An Artificial intelligence approach for predicting compressive strength of eco-friendly concrete containing waste tire rubber

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Abstract. Using waste tire rubber as a aggregate replacement in the production of concrete can be considered as an effective way for environment and economies. This study presents an approach based on a prediction model using Artificial Neural Networks (ANN) to predict compressive strength of eco-friendly concrete containing waste tire rubber (RC). A data set with nine influencing features including water, cement, supplementary cementitious materials, coarse aggregate, coarse rubber aggregate, fine aggregate, fine rubber aggregate, superplasticizer, age using for training and validating models have been collected from the literature. The output was compressive strength of RC. The combination of root mean square propagation and stochastic gradient descent with momentum method is employed to train the ANN. Using various validation criteria such as coefficient of determination (R\textsuperscript{2}), Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE), the ANN model was validated and compared with two machine learning (ML) techniques Random Forest (RF) and Multilayer Perceptron (MLP). A Sensitivity analysis also was carried out to validate the robustness and stability of these models. The experimental results showed that the ANN model outperformed in comparing with other models and therefore it can be used as a suitable approach to predict compressive strength of eco-friendly rubber concrete.

1. Introduction
The serious environmental problems are caused by the rapid increase in the number of exhaust waste tires and inefficient tire storage. The use of rubber crumbs from recycled tires is one of the effective approaches that can sustain rubber resources. According to the U.S. Tire Manufacturers Association \cite{1}, 255.61 million of rubber tires were produced in 2017. Around 43\% of waste tire was reused as fuel, 25\% was crushed into scrap rubber, 16\% retained in landfills, only 8\% was reused in the civil engineering. The replacement of natural coarse and/or fine aggregate by waste tire rubber significantly alters the properties of concrete. Reducing compressive strength, flexural strength, and modulus of elasticity in comparing with conventional concrete are reported in \cite{2-4}. However, other studies showed many beneficial properties of RC such as: increasing the ductility and preventing brittle failures \cite{5}, having
low unit weight [6], reducing thermal conductivity [7], and increasing in water absorption with increased rubber content [8]. In recent years, artificial neural networks are a widely used as an artificial intelligence technique for solving complex and nonlinear problems with strong proposed to learning and function approximation. Gupta et al. [9] constructed an ANN model to predict mechanical properties of RC exposed to elevated temperature. Modelling the influence of waste rubber the on compressive strength of concrete based on database of experimental results with partial or full replacement by using ANN was reported by Marijana Hadzima-Nyarko [10]. The results showed that ANN model can archive good accuracy with difference architectures of neural networks. Abdollahzade et al. [11] proposed an ANN model for estimating the strength of rubberized concrete in comparing with Multiple Linear Regression (MLR). It is proven that the ANN model is an effective tool for predicting physical and mechanical properties of concrete.

The main of this study proposes an efficiency ANN model to predict compressive strength of eco-friendly concrete containing waste tire rubber. The back – propagation model was then compared with the two machine learning techniques Random Forest and Multilayer Perceptron. A sensitivity analysis was also carried out to validate these models with 200 simulations.

2. Material and method

2.1. Description of dataset

To train and validate the model of ANN, the experimental dataset including 129 samples were collected from literature [12]-[14]. The dataset consists of nine input explanatory (input) variables: water ($X_1$), cement ($X_2$), supplementary cementitious materials (SCM) ($X_3$), coarse aggregate ($X_4$), coarse rubber aggregate ($X_5$), fine aggregate ($X_6$), fine rubber aggregate ($X_7$), superplasticizer ($X_8$), and age ($X_9$). The most important mechanical property of RC is the compressive strength set as response variable (output target). In order to validate the efficiency of ANN model, the testing part constitutes for 30% (38 samples) of the total of 129 samples. The initial statistical characteristics of the variables and output target are summarized in Table 1. The training dataset is used to determine the model ANN weights (or parameters) which contains 70 % of dataset (91 samples). For reducing fluctuations in training ANN model, both explanatory and response variables of dataset were scaled into the range of [0, 1].

