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Abstract

Production of concrete by use of conventional materials is unsustainable due to high demand. Henceforth, there is need to upscale the use of alternative materials, including those from waste streams, in concrete. This research aims at developing a suitable predictive model of concrete having partial or 100% glass aggregates. 50 datasets reviewed from 9 sources were adopted and artificial neural network (ANN) models were developed in GNU Octave. The trial models had 7 input variables and 1 output variable (compressive strength) and 1 hidden layer. The selected model, having 24 nodes in the hidden layer and 90.000 iterations, indicated overall root mean square error (RMSE), mean absolute errors (MAE), mean absolute percentage errors (MAPE) and absolute factor of variance (R^2) of 2.679 MPa, 1.422 MPa, 6.951% and 0.996 respectively. The glass fine aggregates between >40% and 50% indicated just over 11% average strengths from the controls. Generally, RMSE, MAE, MAPE and R^2 values showed that the selected model had a good accuracy level and good generalization, particularly considering that the datasets were not from the same experimental program. The study recommends research and utilization of glass fine aggregates up to 50% by weight, with consideration to other influencing factors and also research in cost-effective and environmentally friendly additive and assessment on waste glass aggregates incorporated concrete.

Keywords: concrete, prediction, aggregates, reviews, artificial neural network

Resumen

La producción de hormigón mediante el uso de materiales convencionales es insostenible debido a la alta demanda. De ahora en adelante, es necesario aumentar el uso de materiales alternativos, incluidos los de corrientes de desechos, en el hormigón. Esta investigación tiene como objetivo desarrollar un modelo predictivo adecuado de hormigón con agregados de vidrio parciales o al 100%. Se adoptaron 50 conjuntos de datos revisados de 9 fuentes y se desarrollaron modelos de redes neuronales artificiales (ANN) en GNU Octave. Los modelos de prueba tenían 7 variables de entrada y 1 variable de salida (resistencia a la compresión) y 1 capa oculta. El modelo seleccionado, que tiene 24 nodos en la capa oculta y 90.000 iteraciones, indicó el error cuadrático medio general (RMSE), los errores medios absolutos (MAE), los errores porcentuales absolutos medios (MAPE) y el factor de varianza absoluto (R^2) de 2.679 MPa., 1,422 MPa, 6,951% y 0,996 respectivamente. Los agregados finos de vidrio entre> 40% y 50% indicaron un poco más del 11% de resistencias promedio de los controles. En general, los valores de RMSE, MAE, MAPE y R^2 mostraron que el modelo seleccionado tenía un buen nivel de precisión y una buena generalización, particularmente considerando que los conjuntos de datos no eran del mismo programa experimental. El estudio recomienda la investigación y la utilización de agregados finos de vidrio hasta un 50% en peso, teniendo en cuenta otros factores de influencia y también la investigación de aditivos rentables y respetuosas con el medio ambiente y evaluaciones sobre los agregados de vidrio de desecho incorporados al hormigón.

Palabras clave: concreto, predicción, agregados, revisiones, red neuronal artificial.

1. Introduction

This research is on predictive modeling of compressive strengths for concrete with partial or 100% glass aggregates. This aggregate includes fine, coarse or both and is based on weight. According Żurek *et al.* [1], calculations indicated that GNU Octave was effective when used to determine the expected fitness time, dependent on the reliability function adopted for the reliability of technical transport means analysis. The author's previous work, Ngandu [2] used neural network in Octave 5.2.0 for prediction of compressive strength of rice husk incorporated concrete as cement partial replacement/admixture, and the selected neural network indicated relatively good performance. In the study by Chandwani *et al.* [3] on modelling of slump for ready-mix concrete, neural network models developed using MATLAB 2011b, showed a promising approach in modelling of unstructured problems in relation to concrete behavior. Sathyan *et al.* [4] used random kitchen sink algorithm and regularized least square algorithm, in GURLs toolbar in MATLAB and the model was able to satisfactorily predict hardened and fresh properties of self-compacting concrete. According to Jayaseelan *et al.* [5], neural network model performed well in prediction of fresh properties and compressive strength of flowable concrete using MATLAB; the model exhibited very low root mean square error and mean absolute percentage error and indicated high accuracy level. Hasanzade-Inallu *et al.* [6] used artificial neural network, the model implemented by MATLAB R2019a, and to bring different input and output, variables were normalized with neural network model trained by bat algorithm which indicated superiority when compared to multiple regression model for prediction of compressive strength of concrete with manufactured sand. According to Eaton *et al.* [7], GNU Octave is a freely redistributable software and is a high-level language to solve problems such as linear and nonlinear equations and statistical analysis.

