Parametric Regression Model and ANN (Artificial Neural Network) Approach in Predicting Concrete Compressive Strength by SonReb Method

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***Abstract*—The commonly used NDT methods to predict concrete compressive strength include the rebound hammer test and the Ultrasonic Pulse Velocity (UPV) test. The poor reliability of rebound hammer and ultrasonic pulse velocity due to different aspects could be partially contrasted by using both methods together, as proposed.in the SonReb method, developed by RILEM Technical Committees 7 NDT and TC-43 CND. There are three techniques that are commonly used to predict fc based on the SonReb measurements: computational modeling, artificial intelligence, and parametric multi-variable regression models. The aim of this study is to verify the accuracy of some reliable parametric multi-variable regression models and ANN approach comparing the estimated compressive strength based on NDT measured parameters with the effective compressive strength based on DT results on core drilled in adjacent locations. The comparisons show the best performance of ANN approach.**

***Index Terms*—concrete strength, SonReb method, parametric regression model, ANN approach**

I. Introduction

Recent seismic codes give relevance to procedure and methods to establish the performance levels of existing structures. To this end detailed inspections and tests on materials are required.

Different sets of material and structural safety factors are therefore required, as well as different analysis procedures, depending on the completeness and reliability of the information available. To this purpose, codes require that a Knowledge Level (KL) is defined in order to choose the admissible type of analysis and the appropriate Confidence Factor (CF) values in the evaluation.

The commonly used Non-Destructive Testing (NDT) methods to predict concrete compressive strength fc include the Rebound Hammer test and the Ultrasonic Pulse Velocity (UPV) test. The poor reliability of rebound hammer and ultrasonic pulse velocity methods due to different aspects could be partially contrasted by using both methods together. One of the most employed NDT combined methods in practice is the SonReb method, developed by RILEM Technical Committees 7 NDT and TC-43 CND [1].

There are three techniques that are commonly used to predict fc based on the SonReb measurements: computational modeling, artificial intelligence, and parametric multi-variable regression models.

Computational modeling is based on the modeling of complex physical phenomena and thus is often not practical. Parametric multi-variable regression models, on the other hand, can be more easily implemented and used in practice for future applications (such as the reliability assessment of RC structures incorporating field data). Artificial intelligence including the Artificial Neural Network (ANN) is a nonparametric statistical tool without knowing the theoretical relationships between the input and the output.

The aim of this study is to verify the accuracy of some reliable parametric multi-variable regression models and ANN approach comparing the estimated compressive strength based on NDT measured parameters with the effective compressive strength based on DT results on core drilled in adjacent locations. To this end a relevant number of DT tests and NDT tests have been performed on many reinforced concrete structures.

II. Parametric Regression Model

A number of parametric regression models using the SonReb measurements (UPV and RN) to predict the concrete compression strength have been developed. The combined method SonReb can evaluate the concrete compression strength by combining the experimentally obtained non-destructive parameters with correlations as follow:

$$f_c = f_0\, e^a\, V^b\, (RI)^c \tag{1}$$

where:

f_c is the concrete compression strength, [MPa];
f_0 is the units conversion factor, [usually f_0 = 1MPa s/m];
V is the ultrasonic pulse velocity [m/s];
RI is the rebound index;
a,b,c are dimensionless correlation parameters to be determined by regression analysis.

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Several correlation equations have been developed and presented by numerous authors. In this study, some of the most reliable and employed formulations available in literature [2]-[4] are considered:

$$f_c = 7.695 \cdot 10\ {-11} \cdot (RI)\ 1.4 \cdot (V)\ 2.6 \quad [2] \qquad (2)$$

$$f_c = 1.2 \cdot 10\ {-9} \cdot (RI)\ 1.058 \cdot (V)\ 2.446 \quad [3] \qquad (3)$$

$$f_c = 0.0286 \cdot (RI)\ 1.246 \cdot (V)\ 1.85 \quad [4] \qquad (4)$$

Another formulation proposed in Technical Standards of Tuscany Region [5] is the mean value calculated by the above three formulations (5). In order to evaluate the accuracy of the SonReb formulations, the estimated compressive strength in 16 different locations in existing building have been compared with the effective compressive strength determined by DT on sample extracted in adjacent locations [6], [7]. To compare prediction performance of these formulations, Root Mean Square Error (RMSE) has been calculated. All the comparisons are shown in Fig. 1.

