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DEVELOPMENT OF STATISTICAL MODEL AND NEURAL NETWORK FOR THE ESTIMATION OF COMPRESSIVE STRENGTH OF HIGH-VOLUME GROUND GRANULATED BLAST FURNACE SLAG CONCRETE IN MARINE ENVIRONMENT

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Abstract

In concrete, the utilization of Ground Granulated Blast Furnace Slag (GGBS) as partial replacement for cement is becoming popular as it reduces the cement content used in the production of concrete and thereby reduces the cost of construction and also the carbon footprint caused by cement in concrete. GGBS, to be used as a partial replacement to cement in concrete, the strength parameters of partially replaced GGBS concrete is to be studied in details. In the present study, Multiple Linear Regression (MLR) and Artificial Neural Network (ANN), the two major statistical models are developed for the experimental values of compressive strength of concrete specimens with cement being partially replaced by GGBS up to 70%. Here, the experimentation involves both high strength (M40 Grade) and low strength (M20 Grade) concrete specimens for comparison in Artificial Marine environment and Normal Environment. In addition to all the above parameters, the compressive strength of concrete specimens subjected to Acid Attack and Sulphate Attack is also studied and included. The predicted results of compressive strength from both MLR and ANN are compared for their statistical significance and accuracy to decide the best statistical model out of both for the prediction of compressive strength of concrete.

Keywords: Concrete, Multiple Linear Regression, Artificial Neural Network, Compressive Strength

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1. Introduction

Concrete is widely recognized as a major construction material due to its strength and durability characteristics [1It is a composite material made of cement paste holding together coarse and fine particles. Concrete, the second-most used material in the world [1], is useful for building applications due to its adaptability in shape and size when it is still new. However, creating a mix design with the desired strength and durability is a labour- and money-intensive procedure that involves choosing the exact proportions of the ingredients. Different admixtures, some naturally occurring and others created chemically, are used to increase the strength and durability of concrete. Recently, a number of admixtures and partial cement substitutes have been used to create mixes that are both effective and affordable. Concrete sometimes uses mineral admixtures as partial substitutes for cement, such as fly ash, ground granulated blast furnace slag (GGBS), and rice husk ash [2, 3]. Compared to traditional concrete, this replacement significantly increases the strength and durability of concrete.

The impact of combined cement and mineral admixtures on the characteristics of concrete has been investigated by several researchers [2–8]. In order to increase compressive strength, some researchers have looked into the use of bacteria as additives [5], while others have looked into the effects of field curing on the durability of concrete [6]. With encouraging outcomes, glass fibre reinforced polymer (GFRP) has also been researched as a reinforcing alternative [7]. Additionally, concrete qualities like compressive strength have been predicted using statistical techniques like Artificial Neural Network (ANN) and Multiple Linear Regression (MLR) models [21–25]. In order to examine its impact on compressive strength, this study focuses on the partial substitution of GGBS up to 70% in concrete. The study comprises concrete specimens of varying strengths, including those evaluated in natural and synthetic maritime settings. The compressive strength of concrete specimens subjected to acid and sulphate assaults is also taken into account. To forecast the compressive strength of concrete under the aforementioned parameters, experimental data from these tests will be utilised to create an ANN model and an MLR model using MATLAB® and MiniTab-2021.

In order to better understand how GGBS-replaced concrete performs and how well ANN and MLR models forecast concrete qualities under various environmental exposures and situations, the technical paper's goal is to advance knowledge in these areas. The results of this study can help concrete mix designs be optimised for increased strength and durability, which will assist the building sector.

2. Materials and Methodology

2.1 Cement

The binding material used in concrete is cement, which serves to bind various components together. For this experiment, JK Cement of OPC 53 grade is used. The appropriate tests and standards, in accordance with IS:269/4831 and IS:12269-1987, define the physical properties of cement.

Table 2.1: Physical properties of Cement

Physical Properties	Obtained Values	Values as per IS:12269-1987
Specific Gravity	3.10	-
Normal Consistency	33%	-
Initial Setting Time	95 Minutes	30 minutes (Minimum)
Final Setting Time	250 Minutes	600 minutes (Maximum)

2.2 Fine Aggregates

Sand from nearby rivers is utilised as the fine aggregate. Both the fineness modulus and specific gravity are measured.

Table 2.2: Physical properties of Fine Aggregates

Physical Property	Obtained Value
Specific Gravity	2.62
Fineness modulus	2.72

2.3 Coarse Aggregates

The crushed gravel retained on the IS450 sieve can have a maximum size of 20 mm. For this investigation, coarse aggregates that pass through a 12.5 mm screen are employed in 40% of the samples and a 20 mm filter in 60% of the samples. The coarse aggregates used in the study have the following qualities.

Table 2.3: Physical properties of Coarse Aggregates

Physical Property	Obtained Value
Specific Gravity	2.71
Fineness modulus	6.82

2.4 Ground Granulated Blast Furnace Slag (GGBS)

The ground granulated blast furnace slag utilized here is obtained from the provider and is obtained from the industrial sector of Bykampady, Mangalore.

Table 2.4: Physical properties of Ground Granulated Blast Furnace Slag

Physical Property	Obtained Value
Specific Gravity	2.91
Bulk Density	1247 kg/m^3
Color	Whitish
Fineness	6.91%

2.5 Water

Water used for casting the specimens is clean and potable.

2.6 Testing Specimens

In the current study, M20 grade concrete specimens with a water to cement ratio of 0.50 and M40 grade concrete specimens with a water to cement ratio of 0.40 are taken into consideration in an artificial marine environment as well as in a normal environment with up to 70% GGBS replacing cement. Table 2.5 lists the number of test specimens that make up a set, and each test set will have 32 specimens.

Table 2.5: Number of test specimens under one set.

(TS represents Test Specimen)

GGBS Replacement (%)	M20		M40	
	Normal Environment	Artificial Marine Environment	Normal Environment	Artificial Marine Environment
0 (Normal Concrete)	TS 0.1	TS 0.2	TS 0.3	TS 0.4
10	TS 1.1	TS 1.2	TS 1.3	TS 1.4
20	TS 2.1	TS 2.2	TS 2.3	TS 2.4
30	TS 3.1	TS 3.2	TS 3.3	TS 3.4
40	TS 4.1	TS 4.2	TS 4.3	TS 4.4
50	TS 5.1	TS 5.2	TS 5.3	TS 5.4
60	TS 6.1	TS 6.2	TS 6.3	TS 6.4
70	TS 7.1	TS 7.2	TS 7.3	TS 7.4

2.7 Artificial Marine Environment (AME)

Preparation of AME describes the protocol of developing a simulated marine environment with water in which the concrete specimens to be tested are cured. The Artificial Marine Environment is a solution of 3% of NaCl + $CaCl_2$ with 0.5% of $MgSO_4$ in a curing tank.

