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COMPRESSIVE STRENGTH PREDICTION FOR SELF-COMPACTING CONCRETE USING ARTIFICIAL NEURAL NETWORKS

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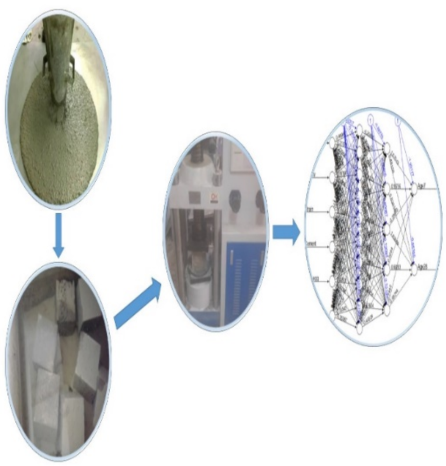
Graphical abstract



Abstract

This study investigates the relationship between concrete constituent materials, slump values, density, strain and compressive strength. The database was set in the laboratory by performing a quality assurance test on the constituent materials to ascertain their suitability for concrete work. For material procurement and selection, the British Standard Department of Environment DOE technique of concrete trial mix designs was used. In this study, twelve concrete mixes were utilized. Two simplified models were developed using the feedback network Artificial Neural Networks architecture (ANNs) with R version 4.0.5 and R studio version 1.2.5033. In the two models, an independent layer comprising six nodes and a dependent layer comprising two nodes were taken. Having carried out the sensitivity analysis, the capacity of the developed equation was evaluated in terms of error metrics MSE and RMSE. The grading envelope for river sand showed that the graph fell perfectly into grading envelope zone 2 while other constituent materials tested were all confirmed suitable for concrete works. The results of compressive strength were obtained from varied water-cement ratios used for the concrete trial mix design which ranges between 0.45 to 0.6. The compressive strength results showed that the results increased consistently for each design mix. It is worthy of note that the strength of the mix fell between grades 15, 20, 25 and 35 respectively for both the 7-day and 28-day strength accordingly. Conversely, the ANN models predicted both 7-day and 28-day strength close to the laboratory value. It is concluded that this research has demonstrated economic viability which would enhance overall construction planning efficiency for future researchers, consultants and contractors in the building industries.

Keywords: Artificial Neural Networks, Compressive strength, Mix Design, Self-Compacting Concrete

1.0 INTRODUCTION

The most common material used for civil engineering structures globally is concrete due to its numerous advantages which include ease of moulding, accessibility of the component materials, elevated compressive strength and durability if properly designed [1], [2]. A type of high-performance concrete known as self-compacting concrete (SCC) can flow under its own weight without external vibration and can consolidate without obstruction or segregation [3], [4]. Self-compacting concrete (SCC) has unique properties that set it apart from traditional concrete. SCC's exceptional flowability and segregation resistance allows it to fill formwork and surround reinforcement without mechanical vibration. This is achieved through a balanced mix design that includes high-range water reducers and viscosity-modifying agents. SCC's self-leveling nature ensures uniformity and a smooth surface, reducing labor and construction time while enhancing structural performance and durability[5], [6]. Additionally, SCC minimizes voids and honeycombing, resulting in improved load-bearing capacity and longevity [7]. These properties make SCC ideal for complex structures with congested reinforcement, where traditional concrete may not achieve adequate compaction, offering significant advantages in construction efficiency and quality. Because SCC has a higher fine content, is more workable, and requires more water than ordinary concrete, its compressive strength cannot be predicted using the same methods [8], [9]. According to Ahmed et al. [10] the advent of SCC demonstrates a substantial advancement in concrete technology, presenting higher-quality and more cost-effective concrete production. In addition to making it easier to modify mix proportions with unlimited trials, early prediction of SCC properties becomes essential for cutting down on the amount of time required to measure these qualities experimentally [10]. To achieve the mechanical properties of an SCC mix, several numbers of experimental trial mix designs and manipulation of several constituent materials variables are necessary to obtain the SCC with sufficient flow and mechanical properties which leads to more time consumption and an increase in materials constant wastage [11]. As strength is mostly ascertained experimentally by destructive and non-destructive tests (NDT) which are uneconomical and time-consuming, the forecasting of compressive strength through mixture proportions by an ANN model can be helpful for the concrete industry as shown in previously researched works [9], [11], [12], [13], [14], using numerical software to study the behaviours of self-compacting concrete in structural elements, like deep beams, has been the subject of some research [15], [16], [17], [18], [19], [20], [21], [22] and other construction applications. Even though self-compacting concrete (SCC) has been utilized extensively in construction over the past few decades, there is currently no reliable quantitative approach that can be found in the literature to forecast the strength of SCC based on the components of the mix. This is primarily because of the gross inelastic behaviour exhibited by the compressive strength relative to the constituents of the concrete mixtures [11] Artificial Neural Networks (ANN) are soft computing techniques designed to simulate how the human nervous system learns from training patterns or data. ANNs can reduce the amount of work required for on-site and laboratory experiments while also producing more accurate predictions of concrete properties [23]. Experimentally testing diverse mix proportions for self-compacting concrete to determine their individual compressive strengths can be highly uneconomical. Therefore, this research is crucial as it employs Artificial Neural Networks (ANNs) to predict the compressive strength of self-compacting concrete. By leveraging ANN predictions, this approach demonstrates economic viability and enhances overall construction planning efficiency.

