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Neural networks for predicting compressive strength of structural light weight concrete

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ABSTRACT

Neural networks procedures provide a reliant analysis in several science and technology fields. Neural network is often applied to develop statistical models for intrinsically non-linear systems because neural networks behave the advantages of simulating complex behavior of many problems. In this investigation, the neural networks (NNs) are used to predict the compressive strength of light weight concrete (LWC) mixtures after 3, 7, 14, and 28 days of curing. Two models namely, feed-forward back propagation (BP) and cascade correlation (CC), were used. The compressive strength was modeled as a function of eight variables: sand, water/cement ratio, light weight fine aggregate, light weight coarse aggregate, silica fume used in solution, silica fume used in addition to cement, superplasticizer, and curing period. It is concluded that the CC neural network model predicated slightly accurate results and learned very quickly as compared to the BP procedure. The finding of this study indicated that the neural networks models are sufficient tools for estimating the compressive strength of LWC. This undoubtedly will reduce the cost and save time in this class of problems.

1. Introduction

Lightweight aggregates are broadly classified in to two types: natural (pumice, diatomite, volcanic cinders, etc.) and artificial (perlite, expanded shale, clay, slate, sintered PFA, etc.). Lightweight aggregates can be used to produce low density concretes required for building applications like cladding panels, curtain walls, composite flooring systems, and load-bearing concrete blocks [1,2].

Structural lightweight concrete has its obvious advantages of higher strength to weight ratio, better tensile strain capacity, lower coefficient of thermal expansion, and superior heat and sound insulation characteristics due to air voids in the lightweight aggregate. Also the reduction in the dead weight of the construction materials, by the use of lightweight aggregate in concrete, could result in a decrease in cross-section of concrete structural elements (columns, beams, plates, and foundation). It is also possible to reduce steel reinforcement [3,4].

Most of the mathematical models used to study the behavior of concrete mixes consist of mathematical rules and expressions that capture relationship between components of concrete mixes. By the way, using mathematical models to take and describe experiences from experimental data of concrete mixes behaviors are most reliable, accurate, scientific, and applicable recommended methods. Mathematical models based on experimental data are called "free models", and generally are in regression forms. However, if the problem contains many independent variables, regression methods cannot be used because of less accuracy and more assumptions in regression form (linear, non-linear, exponential, etc.). In the recent years, new modeling techniques such as artificial neural networks, expert systems as a free model can approximate non-linear and complex relation due to any phenomena and trial and error process by learning real record relationship without any presumptions [5,6].

Free from such limitations, The NN approach (a class of soft computing techniques), has been used recently in predictive models for the field of materials engineering [7–19] because of their specific features such as non-linearity, adaptively (i.e., learning from inputs parameters), generalization, and model independence (no priori models needed).

The present study is aimed to evaluate NN models for prediction of 3, 7, 14, and 28 days compressive strength of a LWC mixtures.

2. Materials and methods

2.1. Data (mix design) collocation

The main objective of this study is developing a neural network model to predict the compressive strength of LWC. For this aim, at first it is needed to prepare data and construct data base for training and testing the neural network model.

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The present study covers the use of crushed hollow block as lightweight coarse aggregate in concrete containing silica fume as supplementary cementations materials at different levels namely: 0%, 5%, 10%, and 15% as an addition to cement. The crushed hollow block aggregate was treated by solution of silica fume and calcium hydroxide (the concentration of silica fume is 10% and 20% and that of calcium hydroxide is 1%). The performance of lightweight concrete made with crushed hollow block as coarse aggregate was studied in terms of compressive strengths for 3, 7, 14, and 28 days. The main variables, experimental program, are described and reported in Table 1.

Mix proportions of concrete were designed to select suitable materials (cement, fine aggregate, coarse aggregate, water, etc.) and determine the quantities of these ingredients for meeting the desired compressive strength. The economy and performance characteristics of the concrete product, thus depends on the proportioning of theses ingredients. The procedures adopted for mix proportioning are still empirical in spite of a considerable amount of work done on the theoretical aspects of mix proportioning of normal weight and lightweight concretes.

2.2. Material properties

Crushed hollow block was used as lightweight aggregate. In this investigation, blocks were broken manually. ASTM D-75 and ASTM C-136 and C-29 were used for sampling, grading, unit weight, and fineness modulus of aggregate. Maximum aggregate size was 10 mm. The fine aggregate was confirmed to ASTM C-33 requirements.

A locally produced ordinary Portland cement was used in this investigation. The cement content weighed for about 450, 400, and 350 kg/m^3, respectively. The water has been used for mixing and curing of all concrete mixes and specimen's was clean, fresh, and free from any impurities.

Silica fume is a fine powder which acts as a microscopic concrete pore filler. It is based on a chloride free pozzolanic material consisting of over 90% silicon dioxide. Its addition to the cement mix will yield a concrete especially able to cope with the middle eastern environment. The physical and chemical properties of the silica fume used in this investigation are reported in Tables 2 and 3, respectively.

