

Application of Artificial Neural Network to Validate and Predict the Physical Properties of Graphene Oxide-Induced Rubberized Concrete

Gyanendra Kumar Chaturvedy*

Department of Civil Engineering, Shivajirao S. Jondhle College of Engineering and Technology, Asangaon, Thane, Maharashtra, India

Abstract: The heap of exhausted rubber tires is a big threat to the sustainable environment. One of the solutions for these exhausted rubber tires is their application in concrete. Conventional concrete (CC) can be converted into rubberized concrete (RC) after the partial or complete substitution of natural aggregates (NA) by rubber aggregates (RA). In this research paper, graphene oxide (GO) is mixed with RC to analyze its effect on the physical characteristics of RC such as workability, density, and air content. Sixteen different concrete samples, having a water to cement ratio (w/c) of 0.252 and 0.3 each, were cast based on the variations of RA and GO as partial replacements of manufactured sand (MS) and cement. The experimental results were then used to model for artificial neural network (ANN) using WEKA software for validation and prediction of the physical properties of RC. The predicted outputs for each physical property had a coefficient of determination (R^2) more than 0.92 for training and testing datasets of each physical property, indicating the developed model had higher goodness of fit. Sensitivity analysis was also performed on the developed model to visualize each variable's effect on RC's physical properties. The results suggest to use RA and GO in concrete, up to 15% and 0.05% respectively, without much affecting its physical properties and encourage the greener construction practices by reusing the waste rubber tires.

Keywords: Rubberized concrete, Rubber aggregate, Graphene oxide, Machine learning approach, Artificial neural network

1. INTRODUCTION

The rubber aggregate (RA) obtained from the exhausted tire rubbers from transport vehicles has several benefits when used in conventional concrete (CC). RA in CC helps reduce the burden of exhausted tires on valuable land and protects the environment and the existing flora and fauna. The harmful chemicals leached out from the tire rubber are also checked to mix in the soil and running water bodies, thus saving the ecosystem. RA also helps to replace the natural aggregates (NA), which are limited in nature and are depleting very fast due to over-demand in construction industries. The rubberized concrete (RC) is produced with the substitution of NA by RA in the required quantity, shape, and size in concrete. The existing literature finds RC to be promising to use as CC if the mechanical strengths of RC are brought near to that of CC. The application of RC in place of CC will save the environment from vast heap of rubber tires, checks the extraction of NA by fulfil the construction demand etc. [1]. Graphene oxide (GO) is a unique material being used to overcome the reductions in mechanical strengths of RC due to its specific capacity of nano-filling ability and increase of density in concrete matrix [1].

The researchers are continuously trying to modify the properties of concrete to achieve a suitable purpose concrete after mixing different materials in the CC. For this, either experimental work (by mixing different materials in the CC) or a forecasting method is applied. In the current years, there is an increased trend to forecast the properties of concrete with the help of available experimental data. In the forecast method, the available experimental data of two different concrete are mixed to obtain the properties of new concrete. Several approaches are available for forecast methods – different regression techniques, artificial neural networks (ANN), fuzzy logic, genetic algorithm, etc. [2-9]. These approaches are becoming popular nowadays due to saving valuable time and resources. These approaches are used in several civil engineering works like concrete analysis, modeling for materials behavior, groundwater monitoring, health monitoring of civil structures, prediction of physical and mechanical properties of concrete, etc. [2].

Biological neural networks served as the basis for the invention of the ANN. Similar to how humans learn, ANN imitates biological neural networks. The ANNs use learning, classification, and generalization procedures to anticipate the results [3-4]. Additionally, ANN can proceed with fresh data (input) without expurgation or pre-treating, creating it further beneficial and cheaper than conservative approaches [5]. ANN is a popular approach that provides workable answers to issues that are difficult to resolve using traditional methods like

*Address correspondence to this author at the Department of Civil Engineering, Shivajirao S. Jondhle College of Engineering and Technology, Asangaon, Thane, Maharashtra, India; E-mail: gyanendrachaturvedy7@gmail.com

multiple regression models and other statistical models. ANN is better than any other technique in solving complex problems with no direct connection between the input and output values by simple equations [6]. Dias and Pooliyadda [7] demonstrated that ANN models are superior to multiple regression models by minimizing the spread of predictions.

Fig. (1) depicts the generalized model for ANN. An ANN needs to be trained before any interpretation of new data can be made, and for this, previous research works mentioned numerous training procedures. A feed-forward back propagation (BP) method is the most used and practical for multilayer neural networks [6-9]. The BP algorithm comprises input, hidden, and output layers to make interconnected layers. The hidden layer node received the yield of the input layer's neuron or node as input, and the hidden layer node's yield was then sent on to the output layer. The complexity of the task determines the amount of hidden layers. The researchers, therefore, implemented the long trial-and-error approach. In the BP network, all nodes (apart from the input layer) had an initiation function and a bias node. The bias includes a persistent input. The activation function filters the accumulated result. Activation functions were used in ANN based on the nature of the work project. The output layer generated computed output vectors corresponding to the issue's resolution. Vectors (here called training pairs) were frequently used to express the input and output data.

The process is repeated for each pair of training data until the network error has been collective to a threshold that is set by an error function. The root mean square error (RMSE) can be helpful in working as an error function. The same method was applied to connect the hidden and output layers. Using the aforementioned method, the network was trained (input to the hidden and hidden to the output layer). Iteration represents a sole stage in the entire training process of ANN. Thus, until the desired output is obtained, the number of iterations is increased (keeping the error

within the stated limit). Although ANN is better than multiple regression analysis, its drawback is it takes a long time to find network features like hidden layers and neurons through trial-and-error methods.

Although several studies have separately examined the effect of RA or GO on the properties of concrete, and although ANN has been used to predict properties of self-compacting concrete [2], polymer-modified bitumen [8] and FRP-confined concrete [9], to the authors' knowledge no previous study has combined RA and GO as simultaneous inputs to an ANN model for predicting the workability, density and air content of concrete. This combination is important because RA and GO affect these physical properties in opposing directions, and a data-driven model is needed to capture their combined, non-linear influence. This represents the specific research gap addressed in this study.

The novelty of this study, therefore, is twofold: (i) it is the first attempt to jointly model the effect of RA and GO on the physical properties of RC using ANN, and (ii) it quantifies, through sensitivity analysis, the relative contribution of each mix ingredient to each physical property, which has not been reported for GO-modified RC.

2. MATERIALS AND EXPERIMENTAL PROCEDURE

Fig. (2) depicts the complete experimental program and ANN methodology for the generation of predicted output.

2.1. Materials

Cement (OPC 53 grade), manufactured sand (MS), RA, silica fume (SF), fly ash (FA), coarse aggregate (CA), GO, superplasticizer (SP), and potable water was mixed to make concrete samples. The average size of RA was 2.1 mm, and the nominal maximum size of CA was 20 mm. MS and RA both belong to zone II of IS:383-2016 [10]. Specific gravity of cement, RA, MS,

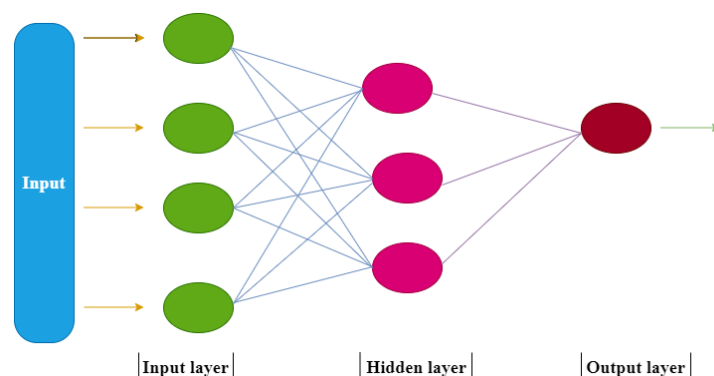


Figure 1: Generalised diagram of ANN work module.