2.0 METHODOLOGY

Locally in Ado-Ekiti, the research procured the following materials: coarse aggregate (granite), fine aggregate (stone dust), water, and cement. Preliminary tests, including quality assurance examinations, were conducted to evaluate the appropriateness of the materials for trial mix design. These quality assurance tests encompassed specific gravity and grading tests on both the coarse and fine aggregates. The British Standard DOE method of concrete trial mix designs was adopted for material selection and sourcing. Four select water-cement ratios with Twelve trial mix design grades ranging between 1:2:1 to 1:2:6.5 respectively were experimented with in this study. For this experiment, thirty-six (36) cubes were cast. Three (3) cubes were cast for each of the design mix ratio grades as mentioned above, for each of the chosen water-cement ratios. After being cast for twenty-four hours, the cubes were de-moulded, cured for seven and eight days in the curing tank, weighed, and examined for compressive strength. The specimens were prepared in the Civil Engineering Department laboratory of the Federal Polytechnic Ado-Ekiti.

2.1 Production of Self-Compacting Concrete (SCC)

To produce Self Compacting Concrete (SCC), the components of the concrete were weighed and combined with cement, fine (granite dust), and coarse aggregate at several mix ratios. To create the SCC, water was added to the mixture. The mix design ratio was determined by nine laboratory-measured parameters, and additional information was gathered in the Material Testing Laboratory of the Department of Civil Engineering, Federal Polytechnic Ado-Ekiti. Three layers of 35 blasts each of the concrete were poured into a 150 x 150 x 150 mm mould, which was then labelled appropriately. Next, the concrete specimens were cured in water for seven and twenty-eight days. Following that, various tests were conducted by the specification.

2.2 Data Division And Processing

When training machine learning tools, features of the data set are scaled using standardization (xstand) and normalizing (ynorm) on the input and output data, respectively, due to the rigorous computations on the high-dimensional data [24]. To boost the network's training rate, normalization sets the observations' range to 0 ≤ ynorm ≤ 1. The available data were split up into subsets to develop the ANNs models. Three sets of data were randomly selected for this study: one for testing the generated model, one for training the model for calibration, and one separate validation set for model confirmation. Approximately 70% of the entire dataset was used for training the model, while the remaining 30% was allocated to testing and validating the model. This split has been applied successfully and reported by Lee et al. [25]. The data that was provided was separated into subsets, and both the input and output were preprocessed and normalized within the range of -1.0 and 1.0.

2.3 Data analyses using ANNs

The laboratory test was carried out by the material testing unit of the Department of Civil Engineering at Federal Polytechnic Ado Ekiti, Ekiti state, Nigeria. For this investigation, R studio version 1.2.5033 and R version 4.0.5 were used [R Core Team 202]. The execution of the developed Artificial Neural Networks (ANN) model was assessed to make sure that the model can perform generally within the pre-defined limits set by the data used for training instead of being peculiar to the input-output relationships encapsulated in the training data. The information from thirty-six (36) data sets was applied to the database to generate various models and statistical correlations, with 30% of the data being used for model evaluation and 70% of the data being used for model building and training. The data were partitioned to standardize the variables. The statistical analysis was conducted using R studio version 1.2.5033 and R version 4.0.5 (R core team, 2021). Since the correlation coefficient is essential for determining the relative relationship between the observed and expected data, the Root Mean Square Error (RMSE) and the Correlation Coefficient R were used to assess how well the predictions performed [11]. This was created by plotting the expected and experimented values for the developed equations on the horizontal and vertical axes, respectively, in order to gauge their efficiency.

