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Prediction of compressive strength of concrete containing construction and demolition waste using artificial neural networks

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HIGHLIGHTS

- ▶ The concrete uses aggregates from construction and demolition waste.
- ▶ The ANN was used to construct an equation for predicting the compressive strength.
- ▶ The compressive strength is predicted at 3, 7, 28 and 91 days.
- ▶ The results show the potential of using ANN for predicting the compressive strength.

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ABSTRACT

In this study Artificial Neural Networks (ANNs) models were developed for predicting the compressive strength, at the age of 3, 7, 28 and 91 days, of concretes containing Construction and Demolition Waste (CDW). The experimental results used to construct the models were gathered from literature. A total of 1178 data was used for modeling ANN, 77.76% in the training phase, and 22.24% in the testing phase. To construct the model, 17 input parameters were used to achieve one output parameter, referred to as the compressive strength of concrete containing CDW. The results obtained in both, the training and testing phases strongly show the potential use of ANN to predict 3, 7, 28 and 91 days compressive strength of concretes containing CDW.

1. Introduction

Currently, there is an environmental concern in relation to the scarcity of natural resources, and an emerging tendency to reduce this impact. The use of construction and demolition waste (CDW), as replacement of natural resources, can decrease the extraction of natural materials and thus preserve the environment. The use of CDW in the production of concrete for building and infrastructure construction and other engineering works is a way of recycling this material. This waste represents a significant percentage of the solid waste generated in urban areas and its destination must be properly determined, according to Conama Resolution 307 (Brazilian Law) [1].

Several researches have been developed with the aim of studying the influence of CDW on concrete properties such as compressive strength [2–6]. However, recycled aggregates have a very heterogeneous composition, since they are made of mortar, concrete, ceramic brick and blocks, natural stone and other materials. According to Lima [7], the CDW's variability represents a limitation to its use in construction, because the composition varies for each region, and the same studies cannot be applied.

In order to improve these studies, reducing the amount of material, testing, time and cost, models based on experimental data can predict with an acceptable error range, the influence of CDW aggregate in the concrete behavior. Some of these models are based on artificial neural networks (ANN), which is an artificial intelligence technique that can be applied to tasks where there is a database of a problem and the ANN model learns by example. According to Braga [8], modeling is performed through the use of input and output variables, without many restrictions on the amount of input.

The ANN model is a powerful tool that gives viable solutions to problems which are difficult to solve by through conventional techniques such as multiple regression models, not invalidating these existing techniques [9].

Some studies have been published, showing that ANN can model complex and nonlinear relationships between parameters affecting the compressive strength of concrete [10–17], the compressive strength of high strength concrete [18], the compressive strength

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of concrete containing fly ash and/or silica [19–22], the compressive strength of concrete containing granulated blast furnace slag [23], and the compressive strength of high performance concrete [24].

As Snell, apud Hong-Guang and Ji-Zong [10], conventional methods for predicting the compressive strength of concrete are mainly based on statistical analysis, through which the linear and nonlinear regression equations are built for forecasting. However, the choice of an appropriate regression equation involves technique and experience, besides not being a simple task.

The purpose of this study is to evaluate the potential of artificial neural networks to concatenate a large amount of experimental data obtained from literature and predict the compressive strength of concrete containing CDW.

2. Artificial neural networks

The study of artificial neural networks was inspired on the study of biological neural networks, and the ANN model resulted in a powerful tool for applications in data mining [20].

Artificial neural networks are parallel and distributed systems, composed of simple processing units, the artificial neurons, which calculate specific mathematical functions, similar to the structure of the human brain, allowing a performance superior to that of conventional models [8].

According to Haykin [25], in an artificial neural network, the neuron is the unit of information processing, which consists of:

- A signal x_m in a synapse's input m connected to neuron k is multiplied by synaptic weights w_{km}.
- An adder to sum the inputs, weighted by the respective neuron's synapses, in which the transactions constitute a linear combiner.
- An activation function $f(\cdot)$, to restrict the amplitude of the output of a neuron. The range of normalized output amplitude can be $[0,1]$ or alternatively $[-1,1]$.
- Bias, applied externally, represented by b_k, whose function is to increase or decrease the influence of the activation function.

