28, 56 days. To compare the conventional concrete M40 strength is 0.015% for 3 to 7 days, 0.28% for 7 to 28 days, 0.041% for 28 to 56 days, 0.059%.And it can be inferred that the strength was also rising as the sodium hydroxide concentration rises and when geopolymer concrete only displays higher strengths from 8 molarity compared to M40 grade concrete. The outcome was also shown in the bar-line format in chart 1 for 3, 7, 28, 56 days, respectively.

Split Tensile Strength Test Results

Split tensile strength was done on the cylinders of 0.30m height and 0.15m diameter. On 3, 7, 28, 56 days, on cement concrete cube of M40 on geopolymer concrete cubes of different molarities, the tensile strength was executed. From the test results, the compressive strength of geopolymer concrete was improved and the tensile strength of geopolymer concrete was higher than M40 concrete for 3, 7, 28, and 56 days, these test results were shown in Table 9. For 3, 7, 28, 56 days of testing, the tensile strength of geopolymer made concrete was double the strength of M40 grade concrete and raises the strength of geopolymer produced with specific molarities Increased strength with an increase in compressive strength of geopolymer concrete. And it can be inferred that the strength was also rising as the sodium hydroxide concentration rises and when geopolymer concrete only displays higher strengths from 8 molarity compared to M40 grade concrete.

Flexural Strength Test Results

It is finding a concrete strength to subject into the prism beam of a lateral compressive force. The size of 0.15x0.15x0.70m was cast on 3, 7, 28, 56 days, on cement concrete cube of M40 on geopolymer concrete cubes of different molarities, the tensile strength was executed. And they listed all the mixes as shown in Table 5.3. From the test results, the flexural strength of geopolymer concrete was improved were higher than M40 concrete for 3, 7, 28, 56 days, these test results were shown in Table 10. For 3, 7, 28, 56 days of testing, the flexural strength of geopolymer made concrete was double the strength of M40 grade concrete and raises the strength of geopolymer produced with specific molarities Increased strength with an increase in flexural strength of geopolymerconcrete. And it can be inferred that the strength was also rising as the sodium

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hydroxide concentration rises and when geopolymer concrete only displays higher strengths from 8 molarity compared to M40 grade concrete.

Mix ID	3 Days	7 Days	28 Days	56 Days
M1	4.1	5.46	6.2	6.14
M2	4.83	5.57	6.27	6.31
M3	5.22	5.65	6.32	6.53
M4	5.57	5.73	6.45	6.63
M5	5.73	5.88	6.54	6.74

Table-9: Test Results of Split Tensile Strength

Table-8: Test Results of Compressive Strength

Mix ID	3 Days	7 Days	28 Days	56 Days
M1	3.1	3.32	3.74	3.43
M2	3.75	3.84	4.05	4.12
M3	3.83	3.95	4.52	4.75
M4	3.94	4.6	4.65	4.82
M5	4.2	4.12	5.02	5.28

Table-10: Test Results of Flexural Strength

Mix ID	3 Days	7 Days	28 Days	56 Days
M1	30	35.6	61.67	70.89
M2	32.1	36.1	65.29	77.5
M3	34.14	36.7	68.34	80.18
M4	38.6	40.3	70.2	83.28
M5	40.8	42.78	73.82	85

