Flexural Strength Prediction of Slabs with Finished Type Tile: A Neural Network Approach

J. Acevedo-Dávila and L. Torres-Treviño

Corporación Mexicana de Investigación en Materiales
Oceania 190, Saltillo, Coahuila, México
ltorres@comimsa.com.mx; jacevedo@comimsa.com.mx

Abstract. An application of neural network has been applied to the development of materials for the construction industry. Different mixes were designed to create a piece which will be used on a roof with an angle of inclination and some tile. The experiments were divided in two stages. The first consisted of the development of mixes with different amounts of cement. The flexural strength was evaluated. In the second stage, a Percetron neural network based on experimental tests was generated and evaluated in order to predict mechanical properties of new mixes. This study shows the correlation of the different mixes and the neural network prediction as well as the behavior of other designed mixes.

1 Introduction

The lack of a worthy ceiling in the housing industry in Mexico is one of the most serious problems that is presented to the population with low resources. According to data emitted by INEGI from XII population Census [1], 35 percent of the population in the country has ceilings made of material classified as low durable. That numbers nearly 7.6 million houses. According to INEGI, these materials, shown in table 1, show a nominal life utility that go from 2 up to 50 years.

Table 1. Font Life utility of the different materials used for the construction of ceilings

Material	Nominal Life utility (years)
Waste material	2
Cardboards	2
Metallic and asbesto	11
Palms, tejamanil and wood [2, 3]	15
Tile [2,3]	30
Concrete slabs, bricks and terrace with a set of beams	50

Advances in Artificial Intelligence and Applications
Research in Computer Science 32, 2007, pp. 38–44

Received 16/06/07
Accepted 31/08/07
Final version 30/09/07

An area of opportunity in the housing industry in Mexico, based on the aforemention problem, is the development of constructive systems for lasting ceilings or cover according to construction norms [4]. COMIMSA has developed a piece which will be used on a roof with an angle of inclination and some tile [5]

The system consists basically of two pieces of slabs of concrete lifting elements and, concrete slabs with finished type tile. The applied process of vibration and compacting during the manufacture of blocks is done in order to increase the volumes of manufacture of concrete slabs proposed [6]. An alternative to improve the properties of resistance to flexion is the increase of cement. Nevertheless, this raw material is expensive, which makes it indispensable to look for methodologies that help to optimize the used cement and to make an experiment design that diminishes the amount of necessary experiments.

Flexural strength is the ability to resist an applied bending force such as that encountered by concrete pavements or other slabs. A determination of the flexural strength is frequently necessary as part of the design of concrete mixtures in order to check compliance with established specifications or to provide information necessary to the design of an engineering structure. In the flexural-strength test, a test load is applied to the sides of a test beam. Although the test can be performed upon beams sawed from existing concrete structures, it is more commonly performed upon beams that are cast for testing purposes.

The use of neural networks is an alterative to make economic designs by the capabilities prediction of these computational paradigms [7, 8, 9, 10, 11, 12]. The principal use of this paradigm is the approximation of functions and processes using experimental data. There are several approaches to neural networks and several learning rules in a single neural structure such as: gradient with momentum, conjugates, gradients, etc. Nevertheless a erceptron neural network with backpropagation Levenberg - Marquardt learning rule is used.

In following section an overview of Perceptron neural networks is given. The third section discusses the experimental procedure to extract the training and validation data. Results are given in section four. Finally, conclusions and future work will be given in the last section.

2 Perceptron Neural Network and the Leverberg - Maquardt Learning Rule

A neural network is an interconnection of processing elements or artificial neurons [13]. The principal use of this paradigm is the approximation of functions using experimental data. The behavior of the neural network is established by its' connection weights. The learning rule adjusts the weights to minimize any error between a desired response and the actual response of the neural network. The desired responses are expressed in a database of patterns of input – output pairs. A single response of a processing element is determined with (1) and (2).

$$O_n = F_A\left(\sum_{i=1}^{N} W_{n,i} X_i\right) \tag{1}$$

$$F_A(x) = \frac{1}{1+e^{-x}} \tag{2}$$

Where n is an artificial neuron and i is the corresponding element of an input vector X. Matrix W represents the connection weights between an element of the input vector X and a neural element n. The activation function F_A regulates the output of the neuron. A Sigmoid function is usually used (2). Since layers of neurons are used, it is necessary to adjust several connection weights in the learning rule. There are several learning procedures to adjust the connection weights; nevertheless, the Levenberg - Marquardt learning rule is used [14]. The rule is a variant of the Gauss-Newton optimization method. The connection weights are calculated as follows:

$$W \leftarrow W - (J^T J + \lambda I)^{-1} J\varepsilon \tag{3}$$

Where ε is the difference between the actual and required response. The Jakobian matrix for a single neuron can be written as follows:

$$J = \begin{bmatrix} \frac{\partial \varepsilon_1}{\partial w_1} & \Lambda & \frac{\partial \varepsilon_1}{\partial w_n} & \frac{\partial \varepsilon_1}{\partial w_0} \\ \mathrm{M} & & \mathrm{M} & \mathrm{M} \\ \frac{\partial \varepsilon_p}{\partial w_1} & \Lambda & \frac{\partial \varepsilon_p}{\partial w_n} & \frac{\partial \varepsilon_p}{\partial w_0} \end{bmatrix} \tag{4}$$

Parameter λ is modified based on the development of the error signal and p represents the available patterns [15, 16].

3 Experimental Procedure

A control mixture was prepared using Type I Portland cement, a limestone coarse or fine aggregate (with a particle size of 6.35 mm in the first case, and of 4.76 mm in the second case), and water. The particle size analysis of all materials used was carried out according to the Mexican NMX-C-077-ONNCCE standard. The four mixtures were prepared by changing the weight fraction of Portland cement. It must be stated that a water/cement ratio equal to 0.8 was used in all mixtures.

In this study, a quick and simple conventional slab-making process was employed. In this process, each one of the studied mixtures was poured into a suitable mold, followed by vibration and compacting under manual pressure applied during a fixed period of time. In this way, concrete slabs with dimensions 62x25x14cm were obtained. After extracting the formed slabs from the mold, these were water cured for time periods of up to 28 days in order to promote the hydration of Portland cement.

The flexural strength tests were conducted according to the ASTM C78 Standard [17]. A Tinus Olsen Machine was used to conduct these tests. The flexural strength of the slabs with finished type tile was measured after a period of water curing of 3, 7, 14 or 28 days. Three tests were carried out for each curing time, per each mixture composition.

The neural network architecture has two inputs and one output (Fig. 1). The first input represents the percent of cement used to build slabs. The second input represents the curing day. The output represents the flexion supported. The experimental data have samples of percentages, curing days (only 3, 7, 14 and 28 curing days) and the resultant flexion. From the experimental data 48 patrons were extracted in order to train the neural network and 16 patrons were used as validation data.

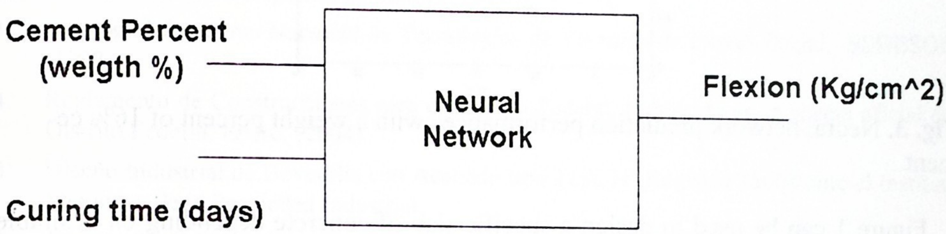

Fig. 1. Architecture of the neural network to approximate the flexion strength.

4 Results and Discussion

A Matlab® neural networks toolbox was used to generate a structure of two layers with 50 inner neurons with tangential activation function and Leverberg-Maquart learning rule. The neural network was used to predict the flexion strength of some mixture not used in training the procedure. Figure 2 shows the prediction of flexion strength through 38 days using an 11% cement mixture. Figure 3 shows the prediction of flexion strength through 28 days using 16 % of cement.

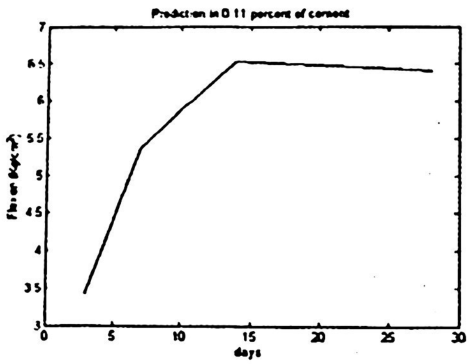

Fig. 2. Neural network prediction performances with a weight percent of 11% cement.

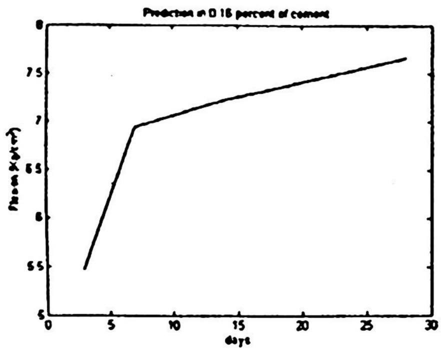

Fig. 3. Neural network prediction performances with a weight percent of 16% cement.

