DOI: 10.48011/asba.v2i1.1073

Computational intelligence applied in the prediction of the compressive strength of Portland cement concrete

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Abstract: Concrete is one of the most widely used building materials, being composed of different components with different properties, which makes the task of dosing and strength determination complex. Artificial Neural Networks is a tool that has the ability to generalize and learn from previous experiences that are provided by a previously built database. This work aims the implementation of RNA in determining the compressive strength of concrete of various ages. The input data is the material quantities and the output is the compressive strength. The results obtained are promising and advantageous from the point of civil engineering, since the average correlation coefficient obtained was 0.96559, with the neural network showing agility and a low error rate in the inserted context, with an efficiency of approximately 95%.

Resumo: O concreto é um dos materiais de construção civil mais utilizados, sendo composto de diferentes componentes com diversas propriedades, o que torna a tarefa de dosagem e determinação da resistência complexas. As Redes Neurais Artificiais (RNA) são ferramentas que possuem a capacidade de generalização e aprendizado a partir de experiências anteriores que são fornecidas por um banco de dados previamente construído. Este trabalho tem como objetivo a implementação de RNA na determinação da resistência a compressão do concreto de várias idades. Os dados de entrada são as quantidades dos materiais e a saída é a resistência à compressão. Os resultados obtidos são promissores e vantajosos do ponto da engenharia civil, uma vez que o coeficiente de correlação médio obtido foi de 0,96559, sendo a rede neural apresentou agilidade e baixa taxa de erros no contexto inserido, com eficiência aproximada de 95%.

Keywords: Concrete; Compressive strength; Artificial neural networks; Dosing; Determination.

Palavras-chaves: Concreto; Resistência à compressão; Redes neurais artificiais; Dosagem; Determinação.

1. INTRODUCTION

Concrete is a structural material used in the construction of houses, buildings, stadiums, bridges, viaducts, tunnels, containment structures, power generation plants, ports, airports, among other works of fundamental importance for the good functioning of society, the that makes this material one of the most important and used by humanity.

Concrete is characterized by heterogeneity due to the fact that it is composed by the union of several components. Basically it is composed of Portland cement, which together with water acts as a binder for aggregates that are subdivided into coarse aggregates (gravel) and fine aggregates (sand).

Moretti (2010) stated that the concrete is heterogeneous and that the mathematical description of this material falls into non-linearity. Its behavior is sensitive to several factors and the generalization and scope of the dosage methods and determination of the compressive strength of this material is difficult. This task falls on previous laboratory experiments that take into account the type of cement and the technical characteristics of the aggregates used. In routine practice, regional materials are used and their successive experiments are conditioned to very representative diagrams. Eventually, new chemical elements and additives are added to the mixture, which enhance their properties both in the fresh and in the hardened state and do not compromise the accuracy of the diagrams commonly used for dosing and predicting the compressive strength of the material.

Colombo et al. (2013) stated that the durability of concrete is a fundamental factor, considering that it depends on the mixture of the components, the consistency, the slump and the curing time. In this mixture, it is necessary for the paste composed of Portland cement and water to present good hydration to obtain an increase in durability.

Younis and Pilakoutas (2013) reported that it is important for concrete to contain coarse porous aggregates to house fine particles, which improves their packaging when filling empty spaces. It is important to pay attention to the material's microstructure, in view of the fact that small aggregates harbor greater water absorption when compared to coarse aggregates. This, when in contact with the mortar cement particles, results in denser and beneficial structures the diffusion of fine cement grains with the outermost layers of the coarse aggregates.

There are several methods for dosing concrete as well as for determining its resistance to compression according to the constituent materials, among which one can mention the one proposed by the American Concrete Institute (ACI) and that of the Brazilian Portland Cement Association (ABCP). Despite the existence of so many methods, none of them can provide a trace (proportion of materials) that does not require experimental adjustment. After obtaining the proportion of the materials that make up the concrete, it is necessary to prepare an experimental mixture and perform its compression test to verify that the desired properties have been achieved, and some corrections in the proportion of the mixture are normally necessary (OLIVEIRA et al. (2007).