3.0 RESULTS AND DISCUSSIONS

3.1 Grading of Aggregates

The process of determining an aggregate's particle size distribution is known as grading. Because these characteristics have an impact on the amount of aggregate used, workability, cement requirements, durability of concrete and pumpability. Figure 1 and Figure 2 showed the results of grading for coarse and fine aggregate, respectively, while Table 1 showed the summary results of other Concrete constituents' materials. The grading envelope for river sand showed that the graph fell perfectly into envelope zone 2, as shown in Figure 1 while other constituent material tested were all confirmed suitable in compliance with specification. The engineering implication of the result is that the selected aggregate is quite suitable for the concrete trial mix.

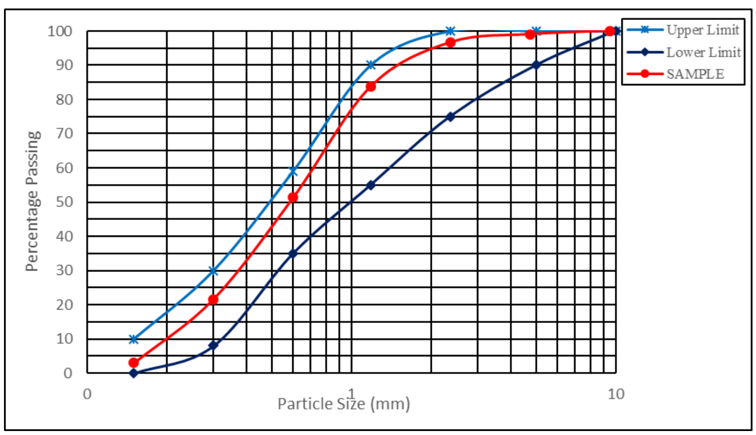


Figure 1 Fine Aggregate Grading Envelope for Concrete Works

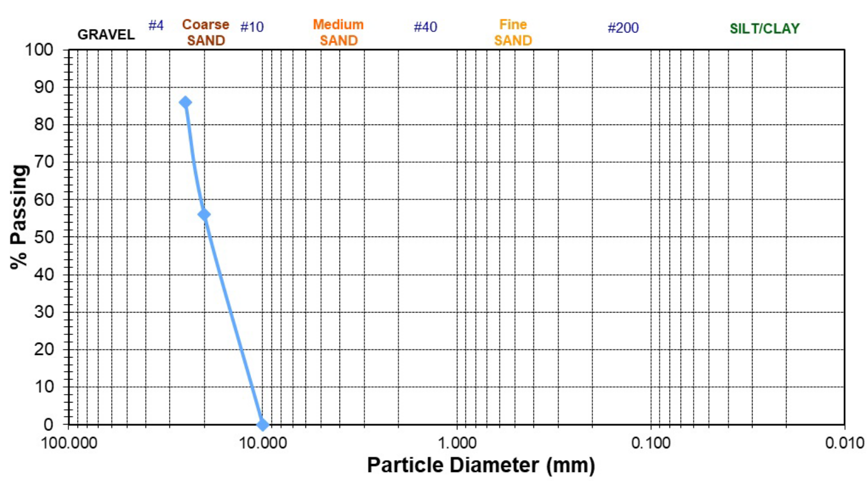


Figure 2 Grading of Coarse Aggregate

Table 1 Results of laboratory testing on materials

Materials	Parameters	Results	Specification	Remarks
Cement	Fineness	1.23%	$\leq$ 10%	Satisfactory
	Consistency	35%	$\leq$ 37%	Satisfactory
	Initial Setting Time	90mins	$\geq$ 60 mins	Satisfactory
	Final Setting Time	210mins	$\leq$ 600 mins	Satisfactory
Fine Aggregate	Soundness	4.50mm	$\leq$ 10mm	Satisfactory
	Silt Content	0%	$\leq$ 6% Zone	Satisfactory
	Grading	Zone 2	1 to Zone 3	Satisfactory
Coarse Aggregate	Grading	Predominantly 20mm		Well Graded
	Aggregate Impact Value	3.13%	< 10%	Satisfactory
	Aggregate Crushing Value	10.53%	$\leq$ 30%	Satisfactory

