Prediction of concrete compressive strength through artificial neural network

Authors:

Pablo Neira, BSc. Physics
Universidad de Concepción, Concepción, Chile Department of Physical Sciences and Mathematics
pablneira@udec.cl

Assoc.Prof. **Leonardo Bennun**, PhD in Nuclear Eng.
University of Concepción, Concepción, Chile Department of Physical Sciences and Mathematics
lbennun@udec.cl
Corresponding author

Assist.Prof. **Mauricio Pradena**, PhD. CE
University of Concepción, Concepción, Chile Department of Civil Engineering
mpradena@udec.cl

Jaime Gomez, BSc. Chem.
Simón Bolívar University, Venezuela
j.gomez@lafargeholcim.com

Research paper

Pablo Neira, Leonardo Bennun, Mauricio Pradena, Jaime Gomez

Prediction of concrete compressive strength through artificial neural networks

Concrete properties, including its compressive strength, are in general highly nonlinear functions of its components. Concrete mix design methods are basically simulations that require costly and time consuming adjustments in laboratory. A useful support tool based on artificial neural networks, using a multilayer perceptron network, is proposed in this paper as a means to predict compressive strength of concrete mixes. The developed models are useful for reducing the quantity of laboratory tests required for concrete mix design adjustments.

Key words:

concrete mix design, compressive strength, laboratory tests, artificial neural networks

Prethodno priopćenje

Pablo Neira, Leonardo Bennun, Mauricio Pradena, Jaime Gomez

Predviđanje tlačne čvrstoće betona pomoću umjetnih neuronskih mreža

Svojstva betona, uključujući i tlačnu čvrstoću, uglavnom se mogu smatrati vrlo nelinearnim funkcijama njegovih komponenata. Metode koje se koriste za projektiranje betonskih mješavina u svojoj su osnovi simulacije koje zahtijevaju skupe i vremenski zahtjevne korekcije u laboratoriju. U ovom se radu predlaže korisna podrška utemeljena na umjetnoj neuronskoj mreži, točnije primjeni višeslojne perceptronske mreže, a može se primijeniti za predviđanje tlačne čvrstoće betonskih mješavina. Razvijeni modeli omogućuju smanjenje broja laboratorijskih ispitivanja koja se provode u svrhu korekcije betonske mješavine.

Ključne riječi:

projektiranje betonskih mješavina, tlačna čvrstoća, laboratorijska ispitivanja, umjetne neuronske mreže

Vorherige Mitteilung

Pablo Neira, Leonardo Bennun, Mauricio Pradena, Jaime Gomez

Vorhersage der Druckfestigkeit des Betons mithilfe künstlicher neuronaler Netze

Die Eigenschaften von Beton, einschließlich der Druckfestigkeit, können im Allgemeinen als nicht lineare Funktionen seiner Komponenten betrachtet werden. Die Methoden, die zur Planung von Betonmischungen verwendet werden, sind im Grunde genommen Simulationen, welche kostspielige und zeitlich aufwendige Korrekturen im Labor erfordern. In dieser Abhandlung wird eine nützliche Unterstützung vorgeschlagen, die sich auf einem künstlichen neuronalen Netz begründet, genauer gesagt auf der Anwendung eines mehrschichtigen Perzeptron-Netzwerkes, und kann für die Vorhersage der Druckfestigkeit der Betonmischungen herangezogen werden. Die entwickelten Modelle ermöglichen eine geringere Anzahl an Laboruntersuchungen, die zum Zweck der Korrektur der Betonmischungen durchgeführt werden.

Schlüsselwörter:

Planung von Betonmischungen, Druckfestigkeit, Laboruntersuchungen, künstliche neuronale Netze

Pablo Neira, Leonardo Bennun, Mauricio Pradena, Jaime Gomez

1. Introduction

During the last century, concrete has become the most widely used construction material in the world, due to its versatility, resistance to water and fire, availability, and price [1]. In general terms, concrete is composed of a mixture of hydraulic cement (25 %), water and aggregates (65 %), which is capable of withstanding large compression efforts at the time of hardening [2, 3]. The most commonly used hydraulic cement is Portland cement [3] composed mainly of aluminium calcium silicate obtained by heating a mixture of finely ground minerals, formed of limestone and clay at temperatures exceeding 1.300 °C. This material is called clinker and 2 % to 5 % of calcium sulfate (gypsum) is added to prevent it from instant setting [4]. Clinker Portland consists of compounds that form four mineralized phases: tricalcium silicate (Ca_3SiO_5) (50-70 %) designated C3S, dicalcium silicate (15-30 %) (Ca_2SiO_4) designated C2S, tricalcium aluminate ($3CaOAl_2O_3$) designated C3A, and tetracalcium ferroaluminate ($Ca_4Al_2Fe_2O_{10}$) designated FAC4, where the silicates (C3S and C2S) correspond to 80 % of the components and are responsible for providing strength to the cement:

- C3S: $3CaO \times SiO_2$
- C2S: $2CaO \times SiO_2$
- C3A: $3CaO \times Al_2O_3$
- C4AF: $4CaO \times Al_2O_3 \times Fe_2O_3$

Water is mixed with cement and the paste hardens as a consequence of setting. One part of the water is fixed (hydration water) in the rigid structure of the paste, and the remaining water is evaporable water [3]. The water/cement ratio is of vital importance to the quality of concrete. A low water/cement ratio (close to 0.3) leads to greater strength and durability, though it may cause blends more difficult to work with. However, this can be solved through the use of plasticisers [5].

On the other hand, aggregates are granular materials such as sand, gravel or construction debris. Crushed stone aggregates have been shown to provide more strength to concrete than rounded aggregates [6]. Regarding the type of aggregate, more strength is obtained from concrete containing crushed quartzite, followed by that containing river gravel and finally that with crushed granite [7]. As to additives, they can be used to modify properties of concrete, making it more suitable to work conditions. These include water reducers, retardants or setting accelerants. The success of high strength concrete, for instance, lies in the use of high-rank water reducing additives, commonly known as superplasticisers [8].

In general, concrete properties, including its compressive strength, are a highly nonlinear function of its components [8]. In order to assure proper technical performance of concrete, and compliance with commercial-economic requirements, the concrete mix design has become a multidisciplinary area of study. The mathematical approach most often used in the past is the approach based on simple regression models.

Such analytical models describe the effects of concrete components on compressive strength and are usually quite complex [8]. Taking this into consideration, soft computing tools have been proposed as an emerging option of methods aimed to achieve robustness, traceability and low cost [10]. Artificial Neural Networks (ANNs) enable multiple analyses and have therefore been widely used for defining mechanical properties of concrete, and for predicting resistance to compression of different components based on initial data [9-11]. Studies on the use of multiple regression and ANN for estimating concrete compressive strength have revealed that ANN models perform better compared to several regression analysis models [12].

The ANNs are an important field within artificial intelligence, due to their capacity to learn and generalize. ANNs consist of a number of simple elements called neurons, which are organized in layers [13]. The first layer, also called input layer sends data signals that are numerical values of "something" (chemical or physical variables, ages or quantified data in general) to the next layer. Each input neuron is connected to other neurons of the next layer through communication links, where each link is associated to a synaptic weight. Each synaptic weight multiplies its corresponding input, defining the relative importance of each input, i.e. weights save the knowledge of the network about a problem. Then, for the total signal to be transmitted to the next layer it must pass through an activation function that regulates that only the strongest signals follow their course. Steps, sigmoid or linear functions are generally used [14]. If neurons succeed in reaching the threshold, an output signal will finally be obtained in this layer.

2. Methodology

In this research, the compressive strength of concrete is modelled through ANN, from a set of 335 mixtures obtained from quality control procedures in standard HOLCIM Laboratory tests. The compressive strength of cylinders is measured after 1, 3, 7 and 28 days, and seven chemical analyses (Loss on Ignition, LI (total amount of material lost by calcination), SiO_2, Al_2O_3, Fe_2O_3, CaO, MgO, SO_3), and three physical evaluations: R45 (amount of material retained in a 45 μm filter), w/c (water/cement relationship), flow (viscoelastic properties of the mixture of cement, sand and water), are made for each mixture. A data set with detailed and precise information about concrete strength is also provided in the paper. These data could be useful for academic and industrial communities, and are suitable for complementing similar studies in order to model strength of concrete by ANNs [15-23].

Regarding application of ANN, one of the most widely used and most successful neural network models is the one involving Multilayer Perceptrons, due to their capacity to deal with highly nonlinear prediction problems [24-27].

Table 1. Correlations between 10 physicochemical variables and compressive strength of concrete after 1 day (R1D), 3 days (R3D), 7 days (R7D) and 28 days (R28D), respectively

	R1D	R3D	R7D	R28D
LI	0.4008	0.3986	0.3159	-0.2951
SiO_2	-0.6299	-0.6832	-0.6011	0.1775
Al_2O_3	0.3977	0.3684	0.3657	-0.0405
Fe_2O_3	-0.2515	-0.1984	-0.2116	-0.2148
CaO	0.6699	0.7195	0.6460	-0.1242
MgO	0.4815	0.5272	0.4455	-0.0614
SO_3	0.2034	0.1530	0.1537	0.0587
R45	0.2028	0.1392	0.1558	-0.0825
W/C	-0.6441	-0.7411	-0.6635	-0.0962
Flow	0.0170	0.0258	0.0415	0.0283
R1D	1	0.8518	0.8120	0.3965
R3D	0.8518	1	0.9080	0.3808
R7D	0.8518	0.9080	1	0.4851
R28D	0.3965	0.3808	0.4851	1

