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PREDICTION OF MECHANICAL CHARACTERISTICS OF SOILCRETE MATERIALS USING ARTIFICIAL NEURAL NETWORKS

P.G. Asteris[1(*)], A. Alexandridis[2], K.G. Kolovos[3], E.G. Anesti[1], M.G. Douvika[1], C.A. Karamani[1], M.G. Kassolis[1], A.D. Skentou[1]

[1]Computational Mechanics Laboratory, School of Pedagogical and Technological Education, Athens, Greece
[2]Technological Educational Institute of Athens, Department of Electronic Engineering, Aigaleo, Greece
[3]Department of Physical Sciences and Applications, Hellenic Army Academy, Vari, Greece
[(*)]*Email:* panagiotisasteris@gmail.com

ABSTRACT

In this paper, the application of soft computing techniques such as surrogate models for the prediction of the soilcrete materials' properties has been investigated. Specifically, the application of Artificial Neural Networks (ANNs) models for the prediction of mechanical properties such as the 28-day compressive strength has been studied. To this end, a new normalization technique for the pre-processing of data is proposed. The comparison of the derived results with the available experimental data demonstrates the capability of ANNs to predict with pinpoint accuracy the compressive strength. Furthermore, the proposed normalization technique has been proven effective and robust compared to the available ones.

Keywords: artificial neural networks, back propagation neural networks, compressive strength, normalization techniques, soilcrete materials, ultrasonic pulse velocity.

INTRODUCTION

Eco-friendly, low-cost, sustainable construction materials for utilization in civil engineering projects have attracted much attention during the last decades. To this end, soilcretes are non-conventional construction materials produced by mixing natural soil such as natural clay or limestone sand with a hydraulic binder and are being under detailed and in-depth investigation by many researchers recently (Kolovos et al. 2013, Asteris et al. 2017, Helson et al. 2017, Kim & Kim 2017). Soilcrete belongs to a family of concretes, which can be used, under conditions, when environmental or economic constraints limit the use of coarse aggregates, since it can exploit amounts of proper soils, rocks, or even recycled concrete materials that are present in abundance. Its main components are fine aggregate (clay and/or sand), ordinary Portland cement, water at an appropriate ratio and rarely mineral admixtures, thus rendering it a composite material.

Artificial neural networks (ANNs) have emerged the last decades as an attractive modelling technique applicable to vast number of scientific fields including material science among others. The main characteristic of this method is that a surrogate model can be constructed after a training process with only a few available data, which can be used in order to predict pre-selected model parameters, reducing the need for time- and money-consuming experiments. So far, literature includes publications in which ANN were used for predicting the compressive strength and modulus of elasticity (Dias and Pooliyadda 2001, Lee 2003, Topçu and Saridemir 2008, Trtnik et al. 2009) and for modelling the characteristics of concrete materials (Waszczyszyn and Ziemiański 2001; Belalia Douma et al. 2016;

Mashhadban et al 2016; Açikgenç et al. 2015). Moreover, similar methods such as fuzzy logic and genetic algorithms have also been used for modelling the compressive strength of concrete materials (Baykasoğlu et al. 2004, Akkurt et al. 2004, Özcan et al. 2009). A detailed and in-depth state of the art report can be found in Adeli 2001, Safiuddin et al. 2016, Mansouri and Kisi 2015 and Mansouri et al. 2016.

Properties of soilcrete materials depict a strong nonlinear nature based on the parameters involved in their composition; furthermore, the nonlinear behavior makes the development of an analytical formula for the prediction of the mechanical properties using deterministic methods a rather difficult issue. In this work, the modeling of the mechanical characteristics of soilcrete materials has been detailed and in-depth investigated using soft computing techniques such as artificial intelligence (AI) techniques. Specifically, the application of ANN models for the prediction of the 28-day compressive strength of sand-crete materials has been investigated.

ARTIFICIAL NEURAL NETWORKS

This section summarizes the mathematical and computational aspects of artificial neural networks. In general, ANNs are information-processing models configured for a specific application through a training process. A trained ANN maps a given input onto a specific output and thereby can be considered to be similar to a response surface method. The main advantage of a trained ANN over conventional numerical analysis procedures (e.g. regression analysis) is that the results can be produced with much less computational effort (Hornik et al. 1989, Adeli 2991, Plevris and Asteris 2014 and 2015, Giovanis and Papadopoulos 2015, Asteris and Plevris 2013 and 2016, Asteris et al. 2016).