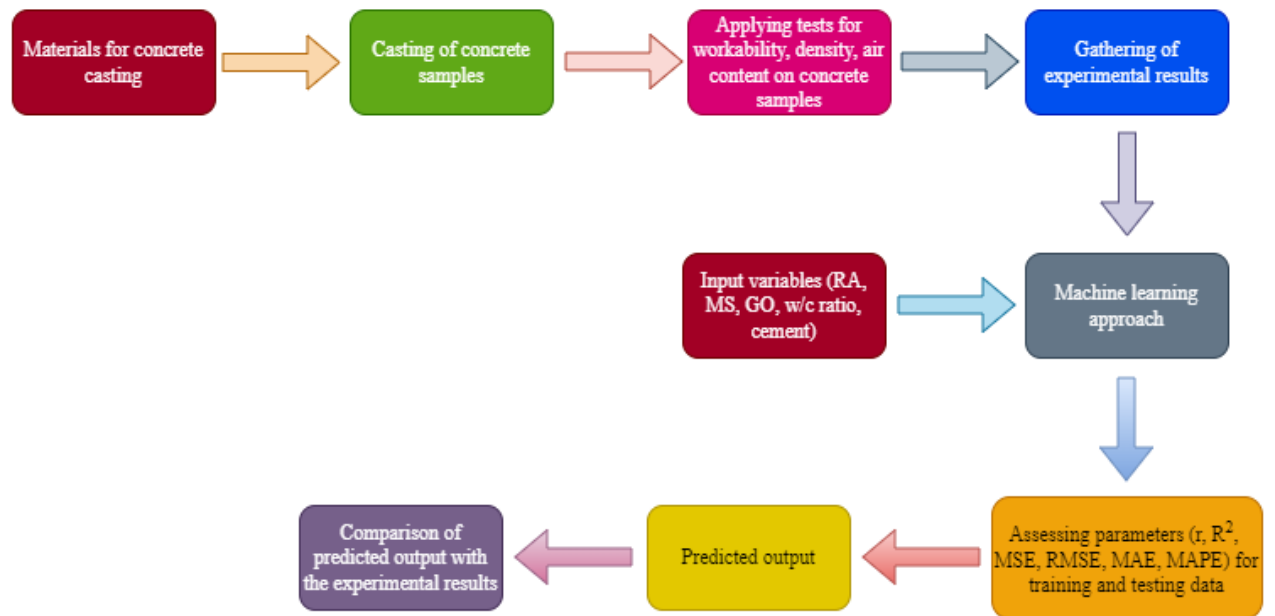


Figure 2: Simplified illustrations of experimental procedures and generation of predicted output.

CA, SF, FA, and SP were 3.15, 0.793, 2.32, 2.71, 2.2, 2.2, and 1.08, respectively. GO, and RA were used as partial replacements for cement and MS, respectively.

2.2. Preparation of Concrete Mix

The concrete samples were made with two different water-cement ratios of 0.252 and 0.3, according to IS:10262-2019 [11]. Sixteen sets of concrete samples, on each water-cement ratio, were prepared using RA and GO as fractional replacements of MS and cement, respectively. RA was used as a partial replacement of 0%, 5%, 10%, and 15% of MS by weight, while GO was used as a partial replacement of 0%, 0.01%, 0.03%, 0.05%, and 0.1% by weight of cement. All the other concrete ingredients were kept constant in all the mixes. FA and SF were used as 15% and 10% by weight of total cementitious materials. Concrete mix details corresponding to w/c ratios of 0.252 and 0.3 are presented in Tables 1 and 2 respectively. In the previous research works on inclusion of GO in high-strength RC, the literature recommends to fix the upper limits of rubber aggregate and GO as 15% and 0.05%, respectively. So, in the present research work, these limits are taken into consideration [12, 13].

2.3. Experimental Work

The workability, density, and air content tests were accomplished to analyze the physical properties of RC. The workability test was performed according to IS: 1199-1959 [14]. The air pressure method was applied for the air content test according to IS: 1199-1959 [14]. The density test was performed according to ASTM C 138 [15].

3. EXPERIMENTAL RESULTS AND DISCUSSION

The experimental results for workability, density, and air content for GO-induced RC, corresponding to w/c ratios of 0.252 and 0.3, are presented in Table 3. The experimental results performed for the physical properties of RC. The experimental results will be treated as a dataset for training and testing work for ANN.

For both w/c ratios, there is a tendency for the slump of the concrete samples to decrease as RA increase in the concrete mixtures. The results show that the inclusion of RA as partial substitution for MS decreases the slump height by up to 15 mm, respectively, in the case of the w/c ratio of 0.252 and by up to 14 mm for the concrete mixes having w/c ratio of 0.3. These results are consistent with earlier research [16-18]. The frictional resistance produced by RA owing to its irregular surface [16], improper gradation of RA that results in the creation of cavities in the RC mixes [17], abnormality in the RA's shape that causes a difficulty during mixing in the concrete mix [18], and the fineness and high surface area of RA [18] are some possible causes of these reductions in slump height. Further addition of GO tends to more decrease in workability. GO, having high affinity of water and surface area, absorbs more water from the concrete mix and decreased the workability of RC [19-21].

The density of concrete mixtures is reduced up to 4.48% and 4.76% by substituting RA partially for MS for the cases of concrete mixes having w/c ratios of 0.252 and 0.3, respectively. These results are consistent with

Table 1: Concrete Mix Details Corresponding to w/c Ratio of 0.252

Mix no.	Cement	FA	SF	MS	RA		SP	GO		Water	CA
	kg/m ³	kg/m ³	kg/m ³	kg/m ³	%	kg/m ³	kg/m ³	%	kg/m ³	kg/m ³	kg/m ³
G1	410.55	82.11	54.74	610.56	0	0	2.74	0	0	138	1081.64
G2	410.55	82.11	54.74	580.03	5	30.54	2.74	0	0	138	1081.64
G3	410.51	82.11	54.74	580.03	5	30.54	2.74	0.01	0.04	138	1081.64
G4	410.43	82.11	54.74	580.03	5	30.54	2.74	0.03	0.12	138	1081.64
G5	410.35	82.11	54.74	580.03	5	30.54	2.74	0.05	0.2	138	1081.64
G6	410.14	82.11	54.74	580.03	5	30.54	2.74	0.1	0.41	138	1081.64
G7	410.55	82.11	54.74	549.5	10	61.08	2.74	0	0	138	1081.64
G8	410.51	82.11	54.74	549.5	10	61.08	2.74	0.01	0.04	138	1081.64
G9	410.43	82.11	54.74	549.5	10	61.08	2.74	0.03	0.12	138	1081.64
G10	410.35	82.11	54.74	549.5	10	61.08	2.74	0.05	0.2	138	1081.64
G11	410.14	82.11	54.74	549.5	10	61.08	2.74	0.1	0.41	138	1081.64
G12	410.55	82.11	54.74	518.98	15	91.62	2.74	0	0	138	1081.64
G13	410.51	82.11	54.74	518.98	15	91.62	2.74	0.01	0.04	138	1081.64
G14	410.43	82.11	54.74	518.98	15	91.62	2.74	0.03	0.12	138	1081.64
G15	410.35	82.11	54.74	518.98	15	91.62	2.74	0.05	0.2	138	1081.64
G16	410.14	82.11	54.74	518.98	15	91.62	2.74	0.1	0.41	138	1081.64

Table 2: Concrete Mix Details Corresponding to w/c Ratio of 0.3

Mix no.	Cement	FA	SF	MS	RA		SP	GO		Water	CA
	kg/m ³	kg/m ³	kg/m ³	kg/m ³	%	kg/m ³	kg/m ³	%	kg/m ³	kg/m ³	kg/m ³
G1	384.68	76.94	51.29	619.28	0	0	2.56	0	0	156	1055.19
G2	384.68	76.94	51.29	588.32	5	30.96	2.56	0	0	156	1055.19
G3	384.64	76.94	51.29	588.32	5	30.96	2.56	0.01	0.038	156	1055.19
G4	384.57	76.94	51.29	588.32	5	30.96	2.56	0.03	0.115	156	1055.19
G5	384.49	76.94	51.29	588.32	5	30.96	2.56	0.05	0.192	156	1055.19
G6	384.3	76.94	51.29	588.32	5	30.96	2.56	0.1	0.38	156	1055.19
G7	384.68	76.94	51.29	557.35	10	61.93	2.56	0	0	156	1055.19
G8	384.64	76.94	51.29	557.35	10	61.93	2.56	0.01	0.038	156	1055.19
G9	384.57	76.94	51.29	557.35	10	61.93	2.56	0.03	0.115	156	1055.19
G10	384.49	76.94	51.29	557.35	10	61.93	2.56	0.05	0.192	156	1055.19
G11	384.3	76.94	51.29	557.35	10	61.93	2.56	0.1	0.38	156	1055.19
G12	384.68	76.94	51.29	526.39	15	92.89	2.56	0	0	156	1055.19
G13	384.64	76.94	51.29	526.39	15	92.89	2.56	0.01	0.038	156	1055.19
G14	384.57	76.94	51.29	526.39	15	92.89	2.56	0.03	0.115	156	1055.19
G15	384.49	76.94	51.29	526.39	15	92.89	2.56	0.05	0.192	156	1055.19
G16	384.3	76.94	51.29	526.39	15	92.89	2.56	0.1	0.38	156	1055.19

