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Compressive strength prediction of environmentally friendly concrete using artificial neural networks

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ABSTRACT

Solid waste in the form of construction debris is one of the major environmental concerns in the world. Over 20 million tons of construction waste materials are generated in Tehran each year. A large amount of these materials can be recycled and reused as recycled aggregate concrete (RAC) for general construction, pavement and a growing number of other works that drive the demand for RAC. This paper aims to predict RAC compressive strength by using Artificial Neural Network (ANN). The training and testing data for ANN model development were prepared using 139 existing sets of data derived from 14 published literature sources. The developed ANN model uses six input features namely water cement ratio, water absorption, fine aggregate, natural coarse aggregate, recycled coarse aggregate, water-total material ratio. The ANN is modelled in MATLAB and applied to predict the compressive strength of RAC given the foregoing input features. The results indicate that the ANN is an efficient model to be used as a tool in order to predict the compressive strength of RAC which is comprised of different types and sources of recycled aggregates.

1. Introduction

Considerations for sustainable development such as through environmental regulations and natural resources protection play a significant role in new requirements of the construction industry. The production of construction debris and demolition waste all over the world has been substantially increasing due to rehabilitation activities. In Tehran, the production of construction waste has been estimated to be as much as 20 million tons annually. Demolished materials are not used for any purpose and may adversely affect useful land spaces if dumped around cities. It is also a well-known fact that concrete is among the world's most common construction materials today where the annual global consumption of natural aggregate for concrete production is estimated at 8–12 billion tons [1]. Such aggregates are considered as essential components of concrete and potentially pose detrimental effects to the environment if associated debris is not managed responsibly. The sheer volume of produced construction waste will undoubtedly result in major environmental concerns.

In recent years, researchers have utilized different techniques to anticipate and evaluate various properties of recycled aggregate concrete (RAC). Methods that are based on the machine learning body of knowledge such as artificial neural networks (ANN) are increasingly gaining traction. However, ANN techniques are rarely adopted to predict performance of RAC and concretes in general due to their complex composition. Topcu and Saridemir (2008) [2] attempted to predict the compressive and splitting tensile strength of RAC that contains silica fume. Duan et al.[3], proposed an ANN model with 14 input features using 168 sets of data. Chopra et al. [4], performed a regression analysis to establish the relationship between recycled coarse aggregate (RCA) properties and the associated compressive strength based on 20 sets of data.

In studying the properties of RAC, Poon et al. [5] highlighted the effect of moisture levels in both natural and recycled that affect the strength of RAC.

Zega and Maio [6], exposed RCA to high temperatures in order to evaluate and compare the characteristics of concrete made of different natural aggregates. Lin et al. [7], outlined the optimal mixture for RAC and proposed a procedure to provide a better way for understanding the real engineering behavior of RAC. Domingo-Cabo et al. [8], worked on creep and shrinkage of RAC and presented an experimental program to assess the different characteristics of RAC while Gomez-Soberon (2002) [9], studied the porosity of RAC. Gonzalez-Fonteboa and Martínez-Abella [10], Yang et al. [11], Gonçalves et al. [12], Guti et al. [13], Kou and Poon [14] and Duan and Poon [15], worked on various properties of RAC particularly from resulting mechanical aspects such as compressive strength and presented several conclusions.

In 2016, Pour and Alam [16] investigated the influence of RAC on the strength of bonds between concrete and steel bars. By considering

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Table 1
Summary of existing models.

