

Prediction of Compressive Strength of "Green" Concrete Using Artificial Neural Networks

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With its growing emphasis on sustainability, the construction industry is more interested in applying environmentally friendly concrete, also known as "green" concrete, in its construction projects. Among other benefits, concrete made with alternative or recycled waste material can reduce pollution and energy use, as well as lower the cost of concrete production. However, the impacts of these alternative materials on concrete properties have not been fully understood, which limits the wide applications of "green" concrete in practice. This study investigates the application of Artificial Neural Networks (ANN) to predict the compressive strength (CS) of concrete made with alternative materials such as fly ash, Haydite lightweight aggregate and Portland limestone cement. A feed-forward Multilayer Perceptron (MLP) model was applied for this purpose. To determine the accuracy and flexibility of this approach, two different input methods (relative and numerical) were tested on the generated ANN models. The results showed that concrete made of Portland limestone cement had slightly better CS than concrete made of Portland cement. Generally, both input methods provided adequate accuracy to predict CS. It was also observed that a proper MLP model with one hidden layer and sufficient neurons (depending on the input variables and type of cement) could effectively predict the CS of "green" concrete.

Key words: Construction, Artificial Neural Network (ANN), Compressive Strength (CS), "Green" Concrete, Lightweight Aggregate, Portland Limestone Cement (PLC)

Introduction

The construction industry has observed an increasing shift toward sustainability in recent years. Many companies are proactively using or are required by their clients to use more environmentally friendly building materials and/or processes to reduce the negative environmental impact from construction activities. "Green" concrete, in this study, is defined as concrete produced using alternative and/or recycled waste materials. This type of concrete is increasingly becoming a common element that can be used to help the construction industry achieve long-term sustainability, although the impact of these alternative or recycled waste materials on various concrete properties has not been fully understood.

The compressive strength (CS) of concrete is one of the most important properties in concrete design. Many experiments have been undertaken to study the CS of "green" concrete that is made of alternative and/or recycled waste materials (Yang et al. 2005; Etxeberria et al. 2007; Kevern et al. 2011). Despite some progress, the available data for "green" concrete is far from adequate due to the emergence of various alternative or recycled waste materials and the complexity of concrete mixture design. Not only is more research needed to advance the understanding of "green" concrete properties, but practical tools for designing "green" concrete are necessary for it to be widely implemented.

Differing from the traditional experimental approach, some researchers have proposed mathematical or statistical models to predict the CS of concrete given its mixture or based on the fresh concrete properties (Atici, 2011). The statistical modeling approach is limited in that the underlying relationships between selected variables have to be known for the researchers to build an acceptable model. In contrast, Artificial Neural Networks (ANN) is a self-adaptive method that can learn and capture the linear or non-linear functional relationships among the variables even when such relationships are hard to identify (Zhang, 1998). Due to this advantage, some studies have employed ANN to predict the CS of concrete (Topçu and Saridemir, 2007; Saridemir et al., 2009; Atici, 2011) and the results of these studies have generally confirmed ANN to be a powerful method for this application.

This study aims to investigate the application and performance of ANN as a tool to provide a more accurate estimation for the CS of "green" concrete. The ultimate goal, if not totally eliminating the need for the experimental determination of the CS or other concrete properties in the future, is to significantly reduce such a need, which will save time and money for the industry. This is extremely helpful for implementing new materials, since extensive experimental data may not be available for them. This paper first introduces a unique composition of "green" concrete, based on which the structure of the generated ANN models (e.g., type of activation function, number of hidden layers and nodes, etc.) is optimized. Then, it compares the prediction accuracy of these models based on two different input methods (i.e., relative and numerical), which has not been attempted in existing studies.

Literature Review

Traditionally, the four main ingredients used to make concrete are water, cement, fine aggregate (sand) and coarse aggregate, although this can be changed depending on the specific properties (e.g., higher compressive or tensile strength, more durability, or lighter volumetric mass density) that are needed for concrete. In these cases, some alternative materials will be added or used to replace certain amounts of the traditional ingredients. For "green" concrete, the commonly used alternative materials are those that contain recycled contents, reduce greenhouse gases in their production, reserve natural resources, are locally available to decrease transportation costs, or improve material performance during their life cycles. For this research, Portland limestone cement (PLC), Haydite lightweight aggregate (LWA), and fly ash (FA) Class F were selected as environmentally friendly alternatives for the traditional ingredients. These three alternative materials are chosen based on the literature review and the results of a survey that was performed by the research team to identify industry interests in using "green" concrete. The results of the survey will be presented in a different paper and are not included within the scope of this paper.