Table 2. Correlations of extreme data between 10 physicochemical variables and compressive concrete strength after 1 day (R1D), 3 days (R3D), 7 days (R7D) and 28 days (R28D)

|	R1D	R3D	R7D	R28D
LI	-0.2275	-0.2655	-0.5166	-0.7703
SiO_2	0.0183	0.0265	0.3655	0.7302
Al_2O_3	0.3844	0.3699	0.1779	0.0908
Fe_2O_3	-0.0362	-0.1072	-0.2137	-0.2273
CaO	0.0795	0.0979	-0.2748	-0.6621
MgO	0.3543	0.2939	-0.0465	-0.3499
SO_3	-0.2826	-0.1766	-0.0938	-0.0624
R45	-0.4266	-0.3503	-0.4244	-0.4327
W/C	-0.4884	-0.5262	-0.2594	0.0321
Flow	-0.0705	0.1759	0.1185	0.0396
R1D	1	0.8603	0.7670	0.5528
R3D	0.8603	1	0.8726	0.6215
R7D	0.7670	0.8723	1	0.8526
R28D	0.6215	0.6215	0.8526	1

The rule or learning algorithm of the network is the mechanism by which network parameters are adapted or modified. The case of multilayer perceptron involves the use of the supervised learning algorithm, i.e. the modification of parameters is performed so that the output of the network is as close as possible to the output specified by the supervisor or to the desired output. Therefore, the learning process of the network is equivalent to finding a minimum of error function. However, one of the greatest weaknesses is the local minimums in the error functions, which cause that the training is stopped although no adequate convergence parameters have been reached. In order to avoid this, it is proposed in this study to apply a random variation of training sets and initial weights. Thus, it will be possible to roughly observe network prediction results, without worrying if it fails in local minimums. The learning algorithm chosen in this paper for network training is the Levenger Marquardt algorithm [28], because it is the most recommended algorithm for supervised learning due to its rapid convergence, and because less iterations are required for its convergence.

Regarding the application of ANNs for prediction of concrete strength, it is important to decide if the data of physicochemical variable, and the ages of concrete evaluation, are suitable for network training. In order to determine this suitability, the Pearson's correlation coefficient was evaluated over each input data. This coefficient measures the linear relation between two variables. The corresponding results are presented in Table 1.

A data subset from one of the largest worldwide companies of cement and concrete is used for analysis in this paper. Hence, ten physicochemical variables have been already (extremely) optimized in order to achieve the compressive strength targets at the Lafarge Holcim concrete laboratories. Because of that, it seems that fundamental variables such as, for instance, the w/c ratio, do not have an important influence on the concrete compressive strength results. However, this occurs because the range of improvement is very narrow.

Also, we have separately evaluated correlations of extreme data. A total of 15 samples with the highest compressive strength, and other 15 samples with the lowest compressive strength, were considered in the case shown in Table 2.

