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Neural Networks with Backpropagation in Engineering

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Abstract. Nowadays, with the amount of data increasing continuously in online networks there is the possibility to use artificial intelligence to analyze large databases. The Artificial Neural Network is a very utilized tool to find patterns in data to optimize the time and efficiency of analysis. Concrete is the most used structural material in Brazil in civil construction. Its resistance depends on the proportion of the materials used in its fabrication. To quantify each material to reach the required resistance for a particular need of a structure is a challenge found by engineering. This article aims to elicit how an Artificial Neural Network is capable of processing data and understanding patterns that are necessary to develop a coherent formula for the concrete based on obtained data in mechanical tests. The program is capable of making interactions among the data in a process of training and learning and it is also capable of finding acceptable solutions. It used a feedforward neural network with backpropagation algorithm to find the resistance of the concrete. The input data were the material used in a 1m³ construction of adensed concrete with different types of traits and tests and the output data, its resistance.

Keywords: Neural Network, Concrete, Backpropagation.

1 Introduction

Artificial Neural Network (ANN) refers to a machine that resembles a human brain full of interactions. A neural network is a group of interconnected elements, units, or simple processing nodes which functionality is vaguely based on animal neuron. The capacity of processing of the network is stored as per weight or connection force between units, obtained by an adaptation process or learning of a group of training patterns.

The architecture of a neural network is formed by the input layer, where the entrance data input takes place, one or more hidden layers, where most of the internal data input takes place, besides being responsible for extracting patterns of the groups of the data, and ultimately an output layer with the function of presenting the final network result [1]

The architecture of an Artificial Neural Network consists of a fully connected line of processing units, which are called nodes. In the neural network structures, the nodes are organized between groups called layers. The input layer receives the input data, the output one produces the output results, and the internal, or hidden ones, are the connection between the input and the output [2].

Haykin [3] has defined neural networks as a distributed processor massively parallel made by a simple processing unit, that has the objective of storing experimental data and making them available for use. The algorithm *backpropagation* divides the learning process into two stages, the first one (*forward propagation*), where input data is passed through the input layer, and the output of each node is calculated. The second stage (*backpropagation)* happens if the output layer fails to obtain the expected result, hence the variable input weight is modified through the descending gradient method seeking to minimize the full error of the function [4,5].

Chandwani, Agrawal e Nagar [6] explains that the unconventional method of deducing information through learning has raised a great amount of interest in the field of neural networks. The capacity of the neural network to function as a universal approximation function has been used to model problems, which the relation between the dependent and independent variable are not clearly understood.

The composition of the concrete is realized by using the ideal proportion of its components, with the intent of being within technical demands related to a determined construction, but this composition depends on a few factors. The resistance to compression is one of its most important characteristics, being the main information provided by the dosage methods. Normally, the dosage of the concrete is made by a diagram and abacus, made from laboratory tests. In the case of failure in the fabrication procedure or the test, the obtained data will be far from reality. Therefore, since the concrete dosage is determined by previous experimentations, this problem is adequate to be applied in a neural network [7].

Concrete is an essential material in civil engineering and is used worldwide. It is a composite material which has in its main constituents, cement, sand, gravel, a pre-established dosage, and water. The properties of the concrete including high resistance to compression are based in a non-linear function of its constituents [6].

De Souza, Lima e Chavarette [8] make an artificial neural network to handle failures in structures and present good results. Moretti [7], Chopra, Sharma, and Kumar [9] apply an artificial neural network in the treatment of the concrete. Their data input is the concrete fabrication composition and the output to maximum compression resistance.

This article seeks to analyze the operation of an artificial neural network bonding two types of different data settings.

2 Artificial Neural Network

Good operation of the network means a group of data with a significant number, which shall be used for the training of the network. Neurons, where the information is going to be stored and an activation function are necessary, to perform minor weight changes. Moreover, at the end of the process, it is possible, using the found weight after the training, to build a function of general use for the specific issue at hand.

After data mining, the articles which have come closer to making the operation of the network possible are Moretti [7] and Chopra, Sharma, and Kumar [9]. 101 data pieces were used.