2.8 Compressive Strength Test

According to IS:516-1959, standard specimens with dimensions of 15 cm x 15 cm x 15 cm are put through a Compressive Strength test. A failure test is performed on the specimens, and the failure load is noted. The compressive strength test is carried out in the current study while adhering to three criteria. After being cured in regular water, in 5% sulfuric acid solution, and in 5% magnesium sulphate solution for 7, 28, 56, and 90 days, respectively, all 32 specimens were evaluated for compressive strength. The failure load is divided by the cross sectional area to get compressive strength.

2.9 Statistical Modelling

In the present study, statistical models for Compressive Strength of M20 and M40 grade concrete subjected to GGBS replacement up to 70% in Normal and Artificial marine environment subjected to Acid Attack and Sulphate Attack is developed using Multiple linear Regression (MLR) and Artificial Neural Network (ANN) and the feasibility of both the models are compared with the original set of values obtained from the experimentation.

3. Results and Discussion

3.1 Experimental results of compressive strength test and discussion

Compressive strength of concrete specimens where cement is partially replaced by GGBS up to 70%, cured in normal water, 5% sulphuric acid solution and 5% magnesium sulphate solution in normal environment and artificial marine environment (AME) is calculated through failure load calculation for 7, 28, 56 and 90 days. The compressive strength is calculated for M20 and M40 grade concrete specimens.

When the results of all the above mentioned specimens are analysed, the optimum GGBS replacement to cement in concrete is found to be around 40% to 45%. There is an increasing trend in the values of compressive strength as the amount of GGBS increases in the case of 5% sulphuric acid solution.

4. Statistical Modeling

In this study, Multiple Linear Regression (MLR), one of the statistical modelling techniques, is used to develop statistical models for Compressive Strength obtained from experiments of M20 and M40 grade concrete subjected to GGBS replacement up to 70% in Natural and Artificial marine environments under Acid Attack and Sulphate Attack.

4.1 Multiple Linear Regression (MLR)

It is a statistical model which is a part of regression, where the data collected is been used as input parameters to determine the output parameters. If a particular analysis includes more than one input variables, then such a regression model will be called as Multiple Linear Regression model or MLR. MLR fits an equation of regression between two or more input variables to predict the output. In this study a software called Minitab-6 is used to develop MLR model and to evaluate the results.

An MLR model can be mathematically expressed in the following way:

$y = a_0 + a_1 x_1 + a_2 x_2 + \dots$

Where, y is the dependent variable, x_1, x_2 … etc. are the independent input variables and a_0, a_1 , a_2,… are the coefficients.

5. Artificial neural networks (ANN)

The artificial neural network is a network of neurons which are identical to that of the biological neuron whose structure is same as that of human brain and it consists of multiple inputs and each input is considered as an output for the next neuron. The inputs gets weighted and finally a weighted average is found as output. The connection patterns of neurons is known as neuron connection pattern. In the present study “nntool” of MatLab is used to build and train an Artificial Neural network.

6. Data used for modelling

Compressive Strength results of M20 and M40 grade concrete is in Normal and Artificial marine environment which are water cured and further subjected to Acid Attack and Sulphate Attack is experimentally attained and the same data is been used for MLR and ANN are explained in table number 4.1

Table Number 6.1: Various Dependent and Independent variables

Dependent Variable for MLR/Output Parameters for ANN	**Independent Variables for MLR/ Input Parameters for ANN**
Compressive Strength of Concrete obtained from experimentation (In Normal Water, Under Acid Attack and Under Sulphate attack)	GGBS Replacement (0 to 70%)
	Cement to water ratio (c/w)
	Exposure Environment (Normal and Artificial Marine environment)
	Curing Period (7,28,56 and 90 days)

4.4 Analysis and Comparison of output received from MLR and ANN

4.4.1 Multiple Linear Regression Model development (MLR)

The usual equation used to predict the compressive strength of concrete is

$$f = b_0 + b_1(w/c) \tag{1}$$

According to Abrams' formula, increasing the water-cement ratio reduces concrete strength while decreasing it increases strength.

The formula of Abrams is $f = A/B^{(w/c)}$ (2)

Equation 2 can be revised and written as

$$\text{Log } f = \log A - w/c \log B = b_0 + b_1\, w/c \tag{3}$$

where, f : compressive strength of concrete

w/c : water-cement ratio

A, B : empirical constants

b_0 , b_1 : correlation coefficient

Another model for the link between strength and the components of concrete is based on the cement-water ratio, or the reciprocal of w/c. According to Lyse's formula[26], cement-water ratio and concrete strength are directly connected. The mathematical simplicity of this formula causes it to become highly well-known.

The following is an illustration of the linear c/w model's general form

$$f = A + B\, c/w \tag{4}$$

where, f = compressive strength c/w = cement-water ratio A, B = empirical constants

In the present study, minitab-6 is used to develop MLR model and to evaluate the predictions. GGBS replacement (0 to 70%), cement to water ratio (2.50 and 2.00), exposure environment (normal and artificial marine environment) and curing period (7,28,56 and 90 days) are the independent variables and compressive strength of concrete in normal water curing, under acid attack and under sulphate attack will be the dependent variables. Since we have three different dependent variables for the above-mentioned independent variables, we get three regression equations. Following are the regression equations by considering the significant independent variables only.