For optimization of the Neural Network Topology, we have developed a program in the language MATLAB®, using the Neural Network Toolbox®, belonging to MATLAB® 2015a program. The number of neurons in the input layer is given by the number of inputs of the network. In this case, there will be ten input neurons because there are ten physicochemical variables. Since this study was aimed to obtain the compression strength for a given time of 7 days (7D) and 28 days (28D), the output layer will only have one neuron that corresponds to the predicted value, Figures 1 and 2.
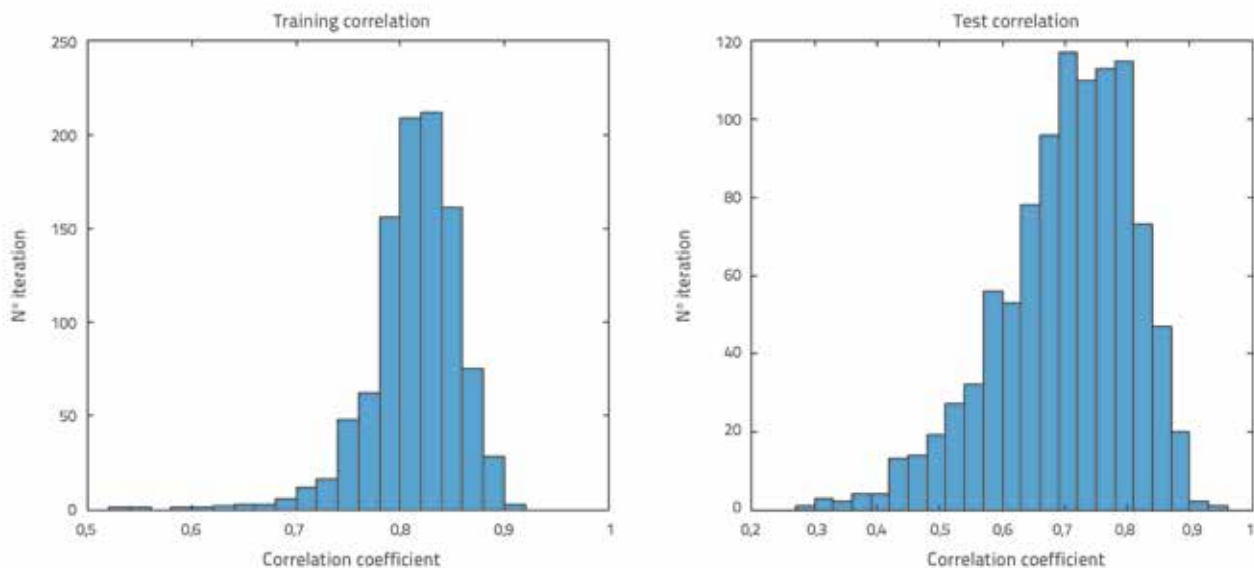
Slika 1. Correlation coefficient obtained via Matlab, as a function of the number of iteration, for the training data (left) and test data (right) of compressive strength at 28 days
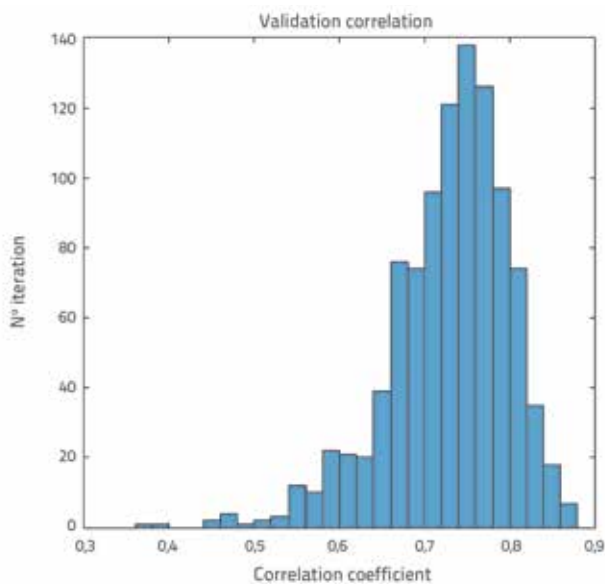
Slika 2. Correlation coefficient obtained via Matlab for the validation data and compressive strength at 28 days

One of common methods for obtaining an optimum Neural Network Topology consists in placing a fixed number of neurons in the second hidden layer and in increasing the number of neurons in the first hidden layer; after the optimum number for the first layer is obtained, the number of neurons for the second layer must be varied until an optimal prediction is once again defined. The criterion used to determine an optimum topology of networks, i.e. the one that best describes the previous problem, is the set of the Pearson's correlation coefficient, which measures the interdependence ratio; in this case, actual compression strength values at 7 and 28 days with the prediction of the model, applied to the average of the three sets (training, validation and testing).

A total of 20 different combinations for obtaining a suitable number of neurons for the first hidden layer were studied, as well as 20 combinations for determining the second hidden layer. For the Neural Network training, the 335 mixtures set was divided into three groups: 245 mixtures as the training set, 55 mixtures as the validation set, and 35 mixtures as the test control set.

3. Results

3.1. Modelling concrete strength at 7 days

In the case of the 7-day prediction, an optimal topology of 4 neurons in the first layer and 6 neurons in the second hidden layer, was obtained (Figure 3).
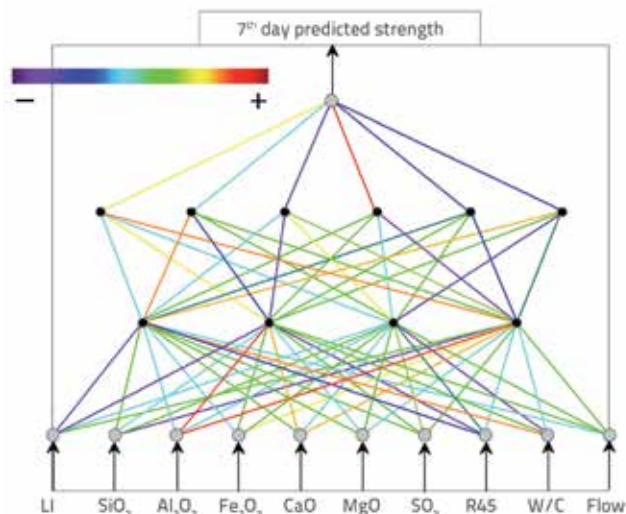