Table 1.A. Input and output of the ANN

Cement (kg)	Water (kg)	Gravel (kg)	Sand (kg)	Plasticizer (kg)
485.00	175.60	1142.80	612.94	0.00
268.00	167.50	1144.70	764.80	0.00
350.00	168.40	1164.70	681.60	2.01
475.00	199.50	1040.25	498.75	2.62
475.00	228.00	869.25	598.50	0.00
495.00	164.00	1161.30	620.70	1.98

Table 1.B. Input and output of the ANN

Granulation Index (kg)	Slag (kg)	Fly Ash (kg)	Days	Resistance (MPa)
1.93	0.00	0.00	28.00	43.90
1.93	67.00	0.00	28.00	34.80
1.93	87.60	0.00	28.00	47.50
0.00	0.00	71.25	56.00	53.58
0.00	0.00	71.25	91.00	48.55
1.93	0.00	0.00	28.00	53.00

Initially, the nine input neurons are composed by: cement (kg), water (kg), gravel (kg), sand (kg), plasticizer (kg), granulation index, slag (kg), fly ash (kg) and the number of days for the rupture of the specimen.

And for each input, the output is the resistance to compression. Figure 1 represents the structure of the neural network.

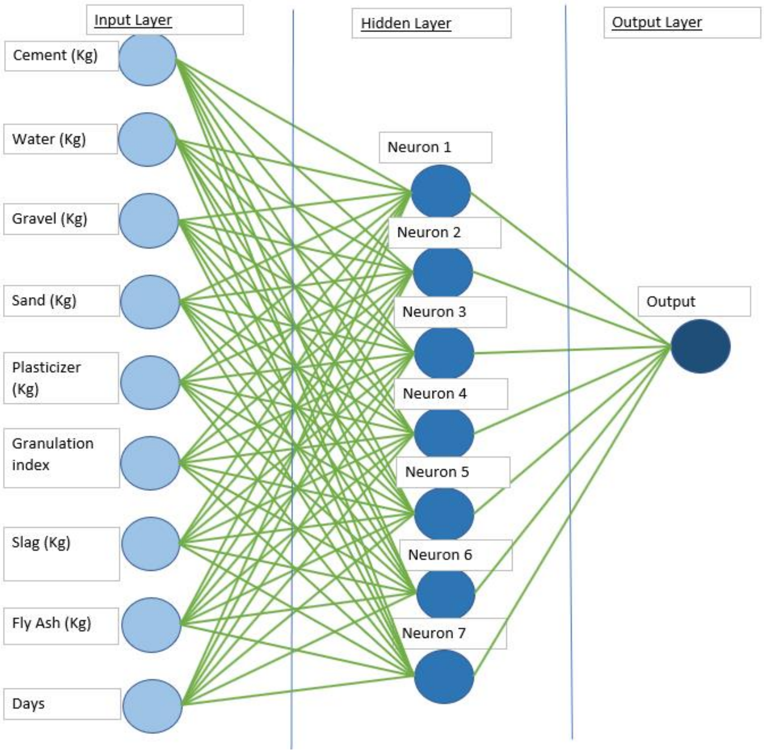

Figure 1. Neural Network's architecture

To perform the training of the network two weight matrices have been created, one to connect the input layer to the hidden layer (number of inputs x number of neurons in the hidden layer), and the other one to connect the hidden layer to the output layer, (number of neurons in the hidden layer x number of outputs). They have been filled with random numbers, respecting a normal distribution (Gaussian) of 0 average and pattern deviation 1. These matrices are used to represent the first weights considered by the network, whereas the function of activation is Sigmoid equation 1. Besides that, the input data have each been patronized with the higher value found in their respective specificity. And the output data has been divided by one hundred.

$$\partial = \frac{1}{(1+e^{-x})}. \tag{1}$$

To conclude a specific learning cycle, the difference between found by the network output value and the real output value is performed, this result is applied in the backpropagation function, so that the weights of each synapsis are updated, thus minimizing error. All processes of the training phase are repeated as per cycle quantity.