Table 3: Experimental Results for Workability, Density, and Air Content for Both w/c Ratios

Concrete Sample	Variables		Workability (mm)		Density (kg/m ³)		Air Content (%)	
	RA (%)	GO (%)	w/c = 0.252	w/c = 0.3	w/c = 0.252	w/c = 0.3	w/c = 0.252	w/c = 0.3
G1	0	0	101	106	2320	2310	3.2	3.4
G2	5	0	96	103	2285	2269	4.4	4.7
G3	5	0.01	94	101	2286	2274	4.2	4.3
G4	5	0.03	93	98	2291	2277	3.8	3.9
G5	5	0.05	91	94	2293	2282	3.5	3.7
G6	5	0.1	89	92	2298	2289	3.1	3.2
G7	10	0	92	96	2236	2222	5.1	5.4
G8	10	0.01	91	93	2239	2227	4.8	5
G9	10	0.03	89	92	2242	2234	4.6	4.7
G10	10	0.05	86	89	2246	2236	4.3	4.5
G11	10	0.1	83	87	2251	2241	4.1	4.2
G12	15	0	86	92	2216	2200	6	6.5
G13	15	0.01	83	89	2219	2209	5.9	6.1
G14	15	0.03	81	87	2225	2213	5.7	6
G15	15	0.05	80	84	2227	2217	5.4	5.6
G16	15	0.1	77	80	2232	2225	5.1	5.2

earlier research [16, 17]. Various factors like exchange of higher density MS by lower density RA [16, 17] and entrapment of air by RA [18] are responsible for decrease in density with the inclusion of RA. The results also revealed that GO improved the density of RC while reducing the losses in concrete density brought on by the addition of RA. The increment in density with the addition of GO is attributed to the development of compact mass due to the response of cement paste and GO [19, 21, 22] and pore-filling property of GO [22, 23].

The investigational results illustrated that the presence of RA considerably enhanced the air content in concrete. With the inclusion of RA, the air content of concrete mix having w/c ratios of 0.252 and 0.3 enhanced from 3.2% to 6% and 3.4% to 6.5% respectively. These results agree with the previous studies [24, 25, 26]. Entrapment of air by RA [25] and water repelling by hydrophobic RA [27] are the main factors behind the air content increment in the RC [25]. The study also reveals that the addition of GO considerably decreased the air content in RC. Void filling action of GO and formation of dense microstructure in RC matrix are responsible for the diminution in air content of RC [21].

4. ANN

Table 4 provides the variables (concrete ingredients used to cast concrete) and their range of variations.

Variables listed in Table 4 are so chosen because only these concrete ingredients tend to vary in the concrete composition affecting the physical properties of concrete. For the model creation, five input variables (RA, MS, cement, GO, and w/c ratio) were taken for each physical property, and the output was one of the physical properties. The experimental results on the physical properties are taken as reference data for the modeling.

Table 4: Details of Parameters Varied for Modelling

Variables	Range of Variations				
MS (%)	100	95	90	85	
RA Content (%)	0	5	10	15	
GO content (%)	0	0.01	0.03	0.05	0.1
Cement (%)	100	99.99	99.97	99.95	99.9
water-cement ratio	0.252	0.3			

Consequently, all the variables were used as inputs, and the physical properties were treated as output to generate a model, according to Eq. (1) given below:

$$\text{Physical properties} = f\{\text{RA, MS, GO, cement, w/c ratio}\} \quad (1)$$

4.1. Application of Experimental Results for ANN Modeling

Tables (5-7) represent the input variables and their corresponding physical properties as output for each

Table 5: Range of Data Used for the Training and Testing at the Different Water-Cement Ratios for Workability

Training Dataset for Workability						Testing Dataset for Workability					
Variables				w/c Ratio	Output	Variables				w/c Ratio	Output
RA %	MS %	GO %	Cement %		Workability (mm)	RA %	MS %	GO %	Cement %		Workability (mm)
0	100	0	100	0.252	101	5	95	0	100	0.252	96
5	95	0.01	99.99	0.252	94	5	95	0.05	99.95	0.252	91
5	95	0.03	99.97	0.252	93	10	90	0.01	99.99	0.252	91
5	95	0.1	99.9	0.252	89	10	90	0.1	99.9	0.252	83
10	90	0	100	0.252	92	15	85	0.03	99.97	0.252	81
10	90	0.03	99.97	0.252	89	5	95	0	100	0.3	103
10	90	0.05	99.95	0.252	86	5	95	0.05	99.95	0.3	94
15	85	0	100	0.252	86	10	90	0.01	99.99	0.3	93
15	85	0.01	99.99	0.252	83	10	90	0.1	99.9	0.3	87
15	85	0.05	99.95	0.252	80	15	85	0.03	99.97	0.3	87
15	85	0.1	99.9	0.252	77						
0	100	0	100	0.3	106						
5	95	0.01	99.99	0.3	101						
5	95	0.03	99.97	0.3	98						
5	95	0.1	99.9	0.3	92						
10	90	0	100	0.3	96						
10	90	0.03	99.97	0.3	92						
10	90	0.05	99.95	0.3	89						
15	85	0	100	0.3	92						
15	85	0.01	99.99	0.3	89						
15	85	0.05	99.95	0.3	84						
15	85	0.1	99.9	0.3	80						

Table 6: Range of Data Used for the Training and Testing at the Different Water-cement Ratios for Density

Training Dataset for Density						Testing Dataset for Density					
Variables				w/c Ratio	Output	Variables				w/c Ratio	Output
RA %	MS %	GO %	Cement %		Density (mm)	RA %	MS %	GO %	Cement %		Density (mm)
0	100	0	100	0.252	2320	5	95	0	100	0.252	2285
5	95	0.01	99.99	0.252	2286	5	95	0.05	99.95	0.252	2293
5	95	0.03	99.97	0.252	2291	10	90	0.01	99.99	0.252	2239
5	95	0.1	99.9	0.252	2298	10	90	0.1	99.9	0.252	2251
10	90	0	100	0.252	2236	15	85	0.03	99.97	0.252	2225
10	90	0.03	99.97	0.252	2242	0	100	0	100	0.3	2310
10	90	0.05	99.95	0.252	2246	5	95	0.03	99.97	0.3	2277
15	85	0	100	0.252	2216	10	90	0	100	0.3	2222
15	85	0.01	99.99	0.252	2219	10	90	0.05	99.95	0.3	2236
15	85	0.05	99.95	0.252	2227	15	85	0.01	99.99	0.3	2209
15	85	0.1	99.9	0.252	2232						
5	95	0	100	0.3	2269						
5	95	0.01	99.99	0.3	2274						

Table 6 (contd.....)

