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PARAMETRIC MODELING OF RECYCLED BRICK AGGREGATE CONCRETE USING NEURAL NETWORK AND REGRESSION

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ABSTRACT: Concrete made from recycled materials is usually produced through a challenging design process. This implies that there is difficulty in producing low-cost concrete with suitable mechanical properties. Hence, this study was conducted to utilize parametric modeling for the optimum mix design of recycled brick aggregate concrete (RBAC). The artificial neural network (ANN) and multiple linear regression (MLR) were utilized to generate the model. The result of the back-propagation algorithm in the ANN model showed that Bayesian regularization with nine (9) neurons is the best mathematical model, with regression (R) and mean squared error (MSE) values of 0.86499 and 0.007996756, respectively. The correlation coefficient for the Multiple Linear Regression (MLR) model, on the other hand, was 0.6508. The results clearly showed that the prediction using a neural network model is more accurate than using a multiple linear regression model. A parametric study was done in Bayesian regularization with nine (9) neurons in the model to assess the effect of each independent variable on the compressive strength of concrete by varying the amount of one independent variable and setting the other independent variables to a constant value. Based on the result of the parametric study, the recommended amounts for each material are as follows: cement = 500 kg; water-cement ratio = 0.4; recycled aggregates = 20–40%; and natural aggregates = 60–80%.

Keywords: Parametric modeling, Recycled brick aggregate, Artificial neural network, Multiple linear regression, Compressive strength

1. INTRODUCTION

The construction industry plays a significant role in the growth and development of a nation. Generally, the construction industry uses three types of aggregates in construction projects [1,2]: (a) virgin (natural), (b) artificial, and (c) recycled.

In recent years, a lot of attention has been given to the utilization of recycled aggregates in concrete due to depleting natural resources and to reduce environmental wastes. There are a lot of waste materials that can be generated from construction activities which may include the following materials: concrete, tiles, metal, paper, wood, glass, and mixed wastes such as trash and organic wastes. As such, these waste materials are considered construction and demolition waste. Construction and demolition wastes (C&DW) are usually recognized as not dangerous, but their accumulation can generate serious environmental problems [3]. It is interesting to note that around 90% of construction waste can be reused and recycled. Construction waste is under the definition of solid waste. Solid waste can be defined as all discarded household, commercial waste, non-hazardous institutional and industrial waste, street sweepings, construction debris, agricultural waste, and other non-hazardous/non-toxic waste.

Concrete is considered one of the most commonly used materials in construction. It is composed of cement, water, and natural (fine and coarse) aggregates. Recycled aggregates can also be used to replace natural aggregates partially or completely. To determine the optimum amount of recycled material, there is a need to apply numerical modeling such as artificial neural network that can simulate and generate a formula to predict the compressive strength of concrete with natural and recycled aggregates. Artificial neural network (ANN) had been widely used as a tool to create a numerical model for experimental data. However, there are few works of literature that focused on modeling the compressive strength of concrete with recycled aggregates. In that case, this study was established and focused on four (4) methods in the prediction of the compressive strength of Recycled Brick Aggregate Concrete (RBAC). The three methods in ANN are the following: (1) Levenberg-Marquardt, (2) Bayesian Regularization, (3) Scaled Conjugate Gradient and the fourth method Multiple Linear Regression (MLR) using Microsoft Excel.

Previous studies revealed that researchers utilized data-driven models such as artificial neural networks (ANN) and multiple linear regression (MLR) to predict the mechanical properties of concrete. Topçu and Sarıdemir [4] proved that compressive and splitting tensile strength values of recycled aggregate concrete with silica fume can be predicted using artificial neural networks and fuzzy logic. Zain and Abd [5] found out that a multiple non-linear regression model can be used to predict the compressive strength at different ages