General

The concept of an artificial neural network is based on the concept of the biological neural network of the human brain. The basic building block of the ANN is the artificial neuron, which is a mathematical model trying to mimic the behaviour of the biological neuron. Information is passed into the artificial neuron as input and it is processed with a mathematical function leading to an output which determines the behaviour of the neuron (similar to fire-or-not situation for the biological neuron). Before the information enters the neuron, it is weighted in order to approximate the random nature of the biological neuron. A group of such neurons consists of an ANN in a manner similar to biological neural networks. In order to set up an ANN, one needs to define: i) The architecture of the ANN, ii) the training algorithm, which will be used for the ANN learning phase, and iii) the mathematical functions describing the mathematical model. The architecture, or topology, of the ANN describes the way the artificial neurons are organized in the group and how information flows within the network. For example, if the neurons are organized in more than one layers then the network is called a multilayer ANN. Regarding the training phase of the ANN, it can be considered as a function minimization problem, in which the optimum value of weights need to be determined by minimizing an error function. Depending on the optimization algorithms used for this purpose, different types of ANNs exist. Finally, the two mathematical functions that define the behaviour of each neuron are the summation function and the activation function. In the present study, we use a back-propagation neural network (BPNN), which is described in the next section.

Architecture of BPNN

A BPNN is a feed-forward, multilayer network i.e. information flows only from the input towards the output with no back loops and the neurons of the same layer are not connected to each other, but they are connected with all the neurons of the previous and subsequent layer. A BPNN has a standard structure that can be written as

$$\mathbf{N} - \mathbf{H_1} - \mathbf{H_2} - \cdots - \mathbf{H_{NHL}} - \mathbf{M} \qquad (1)$$

where N is the number of input neurons (input parameters); $\mathrm{H_i}$ is the number of neurons in the $\mathrm{i-th}$ hidden layer for $\mathrm{i} = 1, \ldots, \mathrm{NHL}$; NHL is the number of hidden layers and M is the number of output neurons (output parameters).

RESULTS AND DISCUSSION

In this section, the whole process for tuning optimum ANNs used for the prediction of the 28-day compressive strength of soilcrete materials based on available in the literature experimental data, is presented step-by-step.

Experimental

The database used herein consists of mixes obtained from literature. Especially, 134 mixes that contained crushed quarry sand of a limestone origin as replacement of the aggregate phase, where metakaolin has been added at variable contents as a mineral additive to the ordinary Portland cement-based binder mix, at different water/binder ratio values (*W/B*) have been used (Table 1). Specifically, the Research Database presents measured physical and mechanical properties, such as the 28 days compressive strength (f_c), (Fig. 1) of a large set of cylindrical specimens with a height-to-diameter (*h/d*) ratio equal to 2 (*h/d*=2), which have been tested under uniaxial compression, as well as the ultrasonic velocity for each one specimen, having been measured before the latter were subjected to uniaxial compression (Kolovos et al. 2016 and Asteris et al. 2017). Detailed and in-depth description of the experimental set-up can be found in the previous mentioned references.

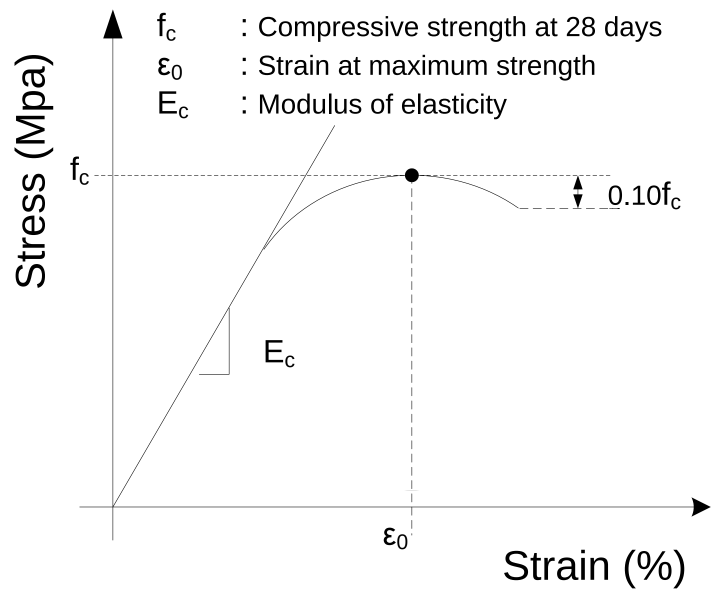

Fig. 1 - Stress-strain curves

Table 1: Experimental data/results and input and output parameters of BPNNs (Asteris & Kolovos 2017)