Training Dataset for Density						Testing Dataset for Density					
Variables				w/c Ratio	Output	Variables				w/c Ratio	Output
RA %	MS %	GO %	Cement %		Density (mm)	RA %	MS %	GO %	Cement %		Density (mm)
5	95	0.05	99.95	0.3	2282						
5	95	0.1	99.9	0.3	2289						
10	90	0.01	99.99	0.3	2227						
10	90	0.03	99.97	0.3	2234						
10	90	0.1	99.9	0.3	2241						
15	85	0	100	0.3	2200						
15	85	0.03	99.97	0.3	2213						
15	85	0.05	99.95	0.3	2217						
15	85	0.1	99.9	0.3	2225						

Table 7: Range of Data Used for the Training and Testing at the Different Water-cement Ratios for Air Content

Training Dataset for Air Content						Testing Dataset for Air Content					
Variables				w/c Ratio	Output	Variables				w/c Ratio	Output
RA %	MS %	GO %	Cement %		Air Content (mm)	RA %	MS %	GO %	Cement %		Air Content (mm)
0	100	0	100	0.252	3.2						
5	95	0.01	99.99	0.252	4.2	5	95	0	100	0.252	4.4
5	95	0.03	99.97	0.252	3.8	5	95	0.05	99.95	0.252	3.5
5	95	0.1	99.9	0.252	3.1	10	90	0.01	99.99	0.252	4.8
10	90	0	100	0.252	5.1	10	90	0.1	99.9	0.252	4.1
10	90	0.03	99.97	0.252	4.6	15	85	0.03	99.97	0.252	5.7
10	90	0.05	99.95	0.252	4.3	0	100	0	100	0.3	3.4
15	85	0	100	0.252	6	5	95	0.03	99.97	0.3	3.9
15	85	0.01	99.99	0.252	5.9	10	90	0	100	0.3	5.4
15	85	0.05	99.95	0.252	5.4	10	90	0.05	99.95	0.3	4.5
15	85	0.1	99.9	0.252	5.1	15	85	0.01	99.99	0.3	6.1
5	95	0	100	0.3	4.7						
5	95	0.01	99.99	0.3	4.3						
5	95	0.05	99.95	0.3	3.7						
5	95	0.1	99.9	0.3	3.2						
10	90	0.01	99.99	0.3	5						
10	90	0.03	99.97	0.3	4.7						
10	90	0.1	99.9	0.3	4.2						
15	85	0	100	0.3	6.5						
15	85	0.03	99.97	0.3	6						
15	85	0.05	99.95	0.3	5.6						
15	85	0.1	99.9	0.3	5.2						

data training and testing set. It should be noted that the total data (experimental results) was separated into 70% for training data and 30% for testing data. The

variables viz., RA, MS, GO, cement, and w/c ratio all affect the physical properties of the RC.

The proposed model was evaluated based on correlation coefficient (r), coefficient of determination (R^2), mean square error (MSE), root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE). The calculations for r , R^2 , MSE, RMSE, MAE, and MAPE can be done as per the equations (2), (3), (4), (5), (6), and (7) presented below:

Coefficient of correlation (r) =

$$\frac{\sum_{i=1}^n UV}{\sqrt{n(\sum_{i=1}^n U^2 - (\sum_{i=1}^n U)^2)} \sqrt{n(\sum_{i=1}^n V^2 - (\sum_{i=1}^n V)^2)}} \quad (2)$$

$$\text{Coefficient of determination } (R^2) = 1 - \frac{\sum_{i=1}^n (U-V)^2}{\sum_{i=1}^n (u-v)^2} \quad (3)$$

$$\text{Mean square error (MSE)} = \frac{1}{n} \sum_{i=1}^n (U - V)^2 \quad (4)$$

$$\text{Root mean square error (RMSE)} = \sqrt{\frac{1}{n} \sum_{i=1}^n (U - V)^2} \quad (5)$$

$$\text{Mean absolute error (MAE)} = \frac{1}{n} \sum_{i=1}^n |U - V| \quad (6)$$

$$\text{Mean percentage absolute error (MAPE)} = \left[\frac{1}{n} \sum_{i=1}^n \frac{|U-V|}{U} \right] \times 100 \quad (7)$$

Here, "U" is the experimental values, "V" is the predicted values, "u" is the mean of experimental values, "v" is the mean of predicted values, and "n" is the total number of datasets.

4.2. Development of Model for ANN

The models were developed in WEKA using a multilayer perceptron trained with the feed-forward back-propagation algorithm and a sigmoid activation function at the hidden and output nodes. Input and output variables were standardized. A learning rate of 0.7 was adopted, consistent with commonly used default configurations for concrete-property ANN models [2, 6]; no learning-rate optimisation was performed in this study, which is acknowledged as a limitation. Model selection (10-fold cross-validation) was used to tune the number of hidden-layer neurons and the number of training epochs, after which the full 70:30 training: testing split reported in Tables (5-7) were used to report the final performance metrics in Table 8. The 10-fold cross-validation was used only during model-selection (to determine the optimal number of hidden-layer neurons and epochs, Figs. (6-8); the final reported performance (Table 8) is based on the fixed 70% training / 30% testing split shown in Tables (5-7). The subsequent step is to estimate the number of iterations that may be executed while maintaining an MSE and R^2 , where the MSE should be as small as feasible, and the R^2 should be close to 1. Additionally,

the MSE and R^2 were significantly influenced by the number of hidden layer neurons.

Figs. (3-5) illustrate the MSE's variation with the rise in the number of iterations for the workability, density, and air content, respectively. According to these graphs, the MSE decreases with the increments in number of iterations and either stays fixed or rises until it reaches the minimum value. At 900, 2400, and 450 iterations, the MSE values for workability, density, and air content were at their lowest. The next step was to calculate the optimal number of hidden layer neurons to include in the model.

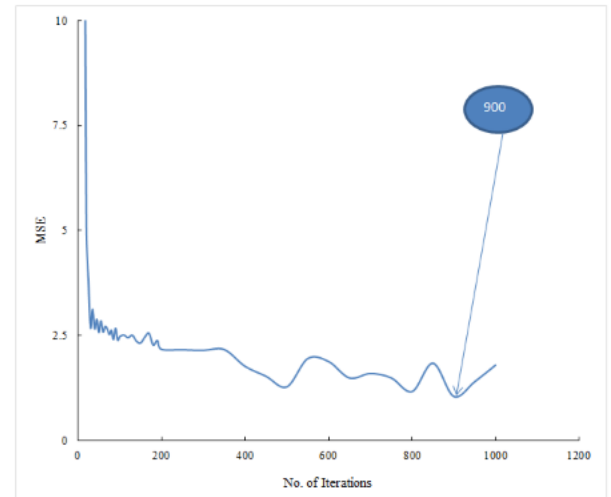


Figure 3: MSE variations with iterations for workability.

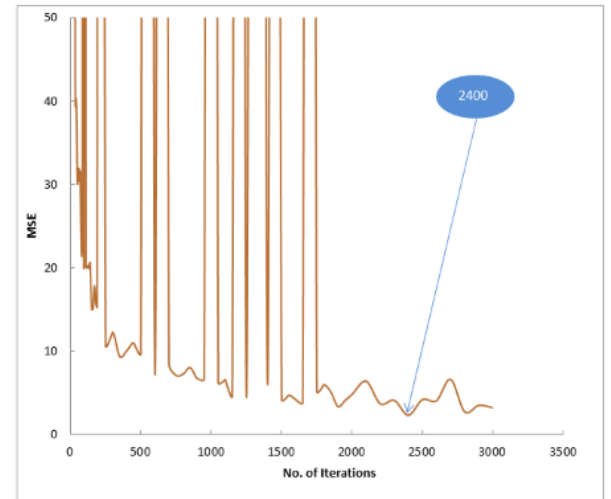


Figure 4: MSE variations with iterations for density.

The impact of MSE and R^2 on the hidden layer neurons is depicted in Figs. (6-8). The highest values of R^2 and the lowest values of MSE were observed at 6, 4, and 4 hidden layer neurons in the cases of workability, density, and air content, respectively. With the enhancement in quantity of hidden layer neurons, either R^2 decreases or MSE rises. For developing a model structure for the workability of RC, five input variables,

one hidden layer, six hidden layer neurons, and one output layer were selected for the analysis purpose.

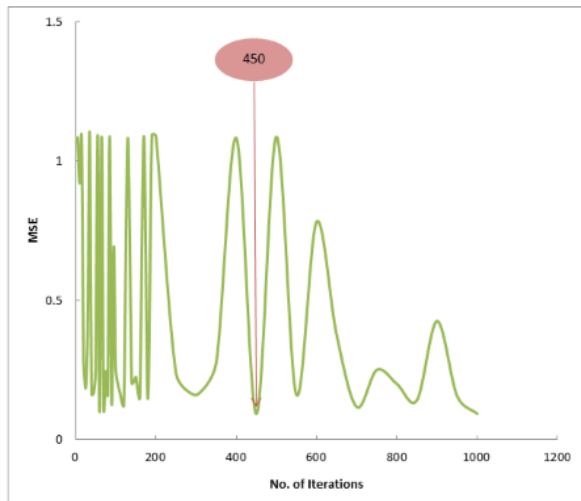


Figure 5: MSE variations with iterations for air content.