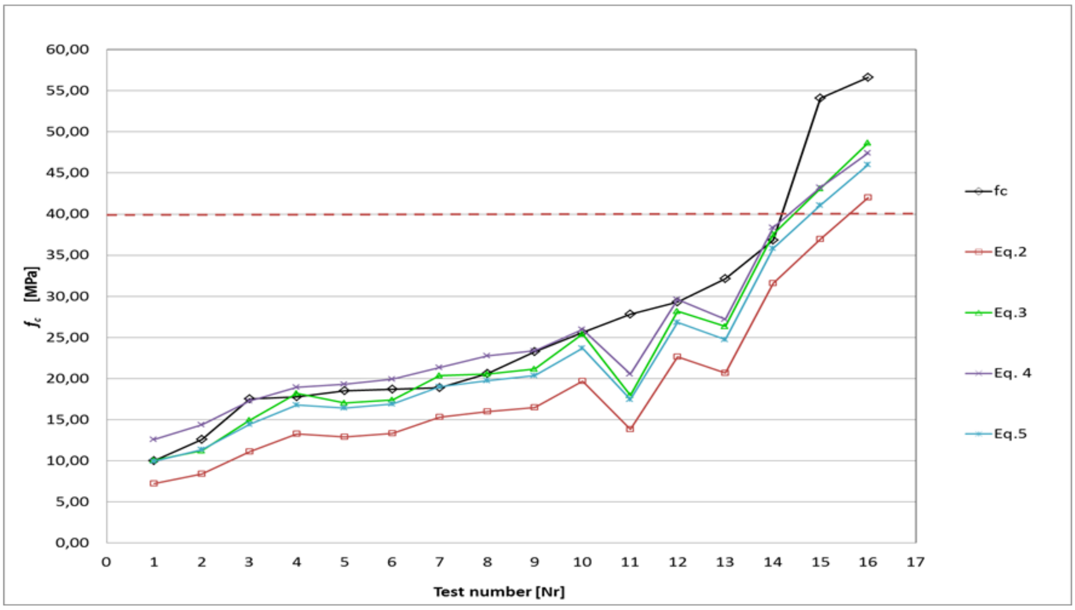

Figure 1. Comparison between DT fc-values and estimated NDT fc-values using different formulations

III. Parametric Regression Model

Prediction of Compressive strength of concrete, using SonReb values in existing reinforced concrete structures, can also be made using recent ANN models [8]-[20].

ANN are information processing systems that try to simulate in a computer program the behavior of biological nervous systems which are constituted by a large number of neurons connected together in a complex network.. The intelligent behavior arises from interactions among numerous interconnected units. Some of these units receive information from the external environment (i.e. input layer), some send responses in the environment (i.e. output layer), others communicate only with other units inside the network (i.e. hidden layer). The input-output ratio, i.e. the transfer function of the network, is not programmed but is simply obtained by a learning process based on empirical data.

There are several types of ANN in relation to the type of connections that link the neurons of the different layers, to the activation functions and learning algorithms. Depending on the type of connections between artificial neurons, it can be distinguishing the three main classes: feed-forward networks, cellular networks and feed-back networks. Depending on the learning process, it can be distinguishing the three main classes: i) supervised learning; ii) unsupervised learning; iii) reinforcement learning. From a mathematical point of view the learning process consists of finding a minimum of a function in a n-dimensional space. This function is given by the variation of the error based on the weights of the network.

The algorithm used in the learning with more supervision is the backpropagation error algorithm, which minimizes the total error of the network through the modification of the weights of the connections. In order to search for a minimum, it is usually used the gradient descent technique. In this analysis a feed-forward network composed of 3 layers (input, output, hidden layers), with sigmoid logistic activation function and supervised learning with backpropagation error algorithm has been employed (Fig. 2).