This study aimed at evaluating, through statistical means the artificial neural network model developed using GNU OCTAVE software for concrete incorporated with waste glass as aggregates. The model datasets were adopted from reviews. 50 datasets from 9 sources were used and in some situations modifications, or (logical) assumptions were made.

Glass, Waste Glass and (Waste) Glass Aggregates

Large scale use of waste glass as concrete aggregate would potentially reduce amount of waste in landfill. Research by Sharba [8], indicated waste glass physical properties values of finesse modulus at 2.31, absorption at 0.41% and specific gravity at 2.17. A study by Du and Tan [9], on waste glass powder as cement replacement indicated specific gravity of 2.53 for waste glass powder; Kuruppu and Chandratilake [10] used different glass types as coarse aggregates substitutes, with specific gravity reported at 2.5. Drzymała *et al.* [11] used waste glass from an electrical company that utilized waste, glass lighting waste, with density and absorbability indicated at 2630 kg/m^3 and 0.1% respectively. Ke *et al.* [12] reported voids at 35.3%, water absorption at 0.38%, particle density of 2.5g/cm^3 for waste glass and density for natural fine aggregate was reported at 2.61g/cm^3. Table I shows values for chemical compositions of glass from reviews, where the percentage composition of SiO_2 is dominant.

TABLE I: SELECTED CHEMICAL PROPERTIES FOR GLASS/WASTE GLASS FROM REVIEWS

SiO_2 (%)	Na_2O &/or K_2O (%)	CaO (%)	MgO (%)	Al_2O_3 (%)	Fe_2O_3 (%)	Source

72.08	13.87*#	10.45	0.72	2.19	0.22	[9]
69.43	8.96	7.67	6.85	1.95	1.24	[8]
70-74	13-15	7-11	3-5	0.5-2	> 0.1	[13]
71-75	12-17*#*	6-12	0.5-4	1-3		[12]

*#Value computed from source; *#* Na_2O

According to Sharba [8], decline in workability as waste glass ratio increased was attributed to weak geometry of glass waste, hence less fluidity mixes and the fineness modulus diminution. According to Dabiri *et al.* [14], addition of micro-silica increased the specimen's compressive strength. As reported by Dabiri *et al.* [14], citing from previous studies, the concern of alkali silica reaction (ASR), could be prevented by addition of micro-silica to the concrete mix.

A study by Drzymała *et al.* [11] indicated the presence of air voids near glass aggregate grains in concrete, the flat shape of glass aggregate being a possible cause of air accumulation under the grain, also with increase in glass aggregate amount, concrete absorption increased this, possibly resulting in air voids in concrete. A study by Sharba [8] indicated the highest value for compressive strength at 25% waste glass as sand replacement (not indicated if % replacement was volume or weight based), with lower strengths compared to the control mix recorded above; that percentage replacement, the lower strength, could be due to reduction in adhesive strength among the surface of cement paste and waste glass aggregates. AL-Bawi *et al.* [15] attributed cracks in concrete to high brittleness and poor geometry of glass aggregate that affect the adhesion between cement paste and glass particles. According to Kuruppu and Chandratilake [10], waste glass use in concrete in architectural form would present greater opportunities for value adding and recovery of cost, and could be utilized instead of expensive materials such as marble and granite.

2. Method

2.1 Data and Output

Dataset were obtained from reviews of 9 sources that produced 50 datasets as shown in Table II, with the modifications indicated. Also, some (logical) assumptions were made in order to obtain variable for model inputs. Seven input variables as shown in Table II included: % difference for super-plasticizer (SP) or admixtures from the control; water to binder ratio; fly ash or micro-silica as a % of binder; control strength (without glass aggregate) or target strength (MPa); % recycled glass; aggregate types i.e., fine or coarse aggregates or both. The compressive strength (MPa), of concrete with partial or 100% glass waste aggregate was the model output. The range for compressive strengths for dataset to be predicted was between 65.2 MPa and 4.23 MPa.

