APLICAȚII ALE METODEI REȚELELOR NEURONALE ARTIFICIALE LA CALCULUL REZISTENȚEI LA COMPRESIUNE A BETOANELOR
APPLICATION OF NEURAL NETWORKS IN DETERMINATION OF COMPRESSIVE STRENGTH OF CONCRETE

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This paper presents the optimization of concrete mixtures composition related to a physical property and the process of production of trial mix design by using the multi-layered feed-forward neural networks. This optimization was conducted because there is no clear method of designing concrete mixture composition and for the purpose of shortening procedure of the trial mix design of concrete. Mix design depend on many variables and deterministic models cannot give good results. The goal of the research was to make a model of a neural network, on the set of available data from 288 trial mix, which would, with highest accuracy, predict the compressive strength of concrete at the age of 28 days. In order to attain as high accuracy of obtained results as possible, three levels of input data to the neural networks were considered. On each of the applied groups of input data, the neural networks with 1 and 2 hidden layers were formed. On the basis of the adopted neural network, an algorithm for usage of the network in actual situations was made, applied on an actual model.

În lucrare se prezintă o modalitate de optimizare a compoziției unor betoane pentru care a fost selectată o proprietate fizică, folosind metoda rețelelor neuronale artificiale tip feed-forward. Acest tip de optimizare a fost ales deoarece proiectarea compoziției betoanelor nu beneficiază de o metodologie clar stabilită dar şi pentru a reduce efortul experimental. Proiectarea betoanelor depinde de un număr mare de variabile şi, de aceea, utilizarea modelelor deterministe nu a furnizat până în prezent rezultate bune. Scopul acestor eforturi de cercetare a fost de a crea un model bazat pe metoda rețelelor neuronale artificiale folosind 288 de amestecuri de test cu ajutorul cărora să poată fi făcută predicția – cât mai corectă – a rezistenței la compresiune a betonului la 28 de zile. Pentru a putea obține cea mai corectă estimare au fost considerate trei seturi de date de intrare. Pentru fiecare dintre grupurile de date de intrare au fost încercate configurații ale rețelelor neuronale cu 1, respectiv 2 straturi ascunse. Pentru fiecare situație specifică a fost dezvoltat algoritmul de lucru corespunzător.

Keywords: *concrete strength, neural networks, prognostic model*

1.Introduction

Compressive strength of concrete at the age of 28 days is very often used to characterize the concrete properties. The compressive strength is one of the most important properties of concrete, which is the most controlled parameter during quality control. Faster identification - prediction of the compressive strength of concrete is a necessity in construction industry, and also a very important parameter for all researchers in this field.

Standard methods for prediction of compressive strength of concrete at the age of 28 days basically rely on the statistical analyses with which many linear and non-linear regression equations are implemented in the prediction model. Usually, all these prediction models take into consideration compressive strength of concrete at early ages such as 1, 3 and 7 days. Yet, obtaining of test parameters after 1, 3 and 7 days is significantly shorter than waiting 28 days for the results. It should be borne in mind that selection of appropriate regression equations requires techniques and considerable experience, and creation of the prediction model is not at all a simple task.

Compressive strength of concrete at 28 days of age depends on many parameters: w/c ratio, cement mass, cement type, particle size distribution of aggregate, maximum aggregate grain size, aggregate type, quantity of used water, consistency, present air, etc. These factors can generally be divided into two groups: chemical and physical. Analytical models, including the statistical methods, which are used to describe the effects of these factors on the compressive strength of concrete can be very complex. Typical trends in mathematical modeling follow three main directions: prediction, optimization and control [1]. In such cases, usage of the soft programming techniques appears to be the adequate approach to solving the issue of prediction of compressive strength of concrete [2]. The subject of this paper is an attempt to create a neural network for prediction of compressive strength of concrete at the age of 28 days. In order to determine to what extent some of the neural networks is accurate in prediction and to mutually compare them, the classic statistical techniques will be used.

Application of ANNs to the problem of forecasting concrete strength is already known in the literature [3-5].