Sample	Input					Output	Comments*
	W/B ratio	MK (% w/w in the dry mix)	B (% w/w in the dry mix)	SP (% w/w of the cementitious materials)	Ultrasonic Velocity (m/s)	Compressive Strength (MPa)	
1	0.40	0	50	2	4070.00	55.35	T
2	0.40	0	50	2	4016.67	62.25	T
3	0.40	0	50	2	4053.33	41.04	V
4	0.40	0	50	2	4100.00	58.00	T
5	0.40	0	50	2	4076.67	50.35	T
6	0.40	0	50	2	4040.00	46.48	Test
7	0.40	0	50	2	4090.00	61.49	T
8	0.40	0	50	2	4016.67	62.25	T
9	0.40	0	30	2	4006.67	62.35	V
10	0.40	0	30	2	4080.00	66.72	T
11	0.40	0	30	2	4040.00	57.17	T
12	0.40	0	30	2	4100.00	60.79	Test
13	0.40	0	30	2	4000.00	50.36	T
14	0.40	0	30	2	4070.00	64.64	T
15	0.40	0	30	2	4040.00	57.17	V
16	0.40	0	30	2	4063.33	50.66	T
17	0.40	5	50	2	3913.33	49.36	T
18	0.40	5	50	2	3931.67	48.30	Test
19	0.40	5	50	2	3916.67	48.86	T
20	0.40	5	50	2	3980.00	49.01	T
21	0.40	5	50	2	3840.00	41.86	V
22	0.40	5	50	2	3900.00	39.87	T
23	0.40	5	50	2	3931.67	48.30	T
24	0.40	5	50	2	3810.00	59.82	Test
25	0.40	3	30	2	4090.00	62.01	T
26	0.40	3	30	2	4053.33	59.44	T
27	0.40	3	30	2	4053.33	59.44	V
28	0.40	3	30	2	4070.00	58.03	T
29	0.40	3	30	2	4003.33	60.87	T
30	0.40	3	30	2	3966.67	46.26	Test
31	0.40	3	30	2	4023.33	63.05	T
32	0.40	3	30	2	3986.67	51.67	T
33	0.40	10	50	2	3926.67	76.90	V
34	0.40	10	50	2	3831.67	56.03	T
35	0.40	10	50	2	3763.33	68.21	T
36	0.40	10	50	2	3810.00	72.48	Test
37	0.40	10	50	2	3873.33	68.86	T
38	0.40	10	50	2	3831.67	56.03	T
39	0.40	10	50	2	3746.67	71.26	V
40	0.40	10	50	2	3756.67	71.57	T
41	0.40	6	30	2	3886.67	64.65	T
42	0.40	6	30	2	3820.00	72.68	Test
43	0.40	6	30	2	3906.67	74.34	T
44	0.40	6	30	2	3880.00	67.92	T
45	0.40	6	30	2	3903.33	75.77	V

*Note: T: Training Data; V: Validation Data; Test: Test Data

Table 1: Experimental data/results and input and output parameters of BPNNs (Asteris & Kolovos 2017)