3.2 Concrete compressive strength

The results of compressive strength were obtained from varied water-cement ratios used for the concrete trial mix design which range between 0.43 to 0.6 as shown in Table 2 for 7 and 28-day curing strength, respectively. The findings of the compressive strength test indicated a constant increase in results for each design mix. It is important to highlight that the mix's strength for both the 7-day and 28-day strength periods fell within the range of grades 15, 20, 25, and 35, respectively.

3.3 Artificial Neural Networks Results

The feedback network Artificial Neural Networks (ANN) architecture was adopted, using R version 4.0.5 and RStudio version 1.2.5033. The neural network consists of one hidden layer, with the sigmoid function as the default activation function for the hidden layers. The backpropagation algorithm was used for training the neural network.

The results, as presented in Figure 3, show the input nodes to the extreme left, which represent the raw data variables: slump, strain, density, fine aggregate, coarse aggregate, and cement. The black arrows and the values connected to them are the contributed weights of the variables to the next node. The nodes at mid-location (regardless of their number) are the concealed nodes. The lines in blue represent the bias weights. Each of these nodes constitutes an element the network is learning to identify, understand and interpret. The nodes to the extreme right are the output nodes; these constitute the final output of the neural network system. The principal function is to feed all the nodes with a trainable constant value (apart from the primary inputs received by the node). To arrive at this, a single bias node with connections to N nodes or N bias nodes is needed, with each having a single link; which would yield the same result.

Table 2 Laboratory results of Compressive strength

Specimen	Mix ratio	Aggregate cement ratio (A/C)	Water Cement Ratio (W/C)	Slump (mm)	Density (kg/m^3)	Strain	Quality of Cement (g)	Quality of Fine agg (FA) (g)	Quality of Coarse agg (CA) (g)	Compressive Strength (Fc) 7 Day	28 Day
1;1	1:2:1	3:0	0.435			0.00197	350	714	1166	20	36.0
1;2	1:2:1	3:0	0.435	10.5	2396	0.0019	350	714	1166	19	35.6
1;3	1:2:1	3:0	0.435			0.00192	350	714	1166	21	37.8
2:1	1:2:1.5	3:5	0.450			0.00187	422	752	1128	22	36.5
2:1	1:2:1.5	3:5	0.450	9.0	2385	0.00188	422	752	1128	19.5	34.5
2:1	1:2:1.5	3:5	0.450			0.0018	422	752	1128	21	33.5
3:1	1:2:1.5	4:0	0.485			0.00179	489	661	1079	20	34.0
3:1	1:2:1.5	4:0	0.485	7.5	2375	0.00188	489	661	1079	21	34.0
3:1	1:2:1.5	4:0	0.485			0.00182	489	661	1079	20	31.0
4:1	1:2:2	4:5	0.505			0.00177	420	680	1109	20	30.0
4:1	1:2:2	4:5	0.505	6.0	2380	0.00173	420	680	1109	18	30.0
4:1	1:2:2	4:5	0.505			0.00179	420	680	1109	17.5	29.5
5:1	1:2:3	5:0	0.51			0.00168	384	698	1091	19	28.5
5:1	1:2:3	5:0	0.51	5.5	2360	0.00176	384	698	1091	17	29.5
5:1	1:2:3	5:0	0.51			0.00169	384	698	1091	16	28.0
6:1	1:2:3.5	5:5	0.51			0.00172	401	699	1140	18	29.5
6:1	1:2:3.5	5:5	0.51	5.0	2345	0.00174	401	699	1140	15	28.0
6:1	1:2:3.5	5:5	0.51			0.00171	401	699	1140	14.5	27.0
7:1	1:2:4	6:0	0.52			0.00169	350	720	1175	13.5	27.0
7:1	1:2:4	6:0	0.52	4.5	2350	0.00176	350	720	1175	14	26.0
7:1	1:2:4	6:0	0.52			0.00169	350	720	1175	15	25.6