Previous work	Sample size	Method	R^2	Concrete type	Input variables
Yeh (1998) [17]	727	ANN	0.914	HPC	Cement; FA; BFS; water; superplasticizer; coarse and fine aggregates; curing age
		Linear regression	0.574		
Gupta et al. (2006) [18]	864	Neural-expert system	0.5776	HPC	Concrete mix grade; size and shape of specimen; curing technique and period; maximum temperature; relative humidity and velocity; period of strength
Zarandi et al. 2008 [19]	458	Fuzzy polynomial neural networks	0.8209	HPC	Coarse and fine aggregates; superplasticizer; coarse and fine aggregate; curing age
Yeh and Lien (2009) [20]	1196	Genetic operation trees	0.8669	HPC	Cement; FA; BFS; water; superplasticizer; coarse and fine aggregate; curing age
		ANN	0.9338		
Chou et al. (2011) [21]	1030	ANN	0.9091	HPC	Cement; FA; BFS; water; superplasticizer; coarse and fine aggregate; curing age
		Multiple regression	0.6112		
		SVM	0.8858		
		Multiple additive regression trees	0.9108		
		Bagging regression trees	0.8904		
Deepa et al. (2010) [22]	300	Multilayer perceptron (ANN)	0.625	HPC	Cement; FA; BFS; water; superplasticizer; coarse and fine aggregate; curing age
		Linear regression	0.491		
		M5P model tree	0.787		
Atici (2011) [23]	135	ANN	0.9801	Concrete contains BFS and FA	Cement; BFS; FA; ultrasonic; pulse velocity; rebound number; curing age
		Multiple regression	0.899		
Erdal et al. (2013) [24]	1030	ANN	0.9088	HPC	Cement; FA; BFS; water; superplasticizer; coarse and fine aggregate; curing age
		Bagged ANN	0.9278		
		Gradient-boosted ANN	0.927		
		Wavelet bagged ANN	0.9397		
		Wavelet gradient-boosted ANN	0.9528		
Omran et al. (2014) [25]	144	M5P model tree	0.9476	Concrete contains FA, Haydite LWA, and PLC	Cement type; curing age; water; cementitious material; FA; sand; pea gravel; Haydite LWA; Micro Air
		M5-Rules	0.9482		
		REPTree	0.9217		
		Multilayer perceptron (ANN)	0.97		
		SMOreg (SVM)	0.968		
		Gaussian processes regression	0.9843		
		Additive regression	0.9843		
		Bagging	0.9816		

Table 2
Inputs and output.

W/C	Water-cement ratio
Wm	Water absorption
FA	Fine aggregate
RCA	Recycled coarse aggregate
NCA	Natural coarse aggregate
W/T	Water-total material ratio
f_{cu}	28-day compressive strength

144 push-out tests, they concluded that under constant mix proportions, an increase in the bar size and the embedment length to bar diameter ratio would lead to a reduction in the bond strength.

Table 1 provides a structured review of some of the primary works on compressive strength prediction. It can be observed that relatively fewer works have been done on compressive strength prediction of RAC wherein most previous studies were particularly centric about high-performance concrete (HPC) containing blast furnace slag (BFS), flay ash (FA) and superplasticizer.

The database utilized in this study, was populated from existing tests documented in the literature on RAC to investigate the relationship between various variables on the resulting compressive strength. Correspondingly, a new model based on ANN is developed and presented herein.

2. Recycled aggregate

The inherent characteristics of recycled aggregate (RA) are often inferior when compared to natural aggregate (NA), due to presence attached mortar and old cement paste. This includes 20–30% of the volume of recycled concrete, and is generally relatable to the original properties of the parent concrete from which it is extracted from.

The salient points below briefly highlight the benefits of using RA over NA:

- Lower bulk
- Higher water absorption
- Inferior strength

Table 3
Statistical properties of experimental data.

Input nodes	$W_m(\%)$	$\frac{W}{C}$	$FA\ (kg/m^3)$	$RCA\ (kg/m^3)$	$NCA\ (kg/m^3)$	$\frac{W}{T}$	$f_{cu}\ (MPa)$
Mean	8.73	0.53	714.71	589.04	411.56	0.09	40.42
Minimum	0.4	0.34	325	0	0	0.04	9.74
Maximum	28.58	0.86	1398	1219	1301	0.21	80.5
Standard deviation	5.88	0.09	192.51	382.42	421.17	0.03	13.24
Coefficient of variation	0.67	0.19	0.27	0.65	1.02	0.38	0.33

Table 4
The scaling equation for input and target nodes.

Parameter	Scaling equation
W_m	$W_{m_{scaled}} = [(0.9-0.1)(W_m - W_{m_{\min}})/(W_{m_{\max}} - W_{m_{\min}})] + 0.1$
W/C	$W/C_{scaled} = [(0.9-0.1)(W/C - W/C_{\min})/(W/C_{\max} - W/C_{\min})] + 0.1$
FA(kg/m^3)	$FA_{scaled} = [(0.9-0.1)(FA - FA_{\min})/(FA_{\max} - FA_{\min})] + 0.1$
RCA(kg/m^3)	$RCA_{scaled} = [(0.9-0.1)(RCA - RCA_{\min})/(RCA_{\max} - RCA_{\min})] + 0.1$
NCA(kg/m^3)	$NCA_{scaled} = [(0.9-0.1)(NCA - NCA_{\min})/(NCA_{\max} - NCA_{\min})] + 0.1$
W/T	$W/T_{scaled} = [(0.9-0.1)(W/T - W/T_{\min})/(W/T_{\max} - W/T_{\min})] + 0.1$
f_{cu}(MPa)	$f_{cu_{scaled}} = [(0.9-0.1)(f_{cu} - f_{cu_{\min}})/(f_{cu_{\max}} - f_{cu_{\min}})] + 0.1$

