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Preliminary communication

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Abstract
There are a number of methods forestimating physical and mechanical characteristics. Principally, the most widely used method is regression, but recently, more sophisticated methods such as neural networks have frequently been applied as well. This paper presents the models of a simple and a multiple regression and neural networks – types Radial Basis Function and Multiple Layer Perceptron, which can be used for the estimate of the Brazilian indirect tensile strength in saturated conditions. The paper includes the issues of collecting data for the analysis and modelling and an overview of the performed analysis with an efficacy assessment of the estimate for each model. After the assessment, the model which provided the best estimate was selected, including the model which could have the most wide-spread application in the engineering practice.

Keywords: estimate, Brazilian indirect tensile strength, saturation, limestone, rock mechanics.

1. Introduction

Although Martin (**1966**) wrote about the impact of humidity on the tensile strength of various rocks, for a long time such issues remained of minor interest to the scientists dealing with uniaxial compressive strength. In the referenced literature on the impact of the saturation on the indirect tensile strength of rocks determined by the Brazilian test (**Briševac et al., 2015**) the important papers are those by **Dube and Singh** (**1972**) which present the impact of the humid climate on sandstone, and the paper by **Vutukuri** (**1974**) who investigated the impact of saturation on limestone with various liquids. **Ojo and Brook** (**1990**) claimed in their paper that saturation reduces the tensile strength more than the uniaxial compressive strength. Recently, there have been a number of papers dealing with the impact of saturation on natural materials, such as gneiss, marble and sandstone (**You et al., 2011**), including the impact of saturation on artificial gypsum (**Wong and Jong, 2013**). All the papers show that saturation reduces the tensile strength. The need to estimate the Brazilian indirect tensile strength in saturated conditions (σ_{BTsat}) may arise upon the preparation of the underground works in the presence of underground waters. Only a few papers deal with the estimate of the indirect tensile strength of limestone, without considering the saturation. These are the paper by the Iranian scientists on simple regression (**Arjmandpour and Hosseinitoudeshki, 2013**) and the paper by the Turkish scientists (**Baykasoglu et al., 2008**), who created the advanced model of estimating tensile strength of limestone via genetic programming. The authors of these papers have reviewed the available literature from the relevant sources and have not found any papers dealing with the estimate of σ_{BTsat} of limestone by means of neural networks on two input parameters. Accordingly, the scientific interest for the creation and application of such a model is understandable.

2. Methodology of model creation and data collection

The most frequently applied method of estimation in rock mechanics is the classical statistical regression presented in the Expression (**1**). Simple Regression (SR) refers to the case when only one independent variable is used, whereas the Multiple Regression (MR) refers to the case when more independent variables are used.

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$$y = \varepsilon + \int(x_1, x_2, x_3 ..., x_k) \quad (1)$$

Where:
y – dependent variable
ε – mean-zero random error term
$x_1, ..., x_k$ - independent variables.

The structure of the artificial neural network is based on the model of the artificial neuron. Such a neuron consists of several inputs and one output. Each input is assigned by the corresponding weight which burdens the input value. Depending on the result, the neuron will remain inactive or it will be activated. The values and conditions of the activation depend on the so-called activation function. Accordingly, the artificial neural network consists of the layers of artificial neurons which are connected in the network. Each neural network has an input layer and an output layer, including one or more hidden layers between them. Principally, the input layer sends a signal from the environment, the hidden layers process the received signal and the output layer collects the results and creates the input (e.g. **Malvić et al. 2008, Malvić and Cvetković, 2009, 2013**). In Croatia, neural networks are used in petroleum geology as interpretation tools (**Malvić et al., 2011**), in petroleum reservoir lithology and saturation prediction (**Cvetković et al., 2009**), to estimate the clastic facies (**Malvić, 2006**) and porosity (**Malvić and Prskalo, 2009**) inoil fields and also in estimating the uniaxial compressive strength and modulus of elasticity of carbonate rocks (**Briševac, 2012**).
This paper required the modelling by means of the software package Statistica 12, which offers the possibility of creating the regression models and the models of artificial neural networks. This software provides the creation of two types of networks: MLP (Multiple Layer Perceptron) and RBF (Radial Basis Function). Although there are differences in the architecture of these two types of neural networks, they can be applied in the same situations but with varying success. Accordingly, it was interesting to apply them for the estimate of the Brazilian indirect tensile strength and to make a comparison of them. The created models are usually evaluated by a number of coefficients, such as the correlation coefficient (R), the coefficient of determination (R^2), the adjusted R-squared (R^2_{Adj}) and the root mean square error (RMSE) which is calculated according to the formula (**2**). The models are more rigorously valuated by the R^2_{Adj} and RMSE.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(P_i - O_i)}{n}} \quad (2)$$

