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APPLICATION OF ARTIFICIAL NEURAL NETWORKS TO DETERMINE CONCRETE COMPRESSIVE STRENGTH BASED ON NON-DESTRUCTIVE TESTS

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Abstract. The paper deals with the neural identification of the compressive strength of concrete on the basis of non-destructively determined parameters. Basic information on artificial neural networks and the types of artificial neural networks most suitable for the analysis of experimental results are given. A set of experimental data for the training and testing of neural networks is described. The data set covers a concrete compressive strength ranging from 24 to 105 MPa. The methodology of the neural identification of compressive strength is presented. Results of such identification are reported. The results show that artificial neural networks are highly suitable for assessing the compressive strength of concrete. The neural identification of the compressive strength of concrete has been verified in situ.

Keywords: concrete, compressive strength of concrete, non-destructive testing, artificial neural networks.

1. Introduction

Artificial neural networks are more and more often applied to solve various civil engineering problems [1–4]. They are a tool suitable for the association of many parameters, through which certain material or strength features, such as the strength of concrete, are identified.

Compressive strength is a basic mechanical characteristic of concrete, which is commonly tested in laboratories, assumed when concrete structures are dimensioned and checked during the erection or service of structures made from this material [5].

Compressive strength can be assessed by non-destructive techniques which are usually based on the empirical relationship between a single parameter (determined by the given non-destructive technique) and the compressive strength [6–10]. This kind of assessment, referred to as a single correlation in the literature on the subject, is most universally used. But, as it has been repeatedly pointed out, such an assessment would be more accurate and thus more reliable if it were based on several parameters determined by different non-destructive techniques [11]. This has been attempted but because of the poor accuracy of such assessments (eg multiple correlation or graphic techniques [11]), due to the lack of a proper computing tool, they proved inadequate in building practice.

The above warranted a search for a modern technique of assessing the strength of concrete. The use of neural networks for this purpose seemed promising [4, 12–15]. To explore this possibility a proper data set for training and testing the neural networks was created from the results of destructive and non-destructive laboratory tests carried out on several concretes representing a wide range of strength. Artificial neural networks suitable for the analysis of experimental results were selected on the basis of the literature on the subject. The networks were trained and tested. A neural strength identification methodology has been developed and tested in situ.

It should be noted that, as literature reports indicate, attempts are made to design the strength of concrete on the basis of its composition. For this purpose a set of data obtained from numerous laboratories is being created for training and testing the artificial neural networks [16].

2. Experimental investigations

An artificial neural network can be represented as a simplified model of the nervous system consisting of a large number of information processing elements [17]. The elements are called artificial neurons. In order to understand the processes which take place in the artificial neural network one must know how the artificial neuron – the basic structural element of such a network – functions. The prototype of the artificial neuron is the biological neuron. In its cybernetic counterpart the neuron's body is referred to as a processor [17–19]. From the nerve cell originate thin, branching dendrites, constituting its "inputs", and a long, thicker axon. In the artificial neuron this corresponds to input and output signals. The junction between two nerve cells is called a synapse. Through the latter signals are transmitted to other nerve cells. Information is transferred in the form of electric impulses called potentials. The structure of the nerve cell and that of its cybernetic counterpart are shown in Fig 1 [17].

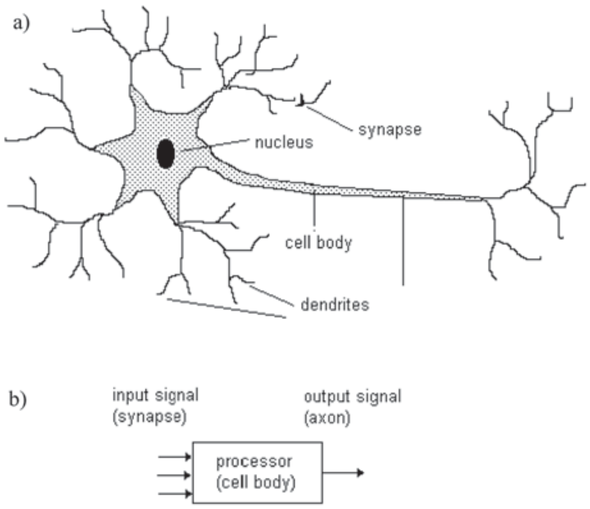

Fig 1. General structure of nerve cell (a) and its cybernetic counterpart (b) [17]

Artificial neurons connected together form a network. The structure of artificial neural networks is, as a rule, layered. Three functional groups can be distinguished in the artificial neural network, ie the inputs receiving signals from the network's outside and introducing them into its inside, the neurons which process information and the neurons which generate results.

A model of the artificial neuron is shown in Fig 2. The model includes N inputs, one output, a summation block and an activation block.