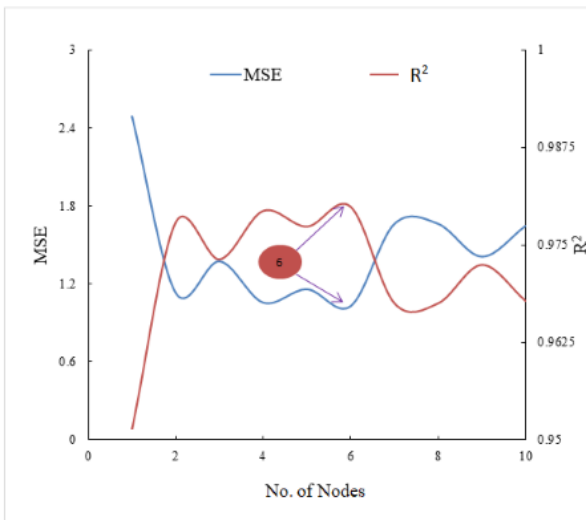


Figure 6: Estimation of the optimum number of hidden layer neurons for the workability of RC.

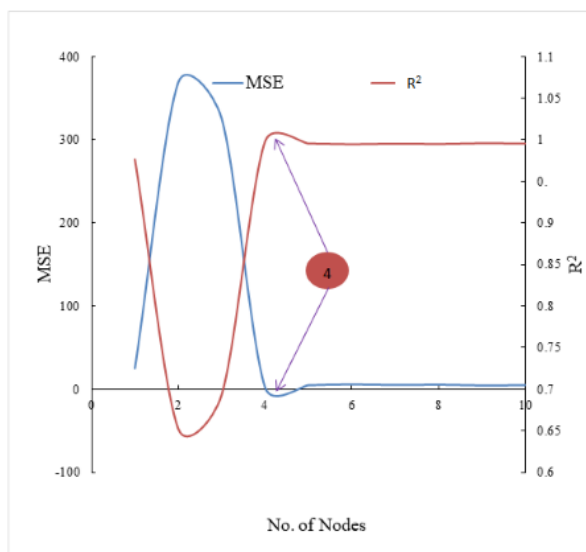


Figure 7: Estimation of the optimum number of hidden layer neurons for the density of RC.

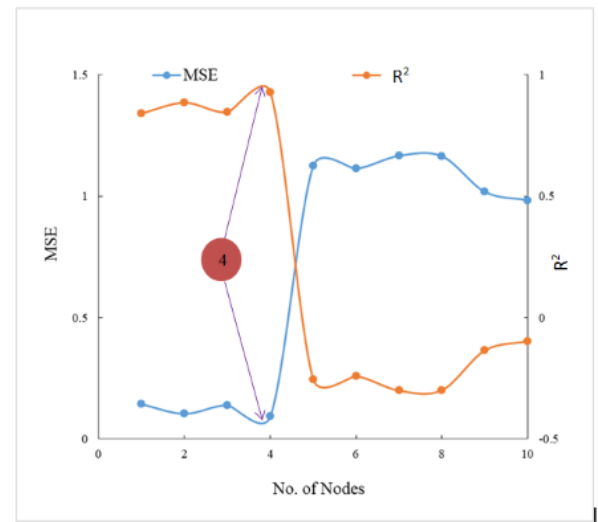


Figure 8: Estimation of the optimum number of hidden layer neurons for the air content of RC.

Fig. (9) presents the developed network for workability. For developing a model structure for the density of RC, five input variables, one hidden layer, four hidden layer neurons, and one output layer were chosen for the investigation. Fig. (10) presents the developed network for the density. For developing a model structure for the air content of RC, five input variables, one hidden layer, four hidden layer neurons, and one output layer were chosen for the investigation. Fig. (11) presents the developed network for the air content. To analyze the prediction accuracy of the developed model, the physical properties of the developed model were compared with the experimental results.

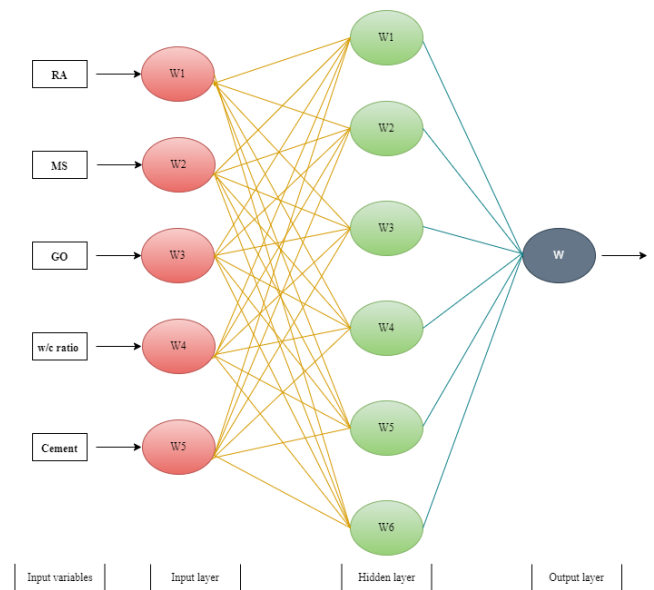


Figure 9: Architecture of the model for the workability of RC.

4.3. Results and Discussion on ANN Model

The statistical parameters shown in Table 8 represent the level of correlation and goodness of fit of

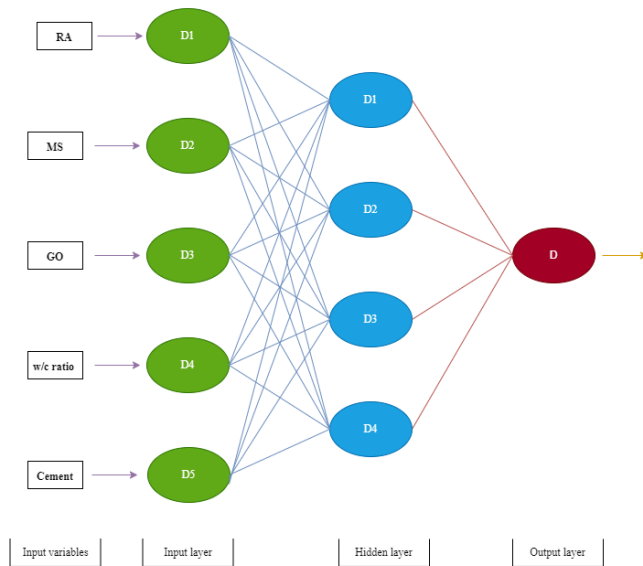


Figure 10: Architecture of the model for the density of RC.

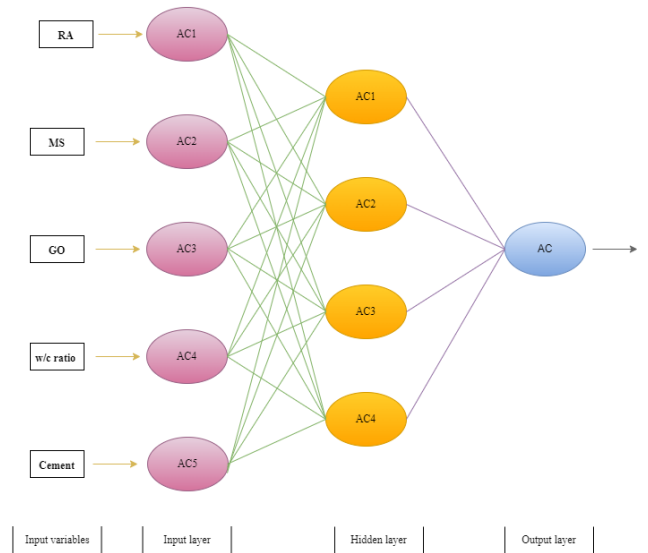


Figure 11: Architecture of the model for the air content of RC.

Table 8: Assessing Parameters for the Developed Model for Different Physical Properties

Physical Properties	Assessing Parameters	Training	Testing
Workability	r	0.9899	0.9902
	R ²	0.9799	0.9807
	MSE	1.0288	0.7277
	RMSE	1.0143	0.8531
	MAE	0.7993	0.6773
	MAPE (%)	0.8779	0.7404
Density	r	0.9989	0.9985
	R ²	0.9978	0.9969
	MSE	2.5878	3.1969
	RMSE	1.6087	1.7880
	MAE	1.0505	1.2911
	MAPE (%)	0.0467	0.0574
Air content	r	0.9626	0.9550
	R ²	0.9266	0.9121
	MSE	0.0657	0.0666
	RMSE	0.2564	0.2581
	MAE	0.1881	0.2035
	MAPE (%)	3.8319	4.0954

the training and testing data for the constructed model's workability, density, and air content. The coefficient of correlation (r) for the workability, density, and air content of the developed model was found to be 0.99, 0.99, and 0.96 for training data and 0.99, 0.99, and 0.96 for testing data, respectively. In the machine learning approach, the r value must be close to 1 (merely lying between 0 and 1 is insufficient for the best ANN model). Table 8 also illustrates that all the assessing parameters are under tolerable limits.