Figure 3. Best configuration topology for network trained at 7 days

The Table 3 presents correlation coefficients for ANN training, validation and testing. Thus, the correlation coefficient for testing is 0.806. The compression strength target and NN predicted result, with the best topology, are shown in Figure 4.
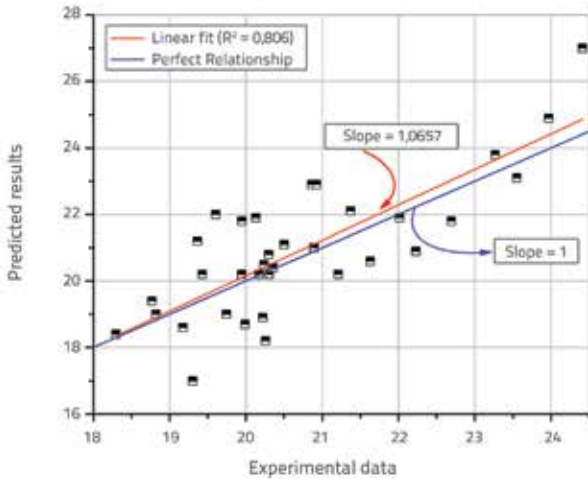
Correlation coefficients for ANN training, validation and testing are presented in Table 4. Thus, the correlation coefficient for testing is 0.7350. The compressive strength target and NN predicted result, with best topology, are shown in Figure 6.

Figure 4. Compression strength target and NN predicted result with best topology, for the 7-day concrete strength
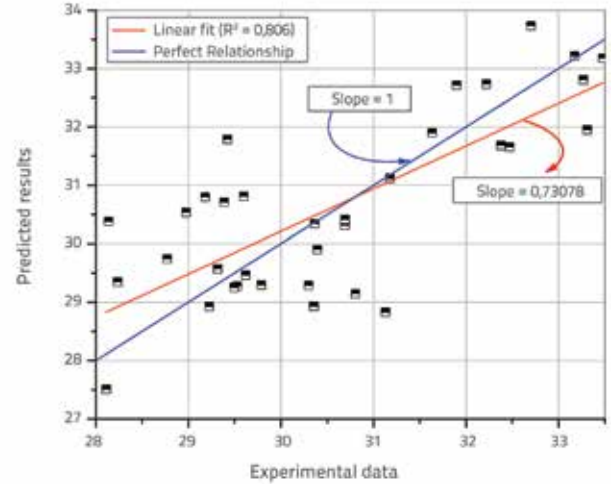

Figure 6. Compression strength target and NN predicted result with best topology, for concrete strength at 28 days

Table 3. Correlation of best network obtained for 7-day prediction

	Training	Validation	Testing
Correlation coefficient	0.866	0.812	0.806

Table 4. Correlations of best network obtained for the 28-day prediction

	Training	Validation	Testing
Correlation coefficient	0.7623	0.6995	0.7350

3.2. Modelling concrete strength at 28 days

The same procedure was performed for the model of neural networks at 28 days. In this case, an optimal topology of 5 neurons in the first hidden layer and 6 neurons in the second hidden layer was obtained (Figure 5).

3.3. Combined modelling of concrete strength at 7 and 28 days

A similar procedure was performed for the combined neural network model for 7 and 28 days. An optimal topology of 6 neurons in the first hidden layer and 4 neurons in the second hidden layer was obtained in this case (Figure 7).
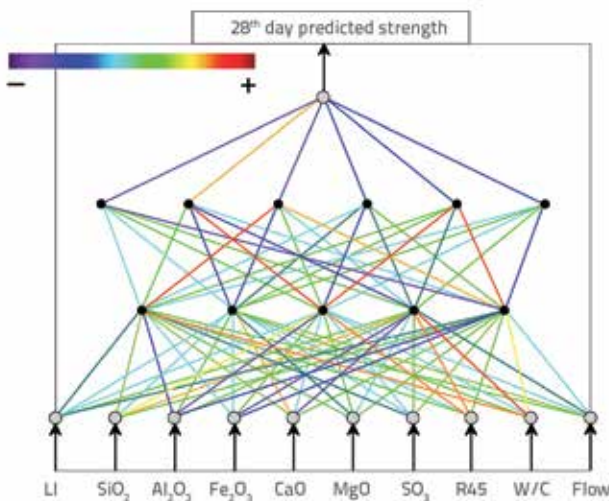

