PROCENA ČVRSTOĆE BETONA PRI PRITISKU, KORIŠĆENJEM VEŠTAČKIH NEURONSKIH MREŽA

ESTIMATION OF CONCRETE COMPRESSIVE STRENGTH USING ARTIFICIAL NEURAL NETWORK

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1 UVOD

Analiza čvrstoće betona pri pritisku predstavlja jedan od primarnih zadataka laboratorijskih ispitivanja za različite potrebe inženjerske prakse, pre svega u zgradarstvu, tunelogradnji, putarstvu, pri izgradnji brana i mostova, kao i pri izvođenju različitih podzemnih i površinskih konstrukcija u rudarstvu. Zavisno od zahteva projekta, ispitivanje čvrstoće betona izvodi se za uzorke različite starosti s promenljivim vodocementnim faktorom, raznim tipovima i količinom aditiva (leteći pepeo, silikatna prašina, metakaolin i mlevena granulisana zgura iz visokih peći kao mineralni aditivi, odnosno plastifikatori, različiti akceleratori i retarderi, kao hemijski aditivi), te u različitim spoljašnjim uslovima ugradnje betona (s naglaskom na otpornost betona pri izlaganju mrazu). Pri tome, pouzdanost dobijenih rezultata najčešće predstavlja direktnu funkciju broja ispitanih uzoraka, tj. veći broj ispitanih uzoraka betona doprinosi pouzdanijem određivanju njegovih svojstava. Međutim, sredstva predviđena programom istraživanja, u najvećem broju slučajeva, nisu dovoljna za analizu brojnih uzoraka, već se najčešće pristupa interpolaciji malog, vrlo često i nedovoljnog broja podataka ispitivanja. U tom smislu, modeli za procenu čvrstoće betona predstavljaju posebno važnu tehniku koja omogućava utvrđivanje relacije između zrelosti betona i njegove čvrstoće,

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1 INTRODUCTION

Analysis of concrete compressive strength represents one of the primary tasks in laboratory studies for different needs of engineering praxis, including architectural engineering, tunnelling, road engineering, construction of dams and bridges, and for the purpose of surface and underground mining activities. Depending on the Project demand, concrete compressive strength is examined for the specimens of different age and with distinct w/c ratio, for different types and amounts of additives (flying ash, silica fume, metakaolin and ground granulated blast furnace slag, as mineral additives, and plasticizers, different accelerators and retarders, as chemical additives). In this case, reliability of the obtained results regularly represents a direct function of the number of examined concrete samples. In other words, the larger the number of analyzed specimens, the more precise their properties are determined. However, only a small part of the project funding is used for laboratory analyzes, which is often scarce for conducting the analysis of larger number of samples. Instead, the analysis is often based on the approximation of small and insufficient data. Therefore, existing models for estimation of concrete compressive strength have valuable importance, enabling us to determine the relation between the maturity of concrete and its compressive

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odnosno ocenu razvoja čvrstoće betona s vremenom na bazi relativno malog broja ispitanih uzoraka. Jedan od prvih uspešnih postupaka procene čvrstoće betona pri pritisku dao je Plouman [1], koji je vezu između čvrstoće i zrelosti po Solu izrazio u obliku logaritamske funkcije. S druge strane, Bernhart [2] je pokazao da je brzina razvoja relativne čvrstoće betona proporcionalna veličini nehidratisanog dela betona, koju je uveo preko konstante proporcije *k*. Karino [3] je takođe predložio ocenu čvrstoće pri pritisku uzoraka betona, pod pretpostavkom da očvršćavanje betona počinje tek nakon određenog vremena od ugradnje betona. Yi i dr. [4] u svoju jednačinu za procenu čvrstoće betona pri pritisku uveli su efekat difuzione ljuske, konstantu brzine, graničnu čvrstoću i reakcioni koeficijent.

Uprkos činjenici da ovi konvencionalni modeli daju ocenu pritisne čvrstoće betona sa zadovoljavajućom tačnošću za potrebe inženjerske prakse, razvoj novih smeša betona, s različitim tipovima i količinom aditiva, povećava broj sastavnih elemenata betona, što otežava uspostavljanje jasnih veza između različitih komponenata. Iz tog razloga, tokom poslednjih godina, sve češća je primena veštačkih neuronskih mreža za potrebe modelovanja različitih svojstava betona, poput skupljanja pri isušivanju [5], trajnosti betona [6], čvrstoće normalnog betona i betona visoke čvrstoće pri pritisku [7–12], konsistencije betona s metakaolinom i letećim pepelom [13–14], mehaničkog ponašanja betona na visokim temperaturama [15], kao i dugotrajnog efekta letećeg pepela i silikatne prašine na čvrstoću betona pri pritisku [16]. Glavna prednost primene veštačkih neuronskih mreža u odnosu na standardne konvencionalne prediktore [1–4], leži u mogućnosti analize čvrstoće velikog broja uzoraka betona s različitim vodocementnim faktorom, uključujući i efekat izlaganja dejstvu mraza. Za razliku od veštačkih neuronskih mreža, konvencionalnim prediktorima procenjuje se razvoj čvrstoće pri pritisku uzoraka betona istog sastava (jednak vodocementni faktor), koji su negovani u izotermalnim uslovima.

Pored navednih konvencionalnih modela i veštačkih neuronskih mreža, neretko se koriste i drugi modeli procene čvrstoće betona pri pritisku, koji se zasnivaju na razmatranju efekta različitih proporcija vode, cementa i agregata [17–18], odnosno koji koriste sisteme na bazi adaptivne mreže [19–21] ili fazi logike [22–24].

U ovom radu razvijen je model procene čvrstoće betona pri pritisku na bazi veštačkih neuronskih mreža, korišćenjem rezultata eksperimentalnih ispitivanja, u zavisnosti od četiri kontrolna faktora: vodocementni faktor, starost betona, broj ciklusa zamrzavanja/otkravljivanja i količina superplastifikatora.

strength, providing, in that way, an evaluation of compressive strength development with time on the basis of relatively small number of examined samples. One of the first successful prediction models was provided by Plowman [1], who expressed the relationship between strength and maturity by Saul as a natural logarithmic function. Soon afterwards, Bernhardt [2] showed that relative strength development ratio of concrete is proportional to the size of unhydrated portion of the concrete and introduced rate constant *k*. Carino [3] also suggested the equation of prediction of concrete compressive strength under the assumption that the hardening of concrete starts at a certain time after the concrete placement time. Yi et al. [4] incorporate the effect of diffusion shell, rate constant, limiting strength and reaction coefficient, as functions of curing temperature, in the equation of concrete strength prediction.

