Prediction of Rubberised Concrete Strength by Using Artificial Neural Networks

A. M. N. El-Khoja, A.F. Ashour, J. Abdalhmid, X. Dai, A. Khan

***Abstract*—**In recent years, waste tyre problem is considered as one of the most crucial environmental pollution problems facing the world. Thus, reusing waste rubber crumb from recycled tyres to develop highly damping concrete is technically feasible and a viable alternative to landfill or incineration. The utilization of waste rubber in concrete generally enhances the ductility, toughness, thermal insulation, and impact resistance. However, the mechanical properties decrease with the amount of rubber used in concrete. The aim of this paper is to develop artificial neural network (ANN) models to predict the compressive strength of rubberised concrete (RuC). A trained and tested ANN was developed using a comprehensive database collected from different sources in the literature. The ANN model developed used 5 input parameters that include: coarse aggregate (CA), fine aggregate (FA), w/c ratio, fine rubber (Fr), and coarse rubber (Cr), whereas the ANN outputs were the corresponding compressive strengths. A parametric study was also conducted to study the trend of various RuC constituents on the compressive strength of RuC.

***Keywords*—**Rubberized concrete, compressive strength, artificial neural network, prediction.

I. Introduction

POLYMERIC waste is non-biodegradable which should be treated to minimise the negative effects on the environment. Polymeric waste can be recycled to save raw material resources. Elastomeric waste accumulation problem has become a global issue due to high consumption of raw polymer materials without recycling [1]. This research research focuses on recycling industrial elastomeric waste into vibro-acoustic and thermal products that could be used in buildings, domestic goods, automotive and as insulation cladding around pipes.

The waste tyre problem is a direct form of pollution that constitutes negative effects on health. One possible solution is to replace the natural aggregate in concrete with rubber [2]. Using rubber in concrete reduces concrete strength. In the past two decades, ANN has been one of the major interests in structural engineering, environmental and water resources engineering, traffic engineering and geotechnical engineering. ANNs represent a class of robust, non-linear models applicable for solving a wide variety of problems. Engineering problems that involve highly nonlinear functional approximations could be solved using ANNs. The first computationally trained neural network was developed by [3] and [4]. The aim of this paper is to present ANN model that predicts the compressive strength of RuC in order to save computational effort. For this purpose, data for developing ANN models were obtained from the literature, which suggested that all applications that predict the compressive strength of RuC use small number of dataset, less than 100.

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II. Basic Principles of ANN

ANN is defined as a soft computing technique that imitates the biological neural system of the human brain [5]. It consists of at least three layers of neurons: An input layer, one or more hidden layers, and an output layer. All hidden layers are connected by weight, transport function and bias, while there is no link between nodes in the same layer [5]. A schematic representation of the neuron is shown in Fig. 1.

Each input is multiplied by a weight and it is then given an independent term or bias. The result of the linear combination is applied to a function that may be either linear or non-linear, which is called the activation function or transfer function that provides the neuron's output [6]. Determining the number of hidden layers and the number of nodes in each hidden layer depends on the problem under investigation [7]. The difference between network output and the target is called an error function.

The error is propagated backward and both the biases and weights are fixed using specific optimization methods that minimizes the error. The entire process called training is repeated for a number of epochs. The training process can occur in a supervised or unsupervised manner. Supervised training means that the network is provided with sets of training data that include the expected output for each set of input. This means that the network is trained to learn specifics. However, in unsupervised learning, the learner has to learn from a set of inputs only, that is, to extract meaningful features from input data [8].

The validation step is used during the training of ANN to monitor the over-fitting of the NN and also act as an index to stop the training of the NN when validation error starts to rise [9]. This process can be expressed as a mathematical model in (1):

$$Y = f(\sum_{i=0}^{n} w_i \cdot x_i - b), \qquad i = 1, 2, 3, \dots, n \qquad (1)$$

where, Y is the output, f is the transfer function, w_i is weight of input x_i and b is a bias.

III. Construction of ANNs

ANNs are a family of massively parallel architecture that can solve complex problems by collaborating with highly interconnected but simple computing. Most research is based on back-propagation neural networks (BPNNs) [4].