Fig. 1 illustrates how information is processed through a single neuron.

Mathematically, a neuron k can be described by the following equation:

$$u_k = \Sigma w_{km} \times x_m \tag{1}$$

and

$$y_k = f(u_k + b_k) \tag{2}$$

where $x_1, x_2, \ldots x_m$ are inputs; $w_{k1}, w_{k2}, \ldots w_{km}$ are synaptic weights of euron k; u_k is the linear combiner output due to inputs; b_k is the bias; $f(u_k + b_k)$ is the activation function; y_k is the output.

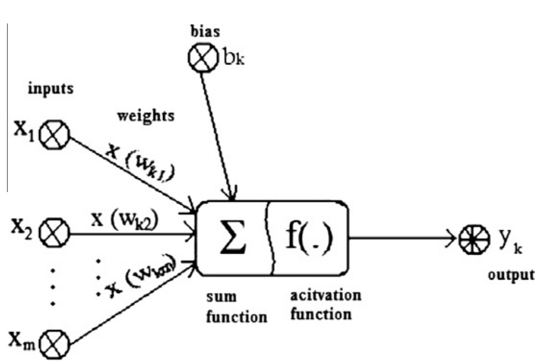

Fig. 1. Schematic Artificial Neuron as described by Haykin [25].

According to Topçu [20], the activation function is a function that processes input obtained with the sum function and determines the output of the neuron. In general, in multilayer models, the hyperbolic tangent function is the most used activation function. Using this, the output neuron is calculated with the aid of Eq. (3).

$$y_k = f(u_k + b_k) = tgh[\alpha \cdot (u_k + b_k)] \tag{3}$$

where α is the constant used to control the slope of the semi-linear curve. The hyperbolic tangent function represented by Eq. (3) adjusts results on the interval $[-1, 1]$.

There is also a linear function, which, according to Nascimento Jr. and Yoneyama [27], is the simplest computational unit, where the bias can be interpreted as another weight coming from a unit whose output is always 1, represented by the following equation:

$$y_k = f(u_k + b_k) = \alpha \cdot (u_k + b_k) \tag{4}$$

The network architecture and the information flow are defined in the modeling of ANN. Neural networks might be single layer or multilayer [16]. ANN architecture presents an input layer, showing or not hidden layers, and an output layer.

Regarding the information flow, it is known that the network structure corresponds to a feed forward network, i.e. outputs depend only on current inputs [8].

The neural network model that uses multilayer architecture and presents feed forward information flow is one of the neural network models most commonly used. Its application might be extended to almost all areas [10,28].

The neural network has two processing stages: training and testing, which represent very different times of operation and are applied at different moments of the analyses [9].

A modification of the weights is obtained using an appropriate method of training [28]. The most popular methods of training are supervised methods, which use, as an algorithm, the delta rule and its generalization to multilayer networks, which is the back propagation algorithm [8]. The back propagation algorithm is a gradient descent technique to minimize the error for a specific training pattern, through adjustments of the weights by a small amount at a time [18,19,22,28]. The weights before training are random and have no meaning, but after training might contain significant information [28]. They represent the degree of influence that each input variable shows with respect to the output variable.

The testing process is the way the network answers to an input without changes in the structure [9].

3. Neural network model

The experimental data used in this work were collected in researches from Leite [2], Vieira [3], Cabral [4], Lovato [5] and Lima [6]. These studies were chosen because they present a complete set of information about materials properties, as well as, mix design parameters.

At the beginning, 24 input variables were divided into four groups, as can be seen in Table 1. After performing a Principal Component Analysis (PCA), the input variables were chosen based on the cumulated explained variance. Then, 24 input variables were limited to 17. This procedure is known as dimensionality reduction of the ANN input vector. In this procedure, the amount of input variables can be limited to the amount of variables associated with a cumulated explained variance immediately above 70%. In this case, even when some variables explained small variance, they were considered in order to obtain approximately 98% of cumulated explained variance.

It should be considered that some variables with small variance were chosen considering technical aspects not only statistical ones.