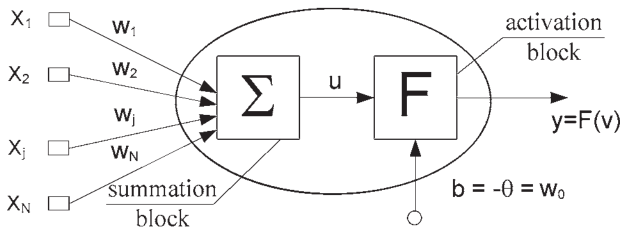

Fig 2. Model of artificial neuron [17]

The following variables and parameters were used to describe the model shown in the figure above:

– an input vector

$$x_i = (x_1, x_2, \ldots, x_N) \tag{1}$$

– a weight vector

$$w_i = (w_1, w_2, \ldots, w_N) \tag{2}$$

– a bias

$$b = -\theta = w_0 \tag{3}$$

– a network potential

$$v = u + b = \sum_{j=1}^{N} w_j x_j - \theta = \sum_{j=0}^{N} w_j x_j \tag{4}$$

– an activation function

$$F(v). \tag{5}$$

A network architecture with inputs, information processing neurons and output neurons is shown in Fig 3.

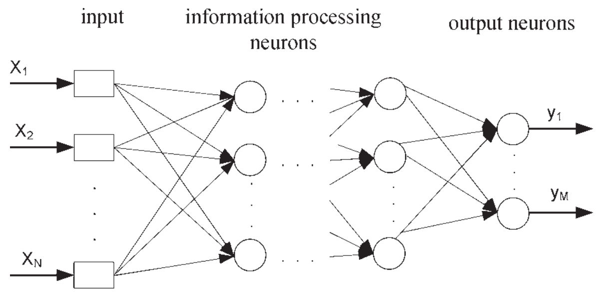

Fig 3. Network architecture

Depending on the way in which the neurons are connected, three basic types of artificial neural networks are distinguished: unidirectional networks, recursive networks and cellular networks [4]. Basic types of artificial neural networks is shown in Fig 4.

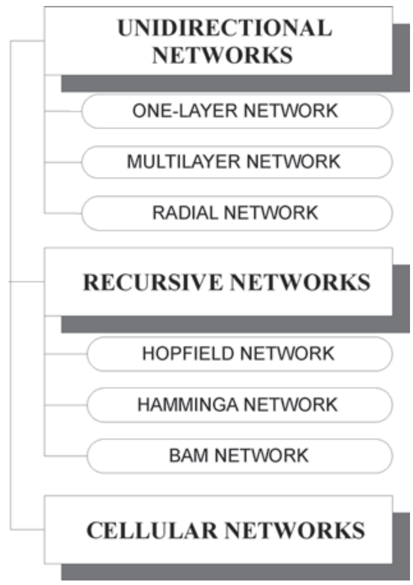

Fig 4. Basic types of artificial neural networks [20]

3. Data set and selected neural networks

The data set for training and testing neural networks was created from results obtained from laboratory tests for seven types of concrete (designated by letters from A to G).

The specifications of the concretes are shown in Table 1. It follows from the table that the compressive strengths of the concretes ranged from 24 to 105 MPa.

Table 1. Specifications of concretes A-G [20]

Designation of concrete	Composition of mixes [kg/m^3]					Type of aggregate / Max grain	W/C	Compressive strength f_{cm} [MPa]
	cement (type)	water	aggregate	super-plasticiser	silica fumes			
1	2	3	4	5	6	7	8	9
A	375 (35)	150	1931	0	0	rounded / 20 mm	0,400	24
B	450 (35)	150	2092	0	0	rounded / 20 mm	0,333	32
C	400 (35)	160	1920	0	0	crushed granite / 16 mm	0,400	43
D	400 (40)	160	2048	0	0	crushed basalt / 16 mm	0,400	45
E	450 (42,5)	180	2029	0	0	crushed basalt / 16 mm	0,400	71
F	450 (42,5)	146	2084	9,00	0	crushed basalt / 16 mm	0,324	85
G	450 (42,5)	140	2069	13,50	31,50	crushed basalt / 16 mm	0,291	105

The data consists of seven sets of parameters determined for 150×150×150 mm concrete specimens A-G after 3, 7, 14, 21, 28 and 90 days of curing by non-destructive laboratory tests. The following non-destructive methods and parameters determined by them were used in the investigations: the ultrasonic method – longitudinal wave velocity V_L, sclerometric methods – reflection number L for the Schmidt sclerometer of type N and impression D for the HPS sclerometer and the pull-out method – force N pulling out a steel anchor previously embedded in concrete. In case of concrete mix A, B, C and D were: V_L, L and T_s and also age of concrete t_b, bulk densities g_o, and strengths f_c determined by destructive methods. This results in a network architecture (5-10-1). The number of hidden layers was 10. In case of concretes E, F and G, they were: V_L, L, D and N and also t_b, g_o and f_c. This results in a network architecture (6-12-1). The number of hidden layers was 12. Some parts of created data base for concrete A and G are shown in Table 2 [20].