Sample	Input					Output	Comments*
	W/B ratio	MK (% w/w in the dry mix)	B (% w/w in the dry mix)	SP (% w/w of the cementitious materials)	Ultrasonic Velocity (m/s)	Compressive Strength (MPa)	
46	0.40	6	30	2	3863.33	70.94	T
47	0.40	6	30	2	3886.67	64.65	T
48	0.40	6	30	2	3890.00	60.81	Test
49	0.70	0	50	0	3523.33	27.87	T
50	0.70	0	50	0	3353.33	22.53	T
51	0.70	0	50	0	3333.33	25.16	V
52	0.70	0	50	0	3381.67	26.68	T
53	0.70	0	50	0	3356.67	25.18	T
54	0.70	0	50	0	3376.67	28.75	Test
55	0.70	0	50	0	3381.67	26.68	T
56	0.70	0	30	0	3486.67	26.72	T
57	0.70	0	30	0	3670.00	28.63	V
58	0.70	0	30	0	3536.67	23.53	T
59	0.70	0	30	0	3343.33	26.07	T
60	0.70	0	30	0	3516.67	28.83	Test
61	0.70	0	30	0	3486.67	26.44	T
62	0.70	0	30	0	3436.67	28.06	T
63	0.70	0	30	0	3413.33	33.32	V
64	0.70	5	50	0	3303.33	35.60	T
65	0.70	5	50	0	3406.67	31.48	T
66	0.70	5	50	0	3303.33	31.61	Test
67	0.70	5	50	0	3333.33	32.59	T
68	0.70	5	50	0	3533.33	30.51	T
69	0.70	5	50	0	3383.33	32.99	V
70	0.70	5	50	0	3333.33	32.59	T
71	0.70	5	50	0	3373.33	32.71	T
72	0.70	3	30	0	3473.33	31.53	Test
73	0.70	3	30	0	3530.00	30.69	T
74	0.70	3	30	0	3516.67	31.00	T
75	0.70	3	30	0	3473.33	29.55	V
76	0.70	3	30	0	3420.00	29.43	T
77	0.70	3	30	0	3493.33	33.11	T
78	0.70	3	30	0	3500.00	30.44	Test
79	0.70	3	30	0	3446.67	35.51	T
80	0.70	10	50	0	3386.67	40.78	T
81	0.70	10	50	0	3396.67	44.13	V
82	0.70	10	50	0	3386.67	38.48	T
83	0.70	10	50	0	3416.67	38.327	T
84	0.70	10	50	0	3416.67	38.33	Test
85	0.70	10	50	0	3386.67	38.28	T
86	0.70	10	50	0	3373.33	39.71	T
87	0.70	10	50	0	3426.67	41.75	V
88	0.70	6	30	0	3473.33	35.68	T
89	0.70	6	30	0	3466.67	34.94	T
90	0.70	6	30	0	3480.00	33.27	Test

***Note:** T: Training Data; V: Validation Data; Test: Test Data

Table 1: Experimental data/results and input and output parameters of BPNNs (Asteris & Kolovos 2017)

Sample	Input					Output	Comments*
	W/B ratio	MK (% w/w in the dry mix)	B (% w/w in the dry mix)	SP (% w/w of the cementitious materials)	Ultrasonic Velocity (m/s)	Compressive Strength (MPa)	
91	0.70	6	30	0	3423.33	35.82	T
92	0.70	6	30	0	3456.67	39.31	T
93	0.70	6	30	0	3440.00	38.16	V
94	0.70	6	30	0	3446.67	33.79	T
95	0.70	6	30	0	3400.00	35.49	T
96	1.00	0	50	0	2996.67	12.21	Test
97	1.00	0	50	0	3076.67	15.41	T
98	1.00	0	50	0	3216.67	17.39	T
99	1.00	0	50	0	3086.67	16.39	V
100	1.00	0	50	0	3026.67	15.05	T
101	1.00	0	30	0	3430.00	17.21	T
102	1.00	0	30	0	3233.33	15.52	Test
103	1.00	0	30	0	3173.33	16.56	T
104	1.00	0	30	0	3083.33	15.28	T
105	1.00	5	50	0	3163.33	17.32	V
106	1.00	5	50	0	3230.00	16.03	T
107	1.00	5	50	0	3053.33	18.64	T
108	1.00	5	50	0	3180.00	17.20	Test
109	1.00	5	50	0	3040.00	14.37	T
110	1.00	5	50	0	2933.33	14.67	T
111	1.00	5	50	0	3010.00	14.74	V
112	1.00	3	30	0	3116.67	16.13	T
113	1.00	3	30	0	3350.00	20.84	T
114	1.00	3	30	0	3130.00	14.28	Test
115	1.00	3	30	0	2993.33	14.16	T
116	1.00	3	30	0	3180.00	14.42	T
117	1.00	3	30	0	3006.67	15.60	V
118	1.00	3	30	0	3063.33	15.74	T
119	1.00	10	50	0	2906.67	19.00	T
120	1.00	10	50	0	2983.33	20.26	Test
121	1.00	10	50	0	2896.67	19.60	T
122	1.00	10	50	0	3060.00	16.73	T
123	1.00	10	50	0	2890.00	18.38	V
124	1.00	10	50	0	3023.33	19.54	T
125	1.00	10	50	0	2930.00	17.85	T
126	1.00	10	50	0	2896.67	18.82	Test
127	1.00	6	30	0	3070.00	16.67	T
128	1.00	6	30	0	3003.33	20.24	T
129	1.00	6	30	0	3013.33	17.89	V
130	1.00	6	30	0	3086.67	14.86	T
131	1.00	6	30	0	2926.67	18.16	T
132	1.00	6	30	0	3046.67	17.95	Test
133	1.00	6	30	0	2986.67	14.92	T
134	1.00	6	30	0	2983.33	14.89	T