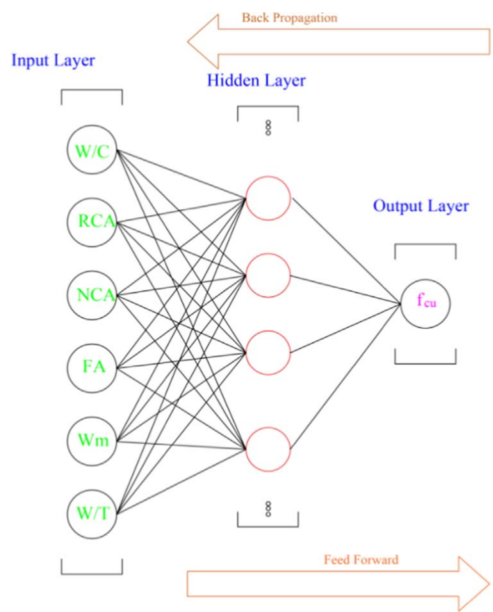

Fig. 1. Schematic diagram of ANN models.

- More angular in shape
- Presence of contaminants
- Lower resistance to mechanical and chemical actions

Regarding the above mentioned details, it would be appropriate to strictly use RCA and not recycled fine aggregate (RFA) as recycled aggregate in RAC applications. Along the same challenge, it is also notably advisable to use RAC in non-structural items. The experimental result on the compressive strength indicated that recycled aggregate (RA) with good quality can be used as an alternative for natural aggregate (NA) to produce concrete with mechanical properties comparable to those made with NA [15].

When completely dried RA is used, this implies reduced effective water-cement ratio which increases the compressive strength of the RAC due to higher absorption rate of dried RA [8].

The initial slump of RAC is mildly affected by the aggregates' relative water absorption while the rate of slump loss increases with the increase of the aggregates capability to absorb water [11].

Experimental results show that properties of conventional concretes and RAC with similar compressive strength can hardly be varied when the amount of RCA that is used is less than 20 percent. An exception to the latter is the elasticity modulus in which there is potential a 10 percent reduction in recycled aggregate. The tensile strength and drying shrinkage of RAC are similar to conventional concrete with the same compressive strength for RAC percentage lower than 50% [13].

Form an environmental point of view, 0.0046 million tonnes of carbon emissions is released in order to produce one tonne of natural aggregate while the similar weight of produced aggregate only releases 0.0024 million tonnes of carbon emissions. Given that the global consumption of aggregate for concrete production is approximately 10 billion tonnes per year, there is a significant room for improving carbon footprint from concrete production by replacing NA with RA [26].

3. Neural network modeling

Appropriate selection of input features is essential for accurate prediction of RAC compressive strength of using ANN models. Parameters that affect the RAC compressive strength are provided in Table 2. A total of six input parameters were identified based on previous experimental works and which are also perceived to be essential variables in determining compressive strength.

Fig. 2. Correlation coefficient NN 6-n-1.

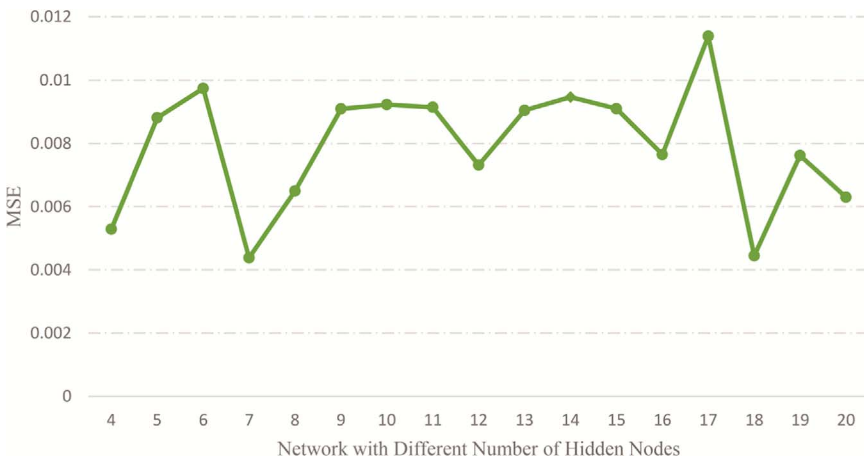

Fig. 3. Maximum squared error (MSE) versus numbers of hidden-layer neurons.