(3,7,14,28 and 91 days) since it yielded a high correlation value. Duan et al. [6] revealed that ANN has good potential to be used as a tool for predicting the compressive strength of recycled aggregate concrete prepared with varying types and sources of recycled aggregates. Amini et al. [7] used a step-wise regression model to predict the compressive strength, abrasion, and salt scaling of concrete considering the individual and combined ultrasonic pulse velocity (UPV) and rebound number (RN) measurements. Dantas et al. [8] stated that ANN can be used to predict the compressive strength of concrete containing construction and demolition waste at 3, 7, 28, and 91 days. Ahmed et al. [9] utilized a polynomial regression model to predict the split tensile strength of concrete and concluded that for split tensile strength of concrete, 28 days prediction models are more accurate compared to 7 days of prediction models. Kalman Sipos et al. [10] demonstrated that the compressive strength of RBAC can be reliably predicted using a neural network. Clemente and Concha [11] demonstrated that parametric modeling can be used to analytically describe the constitutive relationships of the material components and capture the dominant characteristics of concrete samples. Recently, Boudina et al. [12] used the design of experiments (DOE) to optimize the properties of High-Performance Concrete (HPC) containing recycled aggregates. Based on this literature, both a neural network and a regression model can be used to predict the mechanical properties of concrete. However, no research has yet been conducted comparing neural networks and linear regression in predicting the compressive strength of recycled brick concrete aggregates (RBAC). Hence, this study was conducted to compare the accuracy of the two methods as well as to generate the best model for the optimum mix design by applying parametric modeling. This study is significant since it can be used to determine the optimum amount of recycled tile or brick as a partial or full replacement for natural aggregates in a concrete mixture. An ANN model with one hidden layer is developed by using a MATLAB software to generate an appropriate model for predicting the compressive strength of Recycled Brick Aggregate Concrete (RBAC).

2. RESEARCH SIGNIFICANCE

One of the most important characteristics of concrete is compressive strength, which may define its concrete class in a structure. It is essential to generate a model that can predict the compressive strength of concrete. Recently, the artificial neural network is gaining significant attention tool in modeling mainly due to its ability in establishing a complex nonlinear relationship among different parameters. This study is useful in the concrete industry by adapting the model in a form of an equation that they can use as a reference to generate a concrete structure with an optimized compressive strength.

3. LITERATURE REVIEW

Recent studies have shown that crushed brick has the potential as an aggregate in concrete material. Debieb and Kenai [13] used coarse and fine crushed bricks and they reported a reduction in the compressive strength of RBAC concrete from 20% to 30%, depending on the degree of substitution. Cachim [14] concluded that crushed bricks can be used as natural aggregates with substitution up to 15% without any loss in compressive strength of concrete; however, for 30% natural aggregate substitution, there is a reduction of concrete properties (up to 20%, depending on the type of brick).

3.1 Artificial Neural Network (ANN)

There are several algorithms that can be implemented in Artificial Neural Network Modelling, namely, Bayesian regularisation, Levenberg–Marquardt, BFGS Quasi-Newton, Powell–Beale conjugate gradient, One step secant, Gradient descent, Gradient descent with either momentum or adaptive learning rate or both, Fletcher–Powell conjugate gradient, Random order incremental training with learning, Resilient, Polak–Ribiere conjugate gradient and Batch training with weight and bias learning rules [15]. The ANN has a powerful means to learn, train and validate the numerical data to generate a model or equation. Thus, it can be used as an effective tool for engineering applications. The artificial neural network models are developed using the Neural Network Toolbox in MATLAB R2019a software. In this study, three ANN models were generated by applying the following algorithms: (1) Levenberg–Marquardt, (2) Bayesian regularisation, and (3) Scaled-Gradient descent.

3.2 Multi-linear Regression (MLR)

Multiple Linear Regression (MLR) also known as simply multiple regression, it is statistical technique that is used to model a linear relationship between dependent variable(target) and one or more independent variables(predictors). The regression analysis has been carried out using Microsoft Excel 2013. The performance of the model was determined using R^2 and the mean-squared error (MSE). The R^2 is a measure of correlation between the predicted and measured values. An R^2 value close to 1 represents a good agreement between predictions of a model and the measured data.

Similarly, a lower MSE value implies a lesser amount of prediction error. Therefore, higher value of R^2 and lower MSE value means that the performance of the model is better and useful for predicting the dependent variable. The MSE and R^2 can be computed using Eq. (1) and (2) respectively and can be expressed as follows:

$$\mathbf{MSE} = \frac{\sum_{i=1}^{n}(\mathbf{O_i} - \mathbf{t})^2}{\mathbf{n}} \quad (1)$$

$$\mathbf{R^2} = \frac{\sum(\mathbf{O} - \mathbf{t})^2}{\sum(\mathbf{O} - \mathbf{O_{mean}})^2} \quad (2)$$

where n = total number of data sets, O = network output, t = target output, and O_{mean} = average of network output.

4. METHODOLOGY

In this study, four different models have been developed using both ANN and MLR techniques. A total of 147 data sets were collected from 10 international published literatures to examine whether the ANN and MLR is better in predicting the compressive strength of Recycled Brick Aggregate Concrete (RBAC). The ANN training algorithms used are the following: (1) Levenberg-Marquardt (2) Bayesian Regularization and (3) Scaled Conjugate Gradient. A feed-forward back-propagation neural network model is developed to predict the compressive strength in 147 sets of experimental data. From these, 89 randomly selected data were used for training the network and the remaining 58 samples were equally divided for the ANN validation and testing processes (29 of them were selected as the testing data sets and the other 29 were used for validation of network).