The error value $E(x)$ is found by using the mean squared error function where Y_i is the real inputs and $\ddot{Y}_i$the outputs found by the network.

$$E(x) = \sum_{i=1}^{n} (Y_i - \ddot{Y}_i)^2 \tag{2}$$

The choice of the number of neurons in each hidden layer is of utmost importance, for few neurons are chosen "underfitting" might occur, which is when the number of chosen neurons is not enough and they aren´t able to adequately detect the pattern. There is also the "Overfitting" which occurs when the network has so much processing power that the limited data number contained in the training group is not able to train all neurons. Another issue is that with a very high number of neurons the time of training may increase to a point where it is impossible to train the network adequately.

The amount of training cycles chosen for the neural network has the impact of minimizing the error found by the network. This happens because in the backpropagation process the error function is responsible for the error minimization. On the other hand, the higher the number of cycles the higher network training time is going to be.

Table 2 shows the relation between the number of neurons in the hidden layer and the number of cycles with the error found by the network and the processing time.

Table 2. Number of Neurons, cycles, an average of the square error and processing time

Neuron number	Cycles	Square error average	Processing time
3	1000	0.00043	0:00:18
5	1000	0.00039	0:00:19
7	1000	0.00048	0:00:20
3	10000	0.00021	0:03:05
5	10000	0.00023	0:03:06
7	10000	0.00015	0:03:05
3	100000	0.00023	0:29:52
5	100000	0.00006	0:31:38
7	100000	0.00005	0:29:36

The usage of a computer during the execution of the script may alter the processing time. Analyzing table 2 it is possible to choose other networks with reasonable processing time and the number of neurons, not ignoring the error. For this reason, the work network is going to be constituted by seven neurons in the hidden layer.

The graph in figure 1 shows the resistance relation (MPa) found by the network varying the size of the training cycle between one thousand, ten thousand, and one hundred thousand.

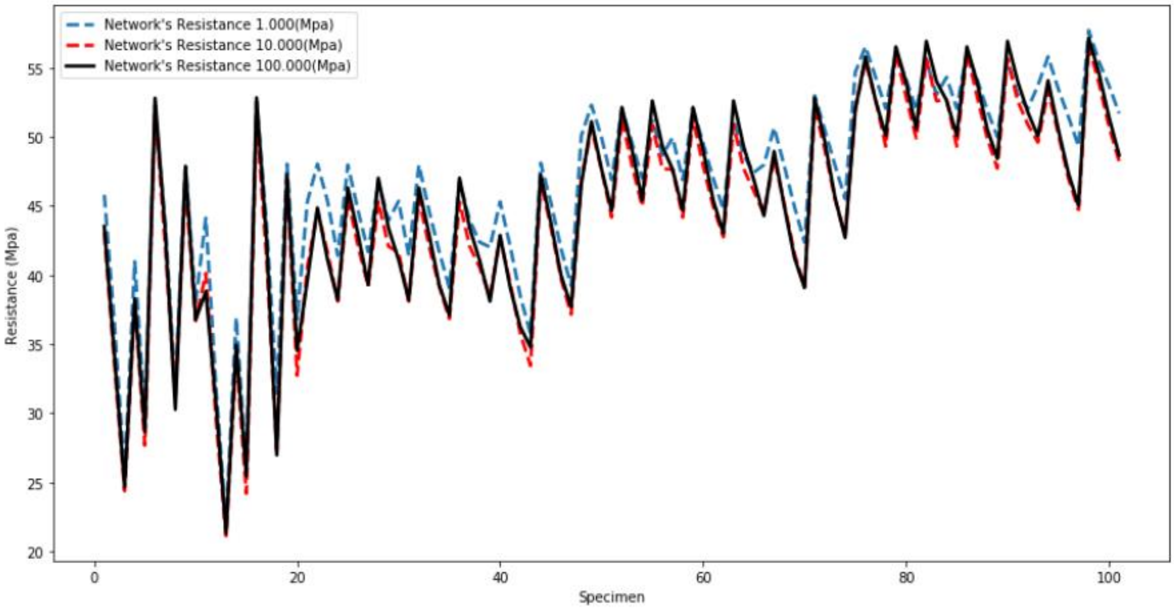

Figure 2. Network resistance with training cycles variation

It is possible to observe that the training results with ten thousand cycles and one hundred thousand cycles are very similar. Although when comparing these results with the ones found in the training of one thousand cycles the discrepancy between data is clear. For that matter training with the 10.000 cycle network was the choice.