The basic principle of operation of an artificial neuron is illustrated by Figure 1 and begins with the presentation of the standardized inputs that are multiplied by their respective weights, in addition to the bias that is an input, always +1 value which is also multiplied by your weight. The results of these operations are summed up and later undergo a function called activation, which introduces non-linearity and provides the neuron's output. An artificial neural network is composed of several units (artificial neurons) that perform a single simple processing, but the set of units that form the network is capable of solving complex problems. Its use for determining the mix strength and compressive strength of concrete can be very promising. ANNs are widely used in several areas of science, including engineering, in view of their ability to learn from previous experiences and generate solutions for new samples of a given problem.

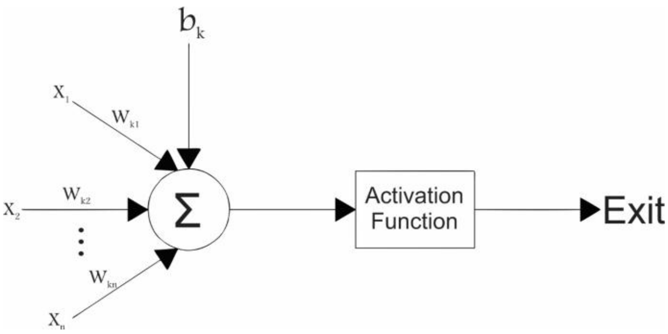

Fig. 1 Artificial neuron.

Using the ability to generalize the ANN, using a pre-existing database that is adequate and consistent with the problem, it is possible to solve complex and non-linear problems such as the dosage of concrete with acceptable errors (AKPINAR et al.; BEHNOOD et al.; NIKBIN et al, 2017; ACUÑA et al., 2014). Arora, Singh and Bhardwaj (2019), in addition to implementing RNA in determining the strength of recycled concrete, made a comparison with Random Forests, which is a learning machine algorithm. The ANN, proposed by him, proved to be a little more efficient than the other technique studied.

For self-compacting concretes, there are studies that implement RNA, both for traditional self-compacting mixtures, and for others that used fly ash, ash from industrial waste incineration and silica fume to partially replace cement in concrete. These researches obtained excellent results with the implementation of RNA to capture non-linear interactions between the various parameters that are added in self-compacting concrete and are not present in conventional concretes, which further raises the dosage task (BEHNOOD et al., 2018; YAMAN et al., 2017; SIDDIQUE et al., 2011).

The objective of the present work is to verify several models and arrive at an artificial neural network that is capable of presenting the compressive strength of the concrete with the least possible error, based on the input data that are the constituent materials of the concrete at different ages. of cure. A database obtained from the existing literature was used to implement the RNA technique in predicting the compressive strength of concrete. The objective of the work was also just to verify the viability of using RNAs to predict the compressive strength of concrete, analyzing whether RNA's are viable and can achieve generalization for this specific type of problem. With the data provided by Prof. I-Cheng Yeh, the work is not concrete production for later application of RNA, this may be addressed in future work.

This work was divided into the following structures: Chapter 1 - Introduction covering the main definitions of literary basis for understanding the scope of the work developed. Chapter 2 - Material and Methods, in which it addresses the quantitative and database used in the project. Chapter 3 - Results and Discussion, in which comments on the comparative advantages of the implemented method are discussed. Chapter 4 - Conclusion, in which he emphasizes the reason for the rise of RNAs in the context addressed.

2. MATERIAL AND METHODS

The data used by I-Cheng Yeh (1998) are composed of 1030 concrete mix samples and their respective compressive strengths, between 2 and 80 MPa, at the most varied curing ages at which the specimens were broken, varying from 3 to 365 days.

In the present work, cement was not replaced, only blast furnace slag and fly ash were added to the concrete composition. The database used was produced by Professor I-Cheng Yeh of Chung-Hua University in Taiwan, so ABNT normative parameters were not considered. The author of the database did not inform the abatement established for the concrete, and only the compressive strength of the material was analyzed. The database does not include drawdowns and unitary features, so this item was not analyzed.

To determine the compressive strength, the following quantitative input data were used to make 1 m³ of concrete:

- Cement (kg/m³);
- Water (kg/m³);
- Coarse aggregate (kg/m³);
- Fine aggregate (kg/m³);
- Blast furnace slag (kg/m³);
- Fly ash (kg/m³);
- Plasticizer additive (kg/m³);
- Age of concrete (days).

The quantitative output value to be achieved through these inputs is the concrete's resistance to compression in MPa (Mega Pascal) shown in Table 1 used in this work. For the training, testing and validation of the ANN, the nftool toolbox of the MATLAB® software, version R 2011 b, developed by MATHWORKS®, was used.