Several iterations with one hidden layer were tried in the ANN structure. The Regression (R) values were compared against various neurons (1,3,5,7,9 and 11) in the hidden layer in order to determine the most optimal topology (maximum R-value) for the compressive strength. The eight (8) input variables to be used in this study are the following: (a) cement (b)water/cement (c)Crushed Tile Ratio (CT) 0-4 (%) (d) Crushed Tile Ratio (CT) 4-16 (%) (e) Crushed Brick Ratio (CT) 0-4 (%) (f) Crushed Brick Ratio (CT) 4-16 (%) (g) Natural Aggregate 0-4 (%) and (h) Natural Aggregate 4-16 (%). The output parameter is the compressive strength (MPa).

As seen in Fig. 1 the theoretical framework of the study. All the data came from Kalman Šipoš [10] and were normalized using Eq. (3) to standardize the input and output values ranging from zero to one. The normalized data were subjected to ANN and MLR.

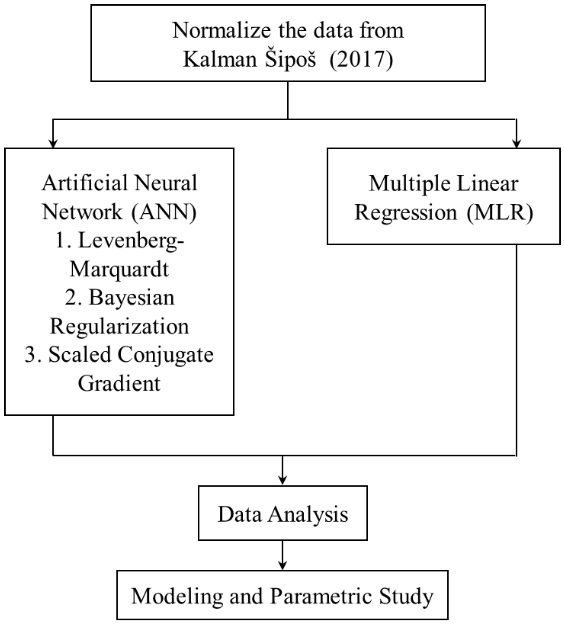

Fig.1 Theoretical Framework

$$\mathbf{x_{new}} = \frac{\mathbf{x} - \mathbf{x_{min}}}{\mathbf{x_{max}} - \mathbf{x_{min}}} \quad (3)$$

Under the process of ANN, three algorithm methods were used such as Levenberg Marquardt, Bayesian Regularization, and Scaled Conjugate Gradient using Matlab 2019a. For each method, all the data were trained, validated, and tested. On the other hand, Multiple Linear Regression was also used to determine whether there is a linear relationship between the independent and dependent variables using Microsoft Excel. All the generated models from ANN and MLR were evaluated by comparing their regression values. The higher value of regression (R) means that the model is a better representation among the generated models. The best model was subjected to parametric study to determine the effect of each independent variable on the dependent variable by varying the amount of one independent variable while the other variables were held constant. Lastly, from the result of the parametric study, a conclusion can be made by determining the optimum range of recycled brick/tile that can be added to the concrete matrix to attain a suitable compressive strength.

It can be seen in Fig. 2 the optimization for the three methods under the ANN. Several hidden neurons were selected ranging from 1 to 11 with an increment of 2. For each iteration process, all the data were trained, validated, and tested. The regression results of each algorithm were recorded and compared. The highest value of regression can be treated as the best model to predict the compressive strength of RBAC.

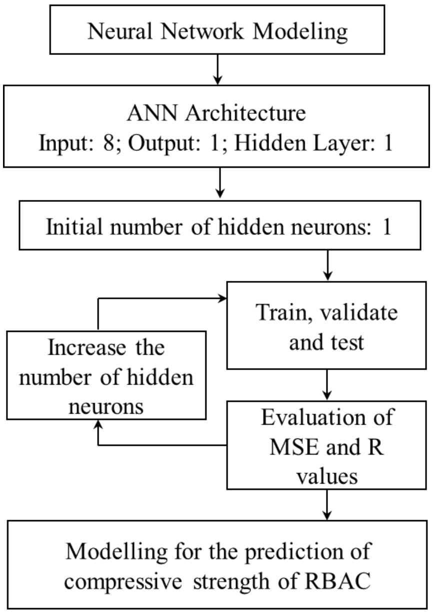

Fig.2 Flowchart for optimizing the neural network model

5. RESULTS AND DISCUSSION

It can be seen in Table 1 the statistical data of input and output variables. Statistical data includes the following parameters: maximum, minimum, median, and standard deviation. It can be observed that the water-cement ratio has a range of 0.4 to 1.08 and relative to the other variables these values are very small. Thus, there is a need to normalize the data so that all the values in the variables are within the range of zero to one.