The graph in figure 2 shows the difference between the resistance of the specimen, and the resistance found by the neural network.

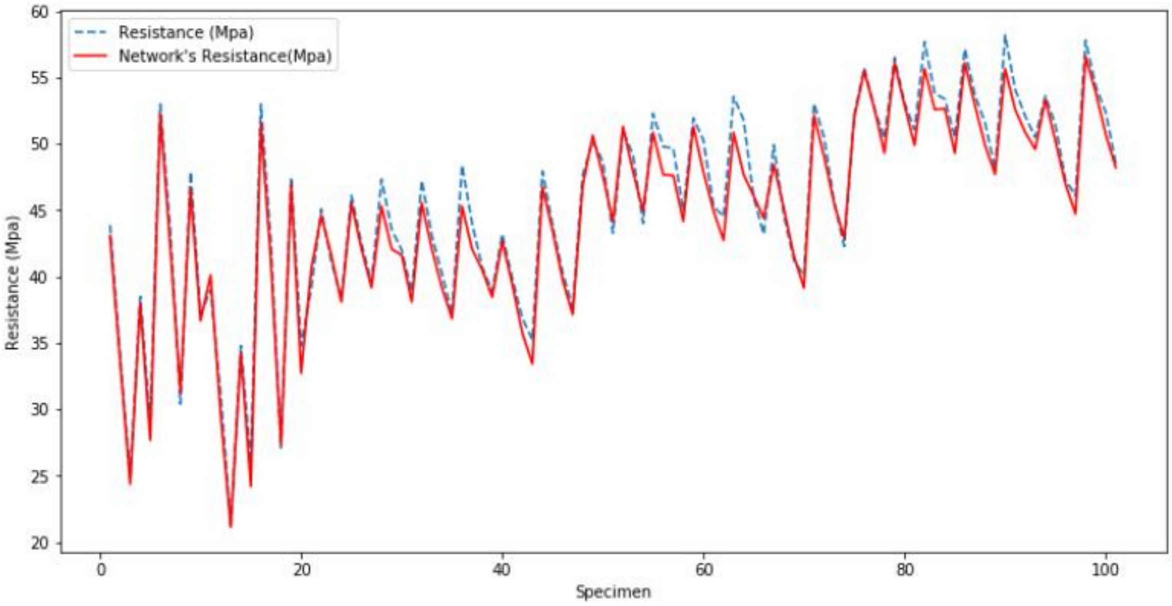

Figure 3. Network's resistance x Real resistance

The dotted line represents the values found by the network, and the non-dotted line the real value of specimen resistance. It is possible to observe that the graphs are nearly overlapping each other, thus showing the efficiency of the neural network. The largest relative error was of 7,94% and the smallest one of 0,045%

Table 3 shows the first weight matrix found by the network, the weights between input data, and the neurons in the hidden layer.

Table 3 – First weight matrix.

Components	Neuron 1	Neuron 2	Neuron 3	Neuron 4	Neuron 5	Neuron 6	Neuron 7
Cement	-0.32523	-1.39745	-4.05918	-1.67975	-0.76219	3.34039	-0.94953
Water	-1.81024	0.29753	3.79016	0.22867	-2.03513	-5.60561	-1.61748
Gravel	-2.4316422	-1.02780	-1.83885	-1.16099	1.64471	-0.55813	-1.85501
Sand	0.54922	-1.06211	4.22366	-0.94913	-0.41040	-4.00066	-1.39596
Plasticizer	-0.28047	0.13029	-1.85455	-1.52464	-0.35648	1.07579	-0.20173
Granulation index	-2.36393	0.24824	-1.67052	-0.40461	-1.14623	2.78433	-0.83181
Slag	0.66733	1.84335	0.47486	-0.56497	0.35819	2.74109	-0.90219
Fly Ash	-2.30668	-2.47689	-1.45364	-1.06176	-0.83218	3.05873	-1.74434
Days	-0.21547	0.13876	-2.31603	0.83626	-2.17657	1.58714	-0.73012

Table 4 shows the second weight matrix, which refers to the multiplying index between the neurons of the hidden layer and the output layer.