Properties of Alternative Concrete Materials

PLC is an eco-friendly alternative to Portland cement (PC). It is produced by blending PC with limestone, or inter-grinding PC clinker, limestone, and calcium sulfate (Thomas et al., 2010). PLC can significantly reduce CO_2 emissions during cement manufacturing by reducing the clinker content in PC (Kenai et al., 2004). According to *Concrete Monthly* (2004), incorporating 2.5% limestone in the PC can lead to an annual reduction of 11.8 trillion Btus in energy use, 2.5 million tons reduction in CO_2 emissions, and 190,000 tons reduction in cement kiln dust in the U.S. The PLC Type GUL used in this research was acquired from the Lafarge cement plant located in Ontario, Canada.

FA is a byproduct from coal-fired power plants. It is the commonly used mineral admixture for general purpose concrete. As the most commonly used Supplementary Cementitious Material (SCM) in the concrete industry, FA Class F was adopted in this study. The chemical and physical analyses were provided by the local supplier and met requirements specified by ASTM C 618 and AASHTO M 295.

Haydite LWA is produced by expanding shale in a rotary kiln, at temperatures over 1000°C. It was originally developed in 1908 and patented in 1918, and since then has been used in many different applications such as concrete masonry, high-rise buildings, and precast and pre-stressed concrete elements. According to the Expanded Shale, Clay and Slate Institute (ESCSI, 2007) some of the advantages of using Haydite LWA include: higher strength and durability of the concrete products, aesthetic value, more feasible design, and improvement in thermal performance. In this study, Haydite size B with a maximum size of 3/8 inch (which was comparable to pea gravel) was acquired from a local hydraulic press brick company.

The conventional concrete materials used as control group were: PC type (I/II), with a 28-day CS at 5.54 ksi; brown sand as fine aggregate (fineness modulus at 2.48); and pea gravel with maximum size at 3/8 inch. Micro Air was used as the air entraining agent (AEA) to increase the air content in the concrete batches.

Application of Artificial Neural Networks (ANN) in Previous Research

ANN is a computational system consisting of simple, highly interconnected processing elements (neurons) that work together to solve specific problems (Caudill, 1987). It is an algorithm inspired by research in biological nervous systems to generate a simplified model of how the brain works (Rumelhart et al. 1994). The first neural network was proposed by two physiologists, Warren McCulloch and Walter Pitts (1943), and since then many other models have been introduced by other researchers. Self-organizing Mapping (SOM), Radial Basis Function (RBF), Multilayer Perceptron (MLP) and Neuro-Fuzzy are among the most commonly used ANN models and have been recently studied by researchers in various fields with high accuracy (Bishop, 2006). Some common learning algorithms employed within these ANN models included backpropagation, reinforcement learning, lazy learning, etc. In recent years, ANN has been extensively used for several purposes, including, but not limited to, estimation, pattern recognition, classification, function approximation, and forecasting.

Applying ANN in solving construction-related problems has become a significant area of research in recent years. For concrete-related research, ANN has been used to predict fresh and hardened properties of concrete products (Alshihri, 2009; Saridemir et al., 2009; Abdeen, 2010; Atici 2011; Khan, 2012). Specifically, Saridemir et al. (2009) employed ANN and fuzzy logic to predict the effect that using ground granulated blast furnace slag would have on the CS of concrete. A comparison between multivariable regression analysis and ANN approaches provided by Atici (2011) identified the effectiveness of these methods for predicting the strength of mineral admixture concrete. Khan (2012) also developed an ANN model for predicting several properties of high performance concrete, including CS, tensile strength, gas permeability and chlorination penetration values. ANN has proven to be effective on the prediction of properties of locally produced LWA concrete (Abdeen, 2010) and structural lightweight concrete (Alshihri, 2009).