Table 1 Characteristics of the data set

	Variables	Max	Min	Median	Standard Deviation
input	Cement	527	250	400	66.42
	w/c	1.08	0.4	0.5	0.11
	CTR_0-4	100	0	0	24.44
	CTR_4-16	100	0	0	24.48
	CBR_0-4	100	0	25	28.41
	CBR_4-16	100	0	25	31.68
	NA_0-4	100	0	50	33.76
	NA_4-16	100	0	50	35.2
output	fc'	81	9	27	13.12

It can be seen in Fig.3 and 4 the comparison of the regression and mean squared error for the three algorithms in ANN. It can be observed that the BR_9 model with 9 neurons gained the highest regression value with a value of 0.86499 and a minimum MSE value of 0.007996756. For the Bayesian Regularization algorithm, the ANN with nine (9) neurons in the hidden layer appeared to be the most optimal topology for the compressive strength of RBAC since this model gained the highest regression value and the lowest MSE value. Meanwhile, the best ANN for data training was BR_7 (Bayesian Regularization with seven neurons). With this optimized network, Regression and Mean Squared Error(MSE) were 0.93918 and 0.0090454755, respectively.

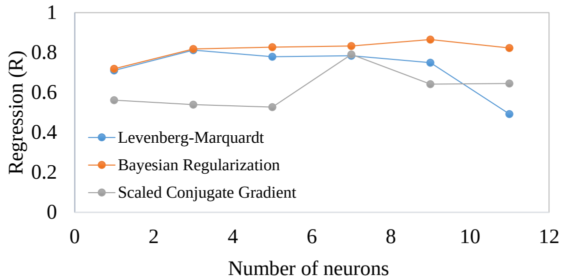

Fig.3 Variation of Regression with respect to the number of neurons

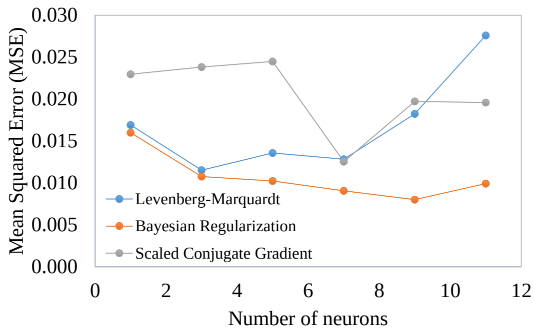

Fig.4 Variation of Mean Squared Error (MSE) with respect to the number of neurons

Table 2 Multiple Linear Regression (MLR) Result

Regression Statistics	
Multiple R	0.650811
R Square	0.423555
Adjusted R Square	0.384565
Standard Error	0.141686
Observations	147

Table 3 Regression Value of ANN and MLR models

Model	Regression Value
LM_3	0.81276
BR_9	0.86499
SCG_7	0.79114
MLR	0.65081

Using Microsoft Excel, the Multiple Linear Regression (MLR) was carried out and the result can be seen in Table 2 in which the regression value is 0.650811271. The comparison of the regression value from four models developed using both Artificial Neural Network and Multiple Regression Analysis in Microsoft Excel can be seen in Table 3. It can be observed that the goodness-of-fit of the ANN models is superior when compared to the regression model. The outcome is analogous to the result of Bingol [16] which states the superiority of the ANN in predicting the compressive strength of concrete. The higher values of R imply that the obtained data corresponds well to the experimental data. Comparing all the models, it can be concluded that the BR_9 model (Bayesian Regularization with 9 neurons) is the best model among the generated models from ANN in Matlab and MLR using Microsoft Excel.