Regression equations for specimens cured in normal water

Exposure Environment			
MARINE	Compressive Strength	=	-69.22 + 42.74 c/w + 0.0020 GGBS Replacement + 0.0224 Curing Period
NORMAL	Compressive Strength	=	-64.26 + 42.74 c/w + 0.0020 GGBS Replacement + 0.0224 Curing Period

S	R-sq	R-sq(adj)	R-sq(pred)	Test S	Test R-sq
3.48792	91.53%	91.13%	90.48%	2.86343	93.05%

Regression equations for specimens cured in 5% Sulphuric Acid Solution

Exposure Environment			
MARINE	Compressive Strength	=	-52.26 + 35.37 c/w + 0.0535 GGBS Replacement - 0.0480 Curing Period
NORMAL	Compressive Strength	=	-50.25 + 35.37 c/w + 0.0535 GGBS Replacement - 0.0480 Curing Period

S	R-sq	R-sq(adj)	R-sq(pred)	Test S	Test R-sq
3.21190	89.68%	89.19%	88.45%	3.32673	88.71%

Regression equations for specimens cured in 5% Magnesium Sulphate Solution

Exposure Environment		
MARINE	Compressive Strength	= -62.25 + 40.11 c/w - 0.0040 GGBS Replacement - 0.0210 Curing Period
NORMAL	Compressive Strength	= -57.68 + 40.11 c/w - 0.0040 GGBS Replacement - 0.0210 Curing Period

S	R-sq	R-sq(adj)	R-sq(pred)	Test S	Test R-sq
3.36351	91.20%	90.78%	90.12%	3.17138	90.76%

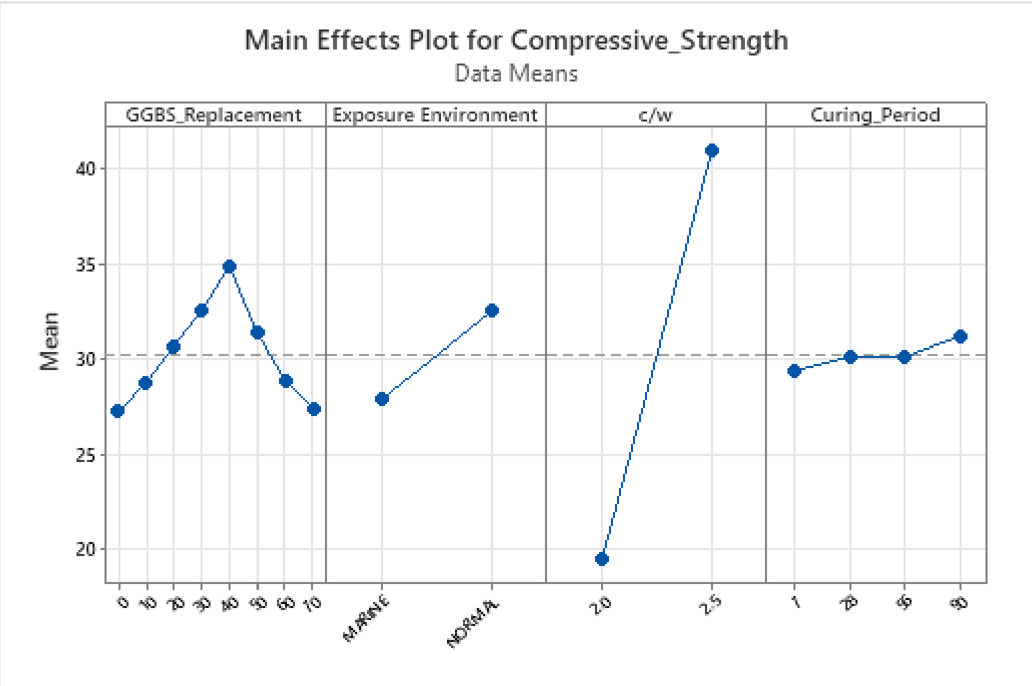

Figure Number 4.1: Main Effect Plot for Specimens cured in Normal Water

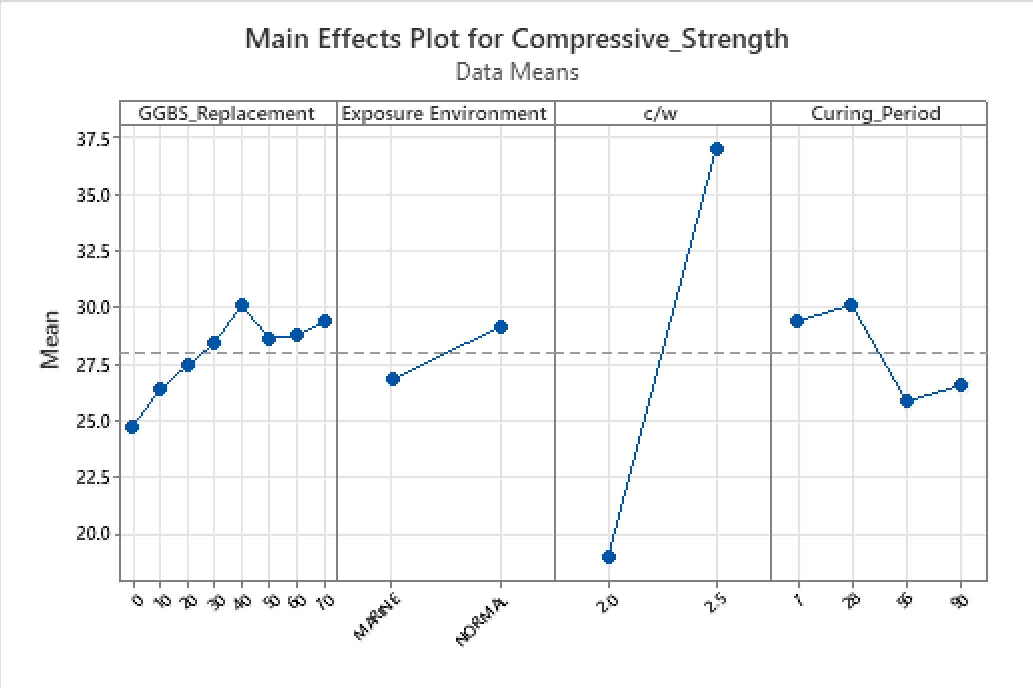

Figure Number 4.2: Main Effect Plot for specimens cured in 5% Sulphuric Acid Solution