Table 1. Examples of samples from the database.

Cement (kg/m³)	Blast furnace slag (kg/m³)	Fly ash (kg/m³)	Water (kg/m³)	Plasticizer additive (kg/m³)	Coarse aggregate (kg/m³)	Fine aggregate (kg/m³)	Days	Resistance (MPa)
540,0	0,0	0,0	162,0	2,5	1040,0	676,0	28	79,99
540,0	0,0	0,0	162,0	2,5	1055,0	676,0	28	61,89
332,5	142,5	0,0	228,0	0,0	932,0	594,0	270	40,27
332,5	142,5	0,0	228,0	0,0	932,0	594,0	365	41,05
198,6	132,4	0,0	192,0	0,0	978,4	825,5	360	44,30
266,0	114,0	0,0	228,0	0,0	932,0	670,0	90	47,03
380,0	95,0	0,0	228,0	0,0	932,0	594,0	365	43,70
380,0	95,0	0,0	228,0	0,0	932,0	594,0	28	36,45

Some architecture of feedforward networks with 1 and 2 hidden layers were tested, in addition to the variation in the number of artificial neurons. For the network of a hidden layer, 8 to 18 neurons were varied in the hidden layer and for neural network with 2 hidden layers, the number of neurons was varied between 8 and 18 for the first layer and between 5 and 15 in the second layer. The number of layers and neurons were defined by trial and error, but the starting point was based on the works developed by Oliveira et al (2007) and Getahun et al. (2018).

For training the artificial neural network, the Levenberg-Marquardt backpropagation algorithm, which is the default of the nftool toolbox, was used. This algorithm has a higher computational cost to the detriment of others available in the toolbox, but has excellent results. The data were divided into 70% for training the neural network, 15% for testing and 15% for validation, configurations also belonging to the software default. The error metric used was the MSE (Mean Squared Error) which is the mean square error, with smaller values being better and for a zero value MSE it means that there is no error. The parameter R was also used, which is a coefficient that indicates the correlation between the obtained output and the desired output for the problem in question.

The training is interrupted at the exact moment when the ability to generalize the neural network stops improving, a moment evidenced by an increase in the mean square error of the samples used for validation. Basically the experimental procedure started with the import of the input and output data properly formatted for the working environment of the software used. Then, the nftool toolbox was accessed and the imported data was added, in addition to defining the percentages of the data that would be used for training, validation and testing. Then, to determine the number of neurons, initially 10 was used, which is the default, for later modification in the script, considering that it is not possible to make this modification in the environment of the nftool toolbox. Then the training algorithm was defined. Finally, the artificial neural network created was trained and tested to extract the results. The experiment was repeated 10 times. Regarding the number of repetitions practiced, this amount is enough to have confidence that the training of the ANN was not by mere luck in the drawing of the initial weights of ANN training, this amount being considered as reliable for this experiment.

3. RESULTS AND DISCUSSION

The choice of the best architecture for artificial neural networks is of paramount importance for the modeling of a network that best suits the problem in question. There are no precise and clear guidelines for determining the architecture, which is usually chosen based on the experience of the network designer or by trial and error. After many attempts, the artificial neural network chosen was a network with two hidden layers, the first consisting of 15 neurons and the second comprising 10 neurons. Figure 2 illustrates the architecture of the chosen ANN, in which the entries are presented in small red rectangles, the artificial neurons of the hidden layers that are expressed by blue circles and the output of the network, presented by a green circle.

Getahun et al. (2018) used an ANN with 15 entrances and only one hidden layer, and two exits that correspond to compressive strength and traction. The proposed RNA overestimated the compressive strength by approximately 12.3%. On the other hand, Acuña et al (2014) used an RNA similar to that used in this work, containing two hidden layers with 10 and 4 neurons. Later they also used an Elman-type RNA with three hidden layers with 9, 8 and 3 neurons. The chosen network was trained, tested and validated, the process was repeated 10 times and the results obtained for the MSE at the time the training was interrupted. The correlation coefficient R between the obtained output and the desired output and the number of times required are shown in Table 2, as well as the mean and the standard deviation value for these values.

Looking at Table 2, it is possible to notice that in the execution of number 6 the artificial neural network obtained the best results. The value obtained for the MSE was 15.8038, which is well below the average obtained in the 10 executions, which was 27.4318. The value obtained for the correlation coefficient between the obtained output and the target output of the network was 0.97070, which was higher than the average found, which was 0.96559.