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Many researchers have studied this problem by considering a large number of input parameters. In some cases were considered the parameters that are difficult to reach. Tools such as ANNs enable us to separate important from less important parameters. Of very great importance increased concrete strength prediction accuracy with as few input parameters. Also of great importance to obtain input parameters as soon as possible and in a simple manner.

If the prediction of the compressive strength of concrete is considered as a map of influential factor on the compressive strength at 28 days of age, then the model of the map can be constructed as a multi-layered feed-forward neural network. The neural networks themselves are conceived on the basis of biological neural networks and on semi-empirical models of behavior of a biological neural cell – neuron. A neuron in the artificial neural network simulates the function of a neural cell in human brains, which has millions of interconnections. These neurons are the building blocks of human nervous system and determine any action. Multi-layered feed-forward neural networks are the most widely used [6] and can be applied to approximation of any function irrespective of the number of input parameters.

2. Parameters that affect the strength of concrete

As the main constitutive materials in concrete, cement and aggregate have a great impact on the concrete characteristics. The properties of these materials are crucial for the quality of concrete. Should we consider concrete as a composite material composed of four basic artificial minerals: C_3S, C_2S, C_3A and C_4AF then it would be possible to assess the impact on the strength on the basis of the composition via the following formula (1):

$$f_{c,28} = a(\%C_3S) + b(\%C_2S) + c(\%C_3A) + d(C_4AF) \quad (1)$$

Such formula is only a provisional as the practice has demonstrated that the role of certain components of concrete is not always equally important. This formula can be adopted only if it is the ordinary Portland cement, while in practice, the cement used has many mineral additions. In practice, for definition of the change of concrete strength in time, the most often used expression is (2) whereas impact of used additions in cement is determined by an empirical coefficient and in (2) as presented in the Figure 1 [7].

$$f_c(t) = f_{c,\infty}(1 - e^{-at}) \quad (2)$$

With the increase of the quantity of water, and with constant content of cement and aggregate, the w/c ratio is increased, and a concrete of increased plasticity is obtained. This

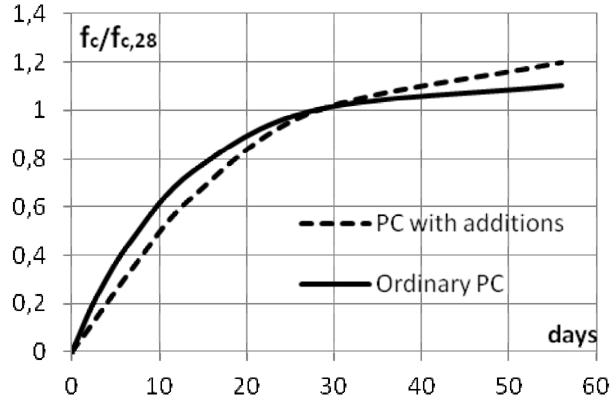

Fig. 1 - The influence of mineral additions in cement on the strength of concrete / *Influența adaosurilor asupra rezistenței betoanelor.*

rule is valid to a certain extent when excess water creates a porous structure and lowers the concrete strength. On this basis it can be concluded that there is an optimal quantity of water for which the concrete of minimum porousness and high strength is obtained [8].

The strength of concrete depends on the strength of cement paste and connections between the aggregate and the paste. The relation between the aggregate and the cement paste is known as the transit zone. The nature of the transit zone is determined by the properties of the aggregate, cement paste and the way in which they react during, mixing, placing and curing of concrete. Transit zone introduces another level of heterogeneousness in the properties of concrete. Transit zone consists of water and finer particles of cement paste. The components act in synergy and create space in transit zone where the products of hydration from the solution crystallize. Bond between the aggregate and the paste is determined by the texture of the aggregate surface, by the shape and purity of the aggregate. The bond is stronger if the surface of the aggregate is rough and enfolding of the aggregate grains is low. Fine materials can have detrimental reactions in concrete, such as alkali-silicate reaction or clay on the surface of the aggregate which can result in weakening the bond and thus the strength of concrete [9].