*Note: T: Training Data; V: Validation Data; Test: Test Data

Each input training vector p is of dimension 1x5 and consists the values of the four parameters of synthesis and the value of the ultrasonic velocity (R=11) namely, the water-to-binder ratio (W/B), the metakaolin addition (MK), the binder (B), the superplasticizer (SP), and the ultrasonic velocity (UV). The corresponding output training vectors are of dimension 1x1 and consist, the value of the 28 days compressive strength of the soilcrete specimens.

Normalization of data

As mentioned previously, the normalization of the input and output parameters has a significant impact on the ANN training. In the present study, during the pre-processing stage, the Min-Max (Delen et al. 2006) normalization methods has been used. In particular, the five input parameters (Table 1), as well as the single output parameter of the 28-day compressive strength, have been normalized using the Min-Max normalization method. As stated in Iruansi et al. 2010, in order to avoid problems associated with low learning rates of the ANN, the normalization of the data should be made within a range defined by appropriate upper and lower limit values of the corresponding parameter. In this work, the input and output parameters have been normalized in the range [-1, 1], respectively. Moreover, in this work a recently proposed transformation technique called Central has been applied (Asteris & Kolovos 2017), in which the origin of the training data is shifted to the centre of the data with the following formula:

$$z_i = x_i - \frac{\max(x)+\min(x)}{2} \tag{2}$$

where x $(x_1, x_2, \ldots, x_n)$ are the original data and z_i is the i^{th} transformed data.

BPNN model development

In this work, a total of 148800 different BPNN models have been developed and investigated. More specifically, 37200 of these, involve ANN architectures implemented in 4 different computers in order to investigate the sensitivity of the ANN results to the very nature of the floating-point arithmetic of each computer. Each one of these ANN models was trained over 90 datasets out of the total of 134 datasets, (66.86% of the total number) and the validation and testing of the trained ANN were performed with the remaining 44 datasets. More specifically, 22 datasets (16.57%) were used for the validation of the trained ANN and 22 (16.57%) datasets were used for the testing (estimating the Pearson’s correlation coefficient R). The parameters used for the ANN training are summarized as follows: After a detailed and in depth investigation among a plethora of training algorithms, the Levenberg-Marquardt algorithm (Lourakis 2005) has been used as the optimum training algorithm for the ANN models. The development and training of the ANNs occurs with a number of hidden layers ranging from 1 to 2 and with a number of neurons ranging from 1 to 30. Each one of the ANNs is developed and trained for a number of different activation functions such as the Logistic Sigmoid and the Hyperbolic Tangent transfer functions.

In order to have a fair comparison of the various ANNs, the datasets used for their training are manually divided by the user into training, validation and testing sets using appropriate indices to state whether the data belongs to the training, validation or testing set. In the general case, the division of the datasets into the three groups is made randomly.

The 148800 developed ANN models were sorted in a decreasing order based on the Pearson's correlation coefficient value and the architectures of the top twenty models are presented in Table 2 for the four computers used. Based on these results, the optimum BPNN model architecture is 5-7-7-1, with a Pearson's correlation coefficient R equal to 0.99001.