Experimental Design and Data Collection

In this study, 36 different batches of concrete were mixed. Each batch contained different substitution rates (SRs) of FA (0%, 20%, 30% or 40% by weight) and Haydite LWA (0%, 33%, 67% or 100% by volume) in addition to the use of different Types (PC or PLC) and quantities of cementitious materials. In this way, the effect of the alternative materials on the CS of "green" concrete can be examined more accurately. Besides these three variables, the actual water-cement (W/C) ratio, sand-cement (S/C) ratio, sand-coarse aggregate (S/CA) ratio, the amount of AEA (ml per Kg of cement) and the concrete curing age were selected as influential variables for the ANN models to be generated. This study also attempted to use the numerical method for input variables. Table 1 shows the range, mean, and standard deviation of the quantity of each raw ingredient used in the experiment.

Table 1: Concrete mixture data set (for one cubic yard or 0.7645 cubic meter of concrete)

Parameter	Min	Max	Mean	StdDev
Age (day)	3.00	90.00	32.00	35.05
Water (Kg)	161.03	161.03	161.03	0.00
PC or PLC (Kg)	173.27	403.70	264.67	78.32
FA (Kg)	0.00	161.48	61.01	55.52
Sand (Kg)	566.99	689.46	587.40	45.96
Pea gravel (Kg)	0.00	573.79	366.86	177.23
Haydite (Kg)	0.00	281.68	101.60	86.97
Micro air (ml)	85.76	103.51	94.64	8.93

All concrete mixed in the experiment was assumed to be air-entrained (intended to be used outdoors in cold climates) by adding AEA into the mixtures and with pea gravel or an LWA of a similar size. The intended slump was 5-6 inches and the air content was 6-7%. Given this information and the selected guideline ACI 211.2 (2004), the amount of water required for each cubic meter of the mixture was calculated to be 210.6 Kg. Concrete was mixed in a laboratory mixer and the whole process of making, pouring and curing concrete was performed based on the ASTM C 31/C 31M – 06 guideline. Three 4-inch-by-8-inch cylinders from each batch of concrete mixture were tested for CS in each of four curing ages of 3, 7, 28 and 90 days. The same was performed for tensile strength.

Modeling with ANN

Figure 1 shows the basic structure of the ANN models created for this study. They consist of an input layer, one or more hidden layers, and an output layer. The symbol "7-3-1" represents 7, 3, and 1 neuron(s) in the input, hidden, and output layers, respectively. Each neuron will receive one or more inputs. The inputs will be multiplied by their weight, and summed together and with the bias (threshold). The weighting and bias values will be initially chosen as random numbers and then adjusted according to the results of the training process (Atici, 2011). The output of each neuron will be generated based on the significance of the summation value and by the means of a predefined specific activation function. Early ANNs generated simple binary outputs in this way, but later it was found that continuous output functions are more flexible. The most common activation functions used by researchers include, but are not limited to, Unipolar Sigmoid Function, Bipolar Sigmoid Function, Hyperbolic Tangent Function, Radial Basis Function, and Conic Section Function (Bishop, 2006).

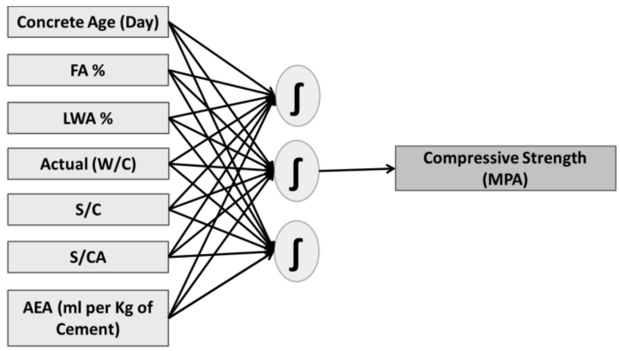


Figure 1: The basic structure of the created ANN models (7-3-1).

This study applied an MLP model to predict the CS of "green" concrete. MLP (Multilayer Perceptron) is a feed-forward neural network developed by Rosenblatt (1958). It is one of the first and most frequently used models in machine learning.

MLP can have one or more hidden layers, depending on the type and complexity of the problem to be solved, although a single hidden layer with a sufficient number of neurons is usually good enough to model many problems. In multi-hidden layer cases, the output from each hidden layer is treated as an input for the next hidden layer. There is no general rule for choosing the number of neurons in the hidden layer. However, it should be large enough to correctly model the problem of interest, but be kept sufficiently low to ensure generalization of the network and to avoid the over-fitting problem (Alshihri, 2009). Some studies related the number of hidden layer neurons to the number of variables in the input and output layers or defined an upper bound for it. However, these rules cannot guarantee the generalizability of the networks (Alshihri, 2009; Atici, 2011). A common way to select the appropriate number of neurons in each hidden layer is to perform a parametric analysis of the network and check the accuracy of the results. The use of a validation set can also help improve the generalization and avoid the over-fitting problem.