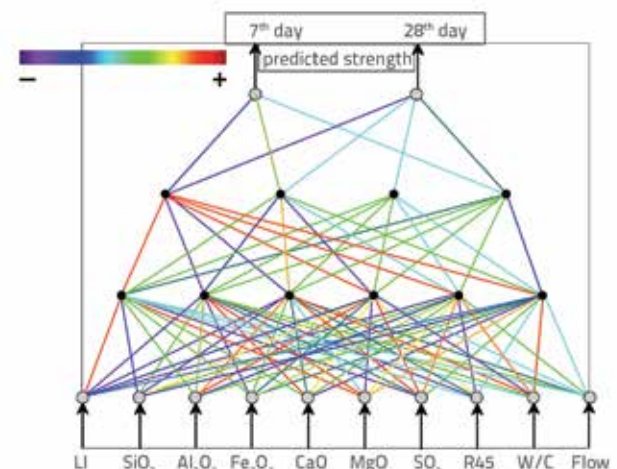**Figure 5. Best configuration topology for network trained at 28 days**

Figure 7. Best configuration topology for combined trained network at 7 and 28 days

The comparison between Figs. (4) and (8), and Figs. (6) and (9) shows a small decrease in the slope of linear relationship between the target and predicted data for simultaneous modelling. That means that the individual NN modelling for 7 or 28 days produces better results. At this point, it is important to remember the objective of this paper. In fact, the aim is not to create a sophisticated ANN for the sake of the tool itself but, on the contrary, the final goal is to propose a useful support tool based on ANN for predicting compressive strength of concrete mixes. Hence, it is not necessary to use the combined ANN, but individual ones. For instance, if the practical requirement is to predict compressive strength at 7 days, then that individual ANN should be applied.

The compression strength target and predicted result (7 and 28 days) obtained using the combined NN with best topology is presented in Figures 8 and 9.
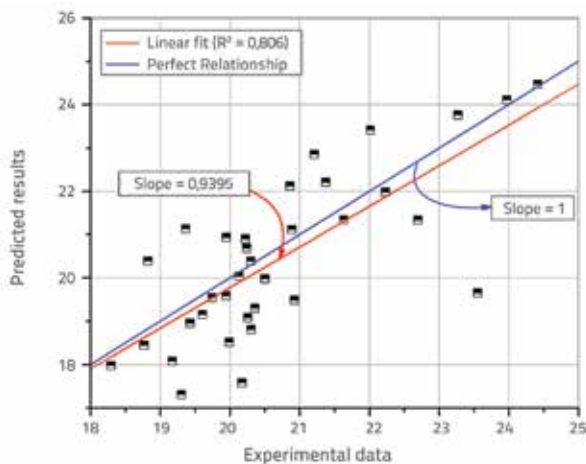

Figure 8. Compression strength Target and Predicted result by combined NN with best topology, for 7-day concrete strength
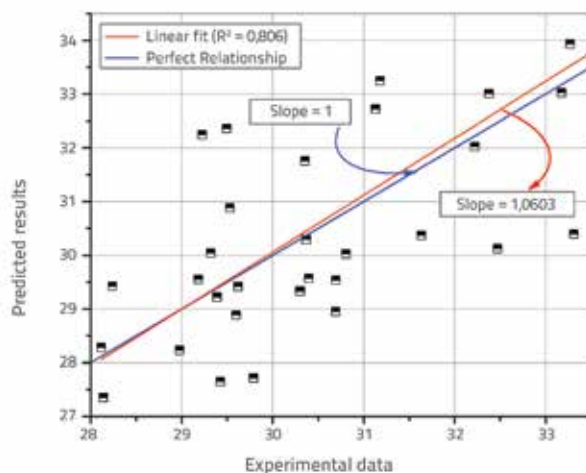

Figure 9. Compression strength Target and Predicted result by combined NN with best topology, for 28-day concrete strength

3.4. Sensitivity analysis

A linear sensitivity analysis was performed in order to quantify relative importance of each of the ten physicochemical variables through compressive strength at 28 days [29, 30]. Relative sensitivities obtained based on the input variables are shown in Figure 10.
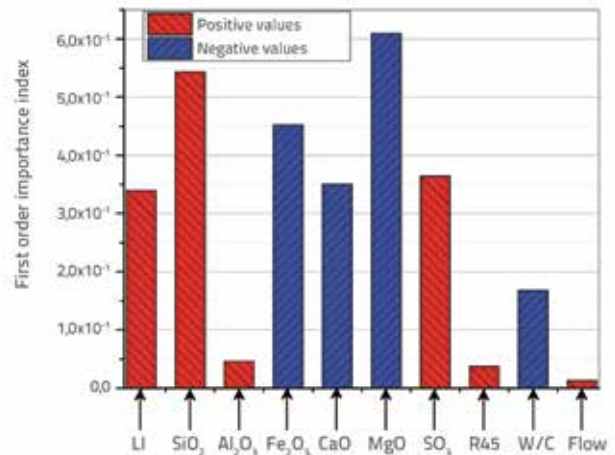