Despite the fact that previous conventional models give reasonable prediction accuracy for engineering purposes in reference to concrete compressive strength, development of new concrete mixtures, with different types and percentage of additives, increase the number of concrete constituents, thus, making harder to obtain reliable results among various concrete components. Therefore, in recent years, artificial neural networks (ANN) have been used for the purpose of modelling different properties of concrete, such as drying shrinkage [5], concrete durability [6], compressive strength of normal concrete and high performance concrete [7-12], workability of concrete with metakaolin and fly ash [13-14], mechanical behaviour of concrete at high temperatures [15] and long term effect of fly ash and silica fume on compressive strength [16]. The main advantage of ANN approach over the standard conventional predictors [1-4] lies in the possibility to examine the compressive strength of large number of concrete specimens with different *w/c* ratio, including the effect of exposure to various freeze/thaw cycles. Opposite to the ANN approach, conventional predictors estimate the development of compressive strength of concrete specimens of the same properties (equal w/c ratio) cured at isothermal conditions.

Besides conventional models and the ANN approach, there are other types of models which are frequently used for prediction of compressive strength. The first of them is based on the combination of input variables, water, cement and aggregates [17-18], while the second approach is using adaptive network-based fuzzy inference system [19-21] and fuzzy logic techniques [22-24].

In present paper, the ANN model is developed for estimation of concrete compressive strength based on the results of a series of experiments. The present research is focused on compressive strength of concrete samples, depending on four main factors: *w/c* ratio, age, number of freeze/thaw cycles and amount of superplasticizer.

2 SVOJSTVA BETONA

2.1 Cement

Za pripremu uzoraka betona za ispitivanje korišćen je CEM I normalni Portland cement (PC 42,5 N/mm^2) sa

2 PROPERTIES OF MATERIALS

2.1 Cement

The examined concrete specimens were made of CEM I normal Portland cement (PC 42.5 N/mm^2) with specifičnom težinom ρ=3,10 g/cm^3. Početno i finalno vreme vezivanja cementa bilo je 2^h 30min i 3^h 30min, redom, dok je specifična površina po Blejnu iznosila 3450 cm^2/g. Fizičko-mehanička svojstva cementa prikazana su u Tabeli 1, dok je njegov hemijski sastav dat u Tabeli 2.

specific gravity ρ=3.10 g/cm^3. Initial and final setting times of the cement were 2^h 30min and 3^h 30min, respectively. Its Blaine specific surface area was 3450 cm^2/g. Physical and mechanical properties of cement are summarized in Table 1, while its chemical composition is given in Table 2.

Tabela 1. Fizičko-mehanička svojstva Portland cementa
Table 1. Physical and mechanical properties of Portland cement

Svojstvo / Property	Vrednost / Value	
Specifična težina Specific gravity (g/cm^3)	3,10	
Specifična površina Specific surface (cm^2/g)	3450	
Početno vreme vezivanja Setting time initial (min)	150	
Finalno vreme vezivanja Setting time final (min)	210	
Povećanje zapremine Volume expansion (mm^3)	0,50	
Čvrstoća na pritisak Compressive strength (MPa)	2 dana / days	28 dana / days
	15,1	49,5
Čvrstoća na savijanje Flexural strength (MPa)	2 dana / days	28 dana / days
	3,5	8,7

Tabela 2. Hemijski sastav Portland cementa
Table 2. Chemical composition of Portland cement

Oksid Oxide	SiO_2	Al_2O_3	Fe_2O_3	CaO	MgO	SO_3	CaO	Na_2O	K_2O
Cement Cement	20.58	6.04	2.54	58.79	2.66	3.08	2.16	0.29	0.76

2.2 Agregat

Kao agregat za betonske smeše korišćen je rečni šljunak, s maksimalnom nominalnom veličinom do 16mm, i s maksimalno 5% učešća veće frakcije. Upijanje vode iznosi 1,5%, dok je relativna gustina agregata zasićenog vlagom i sa suvom vidnom površinom - 2.72 g/cm^3. Granulometrijski sastav agregata prikazan je u Tabeli 3.

2.2 Aggregate

Natural river aggregate was used in concrete mixture. The gravel was 16 mm maximum nominal size with 5% of the oversize particles. The water absorption was 1.5 % and its relative density at saturated surface dry (SSD) condition was 2.72 g/cm^3. Grading of the mixed aggregate is shown in Table 3.

Tabela 3. Granulometrijski sastav agregata
Table 3. Grading of the mixed aggregate

Veličina sita Sieve size (mm)	0,09	0,13	0,25	0,5	1	2	4	8	11,2	16	22,4
0/4 (% prošlih) 0/4 (% passed)	1	4	21	67	76	84	94	100	100	100	100
4/8 (% prošlih) 4/8 (% passed)	0	0	0	0	0	1	12	97	100	100	100
8/16 (% prošlih) 8/16 (% passed)	0	0	0	0	0	0	0	19	67	95	100

2.3 Plastifikator

Superplastifikator (SP) tipa melamin korišćen je radi održavanja konsistencije i sleganja sveže betonske smeše. Količina dodatog superplastifikatora za različte betonske smeše data je u Tabeli 4. Dodavanjem plastifikatora proporcionalno je smanjivana količina vode.

2.3 Plasticizer

A mellamine-type superplasticizing admixture (SP) was used at various amounts to maintain slump and workability of fresh concrete mixture. The amount of SP used in the different concrete mixtures is given in Table 4. The amount of water was decreased for the amount of SP added.

Tabela 4. Proporcije smeša betona i njihova konsistencija
Table 4. Concrete mixture proportions and consistency

Uzorak br. Sample No.	C (kg)	A (kg)	VC	SP (%)	Sleganje Slump (cm)	Vebe (s)	Tečenje Flow (cm)
D1	350	1930	0,45	2,0	8	4	36
D2	350	1930	0,40	2,0	5	5,5	32
D3	350	1930	0,50	1,4	17	1,5	57
D4	350	1930	0,55	1,4	25,5	0	67
D5	350	1930	0,35	4,0	2	10	25

2.4 Priprema uzoraka

Smeše betona pravljene su u laboratorijskom mikseru tipa ,,Eirich", s periodom mešanja od tri minuta za sve smeše. Za testiranje su pripremljeni kockasti uzorci betona (100x100mm). Livenje betona izvedeno je na vibracionom stolu sve do potpune konsolidacije. Konsistencija svežeg betona određivana je pomoću testa sleganja [25], testa po Vebeu [26] i testa tečenja [27].

2.4 Preparation of specimens

Concrete was made in a laboratory counter-current concrete mixer (type "Eirich"). Mixing period was 3 minutes for all mixtures. Cubic samples (100x100mm) were made for testing. Casting was performed at vibrating table until a complete consolidation was achieved. Consistency of fresh concrete was measured by applying the slump test [25], Vebe test [26] and flow test [27].