On the basis of a review of the literature on the subject [17, 19, 21] the following unidirectional, multilayer error-backpropagation networks were selected for the task:

– the network with momentum and the descent gradient algorithm (WPB-GDM),
– the network with the descent gradient algorithm and an adaptive step (WPB-GDX),
– the network with the conjugate gradient algorithm (WPB-CGB),
– the Levenberg-Marquardt network (LM),
– the unidirectional radial network (RFB).

The elements of network structure for concretes A - G are shown in Table 3. It should be noted that each of the above networks was subjected to training and testing for each of the concretes (A-G).

4. Methodology of concrete strength neural identification

A methodology for concrete strength neural identification was developed. It is shown schematically in Fig 5. Three blocks can be distinguished in the scheme.

Experimental results, forming a set of data on concretes A-G, used for training and testing the neural network are an integral part of *block 1*. The data set includes the four parameters determined by the non-destructive techniques [6–10, 22, 23], concrete age t_b, concrete bulk density g_o and destructively determined strength f_c of the investigated concretes.

The experimental results as a set of patterns were saved in a computer file which was then used as the input data for the network in *block 2*. The data were divided into data for training (80 % of the total data) and testing the neural network. They were normalised by applying the procedure of the *MATLAB – Neural Networks Toolbox* simulator so that the mean value of the results equalled zero and the standard deviation equalled 1 [24]. The training patterns were randomly input into the network to train it. In this way the neural network learnt to identify the compressive strength of a given concrete. If the neural network correctly mapped the training data and correctly identified the testing data,

Table 2. Some parts of created database for concrete A and G [20]

Designations of concretes	Number of specimens	Input data							Output
		Age of concrete t_b [day]	Bulk densities γ_o [kg/m^3]	V_L [km/s]	L [-]	T_s [kG/mm^2]	D [mm]	N [kN]	f_c [MPa]
1	2	3	4	5	6	7	8	9	10
A	6	3	2,350 :	3,791 :	18,0 :	20,0 :	-	-	*3,5* :
	6	7	2,380 :	4,251 :	28,0 :	28,7 :	-	-	*14,6* :
	6	14	2,380 :	4,507 :	30,0 :	29,7 :	-	-	*20,5* :
	6	21	2,350 :	4,494 :	34,0 :	33,8 :	-	-	*23,0* :
	6	28	2,380 :	4,544 :	32,0 :	35,6 :	-	-	*23,7* :
	6	90	2,330 :	4,519 :	39,0 :	39,1 :	-	-	*24,4* :
G	10	3	2,490 :	4,11 :	38,0 :	-	4,97 :	49,4 :	*60,3* :
	10	7	2,519 :	4,18 :	40,3 :	-	4,86 :	62,0 :	*68,6* :
	10	14	2,539 :	4,27 :	43,3 :	-	4,80 :	65,2 :	*73,3* :
	10	28	2,565 :	4,34 :	46,0 :	-	4,55 :	80,1 :	*90,7* :
	10	90	2,591 :	4,38 :	51,0 :	-	4,50 :	93,4 :	*101,9* :

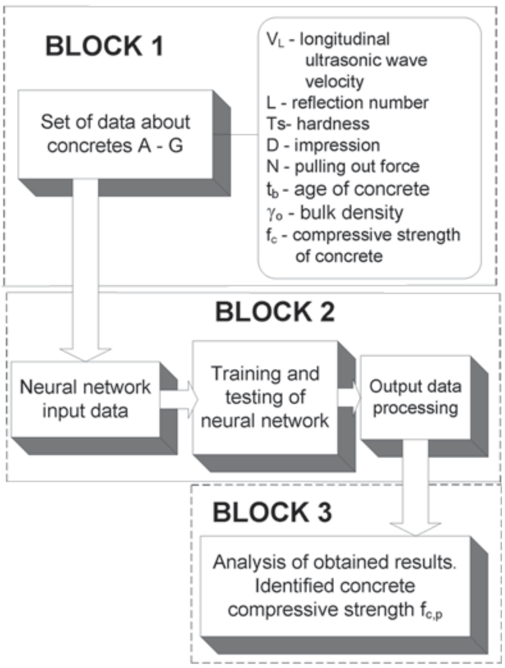

Fig 5. Illustration of concrete compressive strength identification by means of neural networks on the basis of non-destructive tests [20]

it was considered trained. Then the input data were denormalised.

The obtained results were analysed in *block 3* whose output was identified concrete compressive strength $f_{c,p}$.

5. Results of neural network training and testing

All of five neural networks listed in point 3 were trained and tested to find out the best one for the task. The Levenberg-Marquardt network (LM) was ultimately chosen [20, 25, 26]. The structure of the network is shown in Fig 6.

The choice of the Levenberg-Marquardt (LM) neural network for testing proved to be right, as evidenced mainly by the calculated low training and testing *RMSEs* for the network but also by the low values of relative testing error *Maxewp* and relative error standard deviation *Ste* as well as the high values of correlation coefficient *R* (particularly for testing) [20, 27]. The obtained results are shown in Figs 7–10.