Figure 10. Evaluation of impact on concrete compressive strength (28D) of each individual physicochemical input variable

It can be deduced from Figure 10 that fundamental variables, such as the W/C ratio, do not have an important influence on compressive strength results for concrete. However, it is important to notice that an optimized subset data is used in this paper for analysis, and that 10 physicochemical variables have already been (extremely) optimized in order to achieve the laboratory compressive strength targets of one of the largest concrete companies worldwide. Hence, the range of improvement is very narrow.

4. Conclusions

Concrete mix design is a process based on typical technical principles for proportioning ingredients in right quantities, in order to obtain desired properties. Although various methods for concrete mix design are available, the process is predominantly a qualitative knowledge-based approach subjected to variations. In fact, all concrete mix design methods are simulations that require experimental adjustments in laboratory, which is often done by trial and error. Therefore, the entire process is considered to be time consuming and very costly in materials. In addition, concrete properties including compressive strength are, in general, a highly nonlinear function of its components. And, in order to assure its technical performance, and compliance with commercial-economic requirements, optimizations of the concrete mix design processes, as the one presented in this paper, are welcome.

In this paper, a Multilayer Perceptron Neural Network was trained in order to predict results of compressive strength, which is one of the most important properties of concrete. Artificial neural network models were trained to predict compressive strength after two curing periods (7 and 28 days) from a set of 335 mixtures obtained from quality control procedures conducted in the scope of standard HOLCIM Laboratory tests. The compressive strength of each concrete mixture was measured after 1, 3, 7, and 28 days, and 7 chemical analysis and 3 physical evaluations were made.

Once the optimum topology of the network was determined, the models developed presented correlation coefficients for testing higher than 0.8 for 7 days, and higher than 0.7 for concrete compressive strength at 28 days. It can thus be concluded that the neural network models can accurately predict compressive strength tests of concrete based on physicochemical variables of concrete. The proposed model allows reduction of time needed to obtain compressive strength test results, and it is expected to improve the reliability of the product, defining an appropriate combination of materials to meet concrete performance requirements, suitable for specific applications.

The developed models can be useful for reducing the amount of laboratory tests required to adjust a specific concrete mix design. In addition, they can be useful when concrete innovations are investigated. This is actually a very important potential application because nowadays the research community is investing a lot of effort in the development of new concrete mixes to increase the durability and sustainability of concrete. Moreover, the developed models can also be applied when numerous mix design laboratory data are already available, and when concrete mix optimizations must be performed. In all potential applications, the use of ANNs can reduce the laboratory-related costs.

Finally, a data set with detailed and precise information about concrete strength is also presented in this paper. This information could be useful for the academic and industrial communities, and it is also suitable for complementing other studies and for modelling strength of concrete by ANNs.

Acknowledgements

REFERENCES

[1] Mehta, P., Monteiro, P.: Concrete: Microestructure, Properties and Materials, 3rd Edition, USA: McGraw-Hills, 2006.

[2] Sánchez, D.: Tecnología del concreto y del mortero, Colombia: Bhandar Editores, 2001.

[3] Bogas, J., Gomes, A.: Compressive behavior and failure modes of structural lightweight aggregate concrete – Characterization and strength prediction, Materials and Design, 46 (2013), pp. 832–841.

[4] Taylor, H.: Cement Chemistry, London: Thomas Telford Services, 1997.

[5] Aïtcin, P.C.: Review Cements of yesterday and today Concrete of tomorrow, Cement and Concrete Research, 30 (2000), pp. 1349-1359.

[6] Yaqub, M., Bukhari, I.: Effect of size of coarse aggregate on compressive strength of high strength concerts, 31st Conference on our world in Concrete & Structures, Singapore, 16 – 17 August 2006.

[7] Abdullahi., M.: Effect of aggregate type on Compressive strength of concrete, International Journal of Civil and Structural Engineering, 2 (2012) 3, pp. 791-800.

[8] Baykasoğ, A., Delhi, T., Tanış, S.: Prediction of cement strength using soft computing techniques, Cement and Concrete Research, 34 (2004), pp. 2083-2090.

[9] Yeh, I.C.: Modeling of strength of high-performance concrete using artificial neural networks, Cement and Concrete Research, 28 (1998) 12, pp. 1797-1808.