Table 4 Coefficients of all the input variables using Multiple Linear Regression (MLR)

	Coefficients
Intercept	0.130912093
Cement	0.35288032
Water/cement	-0.179805552
Crushed Tile Ratio (CT) 0-4	0.013143038
Crushed Tile Ratio (CT) 4-16	-0.182980652
Crushed Brick Ratio (CT) 0-4	0
Crushed Brick Ratio (CT) 4-16	0
Natural Aggregate 0-4	0.064598444
Natural Aggregate 4-16	0.057082633

From Table 4, it can be seen that the largest factor for the compressive strength of concrete is the cement followed by the natural aggregate and the crushed tile ratio of 0-4. On the other hand, the water-cement ratio and crushed tile ratio 4-16 have a negative effect on the strength of concrete while the crushed brick ratio does not have any significant effect on the strength. Equation (4) can be generated in MLR considering the same set of data in ANN.

$$fc' = 0.3529X_1 - 0.1798X_2 + 0.01314X_3 - 0.1830X_4 + 0X_5 + 0X_6 + 0.06460X_7 + 0.05708X_8 + 0.1309 \quad (4)$$

5.1 Parametric Study for the Components of Concrete

A parametric study was done to determine the effect of each independent variable on the compressive strength of concrete by varying the amount of one independent variable and setting the other independent variables to be a constant value. The constant value selected is the median value for each variable involved in the parametric study. The model adapted in the parametric study is the BR_9 model (Bayesian Regularization with 9 neurons) since this is the best model among the generated models from ANN and MLR. The researcher used nine hidden neurons, which is an ideal number given that researchers typically use a range of 3 to 33. The value of nine hidden neurons is the same as that used by Kalman Sipos [10] in parametric modeling, but the algorithm method is different.

5.1.1 Cement

This component is generally used as a medium to bind all of the materials in the concrete mixture through the process of hydration. Generally, increasing the cement content would increase the unit weight and workability of the concrete mixture. A simulation of cement type influence was carried out with a w/c ratio of 0.5, and the content of cement varied from 250 to 550 kg with a constant value of crushed brick and natural aggregate content.

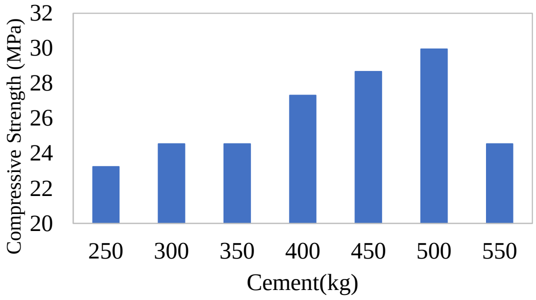

Fig.5 Compressive strength of RBAC with varying amounts of cement

The strength of concrete is independent of the cement content for a given w/c: increasing cement content does not affect strength [17-19]. An increase in the cement content results in an increase of strength in concrete for a given workability in a concrete matrix. Based on Fig.5, it can be seen that as the amount of cement increases, the compressive strength also increases up to 500 kg of cement. This shows that at 500 kg cement content, it is more likely that the mixture already reached its optimum workability, hence any cement added to the mixture would substantially decrease the concrete strength. A maximum compressive strength increase of 11.25% can be obtained within the range of 350 to 400 kg. This range reflects a suitable range to be used obtain an optimum strength in a concrete mixture.

5.1.2 Water-Cement Ratio

This is defined as the mass of water divided by the mass of cement in the concrete mix and this is usually abbreviated as w/c. A simulation of water cement influence was carried out with a cement content of 400 kg, and the content of water cement ratio varied from 0.4 to 1.2 with a constant value of crushed brick and natural aggregate content. It can be noted that as the water-cement ratio increases, the porosity of the cement paste would also increase. Hence, the compressive strength will decrease because the porosity will increase as the void in the concrete matrix will be filled by water or air.

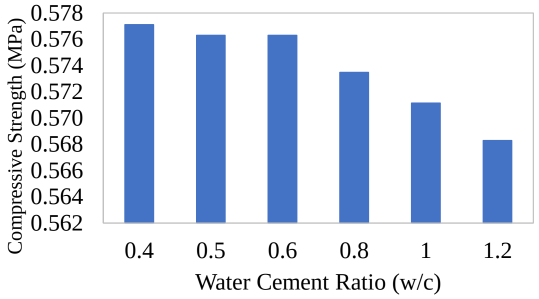

Fig.6 Compressive strength of RBAC with varying amounts of water cement ratio

Strength is primarily a function of the water-cement ratio as long as there is sufficient paste to fill the voids between the aggregate particles and the mixture is adequately consolidated [20-22]. One theory that would relate the water-cement ratio to the strength of concrete is Abrams' law. This law states that the strength of a concrete mix is inversely related to the mass ratio of water to cement [23]. As the water content increases in the concrete mix, the compressive strength of the concrete decreases. It can be seen in Fig.6 that the compressive strength decreases as the water-cement ratio increases. The maximum decrease in strength can be observed from 1.0 to 1.2 with a 5% decrease. Thus, the maximum value of the water-cement ratio should be 0.4 only to obtain a desirable concrete mix. This value is also recommended by Adnan [24] in which the authors state that Recycled Aggregate Concrete (RAC) with a water-cement ratio of 0.4 had the highest strength at the age of 28 days.