Table 2: Ranking of the top twenty best architectures of BPNNs based on Pearson's correlation coefficient R (all computers)

Ranking	**Computer**	**Preprocess**	**Cost Function***	**Training Functions****	**Initial Weights**	**Architecture (Code)**	**Pearson's R**	**Number of Epochs**
1	C02	Central	MSE	T-L-T	-0.1	5-7-7-1	0.99001	180
2	C04	MinMax	MSE	T-L-T	-0.7	5-30-7-1	0.98985	218
3	C03	MinMax	MSE	T-L-T	0.9	5-6-24-1	0.98917	215
4	C03	MinMax	MSE	T-L-T	0.9	5-6-27-1	0.98870	215
5	C02	MinMax	MSE	T-L-T	-0.9	5-4-3-1	0.98859	211
6	C02	Central	MSE	T-L-T	0.1	5-30-3-1	0.98858	180
7	C02	Central	SSE	T-L-T	-0.7	5-30-12-1	0.98846	225
8	C02	Central	MSE	T-L-T	0.9	5-14-29-1	0.98823	180
9	C03	NoPreprocess	SSE	T-L-T	-0.7	5-22-15-1	0.98820	202
10	C03	Central	SSE	T-L-T	-0.5	5-6-3-1	0.98802	250
11	C03	Central	MSE	T-L-T	-0.9	5-7-4-1	0.98790	225
12	C03	MinMax	MSE	T-L-T	-0.5	5-24-14-1	0.98786	215
13	C01	MinMax	SSE	T-L-T	0.1	5-9-27-1	0.98774	141
14	C04	NoPreprocess	SSE	T-L-T	-0.1	5-7-9-1	0.98772	210
15	C02	NoPreprocess	SSE	T-L-T	-0.1	5-10-4-1	0.98769	153
16	C02	Central	SSE	T-L-T	-0.1	5-10-24-1	0.98768	180
17	C04	MinMax	SSE	T-L-T	-0.5	5-5-22-1	0.98761	159
18	C04	MinMax	MSE	T-L-T	0.3	5-5-17-1	0.98730	159
19	C03	NoPreprocess	MSE	T-L-T	-0.3	5-7-1-1	0.98716	202
20	C01	MinMax	SSE	T-L-T	-0.9	5-7-5-1	0.98714	223

*****Note I : MSE : Mean Square Error; SSE : Mean Square Error
******Note I : T: Hyperbolic tangent sigmoid transfer function (tansig)
L: Log-sigmoid transfer function (logsig)

Figures 2 and 3 depict the comparison of the exact experimental values with the predicted values of the optimum BPNN model with topology 5-7-7-1. These results clearly show that the 28-day compressive strength of sand-crete material predicted from the multilayer feed-forward neural network, are very close to the experimental results.

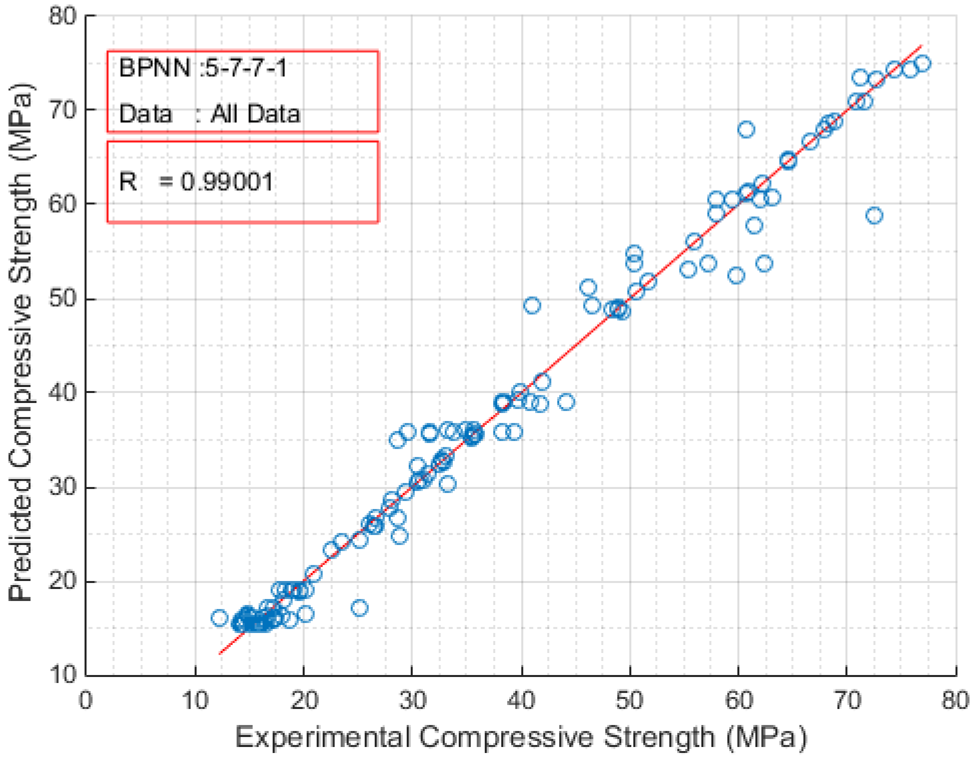

Fig. 2 - The Pearson's correlation coefficient R of the experimental and predicted Compressive strength for the best with two hidden layers BPNN (5-7-7-1)

