ESTIMAREA REZISTENȚEI LA COMPRESIUNE A MORTARELOR DE CIMENT
ESTIMATION OF COMPRESSIVE STRENGTH OF CEMENT MORTARS

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Due to several advantages of cementitious materials especially mortars, they are widely used in construction works. It is important to determine the mechanical properties of cementitious materials to understand their behavior under different effects. In this study, Artificial Neural Networks (ANN) analysis is used to predict the 7 and 28 days compression strength values of cement mortars. Physical-mechanical properties such as flow, setting time and compressive strength of cement mortars incorporating of different chemical admixtures such as air-entraining admixture (HS), naphthalene sulfonate based (SPNS) and modified polymer (SPMP) based admixtures have been determined. The aim of the usage of combinations of air-entraining admixture with two different based superplasticizers is to form different inner structure affecting on compressive strength. All admixtures are used with three different ratios by cement weight and one of them is for overdosage effect. ANN analysis has been performed to predict the compression strength values after 7 and 28 days, in correlation with experimental part of the study. According to this view, 28 sets have been prepared with different combination of admixtures. At early ages, HS015-SPNS2.0 series had the lowest strength whereas the highest compressive strength at 28 days were obtained for HS005-SPMP0.8 series. Obtained compression strength values after 7 and 28 days have also been predicted by ANN analysis. It is stated that the established ANN model indicates a great capacity to predict the compressive strength values in the end.

Keywords: *ANN; admixtures; superplasticizer; compressive strength; cement mortars*

1. Introduction

Compressive strength is the most important property of hardened concrete that describes its quality and performance for construction works. In addition, most of other properties as tension, flexural, shear and bond strengths, with steel reinforcement are improved in parallel with increase in compressive strength. Furthermore, the ultimate 28-day compressive strength is taken into account in structural analysis. This strength is usually determined based on a standard uni-axial compressive strength test and is universally accepted as a general index of concrete strength.

In concrete technology, cement based materials such as cement mortars and concrete are mostly used ones. To aim requested properties, form a structural member could be met by using not only conventional concrete components such as cement, aggregate and water together, but also chemical and mineral admixtures. Admixtures are defined as materials other than water, aggregate, cement and also fiber reinforcement used as component in concrete or cement mortar production and added to the batch before or during mixing [1,2].

Needs for more durable materials and structural members lead site engineers to use admixtures. Chemical admixtures have some benefits on workability, set controlling, strength and durability properties of cementitious materials [3]. These admixtures bring benefits on set controlling, air-entrainment, water reduction and increasing workability of cement based materials such as cement mortars and concrete.

Thus, all desired properties couldn't be achieved by using chemical admixtures. Although usage of chemical admixtures is useful to improve early and ultimate mechanical properties of cementitious materials; they do not have any benefits on materials prepared with poor mix materials (with lower quality) and unqualified workmanship during transportation, settlement and vibration [4].

On the other hand, using different admixtures at the same time may defeat aggressive media actions such as physical, biological and chemical attacks during service life of a building. Therefore; the gap of knowledge of the interaction between these different types of admixtures results in unexpected problems.

Since cementitious materials are non-homogenous ones, modeling their behavior and effects on macro properties such as strength is a difficult task, indeed. Because of this reason, ANN analysis has been proved to be able in the prediction of compressive strength, without the need of specific and complex equations. By this way, application of ANN would reduce the time and cost amounts which

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are required for preparing specimens and the 28 day waiting period before they could be tested.

ANN analysis is one of the artificial intelligence applications that are being widely used to model some of human interesting activities in many areas of science and engineering [5–8]. It is possible to create software on test results by ANN. Reliable results can be obtained by successful input-output data relationship of ANN. Many studies have been published by using ANN analysis in the literature [9–15]. Considering the studies in the literature, this study provides an additional view. So, compressive strength values according to different admixtures are obtained in experimental studies and ANN analysis is performed according to advanced software to compare the both experimental and predicted results.

2. Experimental

2.1. Materials

CEM I 42.5 Portland cement is commonly used for the experimental studies. The chemical, physical and mechanical properties are presented in Table 1. Air-entraining admixture according to ASTM-C 260 [16] is a liquid containing a superficial active substance. The naphthalene sulfonate and modified polymer based superplasticizers agree with ASTM-C 494 [17] TYPE G and ASTM-C 191 TYPE A/D/G [18] respectively. The detailed properties of admixtures are presented in Table 2.