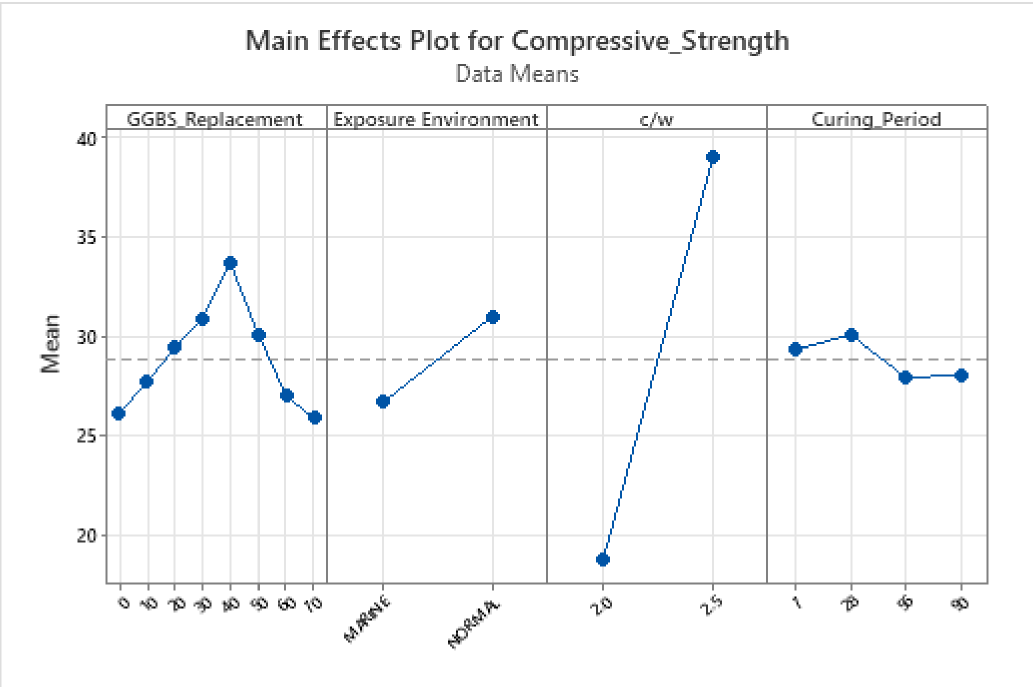

Figure Number 4.3: Main Effect Plot specimens cured in 5% Magnesium Sulphate Solution