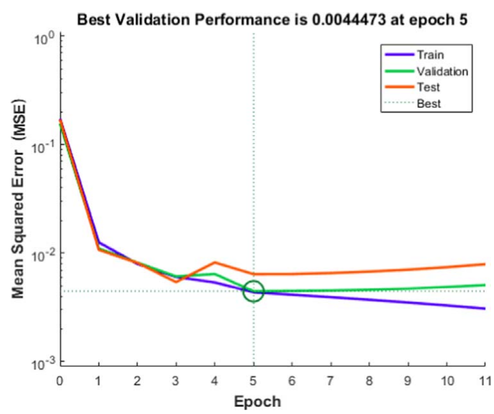

Fig. 4. The performance of NN 6–18–3.

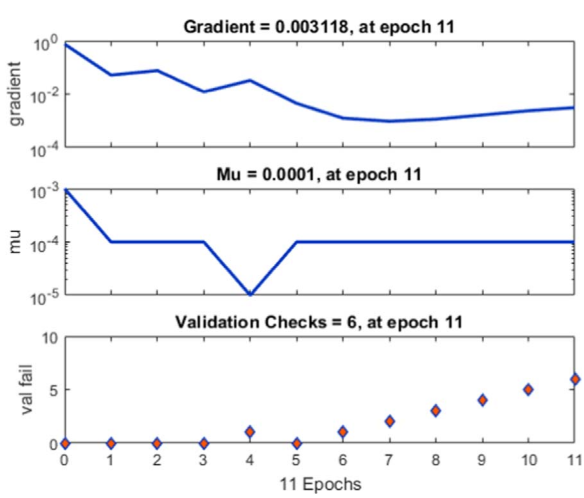

Fig. 5. Training state of NN 6–18–3.

From experimental results and existing strength models in the literature, it can be inferred that the compressive strength of RAC is primarily affected by water (W), cement (C), water-cement coefficient (W/C), water absorption (Wm), percentage of fine aggregate (FA), recycled coarse aggregate (RCA), natural coarse aggregate (NCA) and water-total material coefficient (W/T). In order to provide sufficient data for validating the trained neural network, a general set of test results on the compressive strength of RAC specimens was compiled. The selected database consists of 139 test results containing results from important test programs conducted in recent years.

The six parameters as listed above (W/C, Wm, FA, RCA, NCA, W/T) are utilized as the input layer with one hidden layer in the architecture of the ANN model. All nodes in the ANN model utilize the log-sigmoid function as their activation. The output neuron is then intended to predict the compressive strength of concrete. Statistical properties of experimental data are summarized in Table 3.

In order to reduce unwanted feature scaling effects, normalization/scaling was performed for all of the data sets before training the ANN.

This was an important pre-processing step because log-sigmoid transfer functions can only recognize values from 0 to 1. To scale the data from 0.1 to 0.9, minimum and maximum values were taken into account for application in the linear relationship between the values. Statistical properties of experimental data are listed in Table 4 shows needed equations for scaling each parameter value into interval of 0.1–0.9 [27–29].

4. Methods

The network type utilized in this study is the Back-propagation ANN. It is the generalized learning of Widrow-half to multi-layer networks and differentiable transfer functions. A typical neuron in the network contains biases, a sigmoid activation function and a linear output layer which is able to approximate any function having a finite number of discontinuities. The term 'back-propagation' indicates a method in which the correction gradient is calculated for nonlinear multi-layer networks [30].

Network training is performed by back-propagating the computed errors followed by subsequent adjustment of neuron weights. Post training, the application of the developed ANN in this study only operates strictly in a feed-forward manner, although it should be remarked that other techniques such as recurrent neural networks may operate with back propagation, more than often in real time throughout its life span.