TABLES II DATASET VARIABLES INCLUDING MODIFICATIONS AND ASSUMPTIONS / LOGICAL ASSUMPTIONS

****% SP/ admix. from control**	**#W/B ratio**	*****fly ash/ micro-silica % of binder**	**#* control strength (MPa)**	**§ % recycled glass weight**	**ξ aggregate type replaced/ Added**		*** comp. strength (MPa)**	**ref.**
*§ 0	§§ 0.60	§# 13.79	46.19	10	F	C	39.95	[11]

				30			31.17	
				50			14.16	
				100			4.23	
0.2				25			56.9	
0.3	§§ 0.47	§# 22.48	## 45.9	50	F		## 57.5	[16]
0.3				100			59.1	
				Ƭ10			Ƭ35.9	
	0.5		Ƭ37	Ƭ20	F		Ƭ34.2	[17]
				Ƭ30			Ƭ28.8	
				Ƭ40			Ƭ22.7	
				10			53.2	
				30			50.0	
				60			44.7	
	§§ 0.51		## 54.8	100	F		## 37.5	[12]
				10			46.0	
				30		C	44.0	
				60			42.9	
1				100			25.6	
	0.54		*§ 31.9	10			16.0	
				20			27.3	
				10			23.7	
				20	F		*§ 37.8	[14]
	§§ 0.518	57.5	*§ 31.4	30			38.9	
				40			46.5	
				50			50.4	
				4.3			37.36	
	§§ 0.52		30.53	φ 8.6		C	37.75	[18]
				13.0			32.37	
				17.3			31.17	
-0.01				20.9	F		65.2	
-0.12				100.0	F		53	
-0.03	0.35	20	∞ 66.7	φ 19.2		C	63.1	[15]
-0.12				100		C	51.7	
-0.03				φ 20.0	F	C	62	

-0.12				100	F	C	46.6	
-0.03				φ 41.4	F		## 62.4	
-0.096				φ 61.4	F		## 58.8	
-0.11				φ 80.9	F		## 56.6	
-0.06				φ 38.7		C	## 60.8	
-0.09				φ 58.7		C	## 58.7	
-0.06				φ 40.1	F	C	## 59.3	
-0.09				φ 60.1	F	C	## 56.0	
-0.10				φ 80.0	F	C	## 48.4	
	0.45		32	100		C	24.6	[19]
	0.6		30.67	φ 15.1 φ 25.5 φ 35.6 φ 44.9	F		32.67 ## 27.75 ## 27.5 ## 27	[20]
				50			## 27	

Notes: * Compressive (comp.) strengths or their averages, close or at ultimate strengths or strength development pattern assumed similar to the ultimate; ** Super-plasticizer (SP) or admixtures (admix.), difference from the control calculated based on binder weight, if indicated/seen, otherwise assume 0 or negligible; # Water to binder ratio the proportions are indicated, calculated or assumed (logically) to weight based; #*Control strength: (averages) compressive strength at 0% glass waste or target strength; § % recycled glass weight as indicated in source or converted or calculated in weight or assumed to be so; ξ F (fine aggregate) C (coarse aggregate): Numerical value were assigned, for the purpose of predictive model input, where one (1) was assigned if glass fine or coarse aggregate, otherwise zero (0); *§ Constant admixture used for different mix ratios; §§ Water to binder ratio calculated from given values; §# Fly ash ratio calculated from given values; *** Fly ash or micro-silica proportion by weight or assumed/taken to be so; ## Values estimated/gotten from graph; ƫ: Translated from Arabic to English; *§ Conversion to MPa; φ % calculated from given values; ∞ Value based on graph or/and values given;

Dataset were divided into 3, namely: training, validation/check and testing. Randomization of datasets was conducted multiple times, while the % differences of averages for 3 categories of datasets from the overall dataset were checked to ensure datasets were not extremely biased. The datasets were normalized between values of 0 and 1. For better generalization, ability of artificial neural networks and better comparison and avoidance of influence of greater parameter inputs and outputs are normalized, within a range of between 0 and 1, using equation (1) and the normalized output is de-normalized to actual values using equation (2) as indicated by Henigal *et al.* [21]; equations (1) and (2) were used for this study.