3 POSTUPAK TESTIRANJA

Nakon što je beton izliven u metalne kalupe, uzorci su ostavljeni na sobnoj temperaturi (+20°±2^{0}C) sa 90 – 95% RH. Nakon 24,^{h} uzorci su izvađeni iz kalupa i potopljeni u vodu na istoj temperaturi (+20°C) sledećih šest dana. Sedmog dana, četiri serije od osam serija uzoraka betona izlagane su mrazu. Čvrstoća pri pritisku određivana je nakon 50 i 100 ciklusa zamrzavanja/otkravljivanja (jedan ciklus podrazumeva izlaganje uzorka mrazu u trajanju od 4^h u komori na temperaturi –20°±2^{0}C, a potom se uzorak izlaže sobnoj temperaturi od 20°±2^{0}C u vodi u trajanju od 4^h). Nakon toga, izmerena vrednost čvrstoće poređena je sa čvrstoćom kontrolne grupe uzoraka (koji su neprekidno negovani u vodi na temperaturi 20°±2^{0}C) za ekvivalentnu starost [28–29]. Čvrstoća na pritisak i nasipna gustina određeni su prema važećim standardima [30–31]. Čvrstoća pri pritisku uzoraka betona određivana je pomoću ,,Amsler" hidrauličke prese kapaciteta 2000 kN, pri brzini pritiska od 0,4 MPa/s.

3 TEST PROCEDURE

After the concrete was casted in metal moulds, samples were left at ambient room temperature (20°±2^{0}C) with 90 – 95% RH. After 24 h the concrete samples were demoulded and soaked in the water at the same temperature (20°C) for the next six days. After seven days, four out of eight series of the concrete samples were exposed to freezing and thawing. Compressive strength was determined after 50 and 100 cycles (one cycle lasted for 4^h in environmental chamber at –20°±2^{0}C and 4^h soaked in water at 20°±2^{0}C). Afterwards, measured strength was compared with the strength of control group of specimens (continually cured in water at 20°±2^{0}C) at the equivalent age [28-29]. The compressive strength and bulk density of hardened concrete were tested according to the existing standards [30-31]. Compressive strength measurements were carried out using "Amsler" hydraulic press with a capacity of 2000 kN and 0.4 MPa/s loading rate.

4 EKSPERIMENTALNI REZULTATI

Eksperimentalno dobijeni rezultati jasno ukazuju na uticaj vodocementnog faktora na čvrstoću betona pri pritisku (Tabela 5). Uzorci betona s nižim vodocementnim faktorom pokazuju mnogo veću čvrstoću pri pritisku, koja je određena granulometrijskim sastavom agregata i

4 EXPERIMENTAL RESULTS

The obtained results clearly indicate the impact of *w/c* ratio on compressive strength of concrete (Table 5). Samples of concrete with lower *w/c* ratio have higher compressive strength which is determined by the aggregate grading and amount of cement in the mixture.

količinom cementa u betonskoj smeši. Dalje smanjivanje vodocementnog faktora dovodi do smanjenja čvrstoće pri pritisku, s obzirom na to što beton gubi konsistenciju. S druge strane, izloženost mrazu smanjuje čvrstoću betona pri pritisku, naročito pri visokim vrednostima vodocementnog faktora. Kada je reč o aditivu, dodatak superplastifikatora ne utiče negativno na pritisnu čvrstoću betona izloženog dejstvu mraza. Štaviše, uzorci betona sa supreplastifikatorom izloženi dejstvu mraza pokazuju povećanje pritisne čvrstoće već nakon 50 ciklusa, a sasvim jasno nakon 100 ciklusa zamrzavanja/otkravljivanja.

Further decrease of *w/c* ratio also decreases compressive strength due to the loss of workability. Moreover, exposure to freeze/thawing cycles decreases the concrete strength, especially at higher *w/c* ratios. When it comes to effect of additives, addition of SP does not influence compressive strength of the concrete exposed to freezing. On the contrary, concrete samples with SP exposed to freezing show increase in strength even after 50, and more clearly after 100 cycles.

*Tabela 5. Čvrstoća betona na pritisak – eksperimentalni rezultati**
*Table 5. Compressive strength of concrete – experimental results**

Uzorak Sample	VC W/C	SP (%)	starost (dani) t (days)	Z/O F/T	σ_p (MPa)	Uzorak Sample	VC W/C	SP (%)	starost (dani) t (days)	Z/O F/T	σ_p (MPa)
D1-1	0,45	2,0	32	100	50,30	D3-9	0,50	1,4	32	0	43,40
D1-2	0,45	2,0	32	100	51,00	D4-7	0,55	1,4	32	0	36,40
D1-3	0,45	2,0	32	100	49,00	D4-8	0,55	1,4	32	0	37,20
D2-1	0,40	2,0	32	100	51,00	D4-9	0,55	1,4	32	0	39,40
D2-2	0,40	2,0	32	100	55,00	D5-7	0,35	4,0	32	0	55,00
D2-3	0,40	2,0	32	100	50,20	D5-8	0,35	4,0	32	0	56,50
D3-1	0,50	1,4	32	100	43,90	D5-9	0,35	4,0	32	0	51,00
D3-2	0,50	1,4	32	100	44,00	D1-10	0,45	2,0	20	0	42,70
D3-3	0,50	1,4	32	100	39,80	D1-11	0,45	2,0	20	0	48,90
D4-1	0,55	1,4	32	100	40,00	D1-12	0,45	2,0	20	0	48,50
D4-2	0,55	1,4	32	100	43,00	D2-10	0,40	2,0	20	0	51,00
D4-3	0,55	1,4	32	100	37,20	D2-11	0,40	2,0	20	0	49,30
D5-1	0,35	4,0	32	100	59,00	D2-12	0,40	2,0	20	0	47,70
D5-2	0,35	4,0	32	100	59,00	D3-10	0,50	1,4	20	0	40,40
D5-3	0,35	4,0	32	100	59,00	D3-11	0,50	1,4	20	0	40,10
D1-4	0,45	2,0	20	50	49,00	D3-12	0,50	1,4	20	0	39,50
D1-5	0,45	2,0	20	50	48,20	D4-10	0,55	1,4	20	0	30,20
D1-6	0,45	2,0	20	50	47,60	D4-11	0,55	1,4	20	0	31,80
D2-4	0,40	2,0	20	50	50,00	D4-12	0,55	1,4	20	0	31,00
D2-5	0,40	2,0	20	50	47,20	D5-10	0,35	4,0	20	0	51,00
D2-6	0,40	2,0	20	50	50,70	D5-11	0,35	4,0	20	0	49,80
D3-4	0,50	1,4	20	50	30,90	D5-12	0,35	4,0	20	0	49,80
D3-5	0,50	1,4	20	50	35,20	D1-13	0,45	2,0	7	0	39,80
D3-6	0,50	1,4	20	50	38,80	D1-14	0,45	2,0	7	0	20,80
D4-4	0,55	1,4	20	50	32,00	D1-15	0,45	2,0	7	0	38,70
D4-5	0,55	1,4	20	50	32,60	D2-13	0,40	2,0	7	0	36,80
D4-6	0,55	1,4	20	50	31,50	D2-14	0,40	2,0	7	0	43,40
D5-4	0,35	4,0	20	50	51,20	D2-15	0,40	2,0	7	0	43,40
D5-5	0,35	4,0	20	50	53,60	D3-13	0,50	1,4	7	0	25,90
D5-6	0,35	4,0	20	50	49,90	D3-14	0,50	1,4	7	0	26,00
D1-7	0,45	2,0	32	0	51,20	D3-15	0,50	1,4	7	0	26,60
D1-8	0,45	2,0	32	0	44,50	D4-13	0,55	1,4	7	0	24,40
D1-9	0,45	2,0	32	0	48,80	D4-14	0,55	1,4	7	0	24,60
D2-7	0,40	2,0	32	0	50,20	D4-15	0,55	1,4	7	0	23,80
D2-8	0,40	2,0	32	0	50,20	D5-13	0,35	4,0	7	0	46,00
D2-9	0,40	2,0	32	0	36,20	D5-14	0,35	4,0	7	0	44,80
D3-7	0,50	1,4	32	0	44,00	D5-15	0,35	4,0	7	0	35,80
D3-8	0,50	1,4	32	0	43,80						

*V/C – vodocementni faktor, Z/O – broj ciklusa zamrzavanja/otkravljivanja, σ_p – čvrstoća pri pritisku betona.
**t* denotes the age of concrete, *F/T* – number of freeze/thaw cycles, σ_p – compressive strength of concrete.