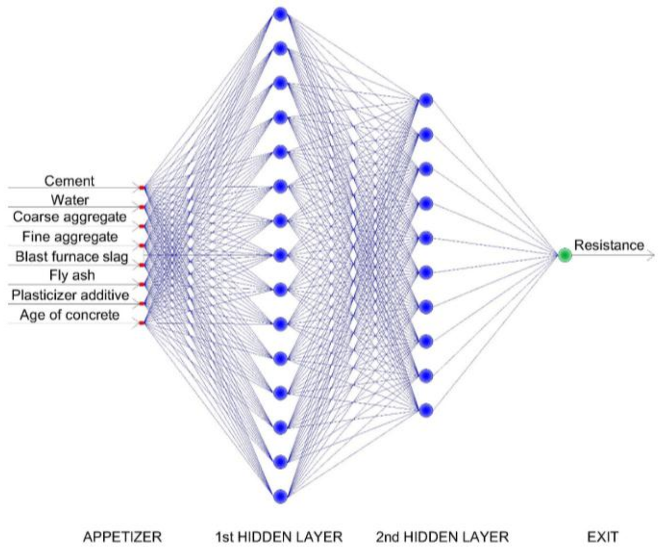

Fig. 2 Architecture chosen for RNA.

Table 2. MSE (Mean Squared Error), parameter R and Times obtained with the RNA used in the study.

Execution	MSE	R	Epochs
1	31,7026	0,96193	17
2	21,4910	0,96968	21
3	37,6369	0,95600	18
4	33,0209	0,95302	16
5	20,3395	0,97344	20
6	15,8038	0,97070	23
7	28,1591	0,96806	23
8	27,2261	0,96496	34
9	30,0285	0,96639	19
10	28,9092	0,97171	27
Mean	27,4318	0,96559	21,8
Standard deviation	6,5313	0,00676	5,39

Acuña et al (2014) obtained values between 0.933 and 0.975 for the correlation coefficient R, values very close to those found in this study. On the other hand, in the sixth execution of the ANN it is observed that 23 times were necessary until the training was interrupted at the moment when the error stops decreasing, and the average number of times required was approximately 22.

In the work by Oliveira et al (2007) the errors were much greater, reaching 20%, which they considered to be high for the standards used in concrete technology. Figure 3 shows the exact point where the smallest error for the artificial neural network was obtained in the graph that relates the number of epochs and the MSE.

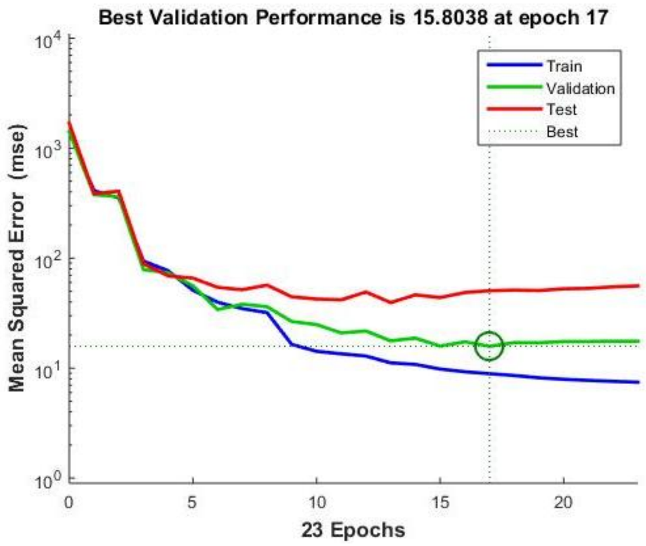

Fig. 3 Graph for the sixth execution of the ANN that lists the MSE and the number of times required.

Figure 4 illustrates the values of the correlation coefficient R in the sixth execution of the ANN. For the training set the value was 0.98412, for the test the value found was 0.90372, and for validation 0.97126 was obtained. Considering all the data, the R value found was 0.97070. The graphs list the values obtained by the artificial neural network and the values that were the targets.