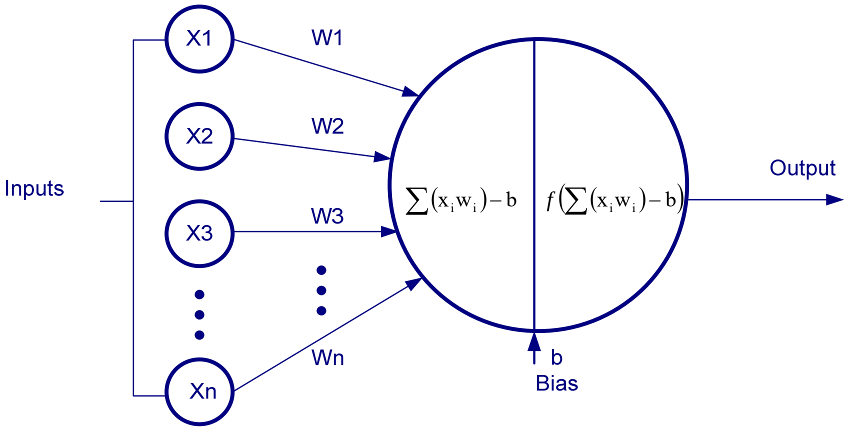

Fig. 1 Artificial neuron model

To train the network, the weights of connections are modified according to the information it has learned. The difference between the output of the trained network and the target is called error. The error is propagated back and the weight and biases are adjusted to minimise the error. This process is repeated for a number of epochs until a desired accuracy in output is achieved.

To test the accuracy of a trained network, the correlation coefficient R is adopted. The coefficient is a measure of how well the independent variables considered account for the measured dependent variable. The higher the R value, the better the prediction relationship. Moreover, the mean squared error (MSE) was used to monitor the network performance for training the current NNs. The closer the value of MSE to zero, the better the prediction is. MSE can be obtained by the following standard formula:

$$\mathrm{MSE} = \frac{\sum_{i=1}^{n}(T_i - A_i)^2}{n} \qquad (2)$$

where T_i and A_i are the target and actual network, respectively, and n is the total number of training dataset. The training process stops when any of the following conditions are satisfied:

- The maximum number of epochs is reached;
- The MSE of validation data set starts to increase for a specified number of epochs;
- The performance gradient falls below a minimum value.

IV. Data Set Collection

The main purpose of this study is to develop an ANN model to predict the compressive strength of RuC. All applications from previous research predicted the compressive strength of RuC with a small number of dataset, less than 100 [10]. The data were obtained from different sources available in the literature and used for training and testing the ANN model [10]-[25]. To construct this model, a total number of 287 different experimental data were collected. Table I shows the range of various concrete ingredients available in the database.

TABLE I
Range of Input Parameters of the Database Used to Train the ANN

Range	CA Kg/m^3	FA Kg/m^3	W/C Kg/m^3	Fr Kg/m^3	Cr Kg/m^3
min	115	58.6	0.35	0	0
max	1650	1256	0.66	473	870

The input data are divided randomly into three phases, namely; 70% for training phase, 15% for validation phase, and 15% for testing phase. The testing phase for assessing the network employs test specimens from the database, which should be used once only after training is complete. The main purpose of the validation phase is to arrest training when generalization stops improving. The frequency distribution of each variable element used in this study for training and testing are shown in Figs. 2-6.

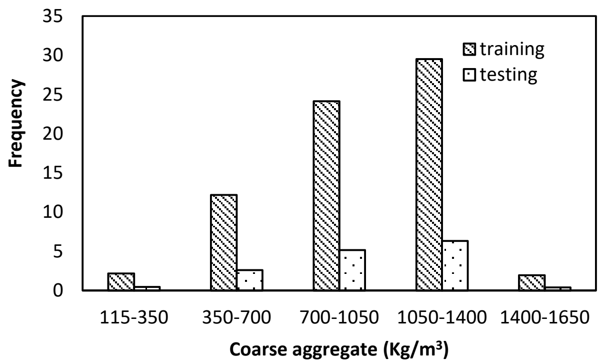

Fig. 2 Frequency distribution of CA

The data used in the proposed neural networks model are arranged in a format of five input parameters, these are CA, FA, water cement ratio (W/C), Fr and Cr.