5 PROCENA ČVRSTOĆE PRI PRITISKU BETONA

U drugoj fazi istraživanja, nakon eksperimentalnog dela, pristupilo se razvoju modela na bazi veštačkih neuronskih mreža, s četiri ulazna podatka i samo jednim izlaznim podatkom (Tabela 6). Sličan pristup je već korišćen u prethodnim istraživanjima [18, 21, 32–33].

5 ESTIMATION OF CONCRETE COMPRESSIVE STRENGTH

In the second phase of the research, after performing experimental tests, we turn to development of a neural network model, with four input parameters and a single output unit (Table 6). Similar approach was already used in [18, 21, 32-33].

Tabela 6. Raspon vrednosti ulaznih i izlaznih podataka za obučavanje neuronske mreže
Table 6. Input-output parameters for the ANN training and their range

Podaci Type of data	Parametar Parameter	Raspon vrednosti Range
Ulazni Inputs	vodocementni faktor (%) *w/c* ratio (%)	0.35–0.55
	starost (dani) age (days)	7–32
	količina superplastifikatora (%) amount of superplasticizer (%)	1.4–4
	broj ciklusa zamrzavanja/otkravljivanja number of freeze/thaw cycles	0–100
Izlazni Output	čvrstoća na pritisak (MPa) compressive strength (MPa)	21.4–55

Na osnovu predloga Rumelharta i dr. [34], Lipmana [35] i Sonmeza i dr. [36], analizirana je veštačka neuronska mreža sa samo jednim skrivenim slojem, dok je broj jedinica u skrivenom sloju određen korišćenjem heurističkih obrazaca [36]. Kao što se u Tabeli 7 može videti, na osnovu broja ulaznih i izlaznih podataka, broj jedinica u skrivenom sloju je u rasponu od 1 do 12. U ovom slučaju, pristupilo se ispitivanju veštačkih neuronskih mreža s jednom jedinicom, tri jedinice, te osam i dvanaest jedinica u skrivenom sloju, radi određivanja modela s najpreciznijom procenom čvrstoće pri pritisku betona.

Following the suggestion of Rumelhart et al. [34], Lippmann [35] and Sonmez et al. [36] one hidden layer was chosen in present study, while the number of hidden neurons was determined using heuristics [36]. As it is clear from Table 7, the number of neurons that may be used in the hidden layer varies between 1 and 12. In present study, the number of hidden neurons was selected as 1, 3, 8 and 12 separately to establish the most effective ANN architecture.

Tabela 7. Heuristički obrasci za određivanje broja jedinica u skrivenom sloju
*(**N_i**: broj ulaznih jedinica, **N_0**: broj izlaznih jedinica)*
Table 7. The heuristics used for the number of neurons in hidden layer
*(**N_i**: number of input neurons, **N_0**: number of output neurons)*

Heuristički obrazac Heuristic	Calculated number of neurons for this study
$\leq 2 \times N_i + 1$	≤9
$3 \times N_i$	12
$(N_i + N_0)/2$	2,5 (3)
$\dfrac{2 + N_0 \times N_i + 0.5 N_0 \times (N_0^2 + N_i) - 3}{N_i + N_0}$	1,1 (1)
$2N_i/3$	2,7 (3)
$\sqrt{(N_i + N_0)}$	2,2 (2)
$2N_i$	8

U svim ispitvanim slučajevima, razmatrani skup podataka podeljen je na sledeći način: 60% za treniranje (45 podataka), 15% za validaciju (11 podataka) i 25% za testiranje (19 podataka), što odgovara predlogu Lunija [37] od 25% podataka za testiranje, kao i preporukama Nelsona i Ilingvorta [38] od 20–30% podataka za testiranje.

Treniranje neuronskih mreža izvedeno je za različiti broj jedinica u skrivenom sloju, kako je već i prethodno definisano u Tabeli 7. Imajući u vidu da se kao aktivaciona funkcija koristi sigmoidna funkcija, koja daje izlazne vrednosti u intervalu od 0 do 1, a s obzirom na to što ulazni i izlazni podaci imaju različite merne jedinice prema SI sistemu, neophodno je najpre izvršiti skaliranje podataka koristeći sledeću relaciju:

In all the examined cases, the total data set has been divided as following: 60% for training (45 recordings), 15% for validation (11 recordings) and 25% for testing (19 recordings), which corresponds well with the suggestion of Looney [37], who proposed 25% for testing, and with recommendation made by Nelson and Illingworth [38] who supported the idea of 20-30% of data for testing.

The possible ANN architectures were trained by using combinations of the number of hidden neurons defined above. Concerning the fact that we use sigmoid function as an activation function, which gives the output values in the range [0,1], and since the input and output data have different units according to IS system, scaling the input and output parameters was necessary, and it was performed in the following way:

$$\text{skalirana vrednost} = \frac{\text{maksimalna vrednost - neskalirana vrednost}}{\text{maksimalna vrednost - minimalna vrednost}}$$

$$\text{scaled value} = \frac{\text{max.value} - \text{unscaled value}}{\text{max.value} - \text{min.value}} \tag{1}$$

Na ovaj način, sve posmatrane vrednosti normalizovane su u intervalu [0,1].

Da bismo odredili neuronsku mrežu s najpouzdanijom procenom čvrstoće pri pritisku betona na osnovu izmerenih vrednosti, koristili smo neuronsku mrežu s prostiranjem signala unapred i s propagacijom greške unazad. Obučavanje neuronskih mreža izvedeno je korišćenjem Levenberg-Markart algoritma obučavanja, kao najbrže metode za treniranje neuronskih mreža srednje veličine [39], što predstavlja prvi izbor kada je u pitanju nadgledano učenje, kao u ovoj analizi. Prethodno je već pomenuto da se kao aktivaciona funkcija koristi sigmoidna funkcija, što je vrlo čest izbor u prethodnim istraživanjima [36].