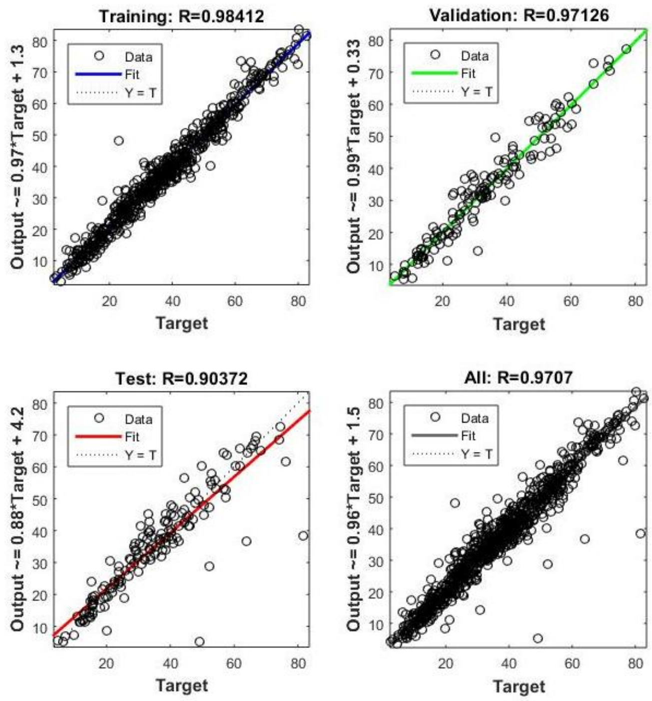

Fig. 4 Values of the correlation coefficient R obtained in the sixth execution of the ANN.

In figure 5, it is possible to observe the histogram of the errors found by the ANN used in this study. The graph lists the error and the number of samples, and it is possible to note that the vast majority of training, validation and test samples are found in the column whose error is 0.6602. The orange colored line on the graph represents the zero error. The ANN training time was 64 seconds.

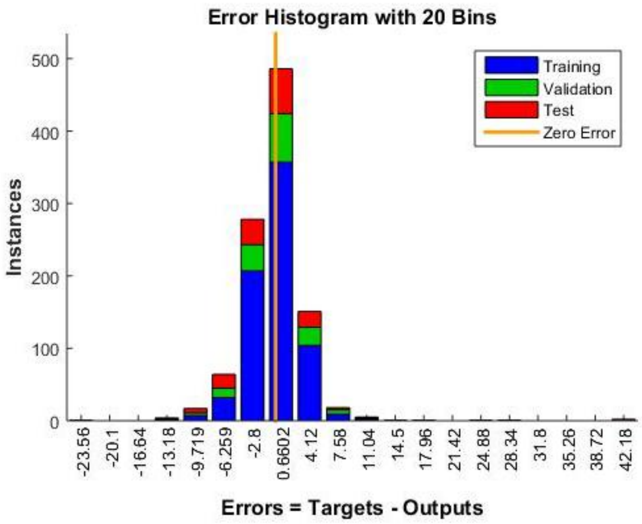

Fig. 5 Error histogram for the sixth ANN execution.

The prediction of compressive strength can pave the way for works that address concrete dosing via RNA, which can facilitate the insertion of alternative materials in concrete such as fly ash, which is the case of this study and recycled aggregates due to the ease of RNA in learn the behavior of concrete with the addition of other materials, which is quite difficult in dosing methods such as the ACI, ABCP method or even the concrete dosing method proposed by Helene and Terzian (1993).

4. CONCLUSION

In this work a model of artificial neural network was developed in order to obtain the strength of the concrete from data of the materials that constitute it beyond the curing time employed. Observing the results found in this work, it is possible to affirm that Artificial Neural Networks are a computational intelligence methodology that can contribute a lot in the field of civil engineering, more specifically in the area of concrete.

The ability to learn and generalize an artificial neural network can be of great value in the arduous task of dosing and determining the compressive strength of concrete. It would be possible to train an ANN for materials from different regions, considering that each region has materials with different characteristics. The average correlation coefficient obtained was 0.96559, which is higher than that found in the study by Oliveira et al. (2007) and very similar to that found by Acuña et al. (2014). The RNA used proved to be agile and reliable in view of the very low errors found. The Brazilian Standard NBR 6118 determines that in the design of reinforced concrete structures the strength of the concrete is reduced by 40% and the value of the actions acting on the structure is increased by 40% and the experimental RNA obtained about 95% efficiency.

ACKNOWLEDGMENT

Thanks to the professors of the Federal University of Lavras for their support.

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