5.1.3 Recycled Fine/Coarse Aggregates

Recycled concrete, or crushed waste concrete, is simply old concrete that has been crushed to produce new aggregate. Concrete made with recycled coarse aggregates and conventional fine aggregate can obtain adequate compressive strength [25]. A simulation of tile aggregate type influence was carried out with a concrete mixture of 400 kg cement and a water-cement ratio of 0.5, and the content of crushed tile aggregate varied from 0 to 40% with decreasing crushed brick and natural aggregate content. Similarly, a simulation of brick aggregate type influence was carried out with a concrete mixture of 400 kg cement and a water-cement ratio of 0.5, and the content of crushed brick aggregate varied from 0 to 44.4% with decreasing crushed brick and natural aggregate content.

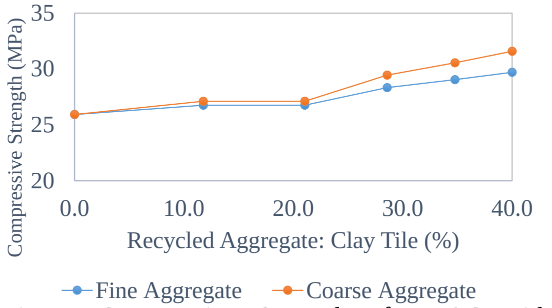

Fig.7 Compressive Strength of RBAC with varying percentages of Clay Tile Recycled Aggregate

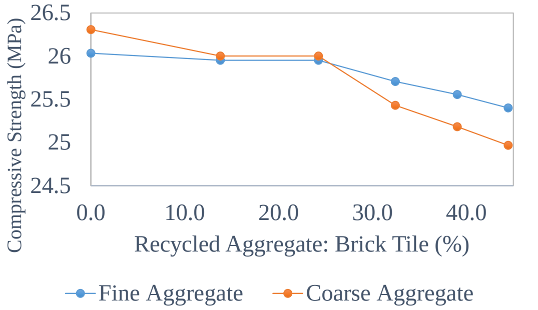

Fig.8 Compressive Strength of RBAC with varying percentages of Brick Tile Recycled Aggregate

It can be observed in Fig. 7 that the compressive strength increases as the percentage of recycled clay tile increases for both fine and coarse aggregates. However, for brick tile there is a substantial decrease of strength after 25% percent and a constant value of compressive strength can be noticed in Fig. 8 for the recycled brick tile within the range of 15 to 25 percent for both fine and coarse aggregates. The recommended percentage replacement of the recycled clay and brick tile is within the range of 15 to 25 percent. This is similar to the study made by Tsoumani [26] which states that the optimal percentage is 25%.

5.1.4 Natural (Fine/Coarse) Aggregates

Around 50 to 60 percent of the concrete mixture is made up of natural aggregates. The natural aggregate can be classified as fine or coarse. A simulation of natural aggregate type influence was carried out with a concrete mixture of 400 kg cement and a water-cement ratio of 0.5, and the content of natural aggregate is varied from 0 to 50% with decreasing crushed brick (fine & coarse).

The larger aggregate percentage in the concrete mix makes it contribute a lot to its strength [27]. Figure 9 shows the variation of the compressive strength with the natural aggregates. It can be noted that this is similar to Figure 8 for clay tile in which compressive strength increase as the percent of fine and coarse aggregates increases up to 40%. Also, the compressive strength of concrete with coarse aggregate is consistently higher than that of concrete with fine aggregate for a percentage up to 38% since aggregate size has a significant impact on the strength of concrete. The larger the size of the aggregates, the lesser will be the presence of voids in the concrete matrix which would increase the value of the compressive strength. Vilane [28] affirmed this study by showing that the mean concrete compressive strength increased with increasing aggregate size.