Razvijena su četiri različita modela neuronskih mreža, s jednom jedinicom, tri jedinice, te osam i dvanaest jedinica u skrivenom sloju, radi određivanja neuronske mreže s najpouzdanijom procenom čvrstoće, i s najboljim poklapanjem u odnosu na eksperimentalno dobijene rezultate. Da bi neuronska mreža dala pouzdane rezultate, najpre je potrebno isključiti mogućnost ,,pretreniranja", odnosno prividnog povećanja tačnosti procene neuronskih mreža, kada se greška pri treniranju mreže smanjuje, a istovremeno povećava pri validaciji i testiranju. U ovom slučaju, kao što se može videti sa slike 1, srednja kvadratna greška (MSE) teži konstantnoj vrednosti s povećanjem broja iteracija za cikluse treniranja, validacije i testiranja za sve ispitivane modele neuronskih mreža, čime se isključuje mogućnost ,,pretreniranja".

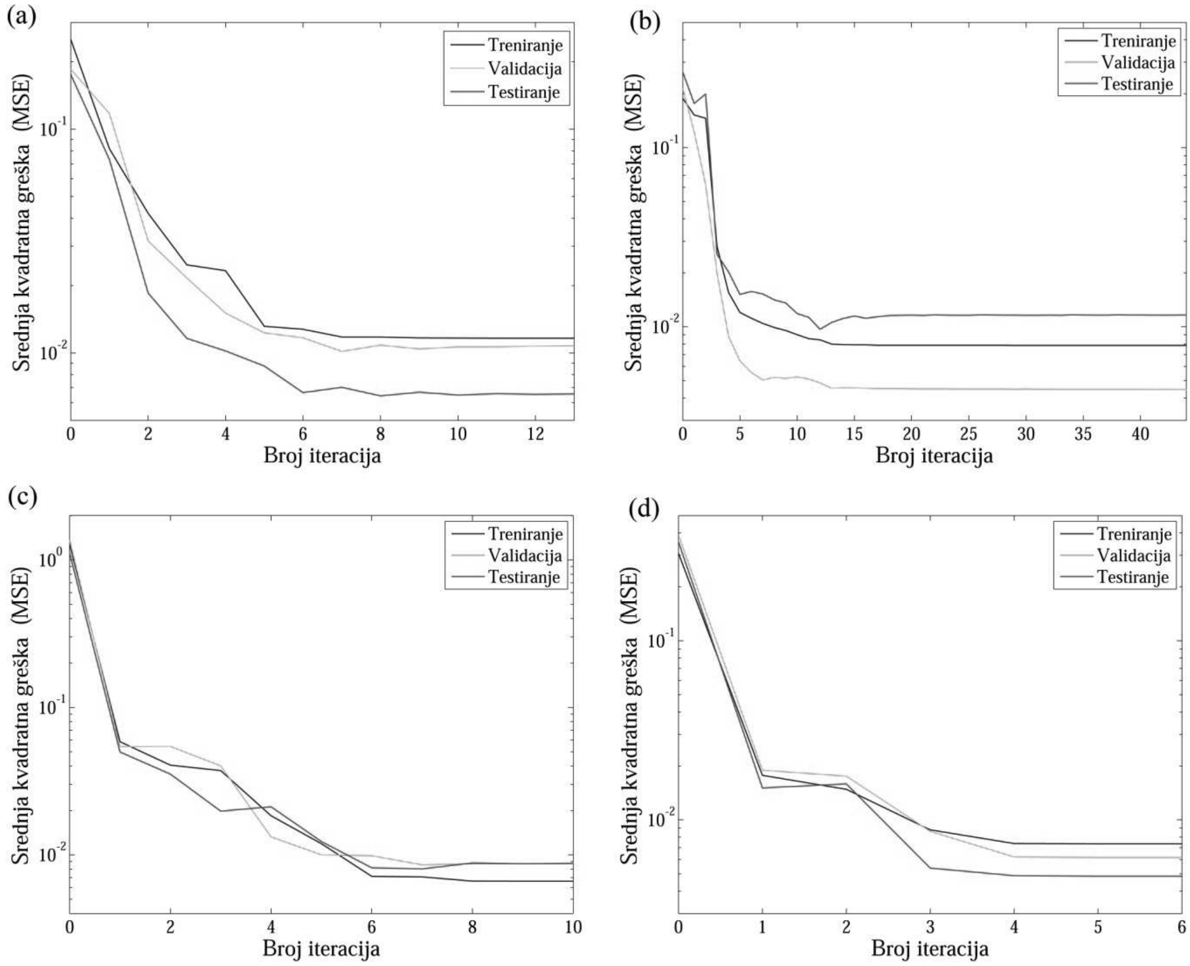
Vrednovanje preciznosti procene pritisne čvrstoće pomoću neuronskih mreža s različitim brojem jedinica u skrivenom sloju, dato je na slici 2. Na osnovu vrednosti koeficijenta korelacije (*R*≈0,97) i srednje kvadratne greške (0,005–0,007), očevidno je da veštačka neuronska mreža sa 12 jedinica u skrivenom sloju daje najpreciznije rezultate u poređenju sa eksperimentalno dobijenim vrednostima čvrstoće pri pritisku betona.

In that way, numerical values of the analyzed parameter were normalized in the range of [0,1].

In this paper, in order to create an adequate ANN model for estimation of concrete compressive strength, based on the recorded data, a three-layer back propagation artificial neural network is chosen using Levenberg-Marquardt learning algorithms. This training algorithm is commonly considered as the fastest method for training moderate-sized feed-forward neural networks [39], and it is the first choice for solving the problems of supervised learning, which is the case in present analysis. A sigmoid function was chosen for the activation function, as the most common transfer function implemented in the literature [36].

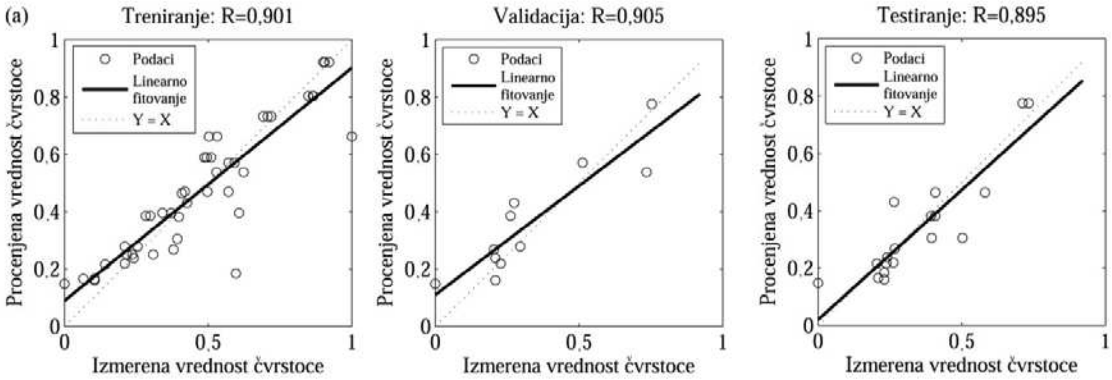
Four different ANN models with 1, 3, 8 and 12 hidden neurons in a hidden layer were developed, in order to create a model with most accurate response, i.e. a response which is most comparable with experimental results. In order to obtain reliable results, we firstly need to exclude the possibility of overfitting, when the ANN model only seemingly learn the data, which is implied by the decrease of training error and the increase of validation and testing error. In present study, as it can be seen from Figure 1, mean squared error (MSE) saturates with the increase of number of epochs for training and validation data, for all four examined cases with different number of hidden neurons, excluding in that way the possibility of overfitting.