$$Norm. = \frac{(Orig. - Min.)}{(Max. - Min.)} \qquad \text{Equation (1)}$$

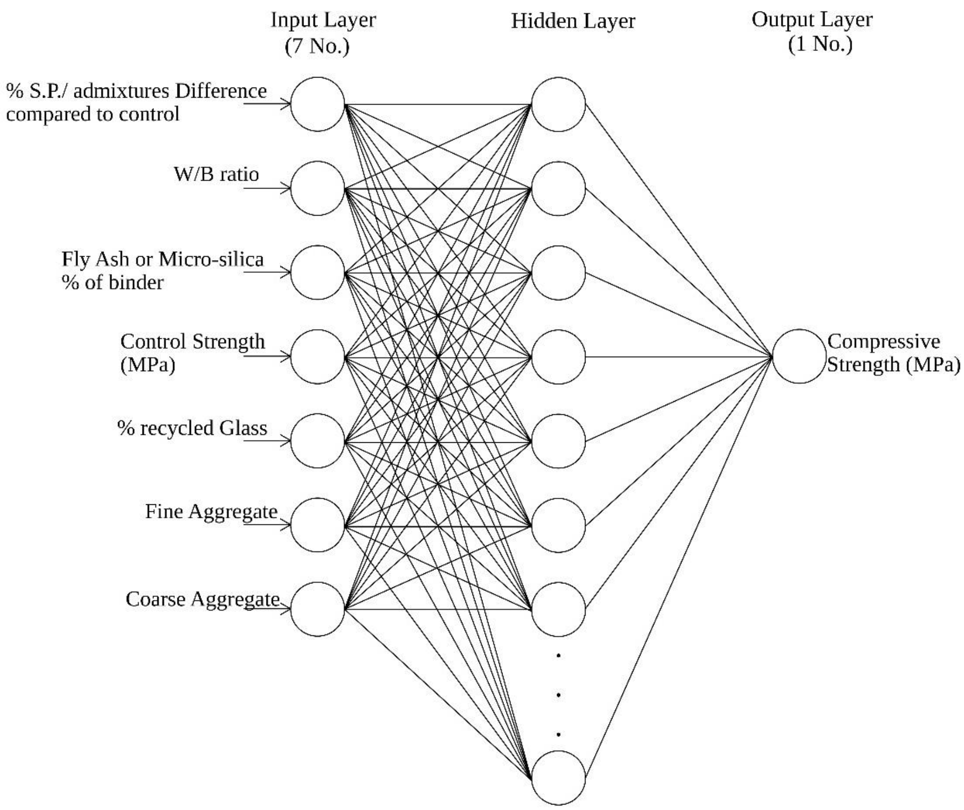
$$Orig. = Norm.(Max. - Min.) + Min. \qquad \text{Equation (2)}$$

Where: Norm.: Normalized value; Orig.: Original value; Min.: Minimum value; Max.: maximum value; Jayaseelan *et al.* [5] dataset for flowable concrete properties prediction, using neural network with BFGS-Quasi-Newton back propagation used 32 datasets for training, 8 datasets for validation, 8 datasets for testing. This represented 66.7% for training and 16.7% each for validation and testing. Previous work by the author, Ngandu [2], used 51 datasets (70.83%) for training, 10 datasets (13.89%) for checking/validation and 11 datasets (15.28%) for testing. This study's overall dataset of 50 was divided into: 34 (68%) for training; 7 (14%) for checking/validation; 9 (18%) for testing.

2.2 Artificial Neural Network (ANN)

The ANN models had 3 layers, namely: an input layer with 7 nodes, one hidden layer and an output layer with 1 node as illustrated in Fig. 1.

FIG 1: STRUCTURE OF ANN FOR THE STUDY



The structure for ANN models was developed and run in GNU Octave. According to Eaton *et al.* [7], GNU Octave is a high-level language to solve problems such as linear and non-linear equations and statistical analysis and other numerical experiments. The network was developed based on Oman [22] illustration on neural network using Octave. According to Oman [22], back propagation algorithm goal is to train the network to minimize cost, with the error at a certain layer in the network taken and propagated backwards through the network. This study adopted Tanh function for the activation function, similar to previous work by the author Ngandu [2], and the one referenced from Tiwari and Rai [23] the same referenced from Sharma [24]. The learning rates for this research were kept constant at 0.06.

Statistical analyses were computed using OCTAVE, including RMSE and R^2 for the normalized compressive strength values. Various trials were conducted with nodes of hidden layer of between 1 and 26. The number of iterations were varied for particular number of nodes of hidden layer and RMSE (normalized values) were evaluated to indicate performance of model. The normalized RMSE values for check/validation dataset were used to evaluate and select models in comparison to other trial models, with the same number of nodes in the hidden layer but different number of iterations. The overall RMSE for normalized values was used to select a suitable model between models having different numbers of nodes in hidden layers. Subsequently, the values were denormalized and the RMSE, R^2, MAE and MAPE were computed for the selected model using Libre Office Calc Spreadsheet.