| Variables | Description | Min | Mean | Median | Max | Std | Skew. |
|-----------|-------------|-----|------|--------|-----|-----|-------|
| $X_1$     | Water       | 155.20 | 194.19 | 200.0  | 210.0 | 19.15 | -0.95 |
| $X_2$     | Cement      | 300.00 | 343.64 | 350.00 | 401.00 | 42.13 | 0.04  |
| $X_3$     | SCM         | 0.00  | 137.20 | 0.00   | 300.00 | 150.03 | 0.17  |
| $X_4$     | Superplasticizer | 0.00 | 4.59  | 6.50  | 7.80  | 3.57  | -0.40 |
| $X_5$     | Coarse aggregate | 290.00 | 1009.01 | 888.00 | 1202.80 | 190.83 | -0.84 |
| $X_6$     | Coarse rubber aggregate | 0.00 | 40.46 | 0.00 | 1160.00 | 190.94 | 4.85 |
| $X_7$     | Fine aggregate | 0.00 | 668.69 | 680.94 | 840.75 | 146.22 | -2.22 |
| $X_8$     | Fine rubber aggregate | 0.00 | 60.81 | 36.84 | 630.00 | 100.67 | 4.23 |
| $X_9$     | Age         | 1.00  | 27.00  | 28.00  | 91.00  | 25.67  | 1.36  |
| $Y$       | Compressive strength | 0.95 | 21.12 | 22.00 | 41.00 | 8.92 | -0.50 |

2.2. Artificial Neural Networks

Many successful applications in data processing and learning capabilities using ANN have been reported in the literature [15-16]. The basic structure of ANN consists of three layers, weighting factors, activation functions and learning function. The input and output layers are single layer, which contain model data and model output respectively. The hidden layer contains one or more layers that is used for data processing. The neurons at these layers have forward or backward connections from the neurons at its previous layer. The ReLu function is employed as activation function for ANN. This function is shown as follows:

$$f(x) = \max(0, x)$$
\[ f(x) = \max(0, x) \]  

An important factor of ANN is an optimization of the weights between neuron connections. A set of these weights was determined by minimizing a cost function which is basically the mean squared error (MSE). The combination of root mean square propagation and stochastic gradient descent with momentum method is used to determine the optimal values of the weights.

Previous studies showed that randomly selecting a number of hidden neurons may lead to underfitting or overfitting of the model [17]. Consistent numbers of hidden layers and neurons in each layer eliminate the overfitting and validate the stability of the training model. This paper presents an efficiency architecture model of ANN that contains three hidden layers. The experimental work was carried out for testing all combinations using 2 to 30 neurons for the model in each hidden layer. The optimal number of neurons for the ANN model was determined by carrying out a 5-fold cross validation using the training set. The stable ANN model contains eleven, eight and three neurons in hidden layers respectively, with nine neurons and one bias in the input layer and one neuron in the output layer. The completely architecture of the ANN model is shown in Figure 1.

![Figure 1. Structure of the proposed ANN model: three hidden layers with eleven, eight and three hidden neurons.](image)

2.3. Multilayer Perceptron

A Multilayer Perceptron (MLP) is a class of feed-forward artificial neural network that can model any function to tackle numerous complex problems [18]. The successful architecture of MLP model for predicting compressive strength of RC has input layer, output layer and single hidden layer with 80 neurons. Each layer consists of nodes fully connected to all nodes in the next layer. The ReLu function (1) is used as an activation function. The Limited-memory Broyden-Fletcher-Goldfarb-Shanno (LBFGS) algorithm with momentum=0.2 is chosen for solving weight optimization.

2.4. Performance Evaluation

These well-known statistical indicators, such as coefficient of determination \( R^2 \), the root mean square error (RMSE) and mean absolute error (MAE) were considered to evaluate the effective and predictive accuracy models. The value of \( R^2 \) indicates the statistical relationship between the actual values and predicted values of output target (compressive strength) while RMSE and MAE show the error evaluation...
of the models. Higher $R^2$ values indicate better performance of the models. Totally, these indicators are defined in following equations:

$$MAE = \frac{\sum_{i=1}^{m}|SA_i-SP_i|}{m}$$  \hspace{1cm} (2)

$$RMSE = \sqrt{\frac{\sum_{i=1}^{m}(SP_i-SA_i)^2}{m}}$$  \hspace{1cm} (3)

$$R^2 = \frac{\sum_{i=1}^{m}(SP_i-SP)^2 \sum_{i=1}^{m}(SA_i-SA)^2}{\sum_{i=1}^{m}(SP_i-SP)^2 \sum_{i=1}^{m}(SA_i-SA)^2}$$  \hspace{1cm} (4)

where $SP_i$ and $SP$ are defined as the values and means of the predicted compressive strength, respectively. $SA_i$ and $SA$ are the values and mean of the actual compressive strength, respectively, $m$ is the number of data samples.