Ratios of other components of cement mortars were kept constant; only admixture dosage, types and combination ratios were changed. All tests were performed in the laboratory conditions such as temperature of 20±2ºC and 75-80% relative humidity. Compressive strength values were obtained for 7 and 28 days.

3. Artificial Neural Networks

ANN are mathematical models inspiring by the structural aspects of biological neural networks. They are computing systems that simulate the biological neural systems of the human brain. ANN are known as complex systems of the neurons that are connected each other with different influence levels and form a great number of interconnected neurons working in unison to solve specific problems. ANN can be trained to recognize input patterns and produce appropriate output responses. Problems having enough training data are suitable for ANN. There are many study fields using ANN analysis because of its modeling and prediction benefits. Prediction of the complex problems and fast evaluation of new examples can be counted as advantages of ANN.

ANN analysis is an alternative way for solving difficult problems in many study fields. ANN is usually formed of three or more layers, which are named input, output, and hidden layers. Neurons are connected to each other with modifiable weighted interconnections. Nodes receiving data from independent variables generate input layer. This means that number of nodes in input layer is equal to the number of input variables of the problem. The information reaches hidden layer from input layer according to pre-specified activation functions. Output layer receives information from hidden layer and finally the results go to an external recreant. The number of nodes in the output layer

Table 1

Chemical and physical properties of CEMI 42.5

Property	Value	Property	Value
% SiO_2	18.38	(Cl^-) amount (%)	0.01
% Al_2O_3	4.80	(SO_3) amount (%)	2.82
% Fe_2O_3	3.53	LOI (%)	3.63
% CaO	63.78	Initial setting time (min)	155
% MgO	0.84	Final setting time (min)	230
% Na_2O	0.45	Specific surface area (cm^2/g)	3640
% K_2O	0.80	(2 day) compressive strength (N/mm^2)	27.60
% SO_3	2.82	(28 day) compressive strength (N/mm^2)	50.40

Table 2

Chemical composition and physical properties of admixtures

Admixture symbol	Base	Density (kg/l)	pH	Type
HS	Liquid with active materials on specific surface	0.99-1.03	5.4	ASTM-C 260
SPNS	Naphthalene sulfonate	1.17-1.21	8.5	ASTM-C 494 TYPE G
SPMP	Modified polymer	1.13-1.17	5.2	ASTM-C 494 TYPE A,D,G

2.2. Methods

Usage of combinations of air-entraining admixture with two different based superplasticizers may cause different inner structure affecting the macro properties such as compressive strength. Some properties such as setting time (by using a Vicat Apparatus), flow values and compressive strength developed of each cement mortar mix were determined.

is equal to the number of output variables. Architecture of ANN is given in Figure 1.

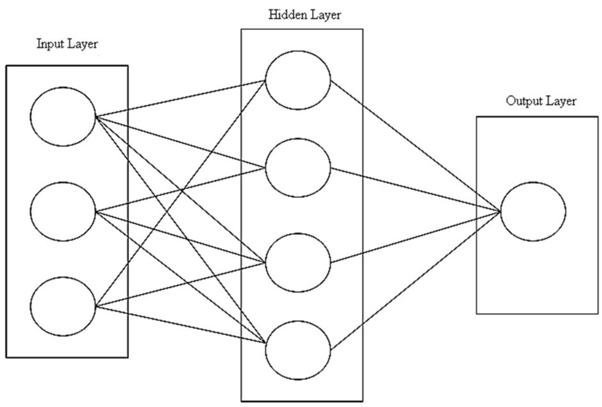

Fig. 1 - Architecture of ANN.

Neural Networks types are commonly used in engineering problems. Because of its simplicity and universal approximation capacity, Back Propagation is the most used learning algorithm of ANN. It defines a systematic way to update the synaptic weights of multi-layer feed forward supervised networks composed of layers. This algorithm tries to reach the minimum error function in weight space by using the method of gradient decent.