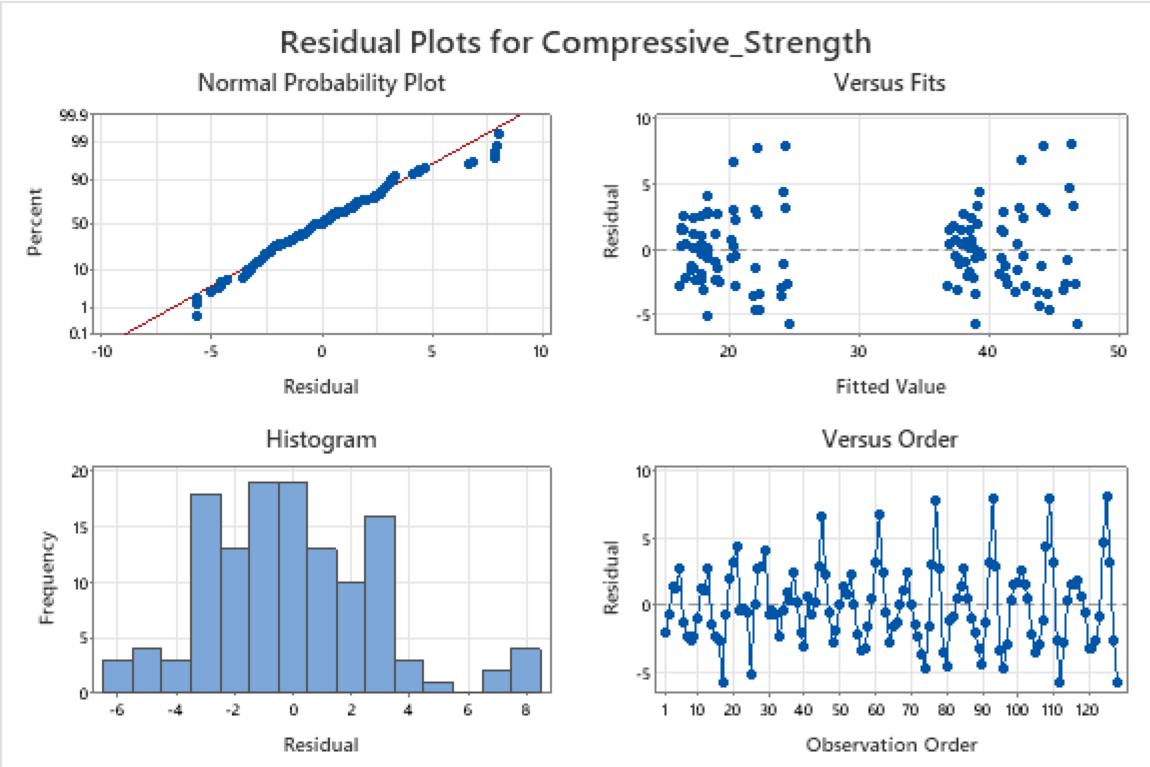

Figure Number 4.4: Residual Plot for Specimens cured in Normal Water

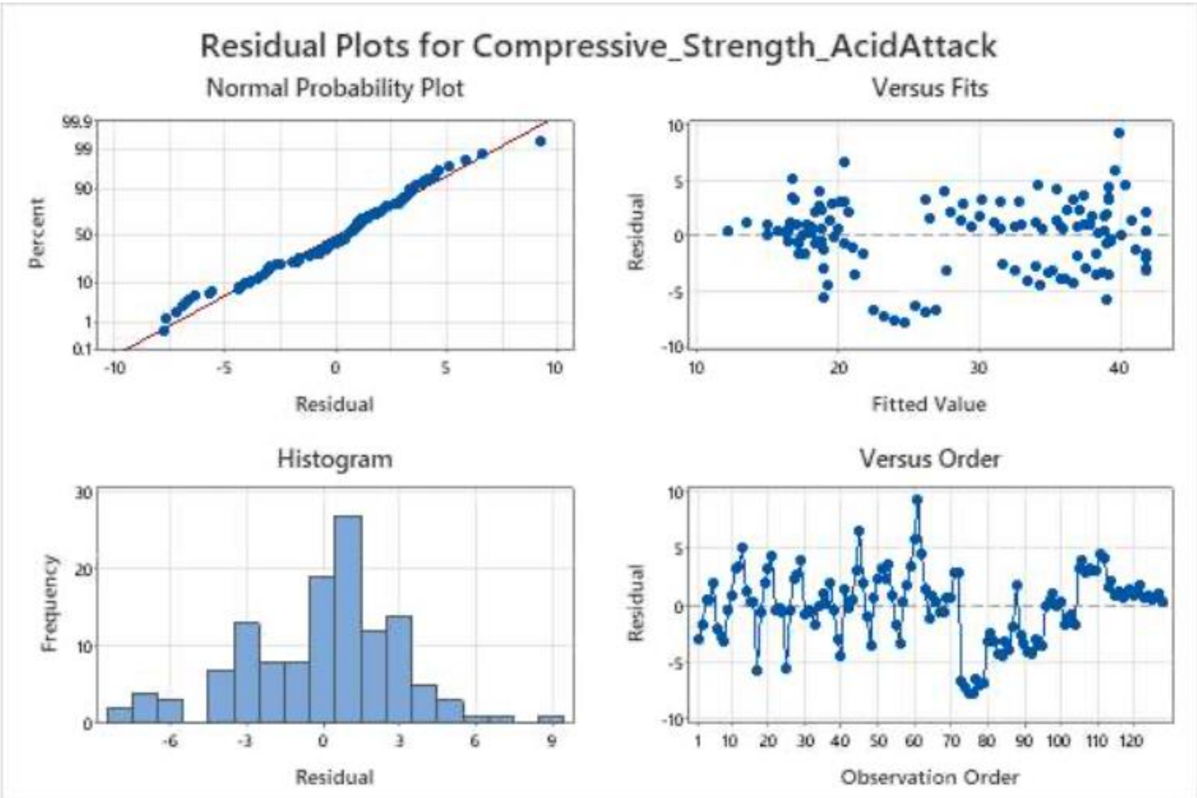

Figure Number 4.5: Residual Plot for Specimens cured in 5% Sulphuric Acid Solution

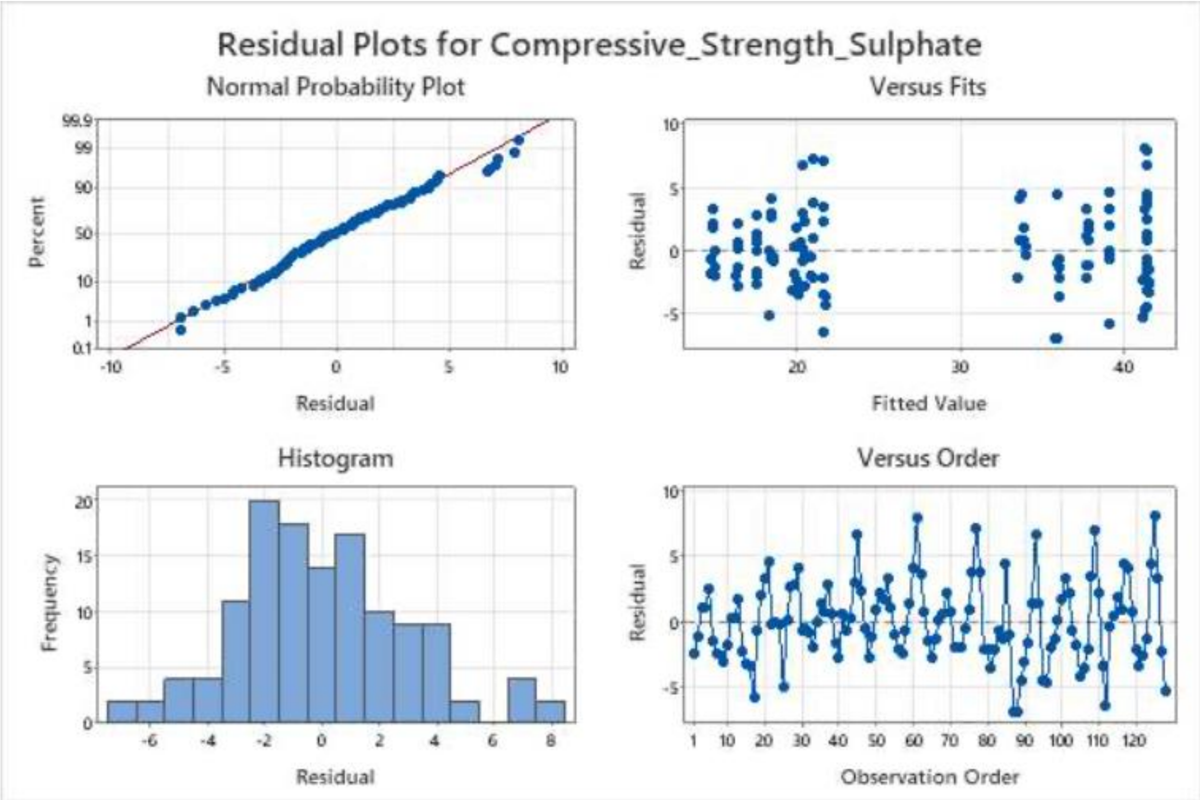

Figure Number 4.6: Residual Plot for Specimens cured in 5% Magnesium Sulphate Solution

The R-Sq value and the regression equations for concrete specimens cured in normal water gives us an illustration that the statistical models are reliable and feasible for the prediction of Compressive strength at 95% confident level interval [21]. At this confidence level of 95%, the above regression is statistically significant because the probability value of all variables are near to 0.05. By referring to the model summary, R-Sq value in it explains the percentage of variables which are been used or explained in the regression equation. In this case the value of R-Sq is 91.53% and the test R-Square value is 93.05% which tells us that so many percentage of data is been explained in the regression equation. R-Sq Adj gives us the number of true predictors and here it is 91.13% which shows that the model fits the data very well. By observation, the model doesn't seem to be overfit and the current model has adequate prediction ability. The values in the normal probability curve in Figure Number 4.4 also tells us that the values are very near to the normal probability line and the number of outliers are very less. The value of standard error is 2.86 which gives us the measure of unexplained data which is very less.