8:1	1:2:4.5	6:5	0.535	4.0	2340	0.00157	361	714	1165	13	25.7
8:1	1:2:4.5	6:5	0.535			0.00172	361	714	1165	14	24.9
8:1	1:2:4.5	6:5	0.535			0.00164	361	714	1165	13.5	24.9
9:1	1:2:5	7:0	0.56	2.0	2355	0.00164	328	746	1166	13.5	20.4
9:1	1:2:5	7:0	0.56			0.00165	328	746	1166	13.0	19.4
9:1	1:2:5	7:0	0.56			0.00165	328	746	1166	13.0	19.8
10:1	1:2:5.5	7:5	0.585	1.0	2335	0.00169	367	717	1171	14.0	18.0
10:1	1:2:5.5	7:5	0.585			0.00151	367	717	1171	13.0	17.5
10:1	1:2:5.5	7:5	0.585			0.00158	367	717	1171	13.0	17.0
11:1	1:2:6	8:0	0.6	1.0	2330	0.00153	320	726	1184	10.5	15.6
11:1	1:2:6	8:0	0.6			0.00154	320	726	1184	10.5	16.0
11:1	1:2:6	8:0	0.6			0.00169	320	726	1184	10.2	16.8
12:1	1:2:6.5	8:5	0.605	1.0	2320	0.00153	300	731	1144	9.5	15.3
12:1	1:2:6.5	8:5	0.605			0.00164	300	731	1144	9.6	14.9
12:1	1:2:6.5	8:5	0.605			0.0016	300	731	1144	9.0	15.3

In an ANN system, weights are quite critically required in transforming input to affect the output. Analogous to this is slope or gradient as in linear regression, where weight is multiplied by the input to form the result. Weights are numerical variables that serve as a pointer to how strongly each of the neurons affects the other. A typical neuron, for which inputs are X_1, X_2, and X_3, the synaptic weights to be applied to them respectively, would be represented as W_1, W_2, and W_3.

Dependent is $y = f(x) = \sum x_i w_i$ (1)

Where i start from 1 to n

The bias is comparable to the intercept added in a simple linear equation. An additional property is made use of to adapt the dependent variable and the weighted sum of the independent variable to the neuron.

The concatenation performed by the neuron can be shown thus: Dependent = sum (weight * Independent) + bias (2)

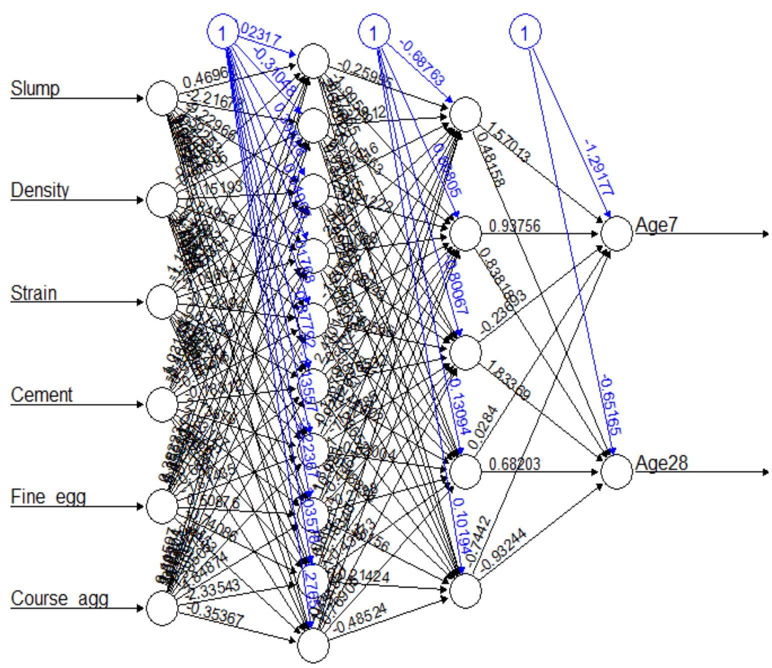


Figure 3 Net plot from neural network

3.4. Comprehensive Estimates and Model from 10 concealed layers (neurons) from ANNs

The Artificial Neural Network plot in Figure 3, illustrates the input coefficients. One hidden layer was deployed to reduce errors and for the best results. These coefficients connote the weights of the inputs and their connections in the hidden layers. For instance, 'Slump.to.1layhid10.469619435' signifies the weight for the connection between the input 'slump' and the first node of the hidden layer. Similarly, 'Density.to.1layhid1-0.870069352' denotes the weight for the connection between the input 'density' and the first node of the hidden layer, while