The root-mean-square error (RMSE) was calculated from the following relation:

Table 3. The elements of network structure for concretes A-G [20]

Designations of concretes	Short name of neural network	The elements of network structure					
		input data	hidden layer	neurons in hidden layer	output	number of epochs	momentum
1	2	3	4	5	6	7	8
A	WPB-GDM	5	1	10	1	5000	0,10
	WPB-GDX	5	1	12	1	1000	0,90
	LM	5	1	10	1	20	-
	WPB-CGB	5	1	8	1	200	-
	RFB	5	1	138	1	138	-
B	WPB-GDM	5	1	8	1	5000	0,50
	WPB-GDX	5	1	12	1	1000	0,90
	LM	5	1	8	1	20	-
	WPB-CGB	5	1	8	1	200	-
	RFB	5	1	143	1	143	-
C	WPB-GDM	5	1	8	1	5000	0,90
	WPB-GDX	5	1	12	1	1000	0,90
	LM	5	1	10	1	20	-
	WPB-CGB	5	1	8	1	200	-
	RFB	5	1	141	1	141	-
D	WPB-GDM	5	1	10	1	5000	0,90
	WPB-GDX	5	1	12	1	1000	0,90
	LM	5	1	12	1	20	-
	WPB-CGB	5	1	10	1	200	-
	RFB	5	1	139	1	139	-
E	WPB-GDM	6	1	12	1	5000	0,90
	WPB-GDX	6	1	14	1	1000	0,90
	LM	6	1	12	1	20	-
	WPB-CGB	6	1	10	1	200	-
	RFB	6	1	191	1	191	-
F	WPB-GDM	6	1	12	1	5000	0,50
	WPB-GDX	6	1	10	1	1000	0,70
	LM	6	1	12	1	20	-
	WPB-CGB	6	1	14	1	200	-
	RFB	6	1	185	1	185	-
G	WPB-GDM	6	1	12	1	5000	0,60
	WPB-GDX	6	1	12	1	1000	0,80
	LM	6	1	10	1	20	-
	WPB-CGB	6	1	12	1	200	-
	RFB	6	1	187	1	187	-

$$RMSE(P) = \sqrt{\frac{1}{P}\sum_{p=1}^{P}(z_i - y_i)^2}\ , \qquad (6)$$

where y_i – the computed network output vector, z_i – the target output vector, P – the number of samples in the database.

The relationship between destructively determined compressive strength f_c and compressive strength $f_{c,p}$ identified by the LM neural network for concretes A and G is shown in Fig 11, where the unshaded circles and the shaded lozenges represent respectively training and testing. The results show that the LM network correctly maps the training data and correctly identifies the testing data. This is evidenced by the fact that the circles and the lozenges lie close to the centre line corresponding to the ideal mapping as well as by the very high correlation coefficient (R) values.

The graphs of LM network training and testing *RMSEs* as a function of the number of epochs for con-

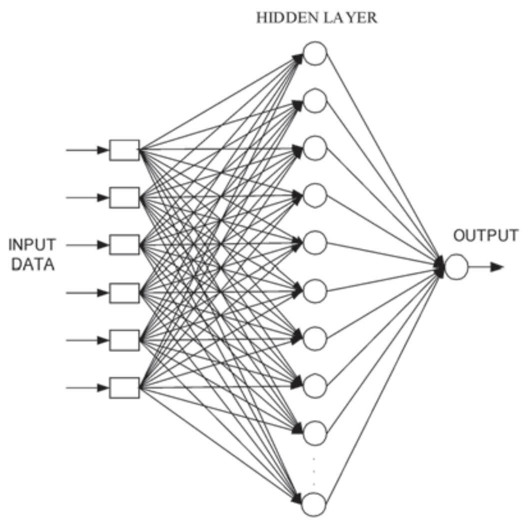

Fig 6. Feed-forward neural network with a single hidden layer: 6-10-1

cretes A and G are shown in Fig 12. It is evident that the *RMSE* decreases rapidly with the growing number of epochs and stabilises at a level of about 0,05 for each of the concretes.

The difference between the LM network training and testing errors (D*RMSE*) as a function of the number of epochs for concretes A-G is shown in Fig 13. It is evident that difference D*RMSE* decreases as the number of epochs increases. When the latter reaches 20, the difference is in a range of 0,0001–0,001.

6. Results of practical verification

The compressive strengths of ordinary concrete in two actual reinforced-concrete multistorey building structures (a residential building and an office building), non destructively assessed by means of neural networks were practically verified using laboratory data. In case of two buildings it became necessary to check the compressive strength of the concrete incorporated in the ground-floor structural elements when the concrete was nearly 28 days old.

