Prediction of compression strength of high performance concrete using artificial neural networks.

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Abstract. High-strength concrete is undoubtedly one of the most innovative materials in construction. Its manufacture is simple and is carried out starting from essential components (water, cement, fine and aggregates) and a number of additives. Their proportions have a high influence on the final strength of the product. This relations do not seem to follow a mathematical formula and yet their knowledge is crucial to optimize the quantities of raw materials used in the manufacture of concrete. Of all mechanical properties, concrete compressive strength at 28 days is most often used for quality control. Therefore, it would be important to have a tool to numerically model such relationships, even before processing. In this aspect, artificial neural networks have proven to be a powerful modeling tool especially when obtaining a result with higher reliability than knowledge of the relationships between the variables involved in the process. This research has designed an artificial neural network to model the compressive strength of concrete based on their manufacturing parameters, obtaining correlations of the order of 0.94.

1. Introduction

High-strength concrete (CAR) is, nowadays, one of the most used construction material among those used worldwide. Manufacture from a number of basic components water, cement, aggregates (fine and coarse) and adding a number of additives, whose proportions largely determine their future mechanical properties. Of all compressive strength at 28 days is the most commonly used for quality control [1].

Since early twentieth century empirical model have been developed by various different authors that relate those parameters with final strength [1-5]. However, correlations obtained generally are rather low.

Artificial neural networks (ANNs) are known as a powerful modeling tools specially when is more important to obtain a highly reliable result from initial data than to know the relationship between the variables involved [6]. ANNs are a mathematical structure that attempts to imitate the functioning of a biological brain. Multilayer perceptron is the most used type of ANN. Its nature as universal aproximator [7] makes it a very useful tool to model and control industrial processes where
traditional modeling techniques are not reliable [8]. Multilayer perceptron is made up of several nodes or neurons grouped in three layers named input layer, hidden layer and output layer (Figure 1). The main problem is that there is no set rule as to how many neurons the hidden layer should include or whether it should include a single or more than one sublayer. The input and output layers have as many neurons as the dimension of the input and output vectors. However, the only way to configure the hidden layer is by trial and error [9].

![Figure 1. Scheme of a multilayer perceptron.](image)

These structures have been widely used in fields ranging from structural wood based panels [10] to alloys [11] and concrete [3,4]

The aim of this study was to develop a multilayer perceptron artificial neural network in order to obtain the compression resistance of concrete by means of its manufacturing parameters.

2. Material and methods
This study used 296 manufactured concrete specimens with different types and quantities of cement, sand, and additives. Test pieces for compression test were made according to ASTM C 192 / C 192M [12] standards. Compression tests were performed according to ASTM C39 / C 39M [13] standards after different periods of curing.

Axial compression tests were performed on a machine: TECHNIK TONI with a 3.000KN cell and TINIUS OLSEN with 1.500KN cell. Of each specimen data input variables were the quantity of cement, amount of sand, cementitious microsilica and curing period. As output variable, resistance to compression was taken. Amount of water (186 l/m³), stone (1066.2 kgf/m³), fineness modules of sand (2.88) and stone(6.5), nominal maximum size of the stone (1) and specific gravity of stone (2.7 t/m³) and sand (2.7 t/m³) were maintained constant.

In order to obtain an optimal curing process, specimens were fully submerged in water pools throughout the process.

A principal components analysis was carried out before developing the multilayer perceptron in order to detect any possible correlations among the input variables. Variables that contribute more than 2% to the variability of the sample were selected [14].
Hyperbolic tangent sigmoid function (Eq. 1) was used as transfer function. This is equivalent to the hyperbolic tangent function and also improves network performance by producing a faster output.

\[ f(\theta) = \frac{2}{1 + e^{-(2\theta)}} - 1 \]  

(1)

\( f(\theta) \): Output value of the neuron; \( \theta \): Input value of the neuron.

To improve the generalizing ability of the ANNs, input data were normalized [14] in accordance with Eq. 2.

\[ \theta' = \frac{\theta - \theta_{\min}}{\theta_{\max} - \theta_{\min}} \]  

(2)

\( \theta' \): Value after normalization of vector \( X \); \( \theta_{\max} \) and \( \theta_{\min} \): maximum and minimum values of vector \( X \).