In practical terms, the MAE values of 0.68-0.80 mm for workability, 1.05-1.29 kg/m³ for density, and 0.19-0.20% for air content (as presented in Table 8) are well within the precision normally required for concrete mix-design and quality-control decisions, indicating that the model could support preliminary mix proportioning of GO-modified RC without requiring a full trial-batch programme for every candidate mix, subject to the limitations as discussed. Figs. (12-17) represent that for both training and testing datasets, the predicted and

experimental values of workability, density, and air content have higher values of R^2 (more than 92% for each physical properties), indicating higher goodness of fit for the experimental results and the developed model. In other words, it also indicates the developed model could be used to predict the output.

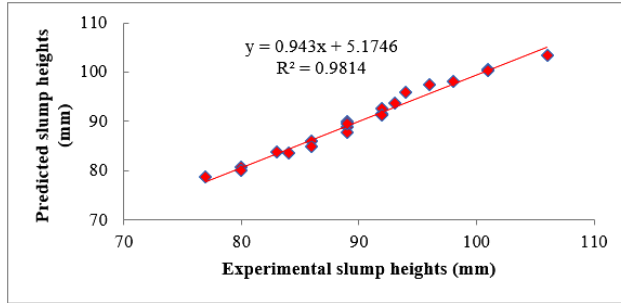


Figure 12: Comparison of predicted and experimental slump height values for training for workability.

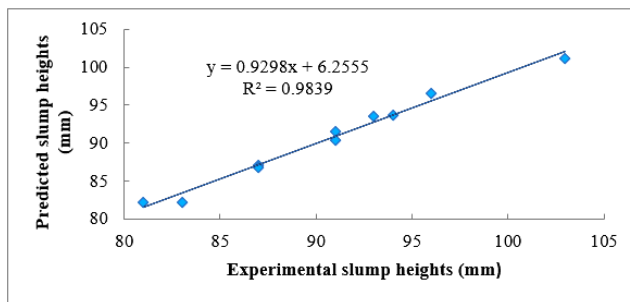


Figure 13: Comparison of predicted and experimental slump height values for testing for workability.

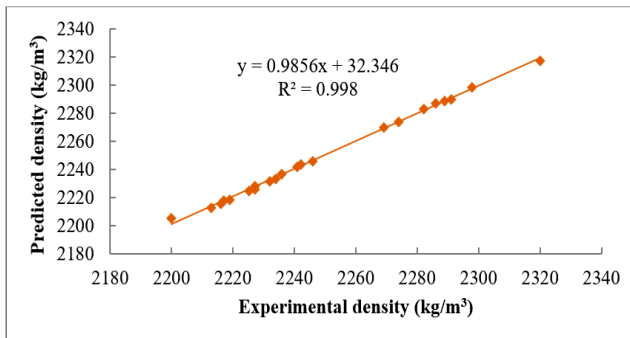


Figure 14: Comparison of predicted and experimental values for training for density.

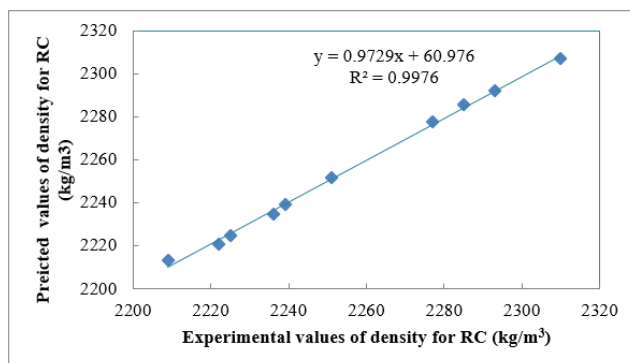


Figure 15: Comparison of predicted and experimental values for testing for density.

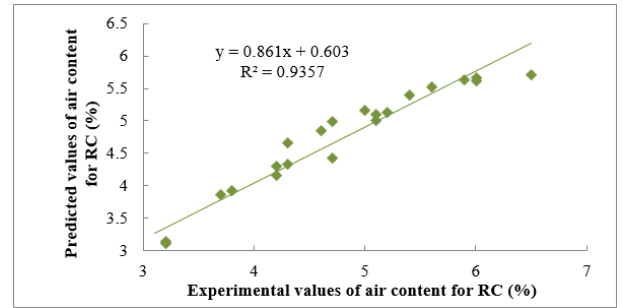


Figure 16: Comparison of predicted and experimental values for training for air content.

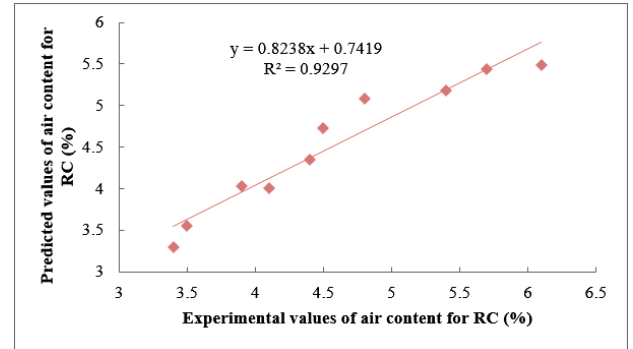


Figure 17: Comparison of predicted and experimental values for testing for air content.

The final connection weights between the input layers to the hidden layer [x_{Aij}] and the hidden layer to the output layer [y_{Ajk}], input bias [z_{Aj}] and output bias [z_A], as well as the matrices of a correlation created, are shown as follows. Equations (8), (9), (10), and (11) represent the generalized form of the matrix for the physical properties and equations for workability, density, and air content, respectively.

The generalized form of the matrix for all the physical properties:

$$x_{Aij} = \begin{bmatrix} x_{A11} & x_{A12} & x_{A13} & x_{A14} & x_{A15} & x_{A16} \\ x_{A21} & x_{A22} & x_{A23} & x_{A24} & x_{A25} & x_{A26} \\ x_{A31} & x_{A32} & x_{A33} & x_{A34} & x_{A35} & x_{A36} \\ x_{A41} & x_{A42} & x_{A43} & x_{A44} & x_{A45} & x_{A46} \\ x_{A51} & x_{A52} & x_{A53} & x_{A54} & x_{A55} & x_{A56} \end{bmatrix}; \quad y_{Ajk} = \begin{bmatrix} y_{A11} \\ y_{A21} \\ y_{A31} \\ y_{A41} \\ y_{A51} \\ y_{A61} \end{bmatrix}; \quad z_{Aj} = \begin{bmatrix} z_{A1} \\ z_{A2} \\ z_{A3} \\ z_{A4} \\ z_{A5} \\ z_{A6} \end{bmatrix}; \quad z_A = [z_A] \quad (8)$$

Matrix for the workability of RC

$$x_{Wij} = \begin{bmatrix} 0.756658 & -0.71642 & -0.31123 & 0.626144 & 0.832535 & 0.557503 \\ -1.57952 & 0.36804 & 0.055223 & -0.83449 & -0.42144 & -0.57078 \\ 0.298463 & -0.37798 & -0.23813 & 0.245998 & 0.589819 & 0.316336 \\ -1.15574 & 0.227684 & 0.006495 & -0.44038 & -0.20974 & -0.35428 \\ -0.10982 & 0.459115 & 0.057418 & -0.35138 & -0.60319 & -0.50352 \end{bmatrix}; \quad y_{Wjk} = \begin{bmatrix} -2.87957 \\ 1.245027 \\ 0.399375 \\ -1.65305 \\ -2.17532 \\ -1.17686 \end{bmatrix}; \quad z_{Wj} = \begin{bmatrix} -0.84926 \\ -0.32583 \\ -0.18239 \\ -0.13814 \\ 0.306097 \\ 0.034608 \end{bmatrix}; \quad z_W = [2.218296] \quad (9)$$