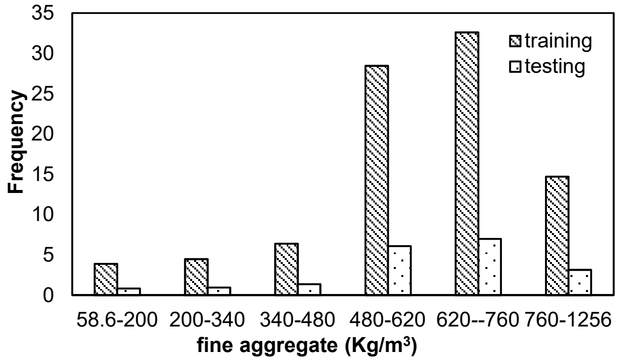

Fig. 3 Frequency distribution of FA

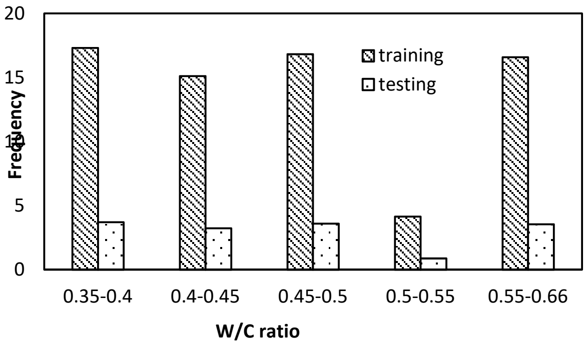

Fig. 4 Frequency distribution of W/C ratio

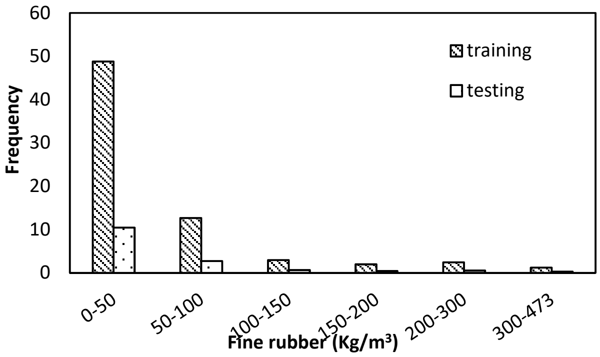

Fig. 5 Frequency distribution of Fr

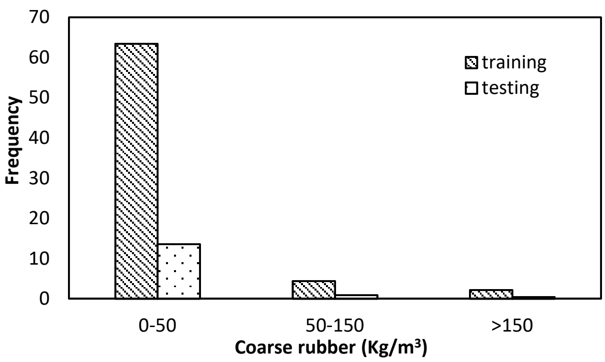

Fig. 6 Frequency distribution of Cr

V. Normalisation of Data

Preprocessing steps can be made in the network input data and targets to enhance the efficiency of neural network training. Raw input data can be prepared to be suitable for the training when the normalisation process is used for such data. There are many types of data normalisation [26], [27]. It will scale the data values to be at the same range to minimise bias within the neural network. Normalized data can also speed up training time by starting the training process for each feature within the same scale. The sigmoid transfer function is sensitive to input values in the range -1 to +1, thus the input data should be scaled to match this range. That was done according to (3):

$$I_{scaled} = \frac{2\times(I_{actual}-I_{min})}{I_{max}-I_{min}} - 1 \tag{3}$$

where I_{scaled} the scaled input variable, I_{actual} the value of the variable to be scaled, I_{min} the minimum value of the variable used in the training set, I_{max} the maximum value of the variable used in the training set. It should be noted that any new input data should be normalized before it is simulated by the network and the corresponding predicted values should be de-normalized before use.

VI. Training and Testing Stage of NNs

The ANN was developed using the popular MATLAB software package (MATLAB R2015a). All the networks were trained using Levenberg–Marquardt algorithm. This algorithm is suitable for training small- and medium-sized problems. The training parameters of Levenberg–Marquardt algorithm include: the maximum number of iterations, target performance which specifies the tolerance between the neural network prediction and actual output, the maximum run time and the minimum allowed gradient.

The most popular technique used for training the network for complex non-linear relationships is a back-propagation algorithm [28]. Generally, the input data are divided into three sets; training, validation, and testing sets. The training set is used to reduce the ANN error. During the training process, it is important to monitor the error in the validation set. The error of the validation and the training sets will normally reduce during the initial stage of training. However, when the network begins to over-fit the data, the error on the validation set will typically begin to rise. When the validation set error increases for a specified number of epochs, the training is stopped.

The testing phase checks the network and employs test specimens from the database, which have not been used in the training process. In the present work, training data set includes 201 data entries, and the remaining 86 data entries are equally divided between the validation and testing sets. The division was done randomly between the three sets and each dataset has been examined manually to ensure that it covers the range of input parameters.