Figure Number 4.1 gives us the main effect of all independent variables. It shows that compressive strength is maximum at a GGBS replacement of 40% and then it reduces as the GGBS content increases. It also shows that compressive strength is less in marine environment and it increases in normal environment. It gives us the effect of curing period where compressive strength increases as curing period increases. It also indicates that, If c/w ratio is more, then compressive strength is also more and it expands linearly as per the statistical model that we have constructed.

The R-Sq value and the regression equations for concrete specimens cured 5% sulphuric acid solution gives us an illustration that the statistical models are reliable and feasible for the prediction of Compressive strength at 95% confident level interval [21]. At this confidence level of 95%, the above regression is statistically significant because the probability value of all variables are near to 0.05. By referring to the model summary, R-Sq value in it explains the percentage of variables which are been used or explained in the regression equation. In this case the value of R-Sq is 89.68% and the test R-Square value is 88.57% which tells us that so many percentage of data is been explained in the regression equation. R-Sq Adj gives us the number of true predictors and here it is 89.19% which shows that the model fits the data very well. By observation, the model doesn't seem to be overfit and the current model has adequate prediction ability. The values in the normal probability curve Figure Number 4.5 also tells us that the values are very near to the normal probability line and the number of outliers are very less. The value of standard error is 3.32 which gives us the measure of unexplained data which is very less.

Figure Number 4.2 gives us the main effect of all independent variables. It shows that compressive strength increases as the amount of GGBS increases. There is slight variation which can be observed in the graph which is because of 28 days water curing of specimens. It also shows that compressive strength is less in marine environment and it increases in normal environment. It gives us the effect of curing period where compressive strength increases as curing period increases. It also indicates that, If c/w ratio is more, then compressive strength is also more and it expands linearly as per the statistical model that we have constructed.

The R-Sq value and the regression equations for concrete specimens cured 5% Magnesium Sulphate solution gives us an illustration that the statistical models are reliable and feasible for the prediction of Compressive strength at 95% confident level interval [21]. At this confidence level of 95%, the above regression is statistically significant because the probability value of all variables are near to 0.05. By referring to the model summary, R-Sq value in it explains the percentage of variables which are been used or explained in the regression equation. In this case the value of R-Sq is 91.20% and the test R-Square value is 90.76% which tells us that so many percentage of data is been explained in the regression equation. R-Sq Adj gives us the number of true predictors and here it is 90.78% which shows that the model fits the data very well. By observation, the model doesn't seem to be overfit and the current model has adequate prediction ability. The values in the normal probability curve Figure Number 4.6 also tells us that the values are very near to the normal probability line and the number of outliers are very less. The value of standard error is 3.32 which gives us the measure of unexplained data which is very less.

Figure Number 4.2 gives us the main effect of all independent variables. It shows that compressive strength increases as the amount of GGBS increase till 40% and then again decreases. There is slight variation which can be observed in the graph which is because of 28 days water curing of specimens. It also shows that compressive strength is less in marine environment and it increases in normal environment. It gives us the effect of curing period where compressive strength increases as curing period increases. It also indicates that, If c/w ratio is more, then compressive strength is also more and it expands linearly as per the statistical model that we have constructed.

4.4.2 Artificial Neural Network Model (ANN)

In this present study, an Artificial Neural Network model is developed using NNFIT of Matlab 2016a by a feedforward network approach of neutron training. The Levenberg–Marquardt algorithm is used to train the architecture of ANN model. In this model, the neural network begins with an input layer and is connected to one hidden layer and connected to the output layer. The input data includes GGBS Replacement (0 to 70%), cement to water ratio (2.50 and 2.00), Exposure Environment (Normal and Artificial Marine environment) and Curing Period (7,28,56 and 90 days) are fed into network model for Compressive strength of concrete in normal water curing, under acid attack and under sulphate attack. The data is divided into three categories and those are training data (70%), validation data (15%) and test data (15%) with 1000 epochs and checks of 100 validations.

Testing and Training the network

The developed network distributes the input parameters in to the hidden layer and from the hidden layer it will be dispersed to the output layer. Figure 4.7 illustrates the Feed Forward ANN model used in the current study. Once the training and testing of ANN model is done, the values of R^2 (Correlation Coefficient) and MSE (mean square error) is noted down. The successful training for the model in Normal water curing is at epoch 19 , MSE 1.705 with 6 number of validations with a value of R^2 = 99.58%. The predicted values by the ANN model are compared with the original set of values

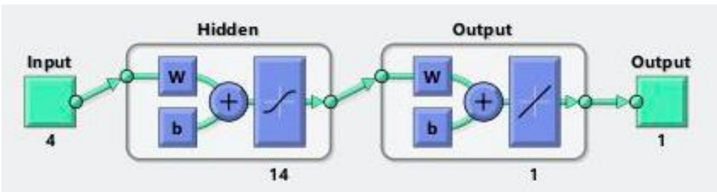

Figure 4.7: Feed Forward ANN model

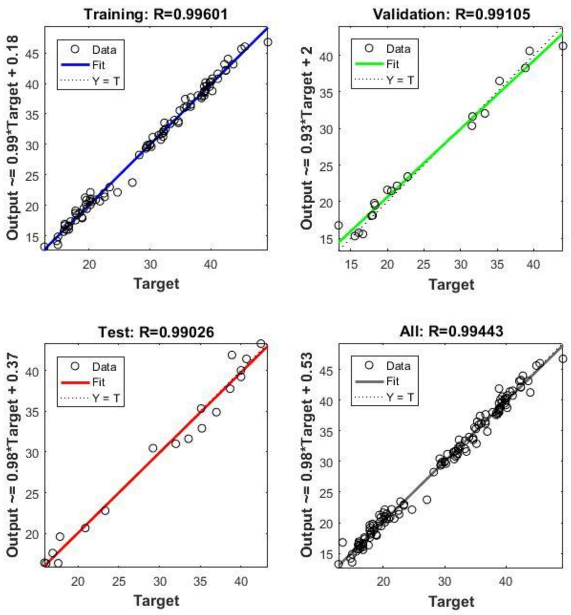

Figure 4.9: Training and Test plots

According to the training and test plots the successful training for the model for compressive strength under Acid Attack is at epoch 12 , MSE 1.856 with 6 number of validations with a value of R^2 = 99.02%. The predicted values by the ANN model are compared with the original set of values