The strength of the aggregate also affects the concrete strength, but majority of conventional aggregates has a strength considerably higher than the cement paste with which they are used in concrete.

Numerically defined particle size distribution of an aggregate gives a possibility to calculate the modulus of fineness of aggregate particle size distribution. This fineness modulus is calculated according to the formula (3).

$$M = \frac{1}{100}\sum_{i=1}^{m} p_i = \frac{1}{100}\sum_{i=1}^{m}(100 - y_i) \quad (3)$$

where
M – fineness modulus
y_i – pass on the sieve m and p_i=100-y_i

It has been experimentally proven that two aggregates with same fineness modulus will give the concretes of approximately same mechanical characteristics, given that all the other conditions are the same.

Granulometry of an aggregate and its specific surface, which is directly related to the quantity of required water, are mutually interrelated. However, there are many grade curves which correspond to the same specific surface area. With the increase of the maximum grain of the aggregate, the total surface area decreases, and consequentially the necessary quantity of water, but this relation is not linear. It can be concluded that the particle size distribution of an aggregate is a decisive factor in terms of fresh concrete properties, and any influence on the fresh concrete reflects on the hardened concrete characteristics. Many authors proposed limits of optimal granulometric mixtures, but in practice two of them proposed by Fuller (4) and EMPA Institute (5) stand out, depending on the maximum grain size of aggregate D_{max} [10-11]. Thus, for the optimal particle size distribution the one lying between these two curves can be adopted.

$$Y = 100 * \sqrt{\frac{d}{D_{\max}}} \tag{4}$$

$$Y = 50 * \left(\frac{d}{D_{\max}} + \sqrt{\frac{d}{D_{\max}}} \right) \tag{5}$$

where Y pass on the sieve opening d.

In many formula for prediction of concrete compressive strength at the age of 28 days, various interpretations of the w/c ratio, type of the aggregate, quantity of air in the concrete can be observed. The basic law on concrete strength was set by Abrams (1924) according to the formula (6) where A and B are empirical constants depending on the test conditions and $f_{c,28}$ compressive strength of 28 days old concrete.

$$f_{c,28} = \frac{A}{B^w} \tag{6}$$

In a later period, many scientists attempted to define their own regularities, so that multiple parameters could be taken into consideration, and one of the most frequently applied is the Skramtayev formula (7).

$$\frac{m_c}{m_w} \le 2.5, f_{c,28} = A_1 * f_{pc} * \left(\frac{m_c}{m_w} - 0.5 \right) \tag{7a}$$

$$\frac{m_c}{m_w} \ge 2.5, f_{c,28} = A_2 * f_{pc} * \left(\frac{m_c}{m_w} - 0.5 \right) \tag{7b}$$

In the formula the coefficients A1 and A2 depend on the quality of cement and the aggregate used for production of concrete. Since many authors assume that for the values of m_w/m_c ratio that are less than 0.4 the strengths progressively depart from the general ratio, this makes the Skramtayev formula one of the most frequently used solutions for predictions of compressive strength of concrete at the age of 28 days.

Research results showed that when considering the compressive strength of concrete a higher attention must be paid to the air absorbed in concrete. Thus Popovics (1985) [12] considered the effects of the quantity of entrained air in concrete on the compressive strength relating the compressive strength, water/cement ratio and entrained air via the following formula (8).

$$f_{c,28} = \frac{A_0}{B_0^{\,w/c}} * 10^{(-\gamma * a)} \tag{8}$$

where the factors are
A_0 - factor dependent on cement,
B_0 - combined factor of sample age and type of cement,
γ - constant value,
a - percentage of entrained air.

In some researches the formula (8) was used in evaluation of the impact of the type of air on the compressive strength of concrete. Formula (8) did not take into consideration the type of air, so the researchers made a distinction in one expression (9) where the impact of entrained and entrapped air on the strength is differentiated.

$$f_{c,28} = \frac{A_0}{B_0^{w/c}} * 10^{(k_1 * a_1 + k_2 * a_2)} \tag{9}$$

k_1 determines the impact of entrapped air,
k_2 determines the impact of entrained air on the compressive strength of concrete.