Table 4 – Second weight matrix.

Neuron	Output
Neuron 1	-0.41618
Neuron 2	-1.04890
Neuron 3	-1.12383
Neuron 4	-3.05496
Neuron 5	-2.90160
Neuron 6	0.84902
Neuron 7	0.59205

With these weight values found it is possible to formulate a mathematical equation to find the resistance of any specimen considering the utilized inputs in the network. So, the Generalized Function is presented in equation 3. Where *O* is the output found by the network, w_1 the values of the first weight matrix, w_2 the values of the second weight matrix, and *x* the input values.

$$o = \frac{1}{(1+e^{-\sum w_{2j}\cdot\sum(\frac{1}{(1+e^{-\Sigma(w_{1i}\cdot x_i)})})})}. \tag{3}$$

Moreover, the network has had its conformity with the analyzed data and has generated adequate weight to be utilized in a simple formulation. Data which is complex with many variables to be analyzed.

3 Conclusions

This work has analyzed the performance of the artificial neural networks in engineering. Showing its capacity to help understand complex problems. Proposing adequate formulations to capture behaviors. The activation function was the sigmoid and the number of neurons in both networks were tested to achieve a better approach. The convergence of the network by the number of cycles was also tested. The results generated by the network were satisfactory considering that the average error by backpropagation was lower than 10^{-3}. Analyzing the errors related to resistance to a few specific specimens a relative error of 8% maximum was obtained. Therefore, it was possible t observe that the utilization of neural networks in engineering problems is in fact a facilitator in specific analysis and calculations. That makes the ANN be attractive to complex calculations with many input and output variables. Avoiding wastes in laboratory tests and guaranteeing results with good precision.

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References

[1] DA SILVA, Ivan Nunes et al. Artificial neural network architectures and training processes. In: Artificial neural networks. Springer, Cham, 2017. p. 21-28.
[2] ERB, Randall J. Introduction to backpropagation neural network computation. Pharmaceutical Research, v. 10, n. 2, p. 165-170, 1993.
[3] Haykin, Simon. Redes Neurais: Princípios e práticas. 2ª Edição. Bookman. 1998
[4] SIREGAR, Sandy Putra; WANTO, Anjar. Analysis of Artificial Neural Network Accuracy Using Backpropagation Algorithm In Predicting Process (Forecasting). IJISTECH (International Journal of Information System & Technology), v. 1, n. 1, p. 34-42, 2017.
[5] SUN, Weiwei; TANG, Jian; BAI, Chunsong. Evaluation of University Project Based on Partial Least Squares and Dynamic Back Propagation Neural Network Group. IEEE Access, v. 7, p. 69494-69503, 2019.
[6] CHANDWANI, Vinay; AGRAWAL, Vinay; NAGAR, Ravindra. Applications of artificial neural networks in modeling compressive strength of concrete: a state of the art review. International Journal of Current Engineering and Technology, v. 4, n. 4, p. 2949-2956, 2014.
[7] MORETTI, José Fernando. Sistema inteligente baseado nas redes neurais artificiais para dosagem do concreto. 2010.

[8] DE SOUZA, Simone Silva Frutuoso; PA LIMA, FERNANDO; ROBERTO CHAVARETTE, FÁBIO. RECONHECIMENTO DE FALHAS ESTRUTURAIS UTILIZANDO UMA REDE NEURAL ARTMAP-FUZZY-WAVELET. Revista Iberoamericana de Ingenieria Mecánica, v. 23, n. 1, 2019.
[9] CHOPRA, Palika; SHARMA, Rajendra Kumar; KUMAR, Maneek. Prediction of compressive strength of concrete using artificial neural network and genetic programming. Advances in Materials Science and Engineering, v. 2016, 2016.