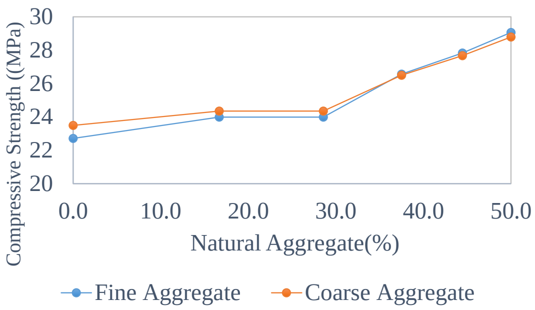

Fig.9 Compressive Strength of RBAC with varying percentages of Natural Aggregate

Based on the result of the parametric study, the optimum amount for each material is as follows: cement = 500 kg, water-cement ratio = 0.4, Recycled Tile (Fine) = 10%, Recycled Tile (Coarse) = 10%, Recycled Brick (Fine)=10%, Recycled Brick (Coarse) = 10%, NA (Fine) = 30%, NA (Coarse) = 30%. Aliabdo et al. [29] supported the recommended values in this study since they suggest that to avoid strength reduction, it is strongly recommended to limit the percentage of coarse aggregate replacement by recycled aggregate to 25% and 50% for concrete containing 350 and 250 kg/m^3, respectively, of cement content.

6. CONCLUSION

The compressive strength of RBAC can be predicted using ANN and MLR models with a regression value ranging from 0.53 to 0.86, and MSE values ranging between 0.008 to 0.02. The result of this study proved that Artificial Neural Network (ANN) models gave a more accurate prediction for the compressive strength of RBAC because of the higher correlation value relative to the MLR in Excel.

The ANN and MLR models developed in this study indicate an accurate prediction of the compressive strength of RBAC. The best result for the mathematical model belonged to the BR_9 model (Bayesian Regularization with nine (9) neurons) with Regression (R) and Mean Squared Error (MSE) values of 0.86499 and 0.007996756, respectively. The best ANN for data training is the BR_7 model (Bayesian Regularization and 7 neurons). With this optimized network, Regression and Mean Squared Error (MSE) were 0.93918 and 0.0090454755, respectively.

The effect (weight factor) of each concrete component can be obtained from the generated ANN matrix function. From the MLR result, cement, and natural aggregates are the most significant contributor to the compressive strength of the RBAC. Meanwhile, the result of the parametric study revealed that to optimize the strength of concrete mixture with recycled brick/clay, it is recommended that the amount for each material are in the following ranges: cement=500 kg, water-cement ratio = 0.4, recycled aggregates = 20 to 40% and natural aggregates = 60 to 80 %.

For future studies, the researchers should consider another set of data that is composed of five (5) to ten (10%) percent increments. Also, it is interesting to note and explore the pozzolanic effect of microsilica and nano-particles such as TiO_2/SiO_2 and to include their effect as an admixture in the generated ANN models for the prediction of the compressive strength of recycled brick concrete aggregates (RBAC).

7. ACKNOWLEDGMENTS

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8. REFERENCES

[1] Ameri M. and Behnood A., Laboratory studies to investigate the properties of CIR mixes containing steel slag as a substitute for virgin aggregates. Construction and Building Materials, Vol. 25, Issue 3, 2012, pp. 1460-1465.
[2] Behnood A. and Ameri M., Experimental investigation of stone matrix asphalt mixtures containing steel slag. Scientia Iranica, Vol. 19, Issue 5, 2012, pp.1214-1219.
[3] Simion I.S., Fortuna M.E., Bonoli A.,

Gavrilescu M., Comparing environmental impacts of natural inert and recycled construction and demolition waste processing using LCA. Journal of Environmental Engineering and Landscape Management, Vol. 21, Issue 4, 2013, pp.273-287.

[4] Topçu I.B. and Sarıdemir M., Prediction of mechanical properties of recycled aggregate concretes containing silica fume using artificial neural networks and fuzzy logic. Computational Materials Science, Vol. 42, Issue 1, 2008, pp. 74-82.

[5] Zain F.M.M. and Abd, M.S., Multiple regression model for compressive strength prediction ofhigh-performance concrete. Journal of Applied Sciences, Vol. 9, Issue 1, 2009, pp. 155-160.

[6] Duan Z.H., Kou S.C., and Poon C.S.,Prediction of compressive strength of recycled aggregate concrete using artificial neural networks. Construction and Building Materials, Vol. 40, 2013, pp. 1200-1206.

[7] Amini K., Cetin K., Ceylan H., and Taylor P., Development of prediction models for mechanicalproperties and durability of concrete using combined nondestructive tests. Journal of Materials in Civil Engineering, Vol. 31, Issue 2, 2019.

[8] Dantas A.T.A., Batista Leite M., and De Jesus Nagahama K., Prediction of compressive strength of concrete containing construction and demolition waste using artificial neural networks. Construction and Building Materials, Vol. 38, 2013, pp. 717-722.