In this study, the Weka GUI-based workbench toolbox was used to generate the required MLP model. A feed-forward backpropagation learning algorithm was selected for the optimization of the networks. A unipolar sigmoid function was selected as the activation function. It is a non-linear logistic function, which gives the network flexibility in modeling more complicated relationships. The learning rate of 0.3 and momentum of 0.2 were selected for the purpose of this study. The training process was set for 500 epochs and the validation threshold was defined as 20 times. Results from different neural network structures were evaluated based on three performance measurements: correlation coefficient (R), root mean squared error (RMSE), and mean absolute error (MAE). A 10-fold cross-validation was used to minimize bias associated with the random sampling of the training and holdout data samples. Cross-validation is a practical technique that evaluates the expected accuracy of a predictive model by dividing a dataset into different subsets and evaluating the accuracy of the model for each of those subsets. The final performance of the model will then be calculated based on the average performance of those subsets. This would improve the generalizability and reliability of the performance measurements provided for the model.

In the literature, researchers either selected the relative or numerical method to input the variables for their ANN models in studying the CS of concrete (Saridemir et al., 2009; Alshihri, 2009; Abdeen, 2010; Atici 2011; Khan, 2012). This study examined both methods on the generated ANN models to assess which form of inputs would lead to better results. Specifically, the relative method used W/C ratios, SRs of FA Class F, SRs of Haydite LWA, S/C ratios, S/CA ratios, amount of AEA (ml per Kg of cement), and the curing age of concrete as inputs. The numerical method used the curing age in days; weight (Kg) of water, PC or PLC, FA, sand, pea gravel, and Haydite LWA; and the volume of micro air (ml). This MLP has the CS of concrete (MPa) as the only output.

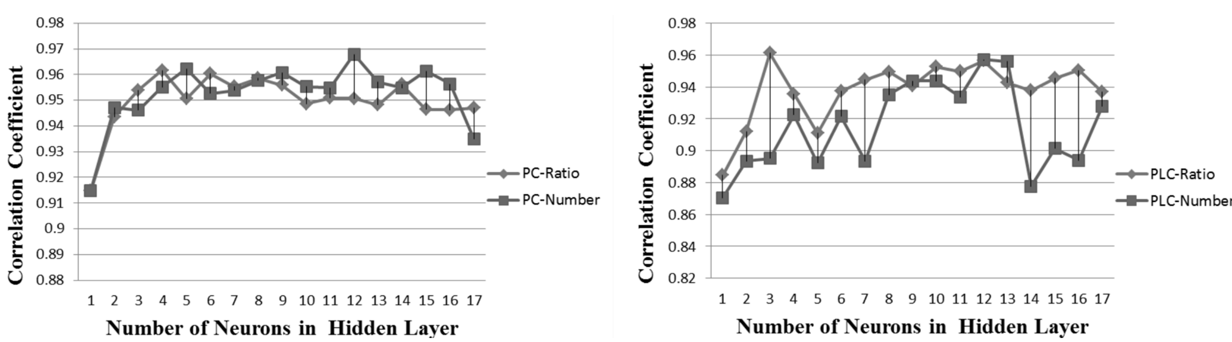
Analytical Results and Discussion

Before starting to model the problem, a simple statistical paired T-Test was performed on the available datasets to determine whether the use of PLC instead of PC has any impact on the CS of concrete. Table 2 shows the result of this paired T-Test, which suggests a significant difference between the average CS of PC and PLC concrete. It shows that with 95% confidence, the average CS of concrete samples made with PLC is 2.76 to 4.36 MPa higher than the average CS of concrete samples made with PC. Because of this difference, the ANN model was trained separately for the dataset of concrete made with PC and PLC.