In the residential building the structural elements were columns of 25 × 35 cm in cross-section and 20 cm thick floor slabs made of concrete B20 based on rounded aggregate (with the maximum grading of 20 mm) at W/C = 0,4. In the office building these were columns 30 × 45 cm in cross-section and walls made of concrete B35 based on rounded aggregate (with the maximum grading of 20 mm) at W/C = 0,36. In both buildings the

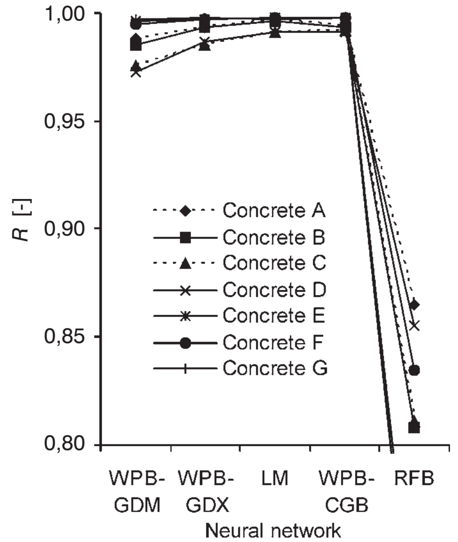

Fig 7. Values of testing correlation coefficient *R* for selected neural networks for concretes A-G

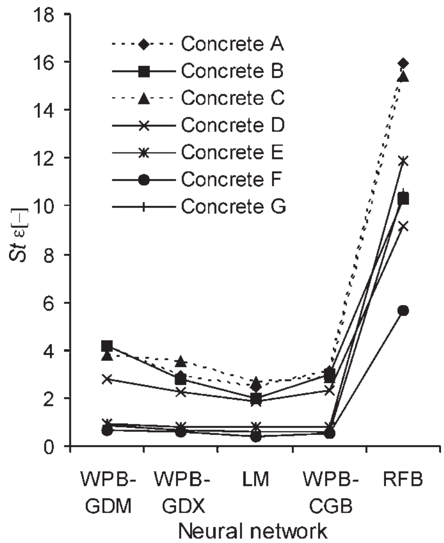

Fig 9. Values of relative error standard deviation *St*e for selected neural networks for concretes A-G

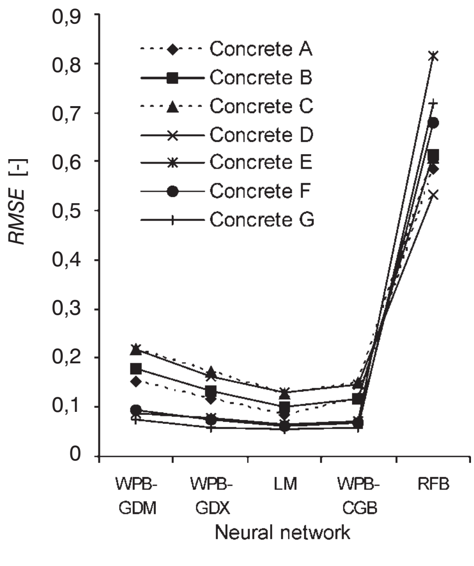

Fig 8. Values of testing root mean square error *RMSE* for selected neural networks for concretes A-G

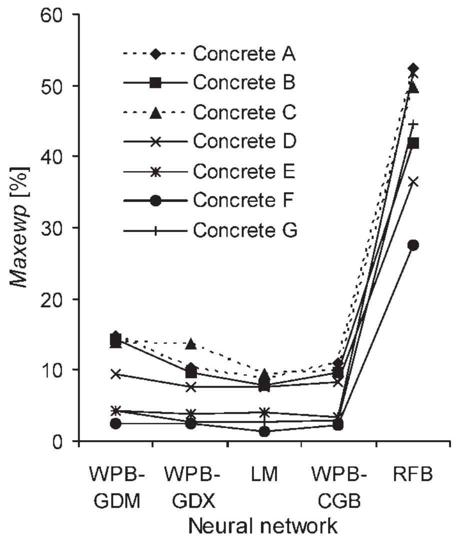

Fig 10. Values of relative testing error *Maxewp* for selected neural networks for concretes A-G