'Strain.to.1layhid1 -1.129430627' represents the weight for the connection between the input 'strain' and the first node of the hidden layer. This style continues for each node in the hidden layers, up to the tenth node. Now, we can utilize the network to make predictions. Thirty percent (30%) of the dataset has been set aside specifically for result validation and Seventy percent (70%) for training.

3.5 Measures of Accuracy for 7 and 28-day Compressive Strength for the Predicted and Actual Values (Goodness of Fit)

Measures of Accuracy between Plotting the observed and the predicted Values for 7- and 28-days compressive strength are presented in Figure 4 and Table 3. They show that about 99.7% and 99.8 % variation of the output are explained by the model. The low errors are indications of reliably predicted values of the compressive strength. In the developed model, every input is significant except Strain and fine egg having p-values greater than the level of significance 0.05. Jurinjak Tušek et al. [26] suggested that if there is a significant correlation between the observed and anticipated values, the R^2 value should be more than 0.8. Furthermore, RMSE is better since it represents the least amount of errors and larger residual errors are handled more delicately. Higher R^2 and lower RMSE values also indicate accurate calibration and excellent model results.

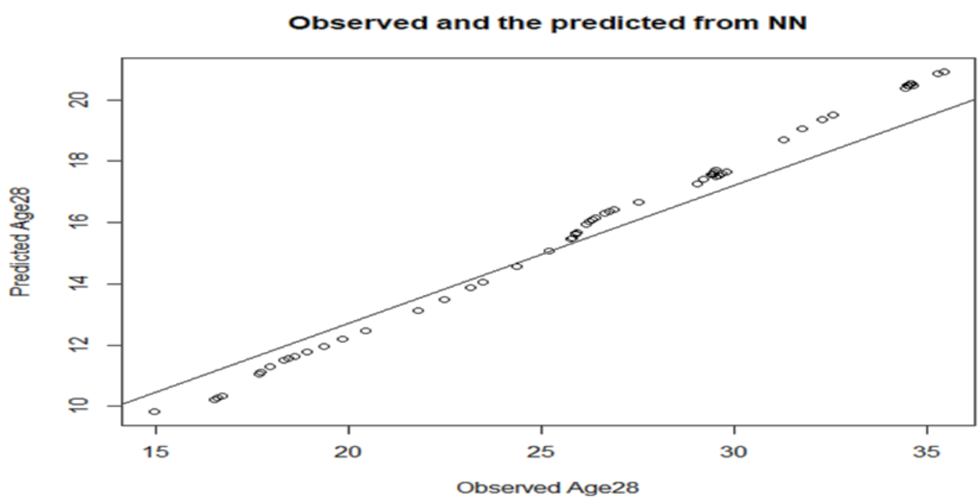


Figure 4 Plotting the observed and the predicted values for the 28-day compressive strength

Table 3 Goodness of fit test for predicted values from ANNs

Performance metrics	RMSE	MAE	R^2
7 days strength	0.1518847	0.1269275	0.9971272
28 days strength	10.89543	10.58233	0.9980366

In the developed model, every input is significant except Strain and fine agg having p-values higher than the level of significance 0.05.

3.6. Sensitivity Analysis

Table 4 presents the testing for the effect of each dependent variable by removing some independent variables to obtain various models. From the table of results, it can be deduced that models without strain and fine egg were the most effective for predicting the output. The high values of the coefficient of determination, 0.9971 and 0.9980366 for 7 and 28 days respectively show that the models are reliable and that the values predicted are close to the actual values.