[9] Ahmed F.B., Ahsan K.A., Shariff T. and Meem S.R., Formulation of polynomial equation predictingthe splitting tensile strength of concrete. Materials Today: Proceedings, Vol. 38, 2021, pp. 3269-3278.

[10] Kalman Šipoš T., Miličević I., & Siddique R., Model for mix design of brick aggregate concrete based on neural network modelling. Construction and Building Materials, Vol. 148, 2017, pp. 757-769.

[11] Clemente S.J. and Concha N., Back Propagation Artificial Neural Network Modeling of Flexural and Compressive Strength of Concrete Reinforced with Polypropylene Fibers, International Journal of GEOMATE, Vol. 16, Issue 57, 2019, pp.183-188.

[12] Boudina T., Benamara D., and Zaitri, R., Optimization of high-performance-concrete properties containing fine recycled aggregates using mixture design modeling. Frattura Ed Integrita Strutturale, Vol. 15, Issue 57, 2021, pp. 50-62.

[13] Debieb F. and Kenai S., The use of coarse and fine crushed bricks as aggregate in concrete. Construction and Building Materials, Vol. 22, Issue 5, 2008, pp.886–893.

[14] Cachim P.B., Mechanical properties of brick aggregate concrete. Construction and Building Materials, Vol. 23, Issue 3, 2009, pp.1292–1297.

[15] Chithra S., Kumar S.R.R.S., Chinnaraju K., and Alfin Ashmita F., A comparative study on the compressive strength prediction models for High Performance Concrete containing nano silica and copper slag using regression analysis and Artificial Neural Networks. Construction and Building Materials, Vol. 114, 2016, pp.528–535.

[16] Bingöl F., Tortum A., and Gül R., Neural networks analysis of compressive strength of lightweight concrete after high temperatures. Materials & Design (1980-2015), Vol. 52, 2013, pp.258–264.

[17] Wassermann R., Katz A., and Bentur A., Minimum cement content requirements: a must or a myth? Materials and Structures, Vol. 42, 2009, pp.973–982.

[18] Dhir R.K., McCarthy M. J., Zhou S., and Tittle, P. A. J., Role of cement content in specifications for concrete durability: cement type influences. Proceedings of the Institution of Civil Engineers - Structures and Buildings, Vol. 157, Issue 2, 2004, pp.113–127.

[19] Schulze J., Influence of water-cement ratio and cement content on the properties of polymer-modified mortars. Cement and Concrete Research, Vol. 29, Issue 6, 1999, pp.909–915.

[20] Mindess S., Young J.F., and Darwin D., Concrete (2nd Ed.). Prentice Hall Pearson Education Inc, 2003, pp.1-644.

[21] Kosmatka S.H., Kerkhoff B., and Panarese W.C., Design and Control of Concrete Mixtures 14th Edition. Portland Cement Association, 2002, pp.1-370.

[22] Kumar Mehta P., and Monteiro P.J.M., Concrete: Microstructure, Properties, and Materials. 4th Edition. The McGraw- Hill Companies Inc., 2014, p.1-653.

[23] Punmia B.C., Jain A.K., Jain A., Basic Civil Engineering. Laxmi Publications, 2005, pp.1-446.

[24] Adnan S.H., Lee Y.L., Abdul Rahman I., Mohd Saman H., and Wimala M., Compressive strength of recycled aggregate concrete with various percentage of recycled aggregate. Conference proceedings in National Seminar on Civil Engineering Research (SEPKA 2007), 2007, pp.11-19.

[25] Kosmatka S.H., Kerkhof B. and Panarese, W., Design and control of concrete mixtures (14th Edition). Portland Cement Association(PCA), 2011, pp.1-370.

[26] Tsoumani A.A, Matikas T.E., Barkoula N.M.,

Influence of recycled aggregates on compressive strength of concrete. In: Proceedings of the 2nd international conference on sustainable solid waste management, 2014, pp.12-14.

[27] Waziri B.S., Bukar A.G., and Gaji Y.Z.A., Applicability of quarry sand as a fine aggregate in the production of medium grade concrete. Continental Journal of Engineering Sciences, Vol. 6, Issue 2, 2011, pp.1-6.

[28] Vilane B.R., The Effect of Aggregate Size on the Compressive Strength of Concrete. Journal of Agricultural Science and Engineering. Vol. 2, Issue 6, 2016, pp.66-69.

[29] Aliabdo A.A., Abd-Elmoaty A.E.M., and Hassan H.H., Utilization of crushed clay brick in concrete industry. Alexandria Engineering Journal, Vol. 53, Issue 1, 2014, pp.151–168.