Table 3

Initial/final setting times and flow values of cement mortar mixes

Set name	Initial setting time (min.)	Final setting time (min.)	Flow (mm.)
CM	153	242	116
HS005	178	280	129
HS010	185	292	132
HS015	210	315	144
SPNS1.0	205	310	154
SPNS1.5	244	345	165
SPNS2.0	275	362	172
SPMP0.8	225	328	156
SPMP1.0	248	342	166
SPMP1.5	280	369	178
HS005-SPNS1.0	185	295	142
HS005-SPNS1.5	218	320	151
HS005-SPNS2.0	245	350	163
HS010-SPNS1.0	230	334	156
HS010-SPNS1.5	255	355	168
HS010-SPNS2.0	275	370	172
HS015-SPNS1.0	240	341	162
HS015-SPNS1.5	270	364	170
HS015-SPNS2.0	278	375	176
HS005- SPMP0.8	190	300	145
HS005- SPMP1.0	225	332	153
HS005- SPMP1.5	260	365	169
HS010- SPMP0.8	235	340	159
HS010- SPMP1.0	272	368	171
HS010- SPMP1.5	285	370	177
HS015- SPMP0.8	245	350	165
HS015- SPMP1.0	275	374	173
HS015- SPMP1.5	287	405	179

Table 4

Compressive strength values

Set number	Set name	Strength values at 7-days (MPa)	Strength values at 28-days (MPa)
1	CM	43.9	53.2
2	HS005	41.3	52.7
3	HS010	39.7	51.1
4	HS015	36.4	44.4
5	SPNS1.0	40.1	54.5
6	SPNS1.5	36.8	45.7
7	SPNS2.0	26.4	39.3
8	SPMP0.8	39.3	57.0
9	SPMP1.0	38.8	55.7
10	SPMP1.5	28.2	44.8
11	HS005-SPNS1.0	39.0	54.1
12	HS005-SPNS1.5	35.5	47.2
13	HS005-SPNS2.0	25.0	37.8
14	HS010-SPNS1.0	37.9	54
15	HS010-SPNS1.5	34.1	45.5
16	HS010-SPNS2.0	23.5	35.9
17	HS015-SPNS1.0	32.8	46.2
18	HS015-SPNS1.5	32.9	42.1
19	HS015-SPNS2.0	20.1	34.7
20	HS005- SPMP0.8	37.8	57.5
21	HS005- SPMP1.0	36.8	53.2
22	HS005- SPMP1.5	26.7	41.9
23	HS010- SPMP0.8	37.2	56.4
24	HS010- SPMP1.0	35.8	51.6
25	HS010- SPMP1.5	23.9	39.1
26	HS015- SPMP0.8	35.1	54.8
27	HS015- SPMP1.0	34.3	50.2
28	HS015- SPMP1.5	22.5	38.3

4. Results

4.1. Experimental

Setting time, flow and compressive strength values of each cement mortar are given in Tables 3 and 4, respectively [19]. Set name is explained by two parts letter and numeric characters. The letter represents the initials of admixture and the numeric characters indicate the used dosages. For example, HS010-SPNS2.0 means a cement mortar mix incorporating an air-entraining admixture of 0.10% (by cement mass) and 2.0% naphthalene sulfonate superplasticizers by cement mass. Indeed, CM means cement mortar without any admixture.

At early ages, HS015-SPNS2.0 series has the lowest strength values whereas the highest compressive strength values at 28 days were obtained for HS005-SPMP0.8 series. Cement mortar samples including air-entraining admixture improved their strength values by using superplasticizers together, in certain ratio. It could be due to propagation of bubbles formed as consequence the presence of air-entraining agent together with superplasticizers, considering better workability.

4.2. Numerical

Numerical analysis is concerned with the prediction of the 7 and 28 days compressive strengths by using ANN. Neural network toolbax of the Matlab software is used to apply multilayer feed forward back propagation neural network in this paper. To reach the optimum results, there have been several Matlab subroutines developed. The database includes 28 sets for 7 and 28 days of strength values according to different admixtures, in total. Each set has the average result of three separate experimental determinations. So, three mortar samples have been prepared for obtaining one strength value. While cement mortar, admixture and superplasticizer are taken as constant inputs, initial setting time, final setting time and flow values are taken as varied ones.

On the other hand, strength values at 7 and 28 days are output parameters of the network. Also, a single hidden layer involves in the architecture of network.

Trials have been made to reach the most suitable architecture of the network which is formed of input, hidden and output layers. Inputs and outputs are normalized in the (-0.9:0.9) range by normalization methods according to Equation (1) where z_n represents the calculated normalized value, z_i is the related i. value, z_{min} is the minimum value and z_{max} is the maximum value in the set.

$$z_n = 1.8\left[\frac{z_i - z_{\min}}{z_{\max} - z_{\min}}\right] \qquad (1)$$

Conjugate Gradient (SCG) is used as the training function and 3000 iterations are performed to find out the optimum result.

The performance of the network has been obtained by using the experimental and predicted values of the data set. The results of training and testing sets are given in Figures 2-5.