All the mentioned formula and expressions take into account only a part of the parameters which may affect compressive strength of concrete. Joining of all the influential parameters in one formula applying classic statistic methods is very complex, moreover, practically impossible.

3. Neural Networks - introduction

Neuron is an element with multiple inputs and one output. Artificial neural network is formed of a large number of neurons connecting outputs of ones with inputs of others. A certain number of neurons represents the connection of the network with the working environment. The input layer of neurons receives information from the environment, while the output neurons generate the signals for certain actions. The other neurons which are not directly linked to the environment are called the hidden neurons, and they are used for internal representation of information about the working environment [13]. Undoubtedly, the best known architecture of neural networks is the layered one. The neurons are organized so as to form layers, and on the input of one neuron are connected outputs of all neurons from the previous layer. The neurons can be static and dynamic depending on whether the time variable signals are processed [14].

Each neuron model is characterized by two functions: a. one gives the dependence of the activation signal on the input signals – function of input interaction and b. the other defines influence of he activation signal on the output signal of the neuron – activation function. [15]. The scheme of one static neuron is presented in Figure 2.

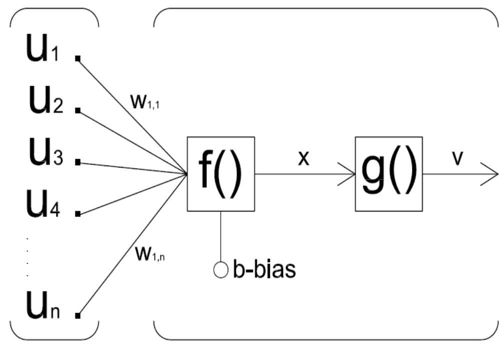

Fig. 2 - Scheme of static neuron / *Reprezentarea schematică a unui neuron static.*

The linear function of the input interaction which expresses the activation signal simply, as a linear combination of incitation signals according to the expression (10) is most often in the use, though their form can be either non-linear or polynomial in order to increase the processing power of the neuron.

$$f(u) = \sum_{i=1}^{n} w_i u_i \qquad (10)$$

Apart from the several different functions of the input interaction, various activation functions are also in use. The simplest is the linear activation function (11) while for solving the non-linear models, the best one is the sigmoidal one (12).

$$g(x) = x - \theta \qquad (11)$$

$$g(x) = \frac{1}{1 + e^{-(x-\theta)}} \qquad (12)$$

The neural networks are in the best case adjusted so that an individual input leads to a certain output parameter – goal. In Figure 3, a general approach of the neural networks is presented. The network is adjusted to compare the output and goal value until the output data of the neural network matches the target value. In some cases it takes many input-target pairs for these data to match. This process is called the network training [16].

The neuron model in the architecture of neural network determines how the input data is transformed into the network output. This transformation can be described as a form of computation.

The neural network training is a modification of behavior based on experience, and in interaction with environment which leads to different reactions to external influences [17]. The neural network training depends on the network architecture, initial weight coefficients, function of input interaction and activation function in the neuron. By virtue of this, when the network is established, it is difficult to make changes, and the learning procedures are divided into two groups: supervised and unsupervised learning.

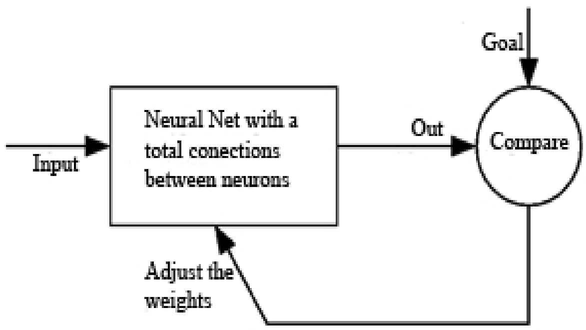

Fig. 3 - Behavior of neural networks / *Modul de lucru cu rețelele neuronale artificial.*

Each learning procedure is based on the learning algorithms in which the error function is formed, which represents a difference between a desired and actual response of a neural network. In this, there are two approaches to formation of the error function: rules based on error correction and mechanisms using gradient rules.