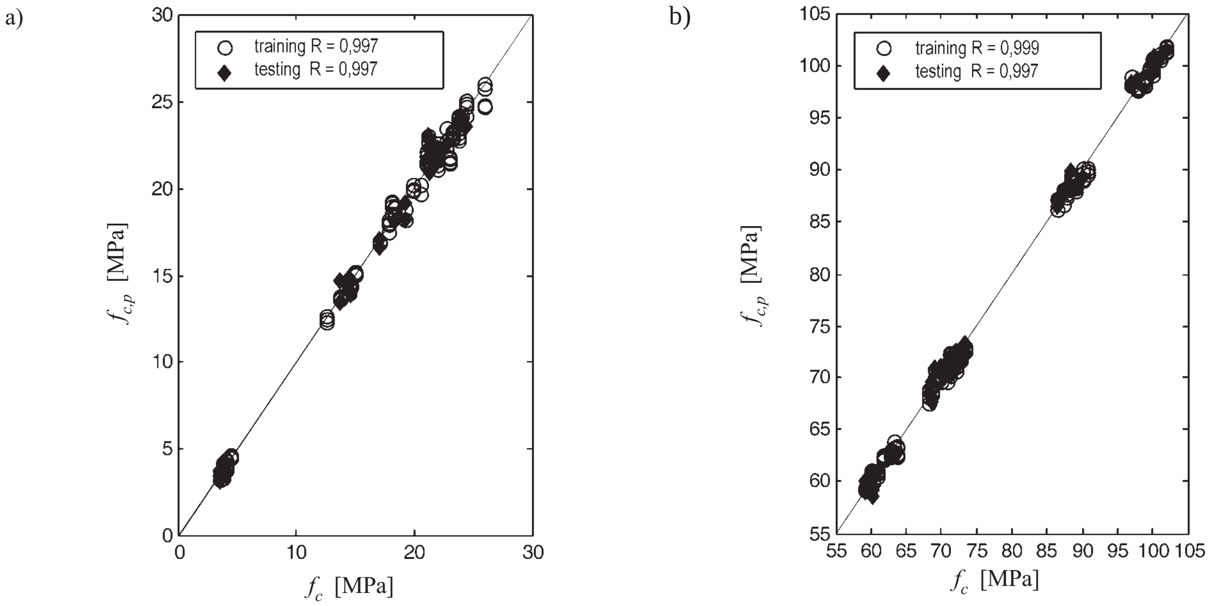

Fig 11. Destructively determined compressive strength f_c versus compressive strength $f_{c,p}$ identified by LM neural network for training set and testing set for: a) concrete A, b) concrete G

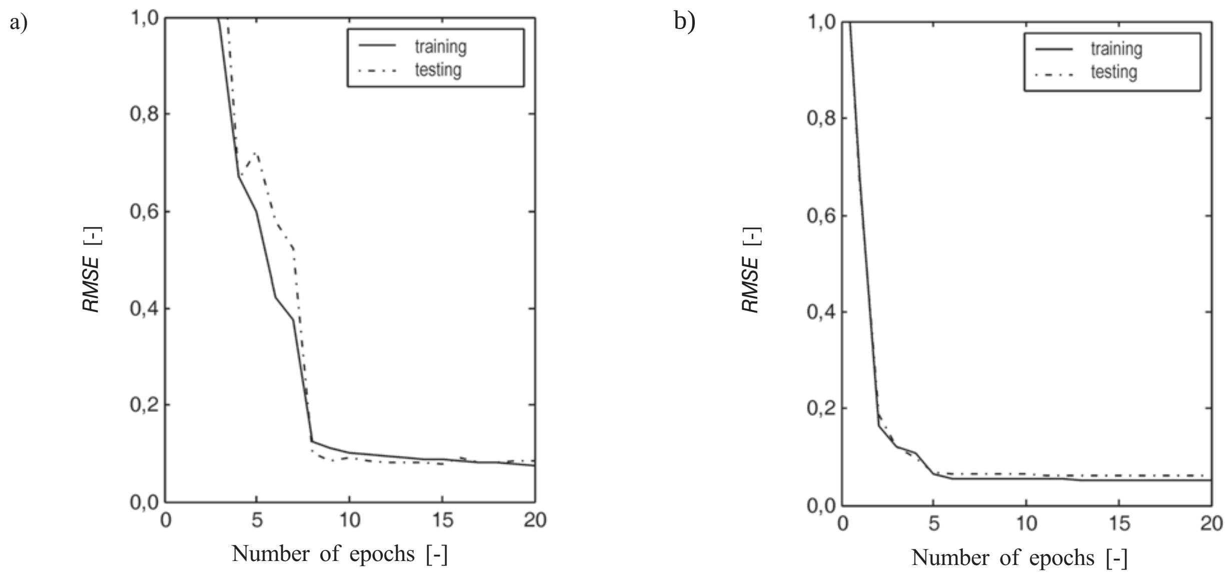

Fig 12. LM network training and testing *RMSEs* versus number of epochs for: a) concrete A, b) concrete G

concrete was made from grade 35 Portland cement without additives.

In each of the building structures the tests were carried out at twelve measuring places. Then in those places f 100 mm cores were taken to destructively determine the compressive strength of the concrete. During the tests non-destructive methods were used and hypothetical curves for the assessment of this strength, separately for the ultrasonic method and the sclerometric methods, were selected. The equations of the curves are given in [28]. The specimens were also used to determine the concrete bulk density γ_o.

The LM network trained on the data set for concrete A and concrete B was selected for the identification of the compressive strength in buildings 1 and 2, respectively. The in-built concretes and concretes A and B had similar composition and compressive strength.