2.3 Evaluation methods

The statistical evaluations methods, RMSE, R^2, MAE and MAPE were used to evaluate the selected model. Study by Zhang *et al.* [25] on examination of differences between predicted and experimental values applied RMSE (equation 3), MAPE and R^2 (equation 4). Chandwani *et al.* [26] used different statistical performance metrics for performance evaluation of trained models including MAE (equation 5) and MAPE (equation 5)- among others.

$$RMSE = \sqrt{\frac{1}{n}\sum_{j=1}^{n}\left(E_j - P_j\right)^2} \qquad \text{Equation (3)}$$

$$R^2 = 1 - \frac{\sum_{j=1}^{n}\left(P_j - E_j\right)^2}{\sum_{j=1}^{n} E_j^2} \qquad \text{Equation (4)}$$

$$MAE = \frac{1}{n} * \sum_{j=1}^{n}\left|E_j - P_j\right| \qquad \text{Equation (5)}$$

$$MAPE = \frac{1}{n} * \sum_{j=1}^{n}\frac{\left|E_j - P_j\right|}{E_j} * 100 \qquad \text{Equation (6)}$$

Where E: Experimental value; P: Predicted value; n: total number in the group; j: Particular values of a data set;

2.4 Comparison of predicted and experimental data

28 datasets, from the 50, with waste glass fine aggregate incorporated concrete were used to compute the % difference from the control. The computed values were averaged based on clustered percentages of glass fine aggregates amounts.

3. Results

The model with 24 nodes in its hidden layer and 90,000 iterations was selected, based on the lower normalized RMSE values. Table III shows the denormalized results for RMSE, MAPE, R^2 and MAE for the selected model.

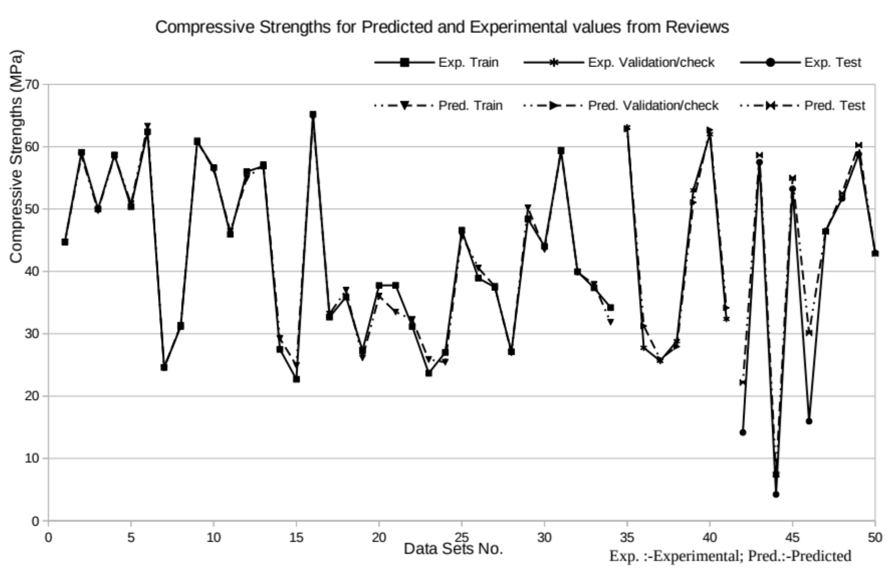
TABLE III: STATISTICAL EVALUATION RESULTS FOR SELECTED ANN MODEL

	Train Dataset	**Check/Validation Dataset**	**Testing Dataset**	**Overall Dataset**
RMSE (MPa)	1.288	1.718	5.594	2.679
MAE (MPa)	0.911	1.335	3.418	1.422
MAPE (%)	2.64	3.918	25.60	6.951
R^2	0.999	0.9985	0.983	0.996

Train dataset indicated RMSE, MAE, MAPE and R^2 of 1.288 MPa, 0.911 MPa, 2.64% and 0.999 respectively, hence showing better performance when compared to the other two datasets. The overall dataset had RMSE, MAE, MAPE and R^2 of 2.679 MPa, 1.422 MPa, 6.951% and 0.996.

Fig. 2 is a graphical representation for the 50 datasets of the experimental and predicted compressive strength values.

FIG. 2: EXPERIMENTAL (REVIEW) AND PREDICTED COMPRESSIVE STRENGT H VALUES



The graph in Fig. 2 shows a visual illustration for experimental values from the review and the predicted values by the selected model. Table IV are values for average % differences, for waste glass fine aggregates from the control, classified based on proportions of glass aggregates.