4. Experimental work

For design of composition of concrete mixtures in preceding concrete research, the Skramtayev formula was used. On its basis water/cement ratio is obtained on the basis of the required compressive strength of concrete, class of cement and the quality of aggregate. Quality of the aggregate was in each individual case assessed on the basis of the test results of the “Los Angeles” method, particle size distribution and presence of fine particles in aggregate during wet sieving. In carrying out the trial mix of concrete, the designed compressive strength of concrete is for 8MPa higher than the required class in real conditions.

On the basis of the formula given by Skramtayev, the water/cement ratio is determined. On the start of determine the quantities of material in the concrete mixture, it is first necessary to adopt the quantity of water, and in this particular case it was adopted according to the Ferret formula (13).

$$m_w = \frac{k_0}{\sqrt[5]{D_{\max}}} \tag{13}$$

where,

D – is the maximum grain size of the aggregate

k_0 – is the parameter depending on the type of the aggregate and the provided for consistency ranging between 330 and 370 for the natural aggregate and concrete of plastic consistency.

Table 1

Requirements for mix design [18]

Cerințe pentru proiectarea amestecului [18]

Class *Clasa*	$f_{c,cube}$ 15 cm	$f_{c,cyl}$ 15/30	$f_{c,cube}$ + 8 MPa (required by / *cerut de* BAB87)
C12/15	15	12	23
C16/20	20	16	28
C20/25	25	20	33
C25/30	30	25	38
C30/37	37	30	43(48)
C35/45	45	35	53
C40/50	50	40	58
C45/55	55	45	63

After designing composition of fresh concrete mixture, laboratory tests are carried out. All concretes were made in the mixer with vertical axis and planetary concrete mixing of 60 to 100l of fresh concrete.

Aggregate (previously dried), cement and water were measured on the same balance. Temperature and air humidity were maintained within the same range, by using air conditioning. Concrete placement was performed by vibrator needle Ø20 mm into metal cube moulds having sides of 15 cm. After casting the specimens rest 24 hours in the same conditions in which the concrete was mixed, after which they are taken out of the moulds and cured in water until the testing, at the temperature from 18 to 22°C.

After the planned ageing the specimens were tested on hydraulic presses of 1000 to 3000 kN depending on the class of concrete which was expected.

Data base was formed on the basis of preceding laboratory tests in the IMS Institute in the period 2004-2009. In this period the preceding laboratory test of concrete of 6 different manufacturers from the area of former Yugoslavia were conducted. There was a total of 21 type of cement (CEM I, CEM A/S, CEM A/(P-Q), CEM A/(S-L), CEM A/M(V-L), CEM B/M(V-L), CEM B/M(P-Q) and CEM B/M(S-Q) and all cements were strength class 42.5. The cement mass per m^3 of concrete ranged between 200 and 460 kg. In all concretes, the aggregate was the river aggregate from three different rivers in Serbia.

In each formula are given the assumed quantities of material per m^3 of concrete volume. Also given are parameters which are measured during trial mix such as Abrams cone slump test, measured density of the fresh concrete, temperature of the room where the preceding tests were carried out and concrete temperature. Apart from these, the data about the origin and type of cement used, origin and type of the aggregate, potential usage of additives in concrete. Application of additives in concrete affects the compressive strength of concrete in a non-linear way; therefore these tests are omitted from considerations. The water used for the tests was a tap water, thus the water quality was not taken into consideration during data processing. A total of 288 previous tests was taken to the processing.

Data processing was performed in three stages. In each stage, the models with one and with two hidden layers were considered and formed. The common fact for all models is that in the input and output layer, the neurons with linear activation function were used, and in the hidden layers were used the neurons with activation function of hyperbolic tangent (because of very simple derivatives). In the output layer, there was one neuron in all models, because the network output is the compressive strength at the age of 28 days.