A feed-forward network has a layered structure; each layer receives its input from units in a layer below and sends its output to units in the upper layers. There are typically no inter-connections between units within the same layer.

The architecture of the developed ANN in this article is short-termed NN6-n-1 where the first digit indicates the number of input features, and as shown in Fig. 1, n is the number of hidden nodes with one target output which is to predict the concrete's compressive strength.

The mean square error (MSE) was used as the ANN stop training criterion. In this regard, lower values are correspond to more idealized network performance. Regression values (R-values) are utilized to measure the correlation between outputs and targets in the networks wherein an R-value of unity indicate strong relationships. MSR and R-values were applied as the criteria for evaluation of the generated networks performance.

In Fig. 2 regression values of the networks having various numbers

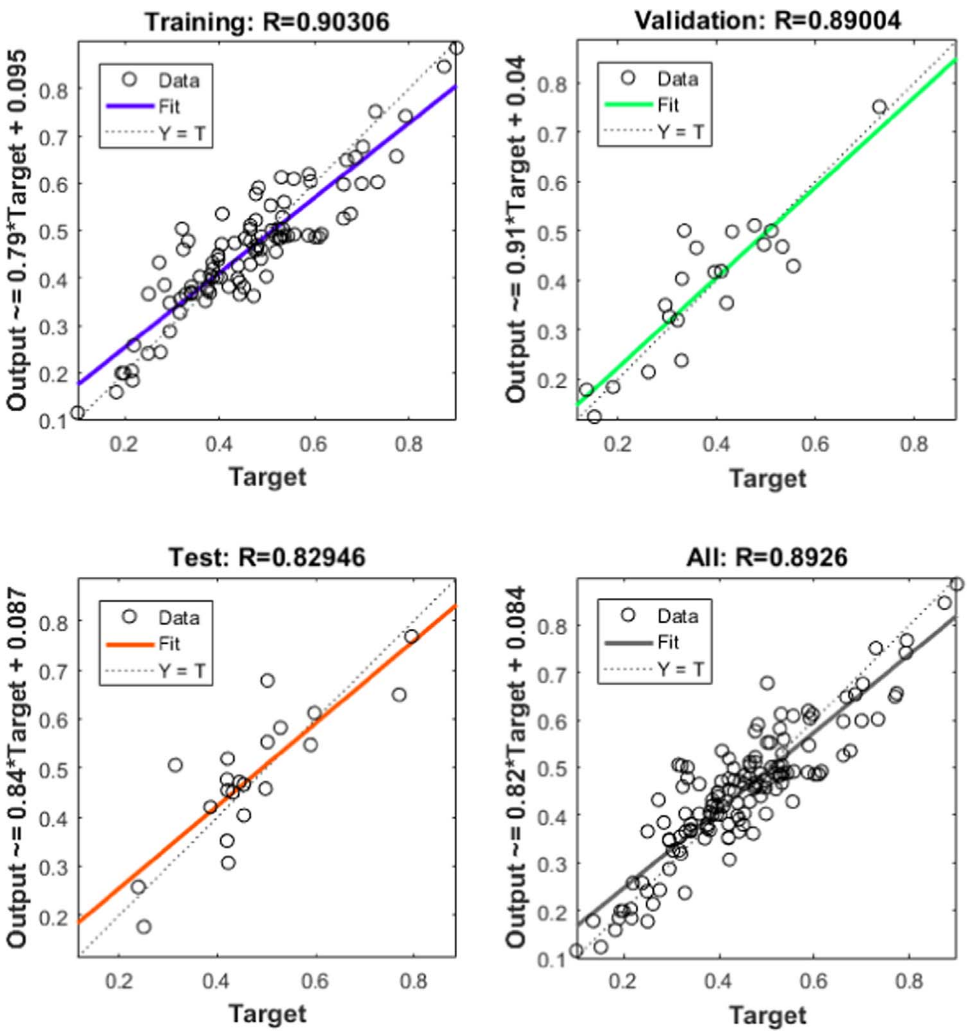

Fig. 6. Regression of training, validation and test simulated by NN 6–18–3.