Figure 1 can be used to design a specific slab of concrete depending on desirable flexion strength characteristics. The plot was generated by setting the curing day input to be 28 days and generating an input set of cement percents in a range between 0.1% to 0.2%.

5 Conclusion

The generation of test slabs takes time and represents a high cost. The neural network can be used to predict the flexion strength in percent of cement not used in the experiment saving cost and time to design mixtures to build slabs of high performance in flexion strength and fulfill the requirements of the construction norms. The plot can facilitate this design. The use and comparison with other neural networks and regression models is a future work.

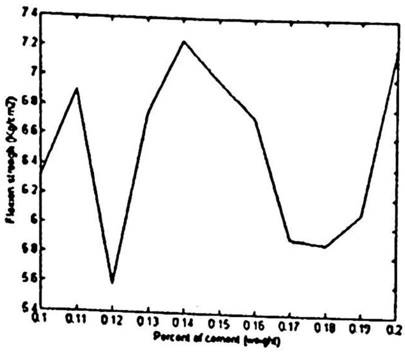

Fig. 4. Different percent of cement versus the flexion strength predicted.

References

1. X Censo General de Población y Vivienda, http://www.inegi.gob.mx/, (2000).
2. Corzo, Vivienda Campesina en México, (1978).
3. Catálogo I Concurso Nacional de Tecnologías de Vivienda de Interés Social, SEDESOL. (1992)
4. Reglamento de Construcciones para el Distrito Federal. Publicado en la gaceta oficial del Distrito Federal, Enero. (2004)
5. Diseño Industrial de Bovedilla con Acabado tipo Teja. N° Registro 15668 ante el Instituto Mexicano de la Propiedad Industrial.
6. J Arrieta F. E Peñaherrera D. Fabricación de Bloques de Concreto con una mesa vibradora, PC-CISMID, (2001)
7. G.B. Barrera, G. Carreón, A. Ruíz, "Control de calidad de piezas cerámicas por medio de análisis de vibraciones y redes neuronales artificiales", Computación y Sistemas, Vol 8, No. 3, pp187-197, (2005)
8. Hewayde, E. Author Hewayde E. Hewayde, E. , Nehdi, M. et al. Neural network prediction of concrete degradation by sulphuric acid attack. STRUCT INFRASTRUCT E 3 (1) MAR (2007) 17-27.
9. Compressive Strength Prediction of Building Blocks from Lightweight Raw Materials: A Neural Network Approach Jorge L. Acevedo D., COMIMSA, FIME-UANL, Mexico Luis M Torres-T., COMIMSA, FIME-UANL, Mexico Lauren Y Gómez Z., COMIMSA, FIME-UANL, Mexico Electronics, Robotics and Automotive Mechanics Conference (CERMA'06) Vol. 2, (2006) 184-190
10. A. Cheang-Martínez, J.L. Acevedo-Davila, L. Treviño-Torres, F.A. Reyes Valdes. Corrosion prediction and annual maintenance optimization of concrete structural components using neural network modeling. In 1st International Conference on Advanced Construction Materials. December (2006) 3 - 6
11. Jorge Acevedo, Luis Torres-T, Mario Trejo, Cesar Juárez. Compression strength prediction of mixtures concrete with scrap tire with neural network approach. In 1st International Conference on Advanced Construction Materials. 3 - 6 December 2006.

12. J.L. Acevedo, Luis Torres, Mario Trejo Aguirre. Aplicación de redes neuronales para predecir la resistencia a la compresión de elementos constructivos: Caso bloques. In 4to. CONGRESO NACIONAL DE METALURGIA Y MATERIALES 27 AL 29 DE SEPTIEMBRE DE 2006, MONCLOVA, COAHUILA, pag. 381-388, 2006
13. Jyh-Shing Roger Jang & Chuen-Tsai Sun & Eiji Mizutani
14. Neuro-Fuzzy and Soft Computing
15. Prentice Hall, (1997)
16. Simon Haykin
17. Neural Networks: A comprehensive foundation
18. Prentice Hall, (1999)
19. Hagan, M.T., and M. Menhaj, "Training feed-forward networks with the Marquardt algorithm," IEEE Transactions on Neural Networks, Vol. 5, No. 6, 1999, pp. 989-993, 1994.
20. Fredric M. Ham & I. Kostanic
21. Principles of Neurocomputing for science and Engineering
22. McGraw Hill, (1997)
23. ASTM C78 Standard Test Method for Flexural Strength of Concrete (Using Simple Beam with Third-Point Loading).