Matrix for density of RC:

$$X_{Dij} = \begin{bmatrix} -0.43392 & 0.42836 & 1.63248 & 3.858369 \\ 2.246672 & -1.03483 & -1.26228 & -2.77385 \\ 2.273368 & -0.08884 & 0.393781 & 0.154954 \\ -0.58187 & -0.24589 & -0.07789 & 0.820366 \\ -0.78679 & 0.705094 & -0.0968 & 0.276719 \end{bmatrix};$$

$$Y_{Djk} = \begin{bmatrix} 3.513555 \\ -1.1929 \\ -1.88848 \\ -4.34022 \end{bmatrix}; Z_{Dj} = \begin{bmatrix} 1.758381 \\ -0.54281 \\ 0.166396 \\ 0.977193 \end{bmatrix}; Z_D = [2.09109] \quad (10)$$

Matrix for air content of RC:

$$X_{ACij} = \begin{bmatrix} -1.47573 & 0.481796 & -0.69454 & 1.645738 \\ 2.412045 & -0.65304 & 1.347255 & -2.80723 \\ 1.150671 & -0.3169 & 1.023691 & -1.39138 \\ -0.21116 & -0.01701 & -0.27578 & 0.173153 \\ -0.24522 & -0.02859 & -0.1879 & 0.298952 \end{bmatrix};$$

$$Y_{ACjk} = \begin{bmatrix} -2.71739 \\ 0.734299 \\ -1.46714 \\ 3.225488 \end{bmatrix}; Z_{ACj} = \begin{bmatrix} 1.083806 \\ -0.26805 \\ 0.584698 \\ -1.12586 \end{bmatrix}; Z_{AC} = [4.724817] \quad (11)$$

5. SENSITIVITY ANALYSIS

Sensitivity analysis is performed to determine the percentage contribution of different input variables (RA, MS, GO, cement, and w/c ratio) on the different physical properties. It helps to determine which variable affects the physical properties to what extent. This analysis was done using a method discussed by [29] and based on the weight configuration. This method has a limitation in that it is based on estimating the absolute weights. This approach calculates an estimate of the finalized connection weight from each input neuron to each hidden layer neuron and from each hidden layer neuron to each output layer neuron. The contribution of each variable to a given input is determined using Eq. (12).

$$IR_{Aj} = \sum_{k=1}^h x_{Ajk} \times x_k \quad (12)$$

where,

x_{Ajk} = connection weight between k^{th} neuron of the hidden layer and j^{th} input variable

x_k = connection weight between the single output neuron and the k^{th} neuron of a hidden layer

IR_j = relative importance of the j^{th} neuron in the input layer

h = number of the hidden layer neurons

The percentage contribution of each input variable on the output (physical properties) is shown in Figs. (18-20). These figures show that RA and MS have much more effect on RC's workability, density, and air content than any other input variables. In other words, these physical properties are much affected by the fine aggregate in the RC. This could be so because RA and MS constitute a larger portion of the volume of RC in comparison to the other concrete ingredients. Being the nano-filler material, GO also significantly affected RC's

physical properties. Although experimentally, it is observed that GO significantly influences the physical properties of RC, ANN gives a clear picture that the rank of GO (for influencing the physical properties of RC) comes after the RA and MS. The ranks of input variables for influencing the output (physical properties) are in the following order: RA > MS > GO > w/c ratio > cement (for the workability of RC); MS > RA > GO > w/c ratio > cement (for density of RC); MS > RA > GO > w/c ratio = cement (for air content of RC).

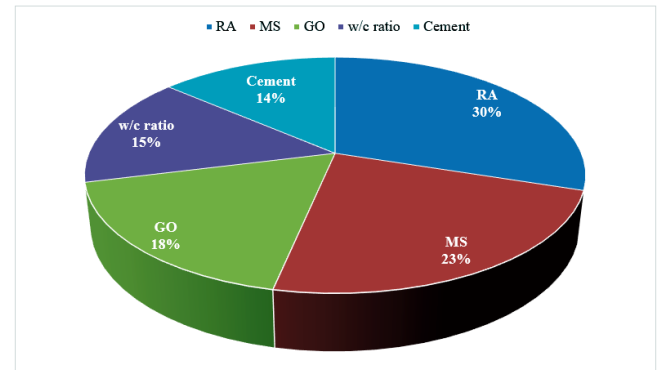


Figure 18: Contribution of each input variable on the workability of GO-induced RC.

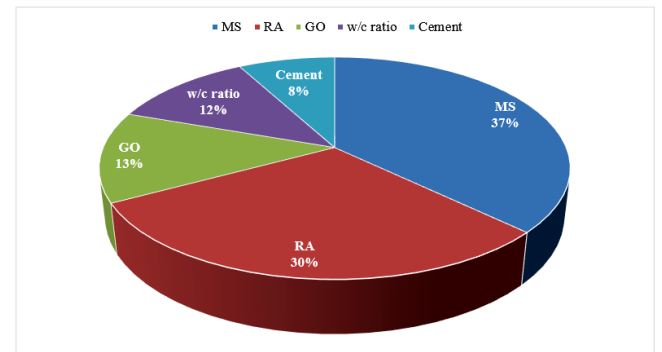


Figure 19: Contribution of each input variable on the density of GO-induced RC.

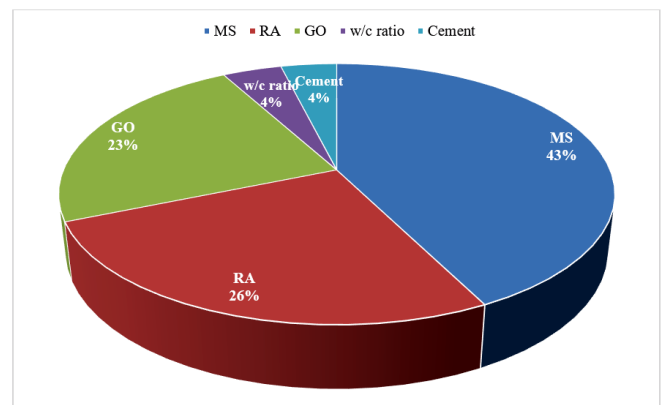


Figure 20: Contribution of each input variable on the air content of GO-induced RC.

6. CONCLUSIONS

With the help of the machine learning technique, the aim was to apply the experimental results of the

physical properties of RC for the development of the model and to compare the experimental results with the predicted results obtained through the ANN approach. The input variables used for the model generation were RA, MS, GO, w/c ratio, and cement, while the output was RC's physical properties like workability, density, and air content. All the experimental results were divided as 70% for training and 30% for testing the datasets, i.e., a total of 22 and 10 datasets were taken for training, and testing works for each physical property. The mathematical parameters, viz. coefficient of correlation, coefficient of determination, mean square error, root mean square error, mean absolute error, and mean absolute percentage error, were taken as checking criteria for the relationship between training and testing values of datasets for each physical property. Also, these parameters were found to be maximum for the sigmoid activation function. The values of the coefficient of determination (R^2) and coefficient of correlation (r) for training and testing datasets of each physical property were found to be more than 0.91 and 0.95, respectively, indicating higher goodness of fit for the development of the model. The graphs between the predicted output values and the experimental values show a higher R^2 of 0.98, 0.998, 0.9357, and 0.9839, 0.9976, 0.9297 for the training and testing datasets for the workability, density, and air content, respectively. In other words, the higher R^2 between the predicted output and the experimental values shows the higher precision of the output and accuracy of the model. Sensitivity analysis showed that RA, MS, and GO have a higher contribution to the resultant physical properties, followed by the w/c ratio and cement. It indicates that RA, MS, and GO have highly influenced the workability, density, and air content of RC.

At the recommended 15% RA replacement level, the mix designs in Tables 1 and 2 correspond to a reduction of approximately 60-93 kg/m³ of manufactured sand per cubic metre of concrete across the two w/c ratios studied, replaced by RA derived from waste tires; scaled to typical concrete consumption in a construction project, this represents a measurable diversion of scrap-tire material from landfill and a corresponding reduction in the extraction of natural/manufactured FA. The GO used in this study is added at only 0.01-0.1% by weight of cement, and at 0.05% partially offsets the density and air-content penalties associated with RA, without requiring an increase in cement content. These findings support the use of RA and GO as a means of achieving partial circularity (waste-tire reuse) without a corresponding mitigation in the fresh-state performance of concrete, provided the practical limits identified in this study are respected. However, a full assessment of the net

environmental benefit would additionally need to account for the embodied energy and cost of producing GO, the processing of scrap tires into RA, and the transport distances involved, which were outside the scope of the present study and are recommended as a direction for future work (e.g., a life-cycle assessment, LCA).