TABLE IV: DEVIATION % BASED ON WASTE GLASS FINE AGGREGATE PROPORTION

Classes for % fine aggregate	Experimental (Reviewed) % Average Deviation	Predicted % Average Deviation
10	-20.11	-5.73
>10 to 20	1.20	-4.34
>20 to 30	0.82	3.07
>30 to 40	-0.37	3.44
>40 to 50	11.11	11.03
>50 to 81	-15.13	-14.53
> 81	-7.86	-9.11

The experimental dataset lowest and highest average % differences, for % glass waste fine aggregates from control, were at 10% and between >40 and 50% fine aggregate data, with -20.11% and 11.11% respectively. The lowest and highest average % differences for predicted data were those within the categories of >50% to 81% and >40 to 50% glass fine aggregate data, with -14.53% and 11.03% respectively. For both experimental and predicted values, the >20% to 40% glass fine aggregates indicated values comparatively closer to the control strengths, compared to their other respective categories of % glass fine aggregates.

4. Discussion

The RMSE of 1.288 MPa for training dataset of selected dataset, indicated lower error margins as compared to the other two datasets categories. The highest RMSE was 5.594 MPa for test dataset, while the overall had 2.679 MPa, for the same. Islam *et al.* [27] model, using statistical regression analysis for prediction of strength of rice husk ash high performance incorporated concrete, indicated 28-days compressive strength RMSE of 4.96, an indicator of accuracy of the model fit. In the author's previous study, Ngandu [2], the selected model indicated a RMSE of 5.10 MPa for the overall dataset, hence an indicator of reasonable accuracy. For this study the overall dataset RMSE of 2.679 MPa shows that the model had a good level of accuracy, while putting into consideration the range of compressive strengths for experimental data from reviews of between 65.2 MPa and 4.23 MPa.

The training dataset indicated MAE, MAPE and R^2 of 0.911 MPa, 2.64% and 0.999 respectively, with better performance compared to the check/validation and testing dataset. The test dataset indicated comparatively lower performance with 3.418 MPa, 25.60% and 0.983 for MAE, MAPE and R^2 respectively. The overall dataset indicated MAE, MAPE and R^2 of 1.422 MPa, 6.951% and 0.996. According to Jayaseelan *et al.* [5], MAPE values for slump flow, V-funnel flow, L-box flow and compressive strength were less than 10% for values of a neural network model using MATLAB, and trained using Levenberg-Marquardt back propagation, hence showing very good model performance. The MAPE values for training, checking/validation and overall datasets were less than 7%, but the test dataset indicated a relatively high error of 25.6% for MAPE. This variation could be due to the fact that datasets were obtained from different sources and other factors could have impacted the compressive strength.

Generally, with overall RMSE and MAPE value of 2.679 MPa and 6.951% respectively, and maximum MAE of 3.418 MPa for test dataset and minimum R^2 of 0.983 for test dataset, the selected model showed good level of accuracy and good generalization. The average percentage differences based on the classifications of percentage glass fine aggregate glass, did not indicate a consistent trend, for the experimental data from reviews. This could be attributed to other factors that possibly affect compressive strengths of concrete mixes. For both experimental and predicted values, the category having greater than 20% to 40% glass fine aggregates indicated values that were comparatively closer to the control strengths and the category greater than 40% to 50% glass fine aggregates had comparatively higher positive percentage differences of just over 11%. Based on this, glass replacement as fine aggregates in structural concrete could be feasible up to 50% by weight, with consideration to other factors that would influence structural performance of the concrete.

5. Conclusions and Recommendations

The overall RMSE, MAPE, MAE and R^2 exhibited by the selected model were generally within acceptable values, and the model showed good level of accuracy and good generalization. This is also illustrated by the graph showing of experimental values from review and predicted values. Furthermore, the performance is commendable, considering that the 50 datasets were not from a single experimental program.

The percentage average differences between the compressive strength values of concrete based on groups of percentages of glass fine aggregates and control compressive strength did not indicate a general trend for the experimental dataset. This indicates that other factors had possible significant effects on the strengths of concrete with partial or 100% fine glass aggregates.

The study recommends:

1) The application of machine learning techniques for modeling, quality control and codes of practice of concrete with partial or full glass fine aggregate.
2) Research on possible utilization of glass fine aggregates up to 50% by weight, with consideration to other influencing factors.
3) Research on suitable cost-effective and environmentally friendly additive to enhance structural performance of glass aggregate in concrete. Economic and environmental assessments on use of glass aggregates.

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