Table 4 Removal of independent variables to check the effect on the models

Measures	gof_LM	gof_slump	gof_dens	gof_str	gof_cem	gof_egg	gof_aggr
ME	-10.74	-0.01	-0.16	-0.05	-0.01	-0.05	-0.04
MAE	10.74	0.32	0.42	0.27	0.45	0.27	0.29
MSE	127.69	0.14	0.26	0.10	0.35	0.10	0.13
RMSE	11.30	0.37	0.51	0.31	0.59	0.31	0.36
R-sqr	0.89	0.98	0.97	0.99	0.96	0.99	0.98

*gof = goodness of fit, *LM = full Model, dens = density, cem = cement, egg = aggregate,
where gof_ full Model = Full model; gof_slump = model without slump; gof_density = model without density gof_strain = model without strain; gof_cement = model without cement; gof_fine aggregate = model without fine aggregate; gof_coarse aggregate = model without coarse aggregate.

3.7. Model Derivation

The multiple regression model is derived from a linear combination of multiple predictor variables to predict the response variable. Let X be a matrix of predictor variables (n observations, k predictors), where X(i,j) is the jth predictor for the ith observation. Let Y be a vector of response variables (n observations). Then, the multiple regression model can be stated as:

$$Y = \beta0+\beta1X1+\beta2X2+...+\beta kXk+\varepsilon \quad (3)$$

where β0 is the intercept term, β1 to βk are the regression coefficients for each predictor, and ε is the error term representing the residual or unexplained variation. The objective is to find the optimal values for the regression coefficients that minimize the residual sum of squares (RSS). The RSS is defined as:

$$RSS = \Sigma(yi-\hat{y}i)^2 \quad (4)$$

where ŷi is the predicted response for the ith observation and can be represented as:

$$\hat{y}i=\beta0+\beta1X(i,1)+\beta2X(i,2)+...+\beta kX(i,k) \quad (5)$$

This optimization problem can be worked out using numerous methods such as the normal equation, gradient descent, or iteratively reweighted least squares. The final solution provides the best estimates of the regression coefficients, which can be utilized to make forecasts for new observations. The developed model is given below as a theoretical and estimated model in Equation (6) to (7) and Equation (8) to (9) for 7 days and 28 days compressive strength respectively, where the first six main components were obtained as contributory variables.

The theoretical model 1 for 7 days strength

$$Age7 = \alpha+ \beta_1 (Slump)+ \beta_2 (Density)+ \beta_3 (Strain)+ \beta_4 (Cement)+ \beta_5 (Fine\_ agg) + \beta_6 (Coarse\_ agg) + \epsilon \quad (6)$$

The estimated model with actual coefficients for 7 days strength

$$\widehat{Age7}=-122.37+0.3(Slump)+0.06(Density)-144.06(Strain) +0.03(Cement)+ 0 (Fine\_ agg)-0.01(Coarse\_ agg) \quad (7)$$

The theoretical model 2 for 28 days strength

$$Age\ 28 = \alpha+ \beta_1 (Slump) + \beta_2 (Density) + \beta_3 (Strain)+ \beta_4 (Cement)+\beta_5 (Fine\_agg)+ \beta_6 (Coarse\_agg) + \epsilon \quad (8)$$

The estimated model with actual coefficients for 28 days strength

$$Age\ 28= 36.1 +1.83 (Slump)- 0.01 (Density) + 7656.35 (Strain) + 0.01 (Cement) – 0.03 (Fine\_agg)- 0.01 (Coarse\_agg) \quad (9)$$

4.0. CONCLUSIONS

This paper investigated the use of artificial neural networks for the prediction of compressive strength in self-compacting concrete. An artificial neural network (ANN) was utilized to examine the experimented values after 36 mixes of concrete were cast for laboratory testing. The outcomes and discoveries led to the following conclusions:

i. The grading envelope for river sand showed that the graph fell perfectly into envelope Zone 2, while other constituent materials tested were all confirmed suitable in compliance with specifications.
ii. The results for compressive strength demonstrated a consistent increase in performance for every design mix. It is noteworthy that the mix's strength for both the 7-day and 28-day strength ranged from grades 15, 20, 25, and 35, respectively.
iii. The accuracy measurements between plotting the observed and projected values for the compressive strength after 7 and 28 days revealed a 99.7% variation in the output that could be explained by the model; the low errors are signs of a trustworthy prediction of the compressive strength values.
iv. Testing for the effect of each dependent variable by removing some covariates to obtain various models from the table of results showed that models without strain and fine aggregate came out as the model for prediction of the output.
v. The Artificial Neural Networks developed simplified general predicting models and estimated models for the prediction of 7 days and 28 days Compressive strength respectively.

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