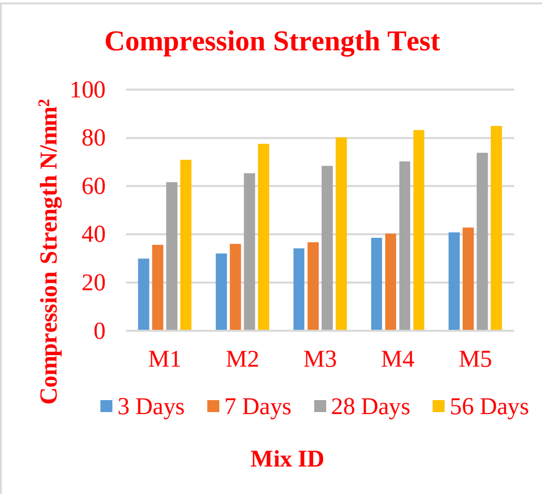

Chart-1: Compressive Strength for 3, 7, 28 and 56 days

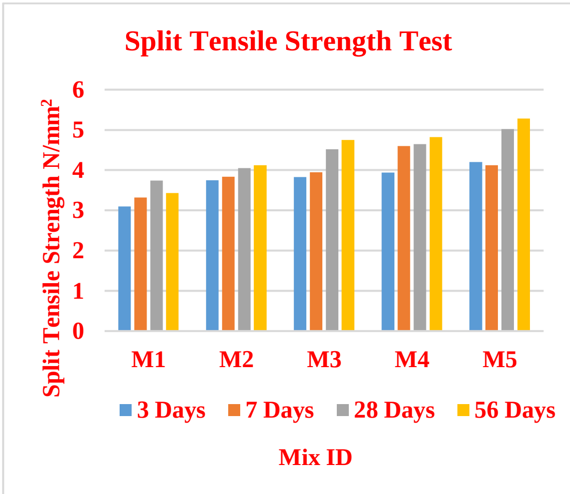

Chart-2: Split Tensile Strength for 3, 7, 28 ,56 days

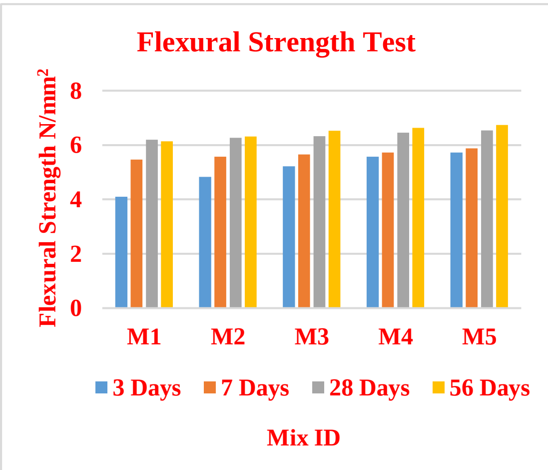

Chart-3 : Flexural Strength for 3, 7, 28 and 56 days

6.CONCLUSION

Experimental study on geopolymer concrete and normal concrete to concluded that:

1. The compressive strength of geopolymer concrete is an increase in 8M and 10M – 0.017% for 3, 7, 28, 56 days. 10M and 12M – 0.031% for 3, 7, 28, 56 days. 12M and 14M – 0.033% for 3, 7, 28, 56 days. 14M and 16M – 0.151% for 3, 7, 28, 56 days.
2. The split tensile strength of geopolymer concrete is an increase in 8M and 10M - 0.003% for 3, 7, 28, 56 days. 10M and 12M – 0.005% for 3, 7, 28, 56 days. 12M and 14M – 0.006% for 3, 7, 28, 56 days. 14M and 16M – 0.007% for 3, 7, 28, 56 days.
3. The flexural strength of geopolymer concrete is an increase in 8M and 10M - 0.0016% for 3, 7, 28, 56 days. 10M and 12M – 0.0016% for 3, 7, 28, 56 days. 12M and 14M – 0.0018% for 3, 7, 28, 56 days. 14M and 16M – 0.0023% for 3,7, 28, 56 days.
4. The compressive strength of concrete was determined as 50.57 kN/mm^2 using ANNs. ANNs were proposed, with feed forward typology, back propagation learning, and multilayer architecture. ANN was the closest to the real results, which was composed of an input layer with six neurons (fine aggregate,Coarse aggregate, GGBS, Fly Ash, Sodium Hydroxide, Sodium Silicate),four hidden layers eighteen neurons each, and the concrete compressive strength as the output.
5. ANN calculated the concrete compressive strength with an error of 3.00%, and when it is evaluated with the error performance indicator, the coefficient of determination (R2) of 0.14. For future work, it is proposed to use various mathematical modeling techniques, data mining, or optimization techniques, to estimate the compressive strength of concrete with greater reliability. These results would allow the creation of software become alternatives to the quality control of concrete in the construction industry.
6. The conclusions based on the limited observations from the present investigation on properties of fresh and hardened are:
   A. Workability of geopolymer concrete increase in GGBS does not affect the workability.
   B. Mechanical properties such as compressive strength, split tensile strength and flexural strength shows in increasing trend with increase of GGBS.

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