The aim of this research work was to create a platform to apply the machine learning approach for predicting the workability, density, and air content of RC with the help of some input variables. As the predicted results followed the experimental values with very little deviance, this technique may be helpful for future investigation by saving time and cost for the experimental results. Expanding this technique with more variables and developing a model with higher precision is further suggested.

DISCLOSURE STATEMENT

1. No funding was received for this study.
2. Author declare no competing interest.

REFERENCES

- [1] Chaturvedy GK, Pandey UK, Kumar H. Effect of graphene oxide on the microscopic, physical, and mechanical characteristics of rubberized concrete. *Innov Infrastruct Solut.* 2023;8:6. <https://doi.org/10.1007/s41062-023-01133-6>.
 - [2] Raja KT, Jayanthi N, Tesfaye JL, Nagaprasad N, Krishnaraj R, Kaushik VS. Using an artificial neural network to validate and predict the physical properties of self-compacting concrete. *Adv Mater Sci Eng.* 2022;2022:1206512. <https://doi.org/10.1155/2022/1206512>.
 - [3] Akis E, Guven G, Lottisadigh B. Predictive models for mechanical properties of expanded polystyrene (EPS) geofoam using regression analysis and artificial neural networks. *Neural Comput Appl.* 2022. <https://doi.org/10.1007/s00521-022-07014-w>.
 - [4] Dantas ATA, Leite MB, Nagahama KJ. Prediction of compressive strength of concrete containing construction and demolition waste using artificial neural networks. *Constr Build Mater.* 2013;38:717-722. <https://doi.org/10.1016/j.conbuildmat.2012.09.026>.
 - [5] Panwar V, Dutta RK. Application of machine learning technique in predicting the bearing capacity of rectangular footing on layered sand under inclined loading. *J Soft Comput Civ Eng.* 2022;6(4):130-152. <https://doi.org/10.22115/SCCE.2022.343236.1445>.
 - [6] Asteris PG, Kolovos KG, Douvika MG, Roinos K. Prediction of self-compacting concrete strength using artificial neural networks. *Eur J Environ Civ Eng.* 2016. <https://doi.org/10.1080/19648189.2016.1246693>.
 - [7] Dias WPS, Pooliyadda SP. Neural networks for predicting properties of concretes with admixtures. *Constr Build Mater.* 2001;15(7):371-379.
 - [8] Golzar K, Jalali-Arani A, Nematollahi M. Statistical investigation on physical-mechanical properties of base and polymer modified bitumen using artificial neural network. *Constr Build Mater.* 2012;37:822-831. <https://doi.org/10.1016/j.conbuildmat.2012.08.011>.
- Ahmad A, Plevris V, Khan QZ. Prediction of properties of FRP-confined concrete cylinders based on artificial neural networks. *Crystals.* 2020;10:811. <https://doi.org/10.3390/cryst10090811>.

- [9] Bureau of Indian Standards. IS 383:2016. Specification for coarse and fine aggregates from natural sources for concrete. New Delhi: Bureau of Indian Standards; 2016.
- [10] Bureau of Indian Standards. IS 10262:2019. Concrete mix proportioning—guidelines. New Delhi: Bureau of Indian Standards; 2019.
- [11] Chaturvedy GK, Pandey UK. Investigating the effect of graphene oxide on the physical and mechanical properties of high-strength rubberized concrete using RStudio. *Multiscale Multidiscip Model Exp Des*. 2024;7(3):1605-1623. <https://doi.org/10.1007/s41939-023-00209-1>.
- [12] Chaturvedy GK, Pandey UK, Singh MP. Analyzing the behavior of graphene oxide on high-strength rubberized concrete properties using different optimization techniques. *Diam Relat Mater*. 2023;140:110485. <https://doi.org/10.1016/j.diamond.2023.110485>.
- [13] Bureau of Indian Standards. IS 1199:1959. Methods of sampling and analysis of concrete. New Delhi: Bureau of Indian Standards; 1959.
- [14] ASTM International. ASTM C138. Standard test method for density (unit weight), yield, and air content (gravimetric) of concrete. West Conshohocken (PA): ASTM International.
- [15] Kaundal A, Chaturvedy GK, Pandey UK. Synergistic effects of montmorillonite and rubber aggregates on concrete properties. *Discover Concrete and Cement*. 2025. <https://doi.org/10.1007/s44416-025-00023-7>.
- [16] Chaturvedy GK, Kothari PK, Pandey UK. Analyzing the effect of reduced graphene oxide on the physical, mechanical, and long-term durability performance of rubberized concrete. *Fullerenes Nanotubes Carbon Nanostruct*. 2025;33(9):946-964. <https://doi.org/10.1080/1536383X.2025.2475977>.
- [17] Chaturvedy GK, Bashar N, Pandey UK. Incorporating multi-walled carbon nanotubes in rubberized concrete: impact on physical, mechanical, and fire resistance properties. *Fullerenes Nanotubes Carbon Nanostruct*. 2024;32(12):1121-1134. <https://doi.org/10.1080/1536383X.2024.2375597>.
- [18] Qureshi TS, Panesar DK. Impact of graphene oxide and highly reduced graphene oxide on cement based composites. *Constr Build Mater*. 2019;206:71-83. <https://doi.org/10.1016/j.conbuildmat.2019.01.176>.
- [19] Reddy PVRK, Darapureddi RP. A study on workability, strength and microstructure characteristics of graphene oxide and fly ash based concrete. *Mater Today Proc*. 2022. <https://doi.org/10.1016/j.matpr.2022.02.495>.
- [20] Devi SC, Khan RA. Influence of graphene oxide on sulfate attack and carbonation of concrete containing recycled concrete aggregate. *Constr Build Mater*. 2020. <https://doi.org/10.1016/j.conbuildmat.2020.118883>.
- [21] Silvestre J, Silvestre N, Brito J. Review on concrete nanotechnology. *Eur J Environ Civ Eng*. 2016;20(4):455-485. <https://doi.org/10.1080/19648189.2015.1042070>.
- [22] Devi SC, Khan RA. Compressive strength and durability behavior of graphene oxide reinforced concrete composites containing recycled concrete aggregate. *J Build Eng*. 2020. <https://doi.org/10.1016/j.jobbe.2020.101800>.
- [23] Chaturvedy GK, Mohan G, Pandey UK. Impact of nano-silica and multi-walled carbon nanotubes on the fire resistance performance of rubberized concrete. *J Build Pathol Rehabil*. 2025;10(2):1-16. <https://doi.org/10.1007/s41024-025-00668-8>.
- [24] Sharma J, Chaturvedy GK, Pandey UK. Sustainable rubberized concrete: the role of nano-titanium dioxide in enhancing mechanical and durability properties. *Front Struct Civ Eng*. 2025;19(9):1418-1439. <https://doi.org/10.1007/s11709-025-1216-1>.
- [25] Saini R, Chaturvedy GK, Pandey UK. Examining the effects of nano iron oxide on physical and mechanical characteristics of rubberized concrete. *Innov Infrastruct Solut*. 2024;9. <https://doi.org/10.1007/s41062-024-01494-6>.
- [26] Kansotiya M, Chaturvedy GK, Pandey UK. Influence of nano-silica and crumb rubber on the physical and durability characteristics of concrete. *Multiscale Multidiscip Model Exp Des*. 2024;7:2877-2892. <https://doi.org/10.1007/s41939-024-00379-6>.
- [27] Boger Z, Guterman H. Knowledge extraction from artificial neural network models. In: *Proceedings of the 1997 IEEE International Conference on Systems, Man, and Cybernetics; 1997; Orlando, FL, USA*. IEEE; 1997. p. 3030-3035. <https://doi.org/10.1109/ICSMC.1997.633051>.
- [28] Garson DG. Interpreting neural network connection weights. *AI Expert*. 1991;6(4):46-51

<https://doi.org/10.66000/2819-828X.2026.02.03>

© 2026 Gyanendra Kumar Chaturvedy.

This is an open-access article licensed under the terms of the Creative Commons Attribution License (<http://creativecommons.org/licenses/by/4.0/>), which permits unrestricted use, distribution, and reproduction in any medium, provided the work is properly cited.