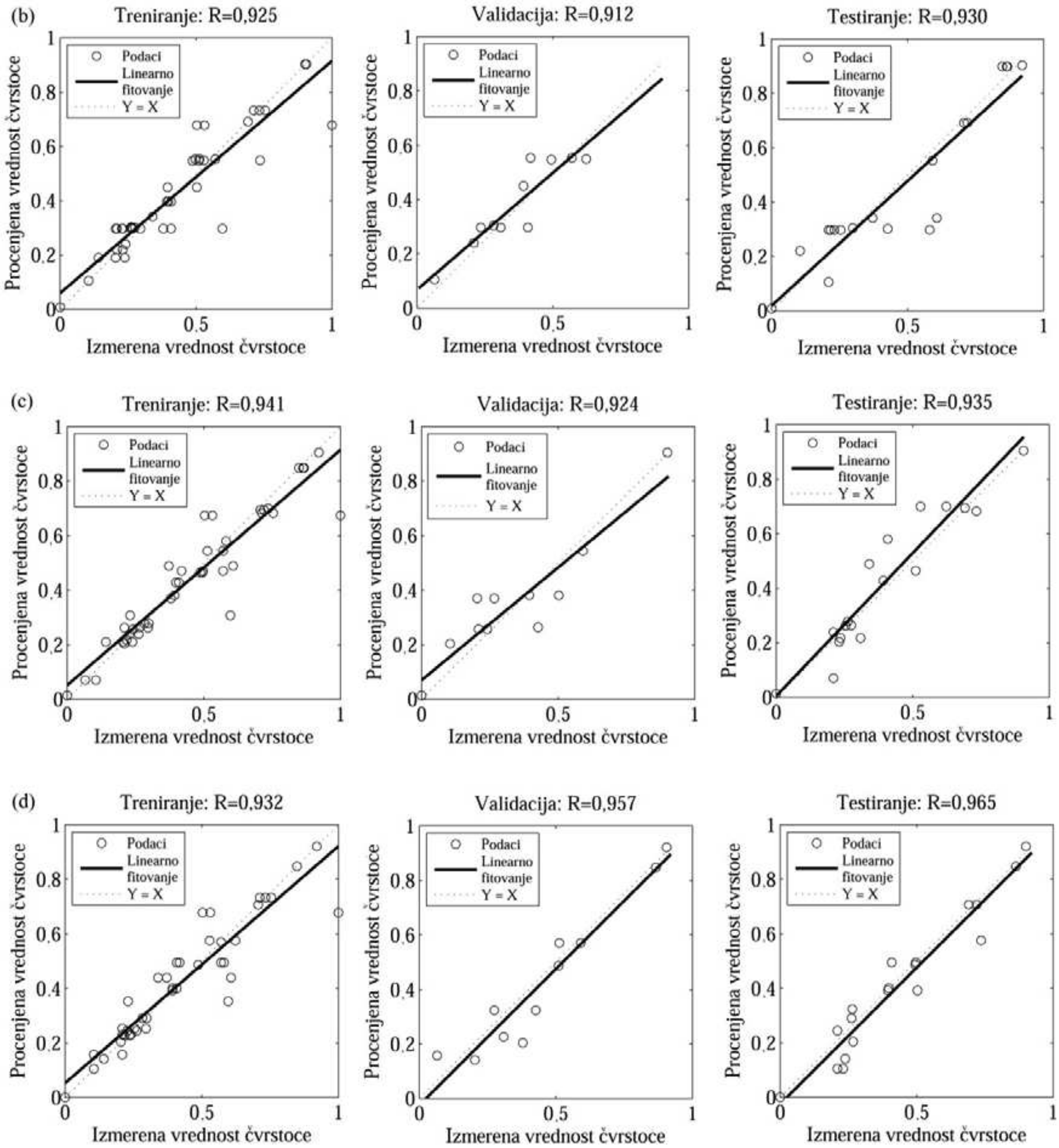
Estimation of the resulting neural network models with scaled values for training, validation and testing set are shown in Figure 2 for different number of hidden nodes. It is clear that the ANN model with twelve hidden nodes has the highest coefficient of correlation (*R*≈0.97) for testing set, approximately the same value of *R* for training and validation set and with statistically small value of MSE (0.005-0.007), indicating good performance of the proposed network.



Slika 1. Srednja kvadratna greška u funkciji broja iteracija za treniranje, validaciju i testiranje, za različiti broj jedinica u skrivenom sloju: (a) 1, (b) 3, (c) 8 i (d) 12

Figure 1. MSE versus the number of epochs for training, validation and testing data, with different number of hidden neurons: (a) 1, (b) 3, (c) 8 and (d) 12.





Slika 2. Poređenje skaliranih procenjenih i izmerenih vrednosti čvrstoće pri pritisku betona za podatke iz ciklusa treniranja, validacije i testiranja, korišćenjem neuronske mreže s različitim brojem jedinica u skrivenom sloju: (a) 1, (b) 3, (c) 8 i (d) 12

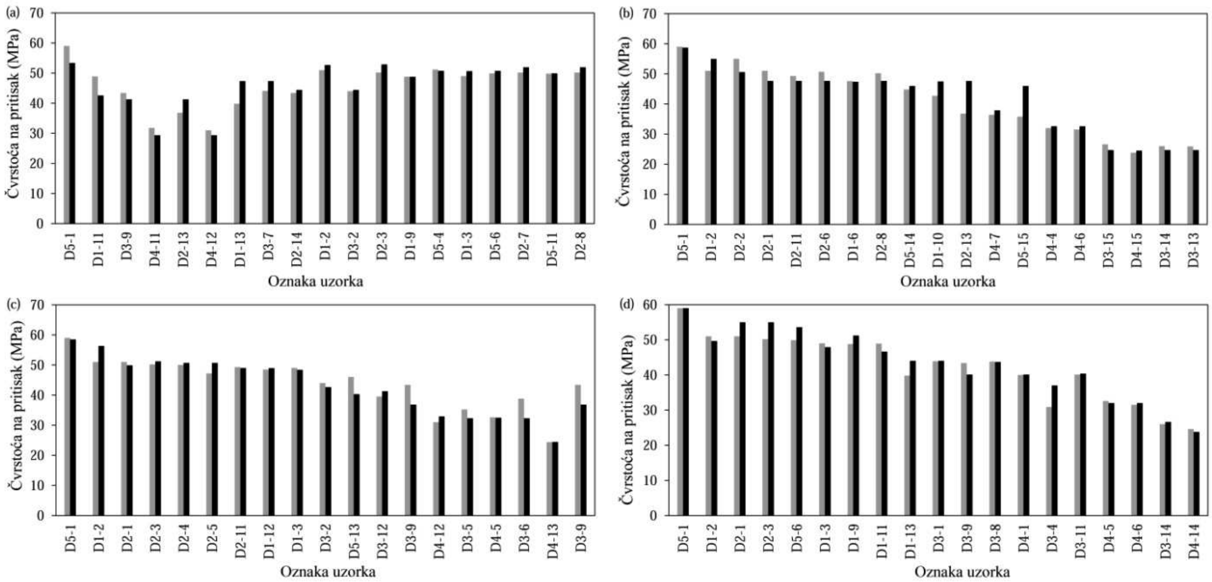
Figure 2. Comparison of the scaled estimated and measured values of concrete compressive strength showing training, validation and testing set, for the following number of hidden nodes: (a) one, (b) three, (c) eight and (d) twelve