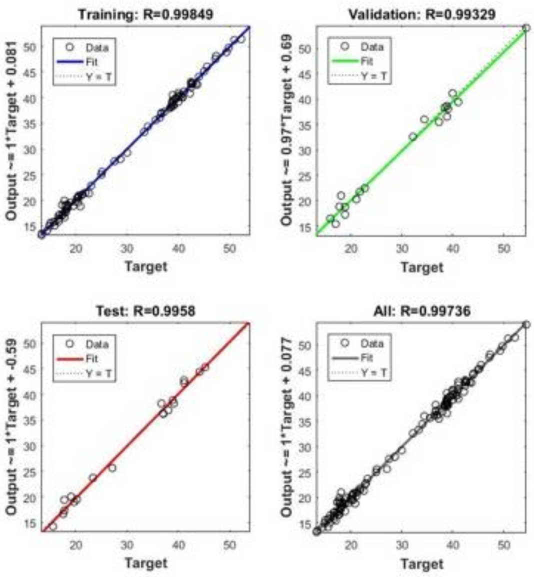

Figure 4.13: Training and Test plots

According to the training and test plots, the successful training for the model for compressive strength under Sulphate Attack is at epoch 32, MSE 1.806 with 6 number of validations with a value of R^2 = 99.07%. The predicted values by the ANN model are compared with the original set of values

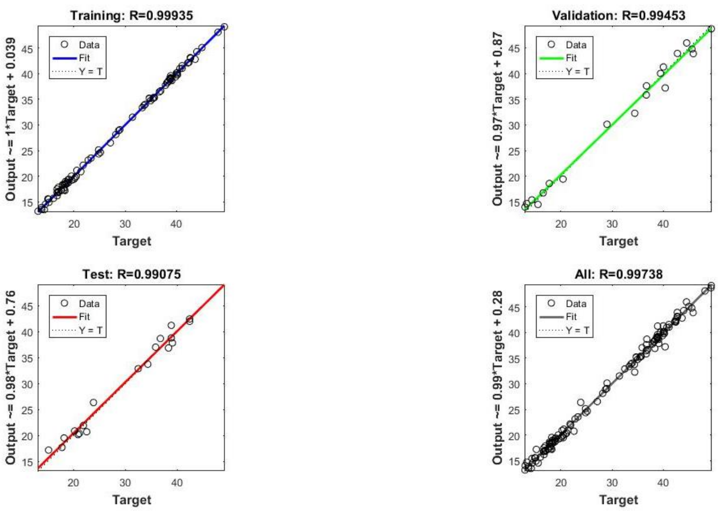

Figure 4.16: Training and Test plots

5. Analysis of prediction by MLR and ANN models

The predicted values of compressive strength of concrete by MLR model and ANN model are compared with the actual experimental values of compressive strength. According to the plot, there is a good relationship between the actual values and the predicted values of MLR and ANN. The values predicted by ANN is very close to the actual experimental value and hence ANN can be a better consistent tool to predict the values of compressive strength when compared to MLR. Figure number 5.1, 5.2, 5.3 illustrates the relationship between the actual values in comparison with the predicted values.

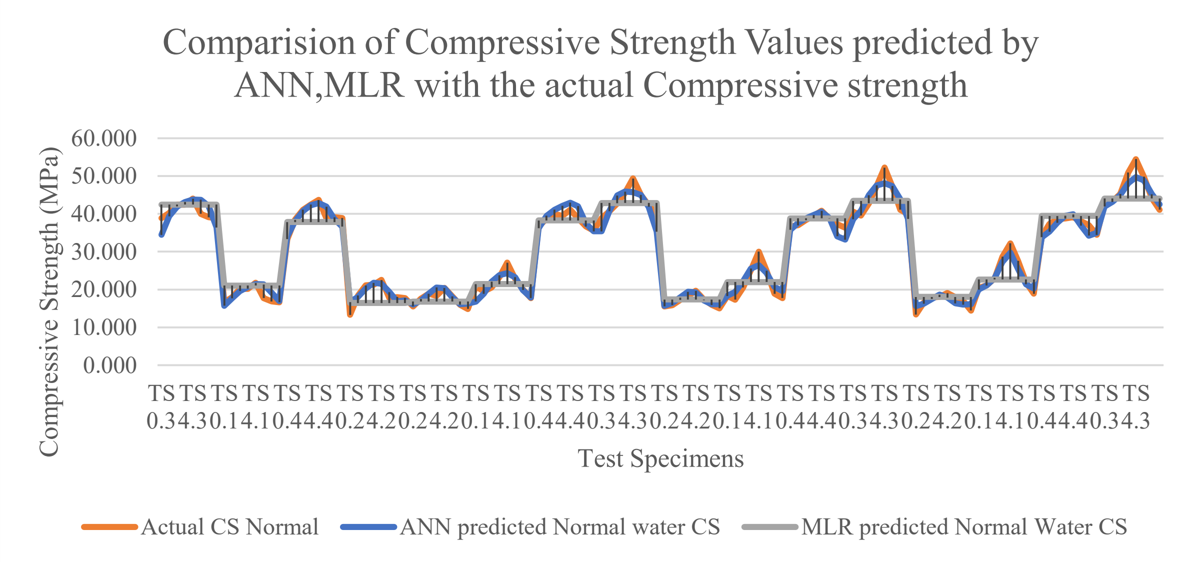

Figure Number 5.1: Comparison of Compressive Strength Values predicted by ANN, MLR with the actual Compressive strength in Normal Water Curing