One data base was used for model learning, and the other data base was used for testing. A total of 288 of preceding tests was divided into two bases, of which the learning base had 240, and the testing base 48 of preceding tests. These 48 pieces of data from the initial base was determined applying random function. In all the models for learning and testing were always used the same data bases formed at the very start of result processing. Formation of these two data bases was done in order to avoid the potential differences in case the learning and testing bases are not the same.

Quantitative indicators used for objective selection of the best neural networks which would be used for actual issues are (a) root mean square of departure, results of compressive strength ($f_{c,28}$) obtained in the neural network model and actual compressive strength results obtained in the laboratory, (b) standard error deviation – standard deviation of difference between the obtained results of compressive strength and actual results of compressive strength ($f_{c,28}$) and (c) accuracy of obtained results at reliability of 95.4% - which is calculated on the basis of standard error deviation.

1st iteration consisted of formation of the neural network model with input layer of 14 neurons. Each of the neurons in the input layer is related with one property of concrete in the data base. The input parameters were the following: 1) cement manufacturer; 2) type of cement; 3) quantity of cement; 4) coefficient ``Los Angeles``; 5) contents of fraction 0/4; 6) contents of fraction 4/8; 7) contents of fraction 8/16; 8) contents of fraction 16/32; 9) total quantity of aggregate in fresh concrete; 10) quantity of water in fresh concrete; 11) water/cement ratio; 12) slump on Abrams cone; 13) density of concrete 14) compressive strength at the concrete age of 7 days. In the Table 2 are given the characteristics for formed neural networks in the first stage.

Table 2

Results of neural networks in first iterations
Rezultatele corespunzătoare diferitelor rețele la prima etapă

Neural network *Rețeaua neuronală*	Root mean square error *Eroare medie*	Accuracy at reliability *Eroarea absolută* 95.4% (N/mm^2)
A1-1	2.92	3.88
A2-1	3.53	4.57
A3-1	3.68	4.94
A4-1	3.86	4.64
A5-1	5.72	6.76
A6-1	5.11	5.96
A7-1	5.10	6.28
A8-1	5.66	7.23
A9-1	4.74	5.62
A10-1	4.69	5.55
A11-2	5.40	7.97
A12-2	5.51	6.29

Table 3

Results of neural networks in second iterations
Rezultatele corespunzătoare diferitelor rețele la a doua etapă

Neural network *Rețeaua neuronală*	Root mean square error *Eroare medie*	Accuracy at reliability *Eroarea absolută* 95.4% (N/mm^2)
B1-1	2.78	3.47
B2-1	2.58	3.48
B3-1	2.33	3.22
B4-1	2.08	3.06
B5-1	1.84	2.71
B6-2	3.04	4.81
B7-2	2.65	4.21
B8-2	2.29	3.75
B9-2	2.14	3.54
B10-2	1.65	2.86
B11-2	2.64	4.21
B12-2	1.60	2.70
B13-2	1.55	2.61

On the basis of these results parameters for the second iteration were selected, where the percentage of aggregate fractions, quantity of aggregate, values related to Los Angeles method were omitted as well as the quantity of water which was indirectly present in the water/cement ratio and cement mass. The input parameter of cement manufacturer was also cancelled, because it was established that there were no identical cements by their mark, and by virtue of this, no overlapping could occur as in case of the same types of cement by different manufacturers. After that the density of concrete was considered and it was established that the measuring were considerably unreliable as the scale accuracy is low, so this parameter was omitted in the next iteration.

2nd stage consisted of formation of the neural network model with 5 input parameters. The input parameters are: 1) type of cement; 2) quantity of cement; 3) water/cement ratio; 4) slump on the Abrams cone measured at the trial mix; 5) compressive strength of concrete at the age of 7 days. In the Table 3 are given characteristics for formed neural measure in the 2nd stage.

3rd stage consisted of formation of the neural network model with 4 input parameters. The input parameters are: 1) type of cement; 2) quantity of cement; 3) water/cement ratio; 4) compressive strength of concrete at the age of 7 days. In the Table 4 are given characteristics for formed neural measure in the 2nd stage.