3. Result and discussion

3.1. Evaluation performance of ANN model

For the ANN model with three hidden layers, RF and MLP, the performance of statistical indicators $R^2$, $MAE$, $RMSE$ for the training and testing part are presented in Table 2. The results showed that the proposed ANN model with three hidden layers archived higher value of $R^2$ (0.928) and the lower values of $RMSE$ and $MAE$ (2.607 and 2.007 respectively) on the testing dataset. Although the coefficients of determination $R^2$ are observed to be nearly the same for ANN and RF model in training set. Table 2. Statistical indicators values of ANN, RF, MLP models for 200 simulations.

| Model             | Training set | Testing set |
|-------------------|--------------|-------------|
|                   | $R^2$ | RMSE  | MAE  | $R^2$ | RMSE  | MAE  |
| ANN model         | 0.973 | 1.264 | 0.925 | 0.928 | 2.607 | 2.007 |
| Random Forest     | 0.974 | 1.361 | 0.992 | 0.912 | 2.864 | 2.195 |
| Multilayer Perceptron | 0.968 | 1.362 | 1.097 | 0.860 | 3.614 | 2.626 |

The evaluation performance has a difference between ANN and MLP models. The observing statistical indicators shows the superiority of ANN model ($R^2=0.928$, $RMSE=2.607$, $MAE=2.007$) than MLP ($R^2=0.86$, $RMSE=3.614$, $MAE=2.626$) in testing set. This can lead to conclusion that the ANN with three hidden layers can achieve better predictability and stability than the MLP model, containing single hidden layer. The predicting results are illustrated in Figure 2. The percentage errors for the training and testing set of ANN model are illustrated in Figure 2d. It can be seen that probability density of absolute error at zero obtained on the training samples is about 0.45, while probability density value at 0.18 is obtained on testing samples.
Figure 2. Performance prediction of ANN model: a - Deviation around the line of best fit in training set; b - Deviation around the line of best fit in testing set; c - The actual vs. the predicted output; d - Probability density of error of training and testing set.

3.2. Sensitivity analysis
As previously mentioned, training and validating set are randomly selected from dataset with ratios 70% and 30% respectively. Corresponding performance of statistical indicators are different for each simulation. For this purpose, a sensitivity analysis was carried out to check the robustness and stability of ANN and two machine learning techniques. 200 different arrangements of dataset were generated using uniform distribution and the values of indicators $R^2$, $RMSE$ in each case were collected and plotted in Figure 3.
Figure 3. Root Mean Squared Error (RMSE) and Coefficient of determination (R^2) of different models for 200 simulations: (a–b) - Multilayer Perception, (c–d) - Random Forest Regression, (e–f) - Artificial Neural Networks.

The variation of these indicators in the training part of ANN and RF model is rather smaller than MLP model. A relatively more stable variation is considered in the RF model of testing set that clearly demonstrate the dependence of the predicted results on input combination. The maximum, minimum and average values of these indicators for 200 simulations are listed in Table 3. In the case of MLP model (Figure 3a–b), the testing set have strong variation around average value, i.e., RMSE = 4.328, MAE = 2.975, and R^2 = 0.781. For RF model (Figure 3c–d) in training set, the average results are RMSE = 1.361, R^2 = 0.974, whereas the testing set are RMSE = 2.864, R^2 = 0.912. Regarding the ANN model, there was no obvious difference of R^2 values in the training set in comparing with RF model (Figure 3e–f) but results in testing set showed the superiority in these values. This indicates that ANN outperforms two ML models.

| Models | ANN | RF | MLP |
|--------|-----|----|-----|
|        | Training set | Testing set | Training set | Testing set | Training set | Testing set |
|        | R^2 | RMSE | R^2 | RMSE | R^2 | RMSE | R^2 | RMSE | R^2 | RMSE |
| Max. value | 0.981 | 1.450 | 0.891 | 3.101 | 0.977 | 1.487 | 0.928 | 3.154 | 0.984 | 4.539 | 0.959 | 6.460 |
| Min. value | 0.969 | 1.150 | 0.937 | 2.451 | 0.969 | 1.279 | 0.890 | 2.651 | 0.712 | 1.041 | 0.555 | 1.96 |
| Ave. value | 0.975 | 1.310 | 0.922 | 2.678 | 0.974 | 1.361 | 0.912 | 2.864 | 0.919 | 2.225 | 0.789 | 4.328 |

4. Conclusion
In this study, the ANN model with three hidden layers was proposed and compared with two machine learning techniques, which are Random Forest and Multilayer Perceptron, for predicting compressive strength concrete with waste tire rubber. A dataset including 129 samples were collected from the literature and served for modelling. Validation of the models was achieved using statistical indicators such as RMSE, MAE, and R^2. The ANN model archived highest R^2 value of 0.927 and lowest RMSE and MAE values 2.607, 2.007 respectively for the testing set. The sensitivity analysis with 200 simulations was carried out to validate these models. The results showed that the ANN was more robust and stable
than other models and can be considered as a suitable approach to predict the compressive strength of eco-friendly concrete containing waste tire rubber.

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