The methodology of neural strength identification is shown in Fig 14. Segment 1 includes parameters non-destructively determined in laboratory for concretes A-G, concrete ages and bulk densities as well as the trained LM network. Segment 3 comprises the experimental results obtained for buildings 1 and 2.

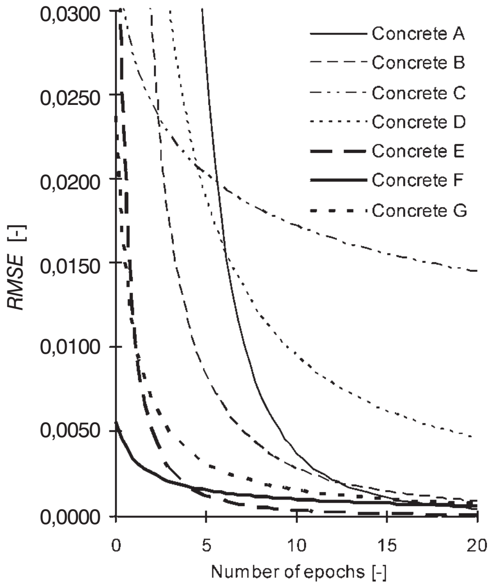

Fig 13. Difference between LM network training and testing errors ($\Delta RMSE$) versus number of epochs for concretes A-G

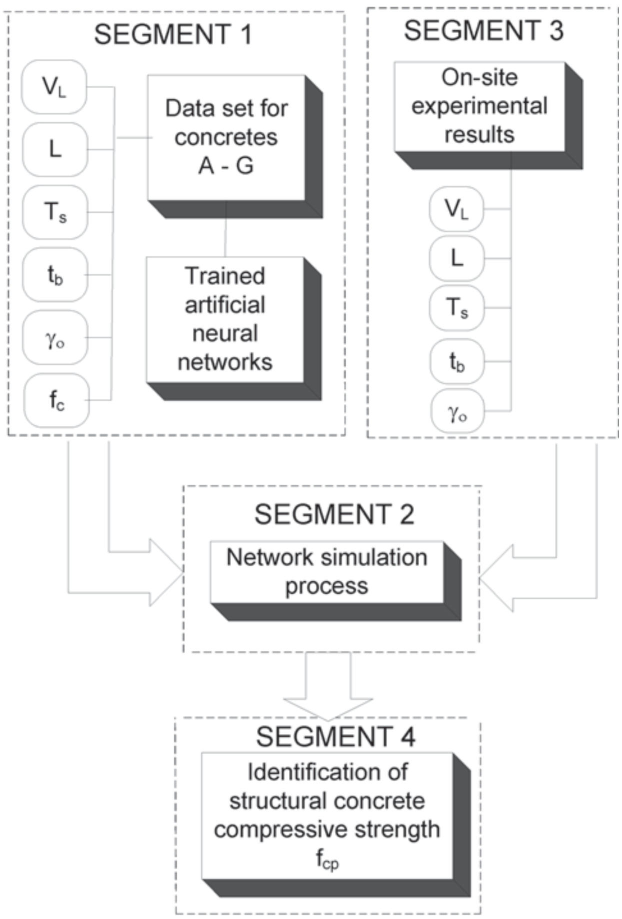

Fig 14. Methodology of neural strength identification in buildings

The network simulation process proceeds within segment 2. Two pairs of input data simultaneously enter a selected neural network (in that case LM). One pair is made up of database parameters (from segment 1) for a concrete of similar composition and strength as the concrete in the investigated building structure. The other pair contains experimental data (from segment 3) for the concrete incorporated in the building structure. After network simulation the network output data are processed and analysed in segment 4 at the output of which identified structural concrete compressive strengths $f_{c,p}$ are obtained.

Typical results of the non-destructive tests performed in the places designated for core taking are shown in Table 4.

Table 4. Typical results of non-destructive tests carried out on structural elements of building 1 and 2 and bulk densities of concrete

Number of building	Number of measur. place	Average values of measured parameters				
		V_L [km/s]	L [-]	T_s [kG/mm²]	t_b [-]	γ_o [kg/m³]
1	2	3	4	5	6	7
1	1	4,33	30,0	31,3	28	2,292
	2	4,41	31,5	34,0	28	2,253
	3	4,37	30,2	31,9	28	2,144
	.	.	.	.	.	.
	.	.	.	.	.	.
	.	.	.	.	.	.
	10	4,33	29,5	30,5	28	2,188
	11	4,34	29,0	27,3	28	2,113
	12	4,34	30,0	30,4	28	2,281
2	1	4,528	38,0	45,2	28	2,180
	2	4,535	39,4	45,8	28	2,200
	3	4,543	39,2	46,1	28	2,220
	.	.	.	.	.	.
	.	.	.	.	.	.
	10	4,563	39,2	44,8	28	2,220
	11	4,614	36,8	45,6	28	2,240
	12	4,522	39,4	45,0	28	2,240