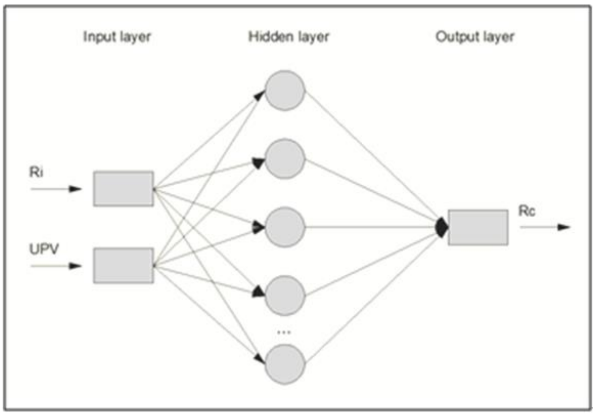

Figure 2. Schematic representation of ANN with UPV and RI as input data

The in-situ compressive strength and the SonReb parameters in 16 locations are reported in Table I.

TABLE I. IN-SITU COMPRESSIVE STRENGTH, RI AND UPV IN 16 LOCATIONS

N.	f_c [Mpa]	RI	UPV [m/s]
1	10.00	34.72	2470
2	12.60	38.89	2450
3	17.50	36.39	2830
4	17.80	31.90	3250
5	18.50	37.22	2960
6	18.70	38.83	2930
7	18.90	34.61	3285
8	20.60	39.34	3120
9	23.25	39.78	3140
10	25.60	36.84	3500
11	27.80	39.00	2965
12	29.30	41.44	3470
13	32.16	38.39	3490
14	36.80	45.45	3750
15	54.10	47.28	3900
16	56.60	47.33	4095

The training and learning phases of the ANN with 5 neurons in the hidden layer are used. Learning is a supervised process that occurs with each cycle or epoch. The principal data of this network are:

NetTrain Param. Epochs	*Best Performance Epochs*	*RMSE* [MPa]
1000	212	1,8438

In order to evaluate the accuracy of this ANN model, the estimated compressive strength in 16 different locations in existing building have been compared with the effective compressive strength determined by Destructive Testing (DT) on samples extracted in adjacent locations (Fig. 3).

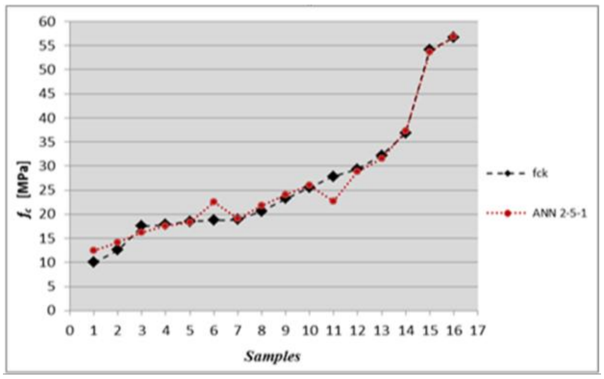

Figure 3. Comparison between DT fc- values and estimated NDT fc- values using ANN 2-5-1

IV. CONCLUSION

The results obtained by taking into account only the non-destructive parameters indicate the good prediction of the proposed SonReb formulations in the evaluation of concrete compressive strength.

Concerning the performance of parametric regression models, the most employed formulations make reliable estimates of compressive strength except Eq. (2) [2], as shown in Fig. 1.

An artificial neural network has been developed and implemented in MatLab language. These networks are able to establish a non-linear correlation between input data obtained using non-destructive tests (such as the Rebound Index RI and the ultrasonic pulse velocity UPV of elastic waves) and output data (such as the concrete compressive strength).

In this analysis a feed-forward network composed of 3 layers (input, output, hidden layers), with sigmoid logistic activation function and supervised learning with backpropagation error algorithm has been employed.

Thus the effectiveness of the network can be investigated as a function of the only variable parameter in their architecture: the number of neurons of the hidden layer.

Fig. 3 shows that the use of ANN approach yields the best performance.