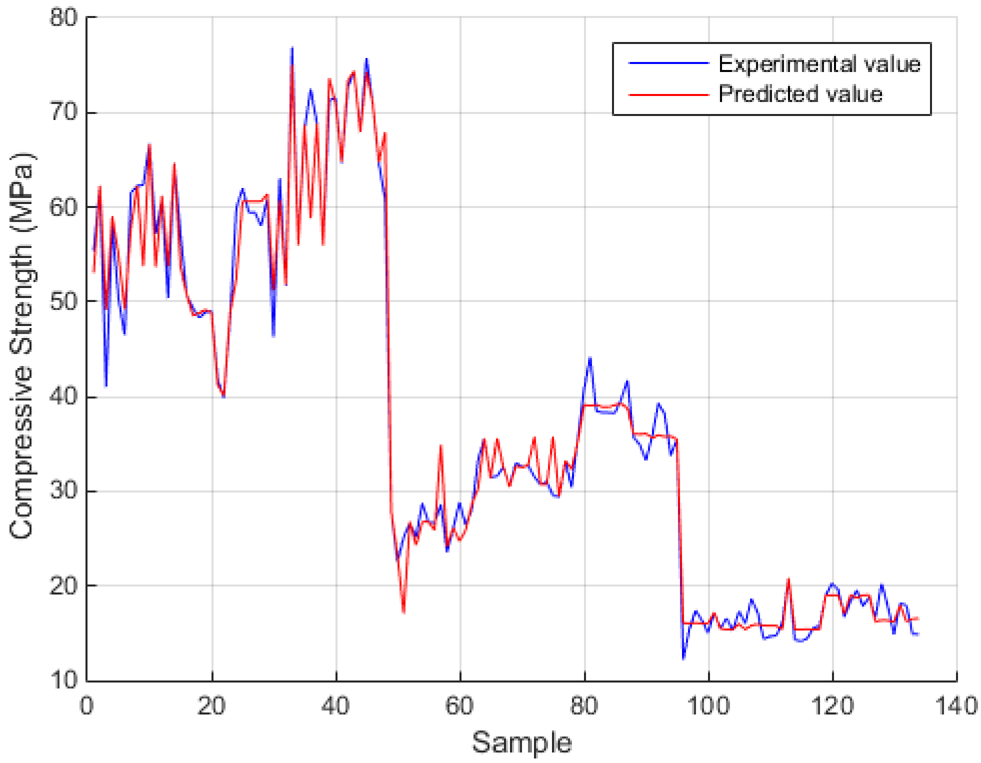

Fig. 3 - Experimental vs predicted values of compressive strength for the best with two hidden layers BPNN (5-7-7-1)

From the presented results, we see that

1. Among the available in the literature training algorithms the best, by far, ANN prediction of the sandcrete compressive strength was achieved by using the Levenberg-Marquardt algorithm.
2. The computational environment may affect the performance of the ANN training and subsequently its performance. This is due to the fact that the algorithms of the computational units ultimately rely on basic arithmetic operations that can yield different results when performed in different environments due to the very nature of floating-point arithmetic. Different optimum ANN architectures were found in different computers.
3. Furthermore, the recently proposed new formula for the normalization of data proved effective and robust compared to available ones.
4. For the top twenty models the optimum number of hidden layers was found to be two.

CONCLUSIONS

The comparison of the derived results with the experimental findings demonstrates the ability of ANNs to predict, in a reliable manner, the compressive strength of sandcrete materials. Furthermore, the results obtained, using the above proposed technique for pre-processing the data were better compared to the results obtained by other known normalization techniques available in the literature. This fact demonstrates the need for the continuation of the research in data pre-processing prior to the use of the data toward the training and the development of ANNs, taking into account the present-day limitations and constraints in this promising research area.

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