[10] Ozturan, M., Kutlu, B., Ozturan., T.: Comparison of concrete strength prediction techniques with artificial neural network approach. Building Research Journal, 56 (2008), pp. 23-36.

[11] Başyigit, C., Akkurt, I., Kilincarsian, S., Beycioglu, A.: Prediction of compressive strength of heavy weight concrete, 2010.

[12] Atici, U.: Prediction of the strength of mineral admixture concrete using multivariable regression analysis and an artificial neural network. Expert Systems with Applications, 38 (2011), pp. 9609–9618.

[13] Artificial Neural Networks, A Practical Course, da Silva, I.N., Hernane Spatti, D., Andrade Flauzino, R., Liboni, L.H.B., dos Reis Alves, S.F. eBook ISBN: 978-3-319-43162-8. HTTPS://DOI.ORG/10.1007/978-3-319-43162-8.

[14] Haykin, S.S.: Neural Networks: A Comprehensive Foundation, Prentice Hall, ISBN 978-0-13-273350-2, 1999.

[15] I-Cheng, Y.: Design of a high-performance concrete mixture using neural networks and non-linear programming, Journal of Computing in Civil Engineering, 13 (1999) 1, https://doi.org/10.1061/(ASCE)0887-3801(1999)13:1(36)

[16] Concrete Strength prediction by means of neural network, Construction and building materials,11 (1997) 2, Sergio Lai and Mauro Serra

[17] Acuña, L., Torre, A., Moromi, I., García, F.: Uso de las redes neuronales artificiales en el modelado del ensayo de resistencia a compresión de concreto de construcción según la norma ASTM C39/C 39M. Información Tecnológica, 25 (2014) 4, pp. 3-12.

[18] Chandwani, V., Agrawal, V., Nagar, R.: Applications of Artificial Neural Networks in Modeling Compressive Strength of Concrete: A State of the Art Review, International Journal of Current Engineering and Technology, 4 (2014) 4, pp. 2949-2956.

[19] I-Cheng, Y.: Modeling Concrete Strength with Augment-Neuron Networks, Journal of Materials in Civil Engineering ASCE, 10 (1998) 4, pp. 263-268.

[20] I-Cheng Y.: Modeling of strength of high performance concrete using artificial neural networks, Cement and Concrete Research, 28 (1998) 12, pp. 1797-1808.

[21] I-Cheng Y.: Design of High Performance Concrete Mixture Using Neural Networks, Journal of Computing in Civil Engineering, ASCE, 13 (1999) 1, pp. 36-42.

[22] I-Cheng Y.: Prediction of Strength of Fly Ash and Slag Concrete by the Use of Artificial Neural Networks, Journal of the Chinese Institute of Civil and Hydraulic Engineering, 15 (2003) 4, pp. 659-663.

[23] I-Cheng Y.: Analysis of strength of concrete using design of experiments and neural networks, Journal of Materials in Civil Engineering, ASCE, 18 (2006) 4, pp. 597-604.

[24] Rosenblatt, F.: The perceptron: A probabilistic model for information storage and organization in the brain, Psychological Review, 65 (1958) 6, pp. 386–408. https://doi.org/10.1037/h0042519.

[25] Minsky, M., Papert, P.: Perceptrons: An Introduction to Computational Geometry, The MIT Press, Cambridge MA, 2nd edition with corrections 1972, 1st edition 1969, ISBN 0-262-63022-2.

[26] Muniz-Valencia, R., Jurado, J.M., Ceballos-Magana, S.G., Alcazar, A., Hernandez, D.: Characterization of Mexican coffee according to mineral contents by means of multilayer perceptrons artificial neural networks, Journal of food composition and analysis, 34 (2014) 1, pp. 7-11, https://doi.org/10.1016/j.jfca.2014.02.003.

[27] Choeh, L.S.: Predicting the helpfulness of online reviews using multilayer perceptron neural networks, JY, Expert systems with applications, 41 (2014) 6, pp. 3041-3046, https://doi.org/10.1016/j.eswa.2013.10.034.

[28] Marquardt, D.: An algorithm for least-squares estimation of nonlinear parameters, SIAM, 1963.

[29] I-Cheng, Y., Cheng, W.L.: First and second order sensitivity analysis of MLP. Neurocomputing, 73 (2010) 10-12, pp. 2225-2233, https://doi.org/10.1016/j.neucom.2010.01.011.

[30] Tenza-Abril, A. J., Villacampa, Y., Solak, A.M.; Baeza-Brotons, F.: Prediction and sensitivity analysis of compressive strength in segregated lightweight concrete based on artificial neural network using ultrasonic pulse velocity, Construction and building materials, 189 (2018), pp. 1173-1183, https://doi.org/10.1016/j.conbuildmat.2018.09.096.