Future work will focus on influence of the number of neurons of the hidden layer on final output.

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REFERENCES

[1] Rilem Report TC43-CND: Draft Recommendations for in situ Concrete Strength Determination by Combined Non-Destructive Methods, 1983.

[2] R. Giacchetti and L. Lacquaniti, "Controlli non distruttivi su impalcati da ponte in calcestruzzo armato (In Italian)," Nota Tecnica 04, Università di Ancona, Facoltà di Ingegneria, Istituto di Scienza e Tecnica delle Costruzioni, 1980.

[3] A. D. Leo and G. Pascale, "Prove non distruttive sulle costruzioni in cemento armato (In Italian)," in *Proc. Conference on Non Destructive Testing and Quality System for Reliability and Safety of Civil Structures*, Bologna, October 21, 1994.

[4] J. Gasparik, "Prove non distruttive in edilizia (In Italian)," Quaderno Didattico A.I.P.N.D., Brescia, 1992.

[5] Regione Toscana, Istruzioni Tecniche: Criteri per lo Svolgimento di Indagini Diagnostiche Finalizzate alla Valutazione della Qualita dei Materiali in Edifici Esistenti in Cemento Armato (In Italian), 2004.

[6] L. Nobile, "Prediction of concrete compressive strength by combined non-destructive methods," *Meccanica*, vol. 50, no. 2, pp. 411–417, 2015.

[7] L. Nobile and M. Bonagura, "Recent advances on non-destructive evaluation of concrete compression strength," *Int. J. Microstructure and Materials Properties*, vol. 9, no. 3-5, pp. 413-421, 2014.

[8] K. Hornik, "Multilayer feedforward networks are universal approximators," *Neural Netw.*, vol. 2, pp. 359-66, 1989.

[9] W. Sukthomya and J. Tannock, "The training of neural networks to model manufacturing processes," *J. Intell. Manuf.*, vol. 16, pp. 39-51, 2005.

[10] T. Y. Lin and C. H. Tseng, "Optimum design for artificial networks: An example in a bicycle derailleur system," *Eng. Appl. Artif. Intell.*, vol. 13, pp. 3-14, 2000.

[11] N. K. Bose and P. Liang, *Neural Network Fundamentals with Graphs, Algorithms and Applications*, New York: McGraw-Hill, 1996.

[12] S. Haykin, *Neural Networks: A Comprehensive Foundation, Upper Saddle River*, New Jersey: Prentice Hall, 1999.

[13] B. Topping and A. Bahreininejad, *Neural Computing for Structural Mechanics*, Edinburgh, UK: Saxe-Coburg Publications, 1997.
[14] H. Adeli, "Neural networks in civil engineering: 1989−2000," *Computer-Aided Civil and Infrastructure Engineering*, vol. 16, pp. 126–142, 2001.
[15] H. Hoła and K. Schabowicz, "Methodology of neural identification of strength of concrete," *ACI Materials Journal*, vol. 102, no. 6, 2005.
[16] N. Langaros and M. Papadrakakis, "Neural network based prediction schemes of the non-linear seismic response of 3D buildings," *Advances in Engineering Software*, vol. 44, pp. 92-115. 2012.
[17] L. Sadowski, "Non-destructive investigation of corrosion current density in steel reinforced concrete by artificial neural networks," *Archives of Civil and Mechanical Engineering*, vol. 13, no. 1, pp. 104-111, 2013.
[18] Z. Waszczyszyn and L. Ziemiański, "Neural networks in mechanics of structures and materials - new results and prospects of applications," *Computers & Structures*, vol. 79, pp. 2261-2276, 2001.
[19] M. Bilgehan and P. Turgut, "Artificial neural network approach to predict compressive strength of concrete through ultrasonic pulse velocity," *Research in Nondestructive Evaluation*, vol. 21, pp. 1-17, 2010.
[20] L. Sadowski and J. Hoła, "Neural prediction of the pull-off adhesion of the concrete layers in floors on the basis of nondestructive tests," *Procedia Engineering*, vol. 57, pp. 986–995, 2013.

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