Superplasticizer is a chloride free, superplasticing admixture based on selected sulphonated naphthalene polymers. It is supplied as a brown solution which instantly disperses in water. Superplasticizer disperses the fine particles in the concrete mix, enabling the water content of the concrete to perform more effectively. The very high levels of water reduction possibly allow major increases in strength that is to be obtained. It was added with dosage 1%, 2%, 3%, and 4% by weight of cement.

The concrete specimens were $150 \times 150 \times 150$ mm ($6 \times 6 \times 6$ in.) cubes to determine the compressive strength of the above mentioned lightweight aggregate concrete. All specimens were immersed in water tank for 24 h after casting (after finishing initial setting time) to complete hydration reaction through different periods of time. These curing periods of time are 3, 7, 14, and 28 days. At the end of curing period, the specimens were removed from water tank and placed it to dry and were left it under the sun rays for at least 6 h and, then tested. Compressive strength tests were performed by universal testing machine, equipment that measures the compressive and splitting bending strengths directly according to the ASTM specifications ASTM C-39.

2.3. Model induction from experimental data

A neural network consists of many simple elements called neurons which are grouped together in layers. A neuron has many inputs and a single output. Each input has a coefficient, referred to as a weight, assigned to it. A neuron works in the following way: inputs of the neuron are multiplied by the corresponding weights. The product is then summed together and applied to a transfer function, to form the output. This can be expressed using the following equation:

$$z = f\left(\sum_{i=1}^{n} w_i x_i + d\right) \tag{1}$$

where z is the output from neuron; $x_1, x_2, \ldots, x_n$ are the input values; $w_1, w_2, \ldots, w_n$ are the connection weights; d is the bias value; and f is the activation function.

Artificial neural network can be visualized as a set of interconnected neurons arranged in layers. The input layer contains one neuron for each of the input variables. In multi layer network, the output of one layer constitutes the input to the next layer. For example, in the ANN architecture shown in Fig. 1, this is called feed-forward type of network where computations proceed along the forward direction only. The neural network has one input layer, one output layer, and two hidden layers. The output obtained from the output neurons constitutes the network output.

The connection weights and bias values are initially chosen as a random numbers and then fixed by the results of training processes. Many alternative training processes are available namely back propagation (BP) and cascade correlation (CC) schemes. The goal of any training algorithm is to minimize the mean square error (MSE) between predicted outputs and observed outputs (in the training dataset) and maintaining good generality of the networks. The generality (network performance) is assessed by testing a new dataset. A reasonably good learning process can be achieved by choosing an appropriate network configuration with regard to the number of hidden layers and their hidden neurons.

2.3.1. Back propagation algorithm

The back propagation learning is an iterated search process which adjusts the weights from output layer back to input layer in each run until no further improvement in MSE value is found. The BP algorithm calculates the error, and then used to adjust the weights first in the output layer, and then distributes it backward from the output to hidden and input nodes (Fig. 2). This is done using the steepest gradient descent principle where the change in weight is directed towards negative of the error gradient, i.e.

$$\Delta w_n = \alpha \Delta w_{n-1} - \eta \frac{\partial E}{\partial w} \tag{2}$$

where w is the weight between any two nodes; Δw_n and Δw_{n-1} are the changes in this weight at n and $n-1$ iteration; α the momentum factor; and η is the learning rate.

After training is completed, the final connection weights are kept fixed, and new input patterns are presented to the network to produce the corresponding output consistent with the internal representation of the input/output mapping.

2.3.1.1. Topology of the BPNN. Every stage of any NN project requires a little trial and error to establish a suitable and stable network for the project. Trial and error may be extended to building several networks, stopping, and testing the network at different stages of learning and initializing the network with different random weights. Each network must be tested, analyzed and the most appropriate network must be chosen for a particular project.

Before deciding on the topology of the network, it is important to select the required number of input and output parameters. The function of the hidden layer neurons is to detect relationships between network inputs and outputs. There is

Table 1
Mix proportions.

Sand replacement (%)	Cement (kg)	Water (kg)	Light weight coarse aggregate (kg)	Light weight fine aggregate (kg)	Normal weight fine aggregate (kg)	Silica fume	
						Used in solution	Used in addition to cement
a. Cement content = 450 kg/m^3							
0%	29.250	19.013	21.571	33.786	0	1.901	2.925
25%	29.250	19.013	21.571	25.340	12.995	1.901	2.925
50%	29.250	19.013	21.571	16.893	25.989	1.901	2.925
75%	29.250	19.013	21.571	8.447	38.984	1.901	2.925
b. Cement content = 400 kg/m^3							
0%	26.325	17.112	21.571	33.786	0	1.711	2.632
25%	26.325	17.112	21.571	25.34	12.995	1.711	2.632
50%	26.325	17.112	21.571	16.893	25.989	1.711	2.632
75%	26.325	17.112	21.571	8.447	38.984	1.711	2.632
c. Cement content = 350 kg/m^3							
0%	23.034	14.972	21.571	33.786	0	1.711	2.303
25%	23.034	14.972	21.571	25.34	12.995	1.711	2.303
50%	23.034	14.972	21.571	16.893	25.989	1.711	2.303
75%	23.034	14.972	21.571	8.447	38.984	1.711	2.303

Mix A: contains first five columns; Mix B: contains first six columns; Mix C contains all seven columns.