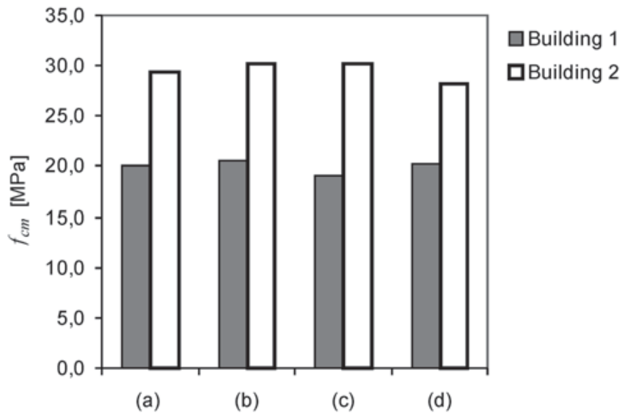

Fig 15. Average compressive strengths f_{cm} of concrete incorporated in structural elements of buildings 1 and 2 determined by: neural identification (a), destructive test (b), ultrasonic method (c) and sclerometric method using Schmidt sclerometer (d)

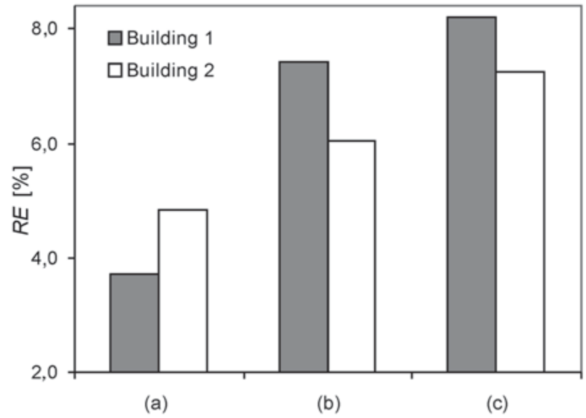

Fig 16. Mean relative errors *RE* for compressive strength of concrete incorporated in structural elements of buildings 1 and 2 determined by: neural identification (a), ultrasonic method (b) and sclerometric method using Schmidt sclerometer (c) in comparison with destructively determined strength

The average compressive strengths of the concrete determined non-destructively by the LM neural network and through destructive tests carried out on the core specimens are shown in Fig 15. Compressive strengths obtained by the hypothetical curves given in [20, 28] are also shown for comparison.

The mean relative errors (*RE*) calculated for the compressive strength of the concrete incorporated in the structural elements of the two buildings are shown in Fig 16. The lowest *RE* values: 3,70 % for building 1 and 4,84 % for building 2 were obtained for neural identification.

7. Conclusions

1. The results presented here demonstrate that the assessment of the compressive strength of concrete by artificial neural networks, particularly by the Levenberg-Marquardt network, on the basis of parameters determined by several non-destructive techniques is a viable method. This is evidenced mainly by the calculated low training and testing *RMSEs* for the LM network but also by the differences between the errors (D*RMSE*) as a function of the number of epochs, the low values of relative testing error *Maxewp*, the low values of relative error standard deviation *St*e and the high values of correlation coefficient *R* (particularly for testing).

2. The average compressive strengths of the concrete incorporated in the structural elements of the two buildings, determined by artificial neural networks and by destructive tests during practical in situ verification, are very similar. It is highly significant that the calculated average relative errors (*RE*) are definitely the lowest for the strength determined by the artificial neural network.

3. In the authors' opinion, having a set of data acquired by means of at least three non-destructive techniques for a group of concretes with different composition and artificial neural networks trained on the data, one can reliably neurally identify the compressive strength of similar concretes incorporated in building structures without the need to determine correlations or fit hypothetical scaling curves.

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DIRBTINIŲ NEURONINIŲ TINKLŲ NAUDOJIMAS GNIUŽDOMO BETONO STIPRIUI NUSTATYTI REMIANTIS NEARDOMŲJŲ BANDYMŲ DUOMENIMIS

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Santrauka

Rašoma apie gniuždomo betono stiprio nustatymą naudojant neuroninius tinklus ir remiantis neardomųjų bandymų duomenimis. Nurodomi dirbtiniai neuroniniai tinklai bei jų tipai, kurie labiausiai tinka eksperimentinių duomenų analizei. Aprašoma neuroninių tinklų mokymui bei testavimui taikyta eksperimentinių duomenų imtis. Šioje imtyje gniuždomo betono stipris kito nuo 24 iki 105 MPa. Pateikiama gniuždomo betono stiprio nustatymo, naudojant neuroninius tinklus, metodika bei skaičiavimo rezultatai. Analizės rezultatai rodo, kad dirbtiniai neuroniniai tinklai gerai tinka gniuždomo betono stipriui nustatyti. Tuo įsitikinta atlikus natūrinius tyrimus.

Raktažodžiai: betonas, gniuždomo betono stipris, neardomieji bandymai, dirbtiniai neuroniniai tinklai.

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