Experimental and predicted results of 7 and 28 days compressive strength values are marked in the figures. Strength values are evaluated according to ANN analysis and correlation coefficients (R2) are obtained according to training and test processes. Suitability levels of the experimental and predicted values are determined by these coefficients according to Equation (2).

$$R^2 = \left[\frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2 \sum(y_i - \bar{y})^2}}\right] \qquad (2)$$

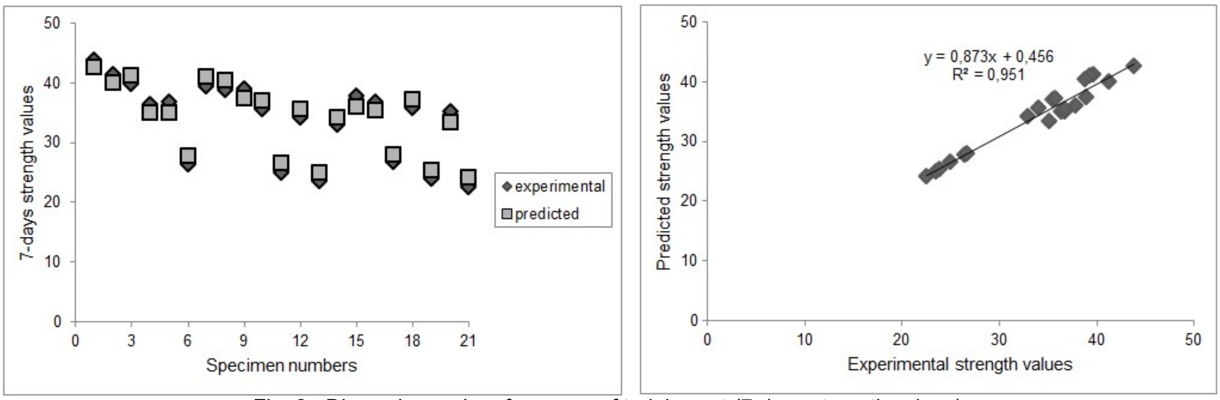

Fig. 2 - Dispersion and performance of training set (7-days strength values).

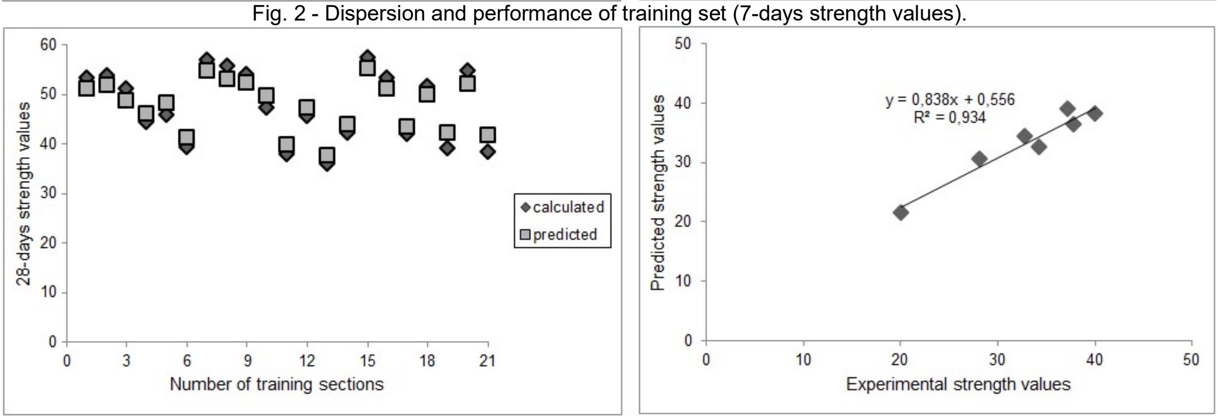

Fig. 3 - Dispersion and performance of testing set (7-days strength values)