6 OCENA USPEŠNOSTI MODELA

Ocena preciznosti predloženih modela veštačkih neuronskih mreža s različitim brojem jedinica u skrivenom sloju može dalje biti izvedena na osnovu poređenja njihovih neskaliranih vrednosti (iz ciklusa testiranja) sa eksperimentalnim rezultatima (slika 3). Jasno je da se u svim ispitivanim slučajevima veštačkim neuronskim mrežama daje pouzdana procena čvrstoće pri pritisku betona. Neophodno je naglasiti da se na slici 3 različiti uzorci koriste za testiranje u svakom od ispitivanih slučajeva s različitim brojem skrivenih jedinica, zbog nasumično odabranih početnih uslova.

6 EVALUATION OF MODEL PERFORMANCE

On the basis of the proposed ANN model with different number of hidden nodes, their precision of estimation could be further evaluated by comparing the unscaled predicted values (testing data) with experimental results (Figure 3). It is clear that in most of the examined cases, ANN gives reasonable value of concrete compressive strength. One should note that different samples are used for testing in each of the examined cases with different number of hidden nodes, due to random initial conditions.



Slika 3. Poređenje neskaliranih procenjenih i izmerenih vrednosti čvrstoće na pritisak uzoraka betona, korišćenjem neuronske mreže s različitim brojem jedinica u skrivenom sloju: (a) 1; (b) 3; (c) 8 i (d) 12. Sivim su označene izmerene vrednosti, a crnim procenjene vrednosti čvrstoće na pritisak betona. Različiti uzorci koriste se za testiranje u svakom od ispitivanih slučajeva s različitim brojem skrivenih jedinica, zbog nasumično odabranih početnih uslova

Figure 3. Comparison of measured and estimated compressive strength of concrete specimens by using ANN models with different number of hidden neurons: (a) 1; (b) 3; (c) 8 and (d) 12. Grey bars stand for the measured values; black bars denote estimated values of compressive strength. Different samples are used for testing in each of the examined cases with different number of hidden nodes, due to random initial conditions

Preciznost razvijenih modela s različitim brojem skrivenih jedinica može se dalje oceniti izračunavanjem vrednosti različitih standardnih statističkih grešaka, datih u Tabeli 8 [40].

Performances of the developed models with different number of hidden nodes could be further evaluated using different standard statistical error criteria given in Table 8 [40].

*Tabela 8. Pregled statističkih grešaka korišćenih za ocenu uspešnosti predloženog modela**
*Table 8. Preview of statistical error parameters used for models' evaluation**

Statistička greška Statistical parameter	Jednačina Equation
Srednja apsolutna greška (MAPE) Mean Absolute Percentage Error (MAPE)	$MAPE = \frac{1}{n} \times \left[\sum_{i=1}^{n} \left| \frac{t_i - x_i}{t_i} \right| \right] \times 100$
Varijansa relativne vrednosti apsolutne greške (VARE) Variance Accounted For (VAF)	$VARE = \frac{1}{n} \times \left[\sum_{i=1}^{n} \left(\left| \frac{t_i - x_i}{t_i} \right| - mean \left| \frac{t_i - x_i}{t_i} \right|^2 \right) \right] \times 100$
Medijana (MEDAE) MEDian Absolute Error (MEDAE)	$MEDAE = median\left(t_i - x_i\right)$
Sračunata varijansa (VAF) Variance Absolute Relative Error (VARE)	$VAF = \left[1 - \frac{\mathrm{var}\left(t_i - x_i\right)}{\mathrm{var}(t_i)} \right] \times 100$

*t_i predstavlja izmerenu vrednost čvrstoće pri pritisku, a x_i predstavlja procenjenu vrednost čvrstoće pri pritisku.
*t_i represents measured value of compressive strength, while x_i denotes predicted value of compressive strength.

Izračunate statističke greške za veštačke neuronske mreže s različitim brojem jedinica u skrivenom sloju date su u Tabeli 9. Jasno je da veštačka neuronska mreža sa dvanaest jedinica u skrivenom sloju daje najmanje vrednosti srednje apsolutne greške (MAPE), varijanse relativne vrednosti apsolutne greške (VARE) i medijane (MEDAE), a najveću vrednost sračunate varijanse (VAF) u odnosu na neuronske mreže s jednom jedinicom, tri jedinice i osam jednica u skrivenom sloju.

Calculated values of statistical errors for neural networks with different number of hidden nodes are given in Table 9. It is clear that ANN model with twelve hidden nodes has the lowest values of MAPE (Mean Absolute Percentage Error), VARE (Variance Absolute Relative Error) and MEDAE (MEDian Absolute Error), and the highest value of VAF (Variance Accounted For), in comparison to the ANN models with one, three or eight hidden nodes.

Tabela 9. Statističke greške u proceni čvrstoće pri pritisku uzoraka betona korišćenjem neuronske mreže s različitim brojem jedinica u skrivenom sloju
Table 9. Statistical errors of the ANN models with different number of hidden nodes for estimation of concrete compressive strength

Veštačka neuronska mreža ANN model	Statističke greške Statistical errors			
Broj jedinica u skrivenom sloju No. of hidden nodes	MAPE	VARE	MEDAE	VAF
1	5,47	5,44	1,74	90,77
3	7,31	7,25	1,65	81,81
8	5,74	5,71	1,35	88,21
12	4,61	4,59	1,10	92,80

7 ZAKLJUČAK

U radu je predloženo nekoliko modela veštačkih neuronskih mreža za procenu čvrstoće pri pritisku betona, korišćenjem rezultata opita na 75 uzoraka s različitim vodocementnim faktorom i količinom superplastifikatora. Uzorci betona izlagani su različitom broju ciklusa zamrzavanja i otkravljivanja, a njihova čvrstoća na pritisak određivana je nakon 7, 20 i 32 dana. Eksperimentalni rezultati ukazuju na to da sa smanjenjem vodocementnog faktora, čvrstoća pri pritisku betona raste do vrednosti koja je određena granulometrijskim sastavom agregata i količinom cementa u betonskoj smeši. Dalje smanjenje vodocementnog faktora dovodi do smanjenja pritisne čvrstoće, s obzirom na to što betonska smeša gubi konsistenciju. S druge strane, smenjivanje ciklusa zamrzavanja i otkravljivanja takođe smanjuje čvrstoću pri pritisku, naročito pri visokim vrednostima vodocementnog faktora. Uzorci betona sa superplastifikatorom izloženi zamrzavanju pokazuju povećanje čvrstoće pri pritisku čak nakon 50 i 100 ciklusa zamrzavanja/otkravljivanja.