VII. Topology of the ANN

The optimal architecture of the neural network depends on the complexity of the problem and the input/output variables. It was determined that there are five input and one output parameters. However, even with the same input variables, the solution for compressive strength might differ, and thus would require different neural network topologies. Research shows that one hidden layer is enough for predictions of concrete strength based on mix composition [29]-[31]. Therefore, one hidden layer structure was adopted for the development of the ANN model used in this study.

Up to date, there are no certain rules to determine the architecture of a BPNN that best suits a certain problem. Reference [32] stated that the numbers of hidden layer neurons are 2/3 of the size of the input layer. Also, [33] mentioned that the number of nodes should be equal in the first and second hidden layers. Hence, the network can be easily trained. Many researchers have tried to find the optimal procedure for calculating the number of neurons that should be in the hidden layer, however, no success was found. Therefore, the choice of the number of neurons in the hidden layer is determined experimentally and it depends on the complexity of the problem. Consequently, five models are constructed for each parameter to be modelled. These networks had 3, 5, 8, 10, and 12 neurons in the hidden layer. Afterwards the most accurate model was chosen by identifying the one with the smallest prediction error.

VIII. Performance of the Developed Neural Network

A total of 5 different NNs with different architectures were created and tested as shown in Table II. Their performance was monitored during the training process as the mean absolute error (MAE) over all training data. The difference between the NN compressive strength output and the experimental compressive strength was an error estimated for each point. The MSE was used to monitor the network performance for training the current NNs. The lesser the MSE, the better the estimates were.

Table II shows different statistical parameters for the measurement of the performance of NN. It also shows the mean and standard deviation (SD) of the ratios of experimental values of compressive strength of RuC to the corresponding NN prediction values for different modelling techniques, the correlation coefficient (R) and the mean absolute percentage error (MAE %). The 5*10*1 NN was selected as the best network due to the statistical parameter shown in Table II.

A comparison between the experimental and predicted values of the compressive strength of RuC for the selected NN model is shown in Figs. 7 and 8 for the training and testing data sets, respectively. It can be concluded from Figs. 7 and 8 that, the ANN was successful in learning the relationship between the input and output data. All the NN models have correlation coefficient almost equal to one. This shows that the NN models have high degree of fitness to the actual values. The R was 0.956 and 0.989 for the training and testing data sets, respectively.

TABLE II
Performance of Different ANNs Developed

NN architecture	Mean	SD	C.O.V (%)	MAE (%)	MSE	R
5*3*1	1.0026	0.249	24.84	24.30	41.39	0.912
5*5*1	1.0103	0.221	21.90	15.83	24.61	0.931
5*8*1	1.0290	0.293	28.50	13.92	18.91	0.948
5*10*1	1.0058	0.172	17.08	9.85	14.89	0.954
5*12*1	1.0140	0.254	25.08	18.02	28.30	0.930

The average ratio of experimental compressive strength to predicted compressive strength of the training and testing data sets is 1.00 and 1.028, respectively. The mean absolute percentage of error is 10.06% and 10.25% for the training and testing data sets, respectively. This MAE is reasonable considering the noisy nature of the experimental results of compressive strength in the database.

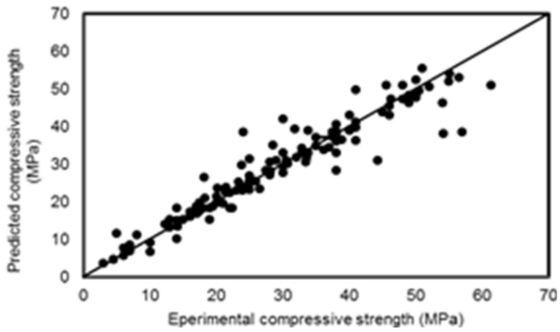

Fig. 7 Performance of training set of compressive strength prediction with ANNs model

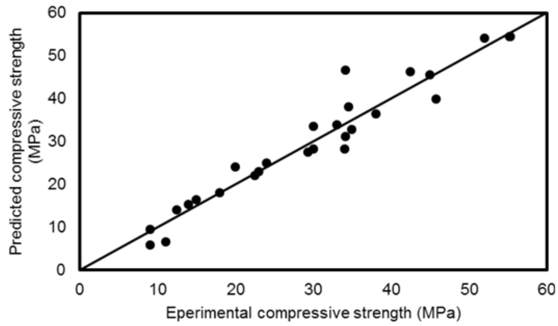

Fig. 8 Performance of testing set of compressive strength prediction with ANNs model

IX. Parametric Study

The trained 5*10*1 NN was applied to conduct a parametric study to investigate the effect of different input parameters on the compressive strength of RuC. The parametric study quantifies the effect of one parameter on compressive strength of RuC when all other parameters are fixed by using the model of NN.