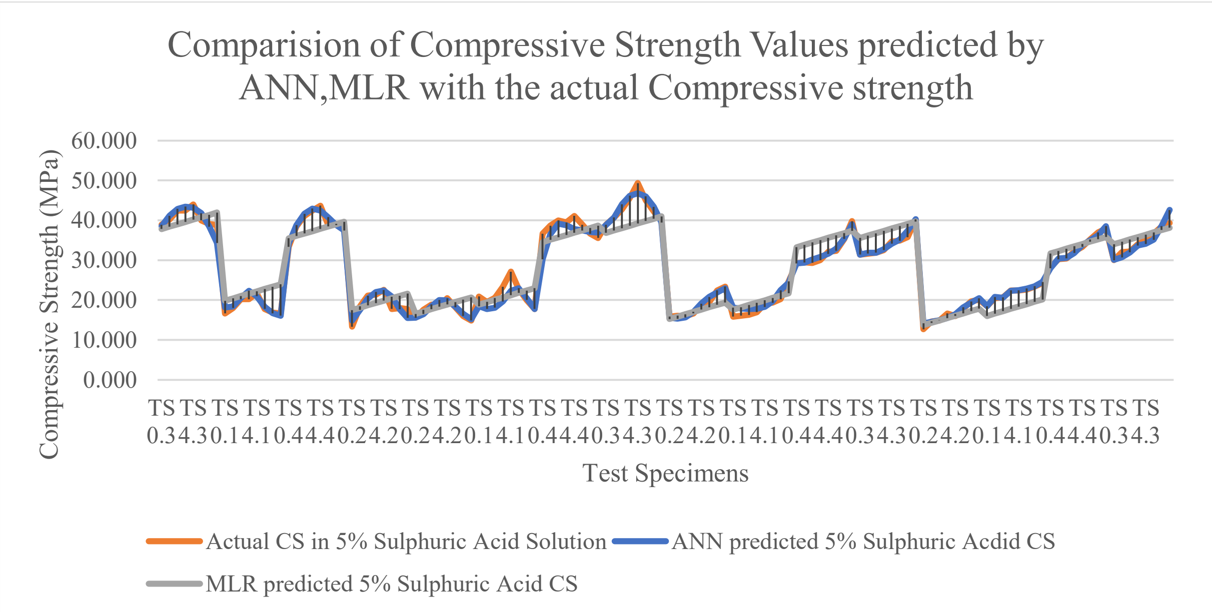

Figure Number 5.2: Comparison of Compressive Strength Values predicted by ANN,MLR with the actual Compressive strength in 5% Sulphuric Acid Solution

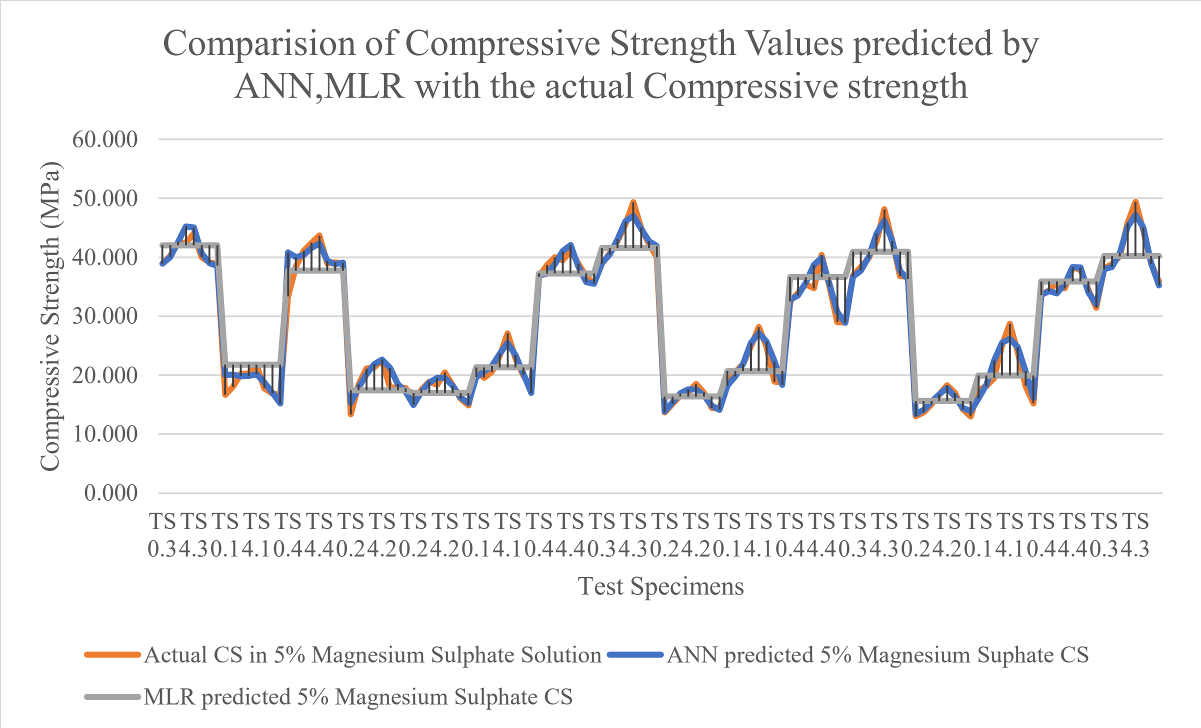

Figure Number 5.3: Comparison of Compressive Strength Values predicted by ANN, MLR with the actual Compressive strength in 5% Magnesium Sulphate Solution

6. CONCLUSION

Compressive strength of concrete with partially replaced GGBS content up to 70%, with two different water to cement ratios in normal and marine environment which are cured in normal water, 5% sulphuric acid and 5% magnesium sulphate is investigated experimentally and based on this investigation, a multiple linear regression (MLR) model and an artificial neural network (ANN) model is structured and the major conclusions drawn from the models are as follows

1. Using the values available in the model summary, we can clearly identify the importance of each independent variable like exposure environment, cement to water ratio, curing period and GGBS replacement. Out of these variables, GGBS replacement is found to be very important for compressive strength of concrete specimens in 5% sulphuric acid solution and in other curing environments such as normal water and magnesium sulphate solution, cement to water ratio and exposure condition plays the significant role in monitoring the compressive strength along with GGBS replacement and curing period is not much significant in finding the compressive strength. The regression equation is also been generated for all three curing conditions.
2. Main effect plots through MLR explains the exact effect of each individual independent variables with the dependent variable. Here, according to the main effect plot, Compressive strength increases as the GGBS content is increased up to 40% and beyond which the compressive strength decreases on increase in percentage of GGBS. This holds good in normal curing water and 5% Magnesium Sulphate. But in 5% Sulphuric acid, as GGBS content increases, the compressive strength of concrete also proportionally increases. Main effect plot also shows that the Compressive strength will always be less in marine environment and more in normal environment. According to the main effect plots, in 5% sulphuric acid solution and 5% magnesium sulphate solution, compressive strength decreases as curing period increases.

3. The experimental and predicted values of compressive strength were proximate and it suggests that the models adrequate. However ANN model has higer digree of acuuracy with a value of $R^2 > 99\%$ has a better control over the output values when compared to values predicted by MLR.

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