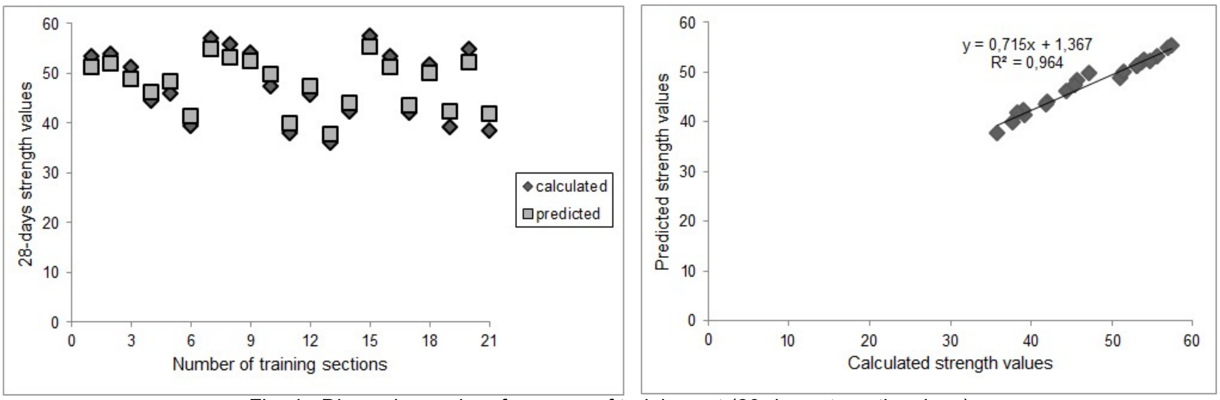

Fig. 4 - Dispersion and performance of training set (28-days strength values)

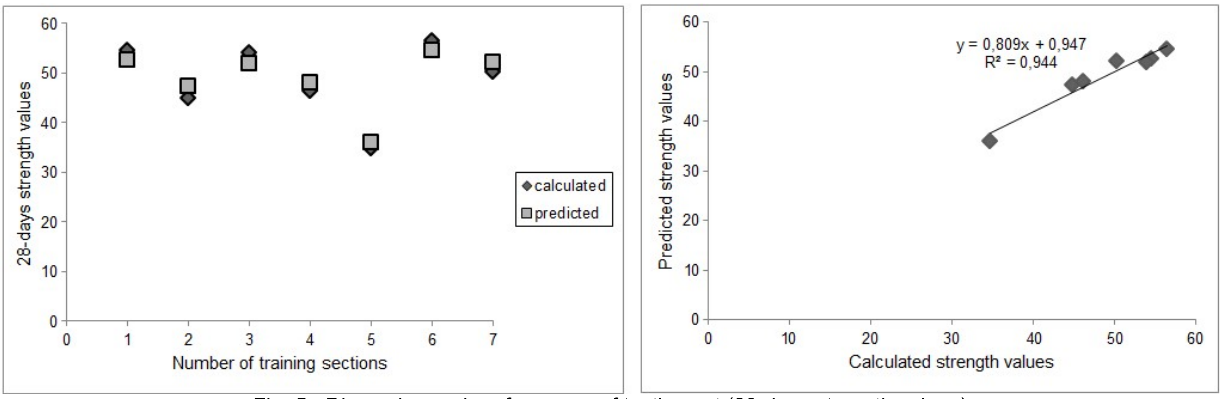

Fig. 5 - Dispersion and performance of testing set (28-days strength values)

It is seen that these values are closely each to others. So, a strong relationship is established between them.

5. Conclusions

Cement mortars have been produced by using chemical admixture; one air-entraining and two different superplasticizers. The physical and mechanical properties of each cement mortar are determined. For HS005 series, flow, setting time and early age strength values were at the lowest level. The highest ultimate strength values were obtained for HS005-SPMP0.8 series.

It is important for engineers to understand the properties and behaviors of cementitious materials such as concrete or cement mortars which are often used in construction technology. There have been a lot of studies completed over technology of cementitious materials by researchers. It takes much time to perform experimental studies in laboratories. Therefore, ANN analysis that can predict experimental data successfully became an alternative way to reduce working time. This analysis performs both linear and non-linear calculations rapidly.

Neural networks usually consist of three or more layers including an input, an output and minimum one hidden layers. In this study, 7 and 28 days strength values are determined by experimental analyses. After that, a computer program is written to obtain the essential coefficients. Strength values are tried to be predicted by ANN analysis. For this purpose, the input and output data have been normalized between the ranges of -0.9 to 0.9.

ANN analysis, being one of the mathematical and numerical methods providing the definition and simulation of the results, is obtained to predict these normalized coefficients. Finally, a strong relationship is established between experimental and predicted values. The correlation coefficient values are determined R^2=0.951 and R^2=0.934 for 7-days strength values and R^2=0.964 and R^2=0.944 for 28-days strength values according to training and test process respectively. These results indicate that a remarkable model has been established between experimental and predicted values.

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Vedere spre marele hemiciclu al Ateneului, cu impunătoarea scară unde tronează George Enescu (pg. 15 - Nicolae St.Noica - ATENEUL ROMÂN ŞI CONSTRUCTORII SĂI)