Table 2: T-Test: Paired Two Sample for Means

Statistical item	CS (MPa) for PLC concrete	CS (MPa) for PC concrete
Mean	37.10912557	33.54779098
Variance	227.6586244	195.3950672
Observations	72	72
Hypothesized mean difference	0	
t Stat	8.857249121	
P(T<=t) one-tail	2.16E-13	
t Critical one-tail	1.666599658	
P(T<=t) two-tail	4.31E-13	
t Critical two-tail	1.993943368	

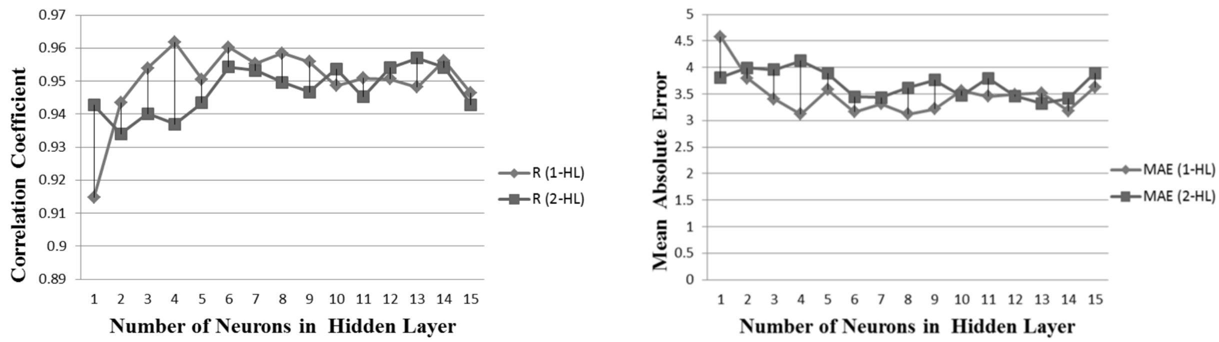
The network was trained several times with different numbers of hidden layers and different numbers of neurons in the hidden layers. The experimental output was compared with the predicted results, by the means of the three previously mentioned performance measurements. Figure 2 illustrates the correlation coefficients of the different ANN models trained for PC or PLC concrete datasets. In Figures 2a and 2b, results associated with the PC-ratio and PLC-ratio were generated based on the relative input method, while PC-Number and PLC-Number represent the results related to the numerical input method. It can be observed in Figure 2a that for PC concrete the numerical input method performs slightly better than the relative method. A maximum R was achieved based on a network with 12 neurons at the hidden layer. On the other hand, Figure 2b shows that for PLC concrete the relative input method gives better correlation and the optimum number of neurons in the hidden layer was 3.



(a) PC-ratio vs. PC-number (b) PLC-ratio vs. PLC-number

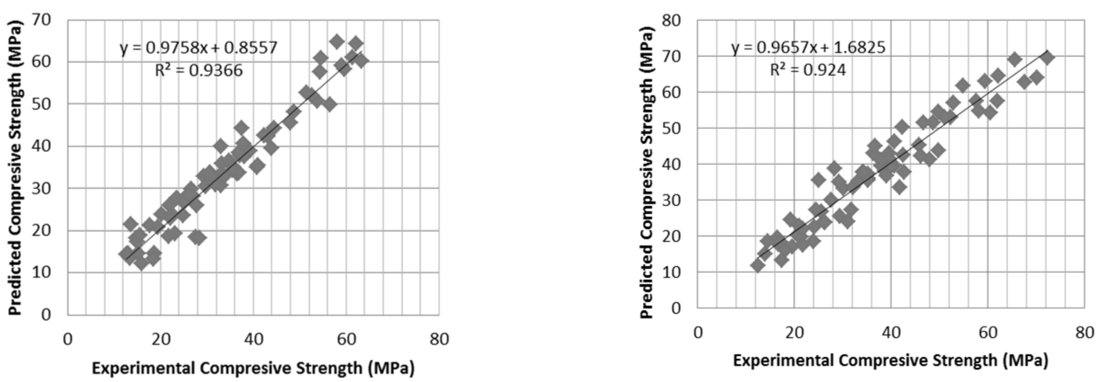
Figure 2: Correlation coefficient (R) trends for the numerical and relative input methods.

Figure 3 shows how R and MAE change between ANN models with one hidden layer (1-HL) and 2 hidden layers (2-HL). The results are for PC concrete and related to the relative input method. Better predictions (less error and higher correlation between the predicted and actual results) were found for the 1-HL MLP models. It is also observed that the optimum result was reached by using 4 neurons at the hidden layer. Figure 4 shows the correlation between the experimental and predicted results for the numerical and relative input methods. The acceptable R-squared of the trend line indicates that the predicted and actual data are fairly close to each other.