Table 4

Results of neural networks in third iterations
Rezultatele corespunzătoare diferitelor rețele la a treia etapă

Neural network *Rețeaua neuronală*	Root mean square error *Eroare medie*	Accuracy at reliability *Eroarea absolută* 95.4% (N/mm^2)
C1-1	2.68	3.49
C2-1	2.18	3.04
C3-1	2.13	3.12
C4-1	1.90	2.70
C5-1	1.61	2.37
C6-1	1.51	2.30
C7-1	1.33	2.08
C8-2	2.75	3.57
C9-2	2.55	3.84
C10-2	2.29	3.24
C11-2	2.51	4.01
C12-2	2.76	2.96
C13-2	1.74	2.94
C14-2	1.56	2.69

Table 5

Results of comparison of neural networks
Analiza comparativă a rezultatelor

Neural network *Rețeaua neuronală*	Regresion line *Linia regresiei*	Regresion coeficient *Coeficientul de regresie,* R^2
Overtrain	Y=X	1.000
A1	Y=0.885X+4.248	0.886
B13	Y=0.969X+1.138	0.939
C7	Y=0.977X+0.836	0.979

For the final decision 3 networks were chosen, with the highest accuracy at reliability of 95.4%. For the 1st stage, it is the A1 network, and for the 2nd stage, it is the B13 network and for the 3rd stage the network C7. In order to make a final choice, the diagrams of relations of actual and predicted values in each network were made. On the basis of these relations, the regression straight lines and regression coefficient were formed. The general results are presented in Table 5. For networks A1 and C7 test results of real and predicted values with regression line are shown on Figure 4. From the obtained results, it is clear that the neural network C7 is the most approximate to the ideal case.

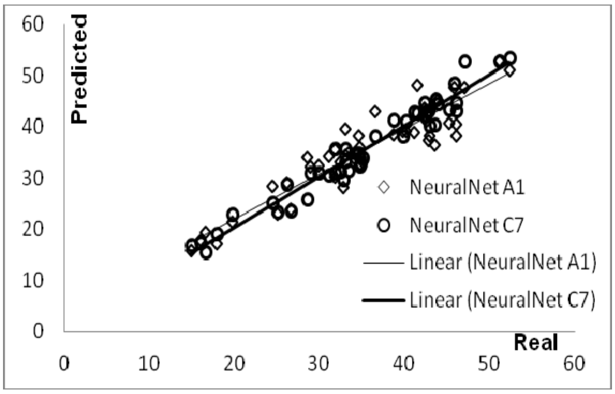

Fig. 3 - Behavior of neural networks / *Reprezentare comparativă a rezultatelor de predicție față de cele reale.*

6. Conclusion

In order to realistically assess the adopted model, their control was performed on the actual problem of 10 trial mix. The models A1 and C7 are tested after obtaining compressive strength at the age of 7 days. The results of predictions, actual results and required results are presented in Table 6.

Table 6

Results of the real requirements
Rezultate de predicție, experimentale şi impuse

No. *Nr.*	Neural Net *Rețeaua neuronală* A1	Neural Net *Rețeaua neuronală* C7	Real $f_{c,28}$	Required by *Cerut de* BAB87
1	25.6	27.4	26.8	28
2	30.6	28.6	29.8	28
3	33.9	35.3	35.1	38
4	40.0	41.1	39.8	38
5	41.6	44.1	44.8	38
6	43.2	45.5	46.5	38
7	41.1	43.8	43.2	43
8	52.1	55.1	54.2	48
9	43.6	47.1	46.7	43
10	49.0	49.0	49.3	48

In actual case, those were concretes of the C20/25 to C30/37 class. The results obtained from both networks A1 and C7 are very close to actual values. The quantities of cement adopted by design are in a very narrow area in respect to the formed data base, thus it can be concluded that the applied models of neural networks are very reliable in cement dosage range of 270 to 380 kg/m^3.

In order to increase the reliability of neural network a very good and extensive data base by all parameters is required. The database of 288 samples is not sufficient to form a forecast model with a large number of input parameters and wide range of input parameters which is clearly obvious from three iterations presented in this paper.

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