Na bazi ovako dobijenih eksperimentalnih rezultata, predloženo je nekoliko modela veštačkih neuronskih mreža, s različitim brojem jedinica u skrivenom sloju, određenih na osnovu broja ulaznih i izlaznih jedinica. U svim modelima primenjena je veštačka neuronska mreža s prostiranjem signala unapred i s propagacijom greške unazad, korišćenjem Levenberg-Markart algoritma obučavanja. Rezultati izvedenog istraživanja pokazali su da neuronska mreža sa 12 jedinica u skrivenom sloju daje najprecizniju procenu pritisne čvrstoće betona, s najmanjom vrednošću statističkih grešaka MAPE, VARE i MEDAE, i najvećom vrednošću sračunate varijanse (VAF).

7 CONCLUSIONS

In present paper, the ANN model for estimation of concrete compressive strength is proposed using the experimental results on 75 specimens with different *w/c* ratio and different amount of superplasticizer. The concrete samples were exposed to different number of freeze/thaw cycles, while their compressive strength was determined at different age (7, 20 and 32 days). Experimental results indicate that by decreasing the *w/c* ratio, the compressive strength increases up to some level, which is determined by the aggregate grading and amount of cement in the mixture. Further decrease of *w/c* ratio also decreases compressive strength because the concrete mixture is losing workability. On the other hand, freezing and thawing cycles also decreases the concrete strength, especially at higher *w/c* ratios. Concrete samples with SP exposed to freezing show increase in strength even after 50, and more clearly after 100 cycles.

On the basis of the obtained experimental results, several ANN models were developed, using different number of hidden nodes, which were determined according to the number of input and output nodes. In all the examined cases, a three layer feed-forward back-propagation network with Levenberg-Marquardt learning algorithm was used. The performed research showed that the ANN model with twelve hidden nodes provides the most accurate estimation of concrete compressive strength, comparable to the experimental results. Further analysis indicated that neural network with 12 hidden nodes has the lowest values of MAPE, VARE and MEDAE, and the highest value of VAF, confirming this model as the most precise one for estimation of concrete compressive strength.

Međutim, uprkos visokoj preciznosti predložene veštačke neuronske mreže, jedno od glavnih ograničenja ove analize predstavlja relativno jednostavan sastav ispitivanih betonskih smeša. Svakako bi važno bilo da se, u okviru budućih analiza, u obzir uzmu i uzorci betona s različitim savremenim aditivima (leteći pepeo,zeolit, topioničarska zgura i dr.), što bi dovelo do poboljšanja predloženog modela neuronske mreže i njegove veće primenljivosti u svakodnevnoj praksi. Sa stanovišta konstrukcije veštačke neuronske mreže, detaljnija analiza pouzdanosti modela s različitim algoritmima učenja i propagacije greške sigurno bi doprinela boljem razumevanju mogućnosti primene ovih metoda za procenu čvrstoće betona pri pritisku.

However, despite the high predictive power of the proposed ANN models, one of the main limitations of the analysis is certainly simple composition of the concrete specimens. What could be interesting in future analyzes are certainly concrete samples with different additives (plasticizer, fly ash, furnace slag, etc.), which would further improve the proposed ANN model and make it more usable in daily practice. Moreover, it would be interesting to examine the estimation accuracy of the ANN models with different learning algorithms, which may further upgrade the presented approach, with better understanding of the possible use of these methods for estimation of concrete compressive strength.

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REZIME

PROCENA ČVRSTOĆE BETONA PRI PRITISKU, KORIŠĆENJEM VEŠTAČKIH NEURONSKIH MREŽA

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U radu se daje procena čvrstoće betona pri pritisku, primenom veštačkih neuronskih mreža s prostiranjem signala unapred i propagacijom greške unazad. Obučavanje mreže sprovodi se korišćenjem Levenberg-Markart algoritma obučavanja za četiri različite arhitekture neuronskih mreža, s jednom jedinicom, tri jedinice, te osam i dvanaest jedinica u skrivenom sloju, radi odbacivanja efekta ,,pretreniranja". Treniranje, validacija i testiranje neuronskih mreža izvodi se na osnovu rezultata eksperimentalnog ispitivanja čvrstoće pri pritisku na 75 uzoraka betona, s različitim vodocementnim faktorom i količinom superplastifikatora tipa melamina. Ispitivani uzorci betona izlagani su različitim ciklusima zamrzavanja/otkravljivanja, a njihova čvrstoća pri pritisku određivana je nakon 7, 20 i 32 dana. Dobijeni rezultati ukazuju na to da neuronska mreža s dvanaest jedinica u skrivenom sloju daje ocenu čvrstoće zadovoljavajuće tačnosti u poređenju sa eksperimentalno dobijenim podacima (R≈0,97, MSE=0,005). Rezultati izvedene analize dodatno su potvrđeni sračunavanjem vrednosti standardnih statističkih grešaka: najmanjom vrednošću srednje apsolutne greške (MAPE), varijanse relativne vrednosti apsolutne greške (VARE) i medijane (MEDAE), kao i najvećom vrednošću sračunate varijanse (VAF) za izabranu arhitekturu neuronske mreže.

Ključne reči: čvrstoća betona, vodocementni faktor, superplastifikator, zamrzavanje/otkravljivanje, starost, veštačka neuronska mreža

SUMMARY

ESTIMATION OF CONCRETE COMPRESSIVE STRENGTH USING ARTIFICIAL NEURAL NETWORK

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In present paper, concrete compressive strength is evaluated using back propagation feed-forward artificial neural network. Training of neural network is performed using Levenberg-Marquardt learning algorithm for four architectures of artificial neural networks, one, three, eight and twelve nodes in a hidden layer in order to avoid the occurrence of overfitting. Training, validation and testing of neural network is conducted for 75 concrete samples with distinct *w/c* ratio and amount of superplasticizer of melamine type. These specimens were exposed to different number of freeze/thaw cycles and their compressive strength was determined after 7, 20 and 32 days. The obtained results indicate that neural network with one hidden layer and twelve hidden nodes gives reasonable prediction accuracy in comparison to experimental results (R=0.965, MSE=0.005). These results of the performed analysis are further confirmed by calculating the standard statistical errors: the chosen architecture of neural network shows the smallest value of mean absolute percentage error (MAPE=, variance absolute relative error (VARE) and median absolute error (MEDAE), and the highest value of variance accounted for (VAF).

Keywords: concrete strength, *w/c* ratio, superplasticizer, freezing/thawing, age, artificial neural network