(a) Correlation coefficient (R) (b) Mean Absolute Error (MAE)

Figure 3: Prediction performance vs. number of neurons in 1- and 2-HL ANN.



(a) For PC-number (b) For PLC-ratio

Figure 4: Correlation between predicted and actual results for the two input methods.

Table 3 below presents a summary of the performance measurements achieved by the suggested ANN models for PC and PLC concrete. Inputs and structures for the networks are also presented in this table. All results are based on cross-validation analysis. The validation set was also used in line with the training and test sets to decrease the probability of the over-fitting problem.

Table 3: Performance results for the generated ANN models

Database	Input variable	No. of optimum neurons in the HL	R	RMSE	MAE
PC-Ratio	Age - FA - HLWA - S/C - S/CA - AEA - W/C	(7-4-1)	0.9617	3.8167	3.1194
PC-Number	Age - PC - FA - HLWA - PG - S - AEA - W	(8-12-1)	0.9678	3.5418	2.7553
PLC-Ratio	Age - FA - HLWA - S/C - S/CA - AEA - W/C	(7-3-1)	0.9612	4.202	3.4335
PLC-Number	Age - PC - FA - HLWA - PG - S - AEA - W	(8-12-1)	0.9573	3.6474	4.5515

To avoid the multicollinearity problem, the seven input attributes were analyzed. The Weka Attribute Selector result suggested that for the relative input method, a subset of concrete curing age, FA, LWA, S/C and S/CA can give the best merit for this problem. The correlation analysis between the seven input variables revealed that, except for concrete curing age, FA, and LWA, other attributes of the model have some level of correlation with each other. An F-Test also confirmed this correlation. On the other hand, a Stepwise Analysis suggested that eliminating correlated attributes would not affect the performance of the models, especially since a 10-fold cross-validation test had been used to estimate the networks' performance.

In response to these correlations, and the need to eliminate the multicollinearity problem, six new different network structures were defined in this study. Table 4 shows the structure and the results of performance analysis for each of the six ANN models. The results suggested that there is not a significant performance loss due to the elimination of the input attributes. It is worth noting that these analyses were only based on the results of the experiments performed in this study to determine the effects of the selected alternative materials on the CS of "green" concrete. As a result, eliminating any of the other variables could reduce the generalizability of the model and is, therefore, not recommended.

Table 4: Performance results for the six new neural networks

Database	Input Variable	No. of optimum neurons in the HL	R	RMSE	MAE
PC-Ratio	Age - FA - HLWA - S/C	(4-4-1)	0.9614	3.8721	3.1169
PC-Number	Age - PC - FA - PG	(4-9-1)	0.9641	3.767	2.9479
PC-Number	Age - PC - FA - HLWA	(4-9-1)	0.9646	3.7397	2.9841
PLC-Ratio	Age - FA - HLWA - S/C	(4-8-1)	0.9554	4.5052	3.5321
PLC-Number	Age - PLC - FA - PG	(4-8-1)	0.9542	4.6015	3.7758
PLC-Number	Age - PLC - FA - HLWA	(4-9-1)	0.9514	4.7021	3.7406

Conclusions

This paper evaluated the application of ANN to predict the CS of "green" concrete made with FA, PLC and Haydite LWA. The generated MLP models were tested separately for PC and PLC concrete to improve their accuracy. Moreover, the different input methods (numerical and relative) were investigated for the created ANN models. The results showed that MLP is a useful tool for predicting the CS of the studied types of concrete. It is efficient enough for both input methods although the numerical method has a small advantage for PC concrete and the relative method is slightly better for PLC concrete. It was also concluded that 1-HL MLP models provide better accuracy for the prediction of the CS compared to the 2-HL MLP models, although the number of optimum neurons in the hidden layer could vary depending on the type and number of the inputs. The paper also analyzed the significance of the input variables and the correlation between them. Results showed that an MLP with four independent input variables and the proper number of neurons in the hidden layer could eliminate the multicollinearity problem between variables and still be accurate enough to predict the CS of concrete, even though it is not recommended.

The scope of this research was limited to predicting the CS of "green" concrete studied, but it could be expanded to the other properties of "green" concrete such as tensile strength, durability or concrete slump. Moreover, there are several other ANN models that can be evaluated, which could also be a topic for future research.

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