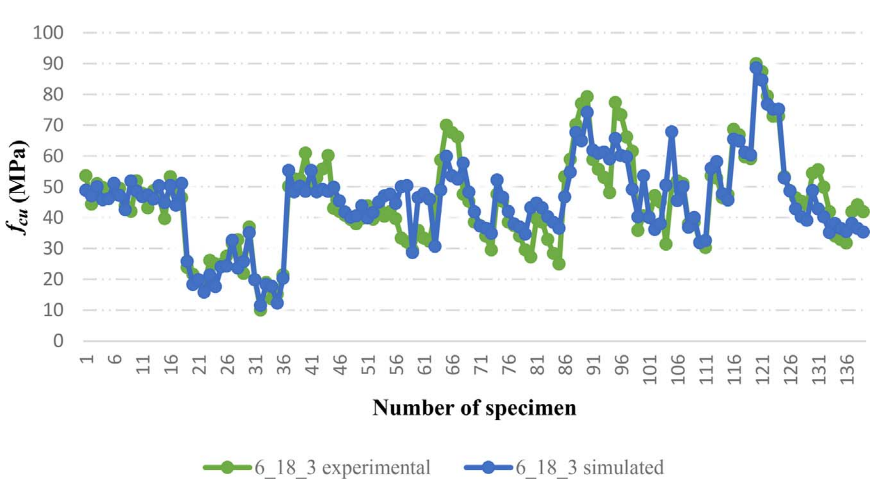

Fig. 7. Verification of simulated results against experimental data.

of hidden nodes is presented. In Fig. 3, another filtering in the pre-evaluation of networks is provided in which the MSE was calculated for all networks.

5. Application and results

The results from sensitivity analyses indicate that the best performant networks are NN6-7-3 and NN6-18-3. In order to preserve the initial intent of a single output node which predicts concrete compressive strength, the NN6-18-1 is selected for this study. It exhibits favorable results in the case of R-values and has the smallest MSE among all networks investigated. A summary of the NN6-18-1 training results is provided in Figs. 4–6.

Fig. 4 shows the network MSE which depicts a decreasing pattern as expected for a well-trained ANN which is also a good indication of the network's learning process. The plot figure contains three lines since the 139 inputs and target vectors are randomly segmented into three sets. Iterative training of the ANN on the designated training vectors

Table 5
Weights derived from idealized neural network.

W_m (%)	W/C (%)	FA (kg/m^3)	RCA (kg/m^3)	NCA (kg/m^3)	W/T (kg/m^3)	f_{cu} (MPa)
1.4622	0.70748	0.68073	0.83191	0.22194	1.2585	0.69913
−0.34182	0.39612	−1.317	0.60341	1.6359	0.71238	−0.1777
1.3589	−0.93009	0.99769	−1.0944	1.5659	0.73108	1.1302
1.561	0.1371	−1.3235	1.1935	−0.029352	0.024743	−0.45966
1.3292	−0.78244	−0.13488	1.417	0.55182	1.081	1.1583
−0.93147	1.3755	0.1578	−0.94098	0.070731	−1.0721	0.58369
−0.73957	1.4828	1.6791	0.084281	0.62355	−0.287	−0.24656
−0.73074	0.24787	−1.3069	−0.63656	−1.4781	−0.60988	1.1076
0.72372	0.65179	1.0694	0.48432	1.3757	−1.0653	−0.13008
−1.8109	−0.52302	0.32968	−0.048906	−0.088824	−1.9736	0.41404
−0.94917	0.52571	−0.42926	1.2575	1.677	1.3268	0.7456
1.0098	−0.48502	1.478	0.15371	0.83623	−1.348	0.32165
−0.8511	−0.12944	0.34932	0.098631	0.1711	1.9971	1.6993
−1.6957	1.1203	−0.090003	−1.479	−0.9359	0.77579	−0.62917
1.474	−0.65453	1.027	−0.51811	−0.70121	−1.7373	1.2804
0.15752	−1.2415	−0.47742	−0.53983	0.99757	−1.3931	−0.34914
−1.0143	−0.54567	1.3189	1.332	0.55869	0.82627	−0.88838
0.063572	−0.016576	0.53757	2.0176	−0.036502	0.037237	−0.1641