To avoid overfitting, which decreases ANN modeling capacity, the early-stopping method was used. For this propose the global set of data was divided in three auxiliary sets: training set with 164 data, validation set with 46 data and testing set with 57 data. The first two sets were used while the development of the ANN and to avoid over-fitting. The test set was used to evaluate the degree of performance of the ANN avoiding any bias introduced by the groups of training and validation [15].

The network creation process was developed through a specific MATLAB® programme which applies automatically a principal component analysis to improve the learning process even when there are few input variables and successively increases the number of neurons in the inner sublayers and compares the results obtained in the training and validation sets every 100 training epochs. Around 20,000 neural nets were evaluated.

To evaluate the outcome a regression coefficient (\( r \)), the coefficient of determination (\( r^2 \)), root mean square error (RMSE) were used.

### 3. Results and Discussion

Table 1 shows input variables and test results obtained in this study.

| Variable | Water (l/m³) | Mf₁ | Mf₂ | TNM | Stone (kgf/m³) | PEₗ (t/m³) | PEₚ (t/m³) |
|----------|--------------|-----|-----|-----|----------------|-------------|-------------|
| Value    | 186.4        | 2.87| 6.5 | 1   | 1066.2         | 2.7         | 2.7         |

| Property | Cement (kg/m³) | Sand (kg/m³) | % cementitious | % microsilica | E_{ens} (days) | R (kgf/cm²) |
|----------|----------------|---------------|----------------|---------------|----------------|--------------|
| Mean     | 632.5          | 376.2         | 2.1            | 7.2           | -              | 752.3        |
| Std. Dev.| 63.3           | 82.3          | 0.3            | 2.1           | -              | 95.8         |
| Min.     | 506.0          | 282.5         | 1.6            | 5             | 7              | 565          |
| Max.     | 708.3          | 546.9         | 2.5            | 10            | 56             | 1022         |
The principal components analysis showed a contribution level to the variability of the samples superior to 2% for each variable.

The best ANN obtained was a multilayer perceptron of three hidden sublayers of 7, 7 and 5 neurons each.

The results of the process of training, validation and testing are given in the following table (Table 2).

| Net  | Set    | $r$  | $r^2$ | Equation  | RMSE |
|------|--------|------|-------|-----------|------|
| Perceptron [5 7 7 5 1] | Training | 0.92 | 0.84  | $y=1.12\cdot x-78.1$ | 36.6 |
|      | Validation | 0.94 | 0.89  | $y=0.86\cdot x+106.1$ | 32.5 |
|      | Testing   | 0.91 | 0.82  | $y=0.71\cdot x+198.2$ | 34.6 |

Figure 2 shows the correlation between observed values and results obtained by the ANN for the testing set.

The coefficients of determination obtained in the test set indicate that the developed model fails to explain at least 82% of the variability of the samples.

There is not much works about the use of ANN in concrete properties modelling, and even less in CAR properties. Results obtained during the development of the network, with correlation coefficients between 0.90 and 0.94, are consistent with those obtained by other authors consulted, which obtained correlation coefficients between 0.81 and 0.98 [16-21].
Similarly, coefficients of determination obtained ($r^2 = 0.82$, $r^2 = 0.84$ and $r^2 = 0.88$) are higher than those obtained by Yeh [3] and similar to those obtained by Ozturan et al. [4] which were maximum of 0.78.

Yeh [3] and Ozturan et al. [4] also modelled concrete strength by means of regression models. However lower values were obtained in those studies. Thus, for these models, Yeh [3] obtained coefficients of determination between 0.46 and 0.89 and Ozturan et al. [4] obtained coefficients of determination between 0.55 and 0.79.

4. Conclusions

These results make ANN capable of being used to improve in-factory control quality as they predict the final resistance with high accuracy and opens up a new area of application for ANNs in the field of concrete by applying neural networks to CARs for the first time.

5. Recognitions / Acknowledgments

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