A. Influence of W/C Ratio

W/C was changed from 0.35 to 0.50 while all other parameters were held constant according to database frequency. Fig. 4 illustrates the influence of W/C ratio on compressive strength of RuC. As shown from Fig. 9, the increase in W/C ratio caused a decrease in the compressive strength from 14 MPa to 20 MPa for w/c ratio 0.35 to 0.55. Results obtained from literature [34], [21], [22] were plotted in the Fig. 9 to compare to the prediction values.

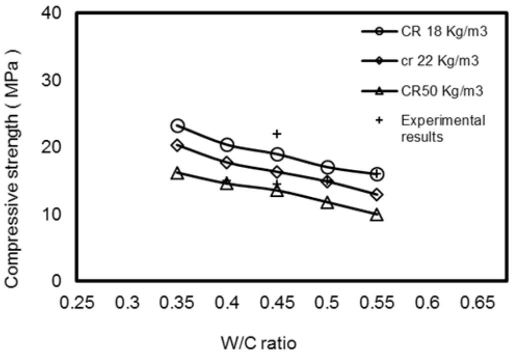

Fig. 9 W/C ratio effect on the compressive strength

B. Influence of Fr

Fr content changed from 0 to 50 kg/m^3 while all other parameters were held constant according to database frequency as shown in Table IV. W/C ratio change was repeated three times for different vales; 0.37, 0.40 and 0.50 respectively. Fig 10 shows the influence of changing Fr content on the compressive strength. It shows that compressive strength decreased by increasing Fr content.

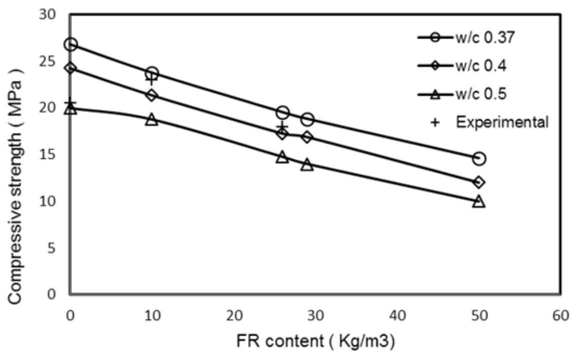

Fig. 10 Effect of Fr on the compressive strength

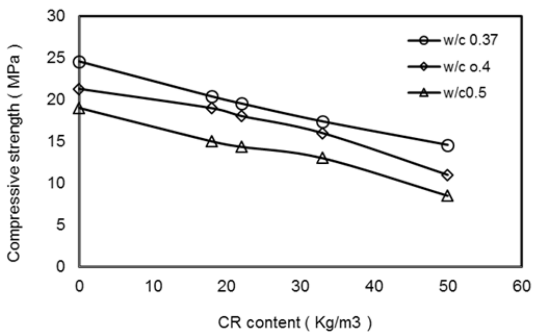

Fig. 11 Effect of Cr on the compressive strength

C. Influence of Cr

Table V shows that the amount of Cr varied from 0 to 50 kg/m³, while other materials were held constant. This change was repeated three times with different w/b; 0.37, 0.4 and 0.5 respectively. As shown in Fig. 11, increasing Cr results in decrease of compressive strength. Also, increasing w/c, the compressive strength decreases for the same volume of CA.

X. Conclusion

In this paper, a NN model for the prediction of the compressive strength of RuC was developed. The developed ANNs and observations from the parameters studied are valid for a range of data sets documented in Table I. Based on the parametric study conducted using the trained ANNs, the following conclusions may be drawn:

- The performance of the 5 *10 * 1 architecture was better than other architectures. This means that, there are five neurons in the input layer; one hidden layer with six neurons and one neuron in the output layer, with an acceptable degree of accuracy (R = 0.954, MSE = 14.894).
- ANN models reasonably predicted the compressive strength of RuC.
- ANN method can be used as an accurate and quick tool for estimating the compressive strength of any RuC.
- Compressive strength prediction decreases with increasing W/C ratio for both fine and Cr.
- For better training of developed ANNs, the database should be increased.

For future works, more data could be collected. Some experimental will be carried out and the results will be added to the database, with focus on some input parameters. Finally, future training and testing of ANNs model will be carried out.

Acknowledgement

The corresponding author would like to thanks the Libyan authorities who funded the whole PhD programme.

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