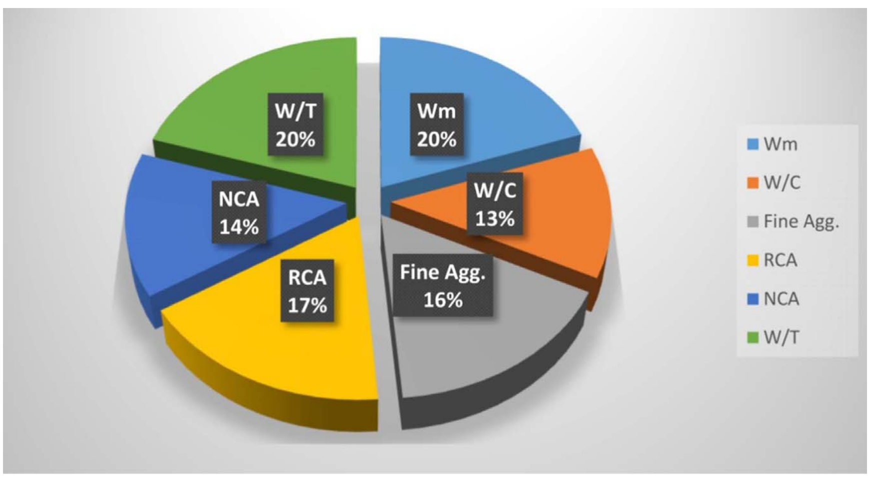

Fig. 8. Influence of each input parameter on compressive strength of RAC.

continues until convergence is achieved for the network's error when tested against the validation vectors. After successfully operating on the training set (at the expense of generalizing more poorly) the training stops which inherently circumvents the problem of over-fitting.

Verification of simulated results against experimental data are presented in Fig. 7. As it can be seen, it may be concluded that the ANN model learnt and predicted the experimental data with acceptable degree of precision.

6. Sensitivity analysis

In the broad field of ANN research, the majority of efforts have focused on developing new rules for learning, improving network architecture as well as expansion into new fields of ANN applications. There are not enough investigations dealing with development of fundamental knowledge which leads to understand the nature of the internal representations generated by an ANN in response to a given problem. More than often, an ANN is presented to its users as a black box with complicated internals which work to convert inputs into desirable outputs. For an ANN of considerable complexity, it is typically not possible to ascertain or understand the detailed mechanisms underlying weights of the network or the activation values of hidden neurons with regards to the problem under study. Hence, unlike classical statistical models, the task to determine the relationship between each explicative and dependent variable in an ANN is highly non-trivial [31].

Sensitivity analysis is aimed to study how the uncertainty in the output of a mathematical model or system can be allocated to various sources of uncertainty in its inputs.

The procedure of recalculating outcomes under alternative assumptions in order to determine the effect of variable under sensitivity analysis can be considered as an efficient method to gain an increased understanding of underlying relationships between the input and output variables in a model.

In this study the relative importance study for input factors has been done based on the importance of weights using the method proposed by Milne [32], see Eq. (1).

$$IIF = \frac{\sum_{j=1}^{n_{hidden}} \frac{w_{ji}}{\sum_{l=1}^{n_{inputs}} |w_{jl}|} \cdot w_{oj}}{\sum_{k=1}^{n_{inputs}} \left(\sum_{j=1}^{n_{hidden}} \left| \frac{w_{jk}}{\sum_{l=1}^{n_{inputs}} |w_{jl}|} \cdot w_{oj} \right| \right)} \quad (1)$$

Where IIF is the importance of input factors, n_{input} is the number of inputs, n_{hidden} is the number of units and n_{output} is the number of outputs.

Table 5 shows the results obtained after training the ANN with experimental data. The sensitivity analysis and the importance of weights were computed using the training set as data, while Milne's method was applied only to the connection weights in the network.

Fig. 8 showcases the effect of each parameter on the compressive strength of RAC, whereby it is clear that W/T and W_m are the most important parameters that influence the compressive strength.

7. Conclusion

In this study, an artificial neural network is developed to evaluate the strength properties of recycled aggregate concrete based on key predetermined input variables. The regression values of the chosen network for training, validation and testing are 0.903, 0.89 and 0.829 respectively. The best validation performance was observed in epoch 5. The MSE of the model was 0.004447 and it is concluded that the ANN method is capable of high accuracy predictions for RAC compressive strength. It is concluded that the ANN method is capable of high accuracy predictions for RAC compressive strength. The water absorption and water-total material ratio with about 20 percent of importance play important role in the compressive strength of RAC. It is also worth to mention that the maximum size of aggregates, water absorption values and saturated surface dry (SSD) specific density are generally affect the resulting properties of recycled aggregates.

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