Where:
P_i – predicted values
O_i – observed values
n – total number of data.

The creation of the model required the collection of a large number of research results. The first 45 data (see **Table 1**) were collected from the published literature, i.e. the paper by **Vásárhelyi**, (**2005**) which contains the research results ofporosity (n), the Brazilian indirect tensile strength in saturated (σ_{BTsat}) and dry conditions (σ_{BTdry}) of the Miocene limestone. The other data (see **Table 1**) is based on the research works performed at the Geo-mechanical Laboratory of the Faculty of Mining, Geology and Petroleum Engineering in Zagreb, which comprised the limestone from the Quarry of Podberam near Pazin (**Čajić, 2015**). In both studies, they were used as the source of data performed to determine the indirect tensile strength according to the **ISRM** (**1978**) suggested method. The input data for modelling make up the total of 55 research results n, σ_{BTsat} and σ_{BTdry} (see **Table 1**).

Table 1: Input data of modelling

No	n	σ_{BTdry}	σ_{BTsat}	References
1	36.4	1.1	0.86	Vásárhelyi, (2005)
2	24.8	2.83	2.62	Vásárhelyi, (2005)
3	38.6	0.75	0.34	Vásárhelyi, (2005)

n - porosity in %; σ_{BTdry} - Brazilian indirect tensile strength in dry conditions in MPa; σ_{BTsat} - Brazilian indirect tensile strength in saturated conditions in MPa

Table 1: Input data of modelling (continuation)

No	n	σ_{BTdry}	σ_{BTsat}	References
4	44.1	0.56	0.25	Vásárhelyi, (2005)
5	36.1	0.14	0.23	Vásárhelyi, (2005)
6	48.7	0.07	0.09	Vásárhelyi, (2005)
7	40.3	0.13	0.1	Vásárhelyi, (2005)
8	45.5	0.09	0.06	Vásárhelyi, (2005)
9	11.4	4.16	3.99	Vásárhelyi, (2005)
10	28	1.98	1.37	Vásárhelyi, (2005)
11	41.1	0.81	0.31	Vásárhelyi, (2005)
12	15.8	3.92	2.23	Vásárhelyi, (2005)
13	38.9	1.64	0.38	Vásárhelyi, (2005)
14	42.6	0.98	0.66	Vásárhelyi, (2005)
15	52.2	0.59	0.62	Vásárhelyi, (2005)
16	30.4	2.37	1.43	Vásárhelyi, (2005)
17	24	3.16	1.23	Vásárhelyi, (2005)
18	25.5	2.92	1.71	Vásárhelyi, (2005)
19	46.4	0.41	0.23	Vásárhelyi, (2005)
20	35.4	0.49	0.18	Vásárhelyi, (2005)
21	44.9	0.35	0.08	Vásárhelyi, (2005)
22	41	0.93	0.78	Vásárhelyi, (2005)
23	37.4	0.8	0.39	Vásárhelyi, (2005)
24	43.9	0.6	0.37	Vásárhelyi, (2005)
25	46.5	0.39	0.34	Vásárhelyi, (2005)
26	31.2	1.92	0.96	Vásárhelyi, (2005)
27	41.6	0.99	0.69	Vásárhelyi, (2005)
28	27.5	2.81	1.91	Vásárhelyi, (2005)
29	28.2	2.45	1.24	Vásárhelyi, (2005)
30	38.4	0.78	0.51	Vásárhelyi, (2005)
31	38.2	0.97	0.62	Vásárhelyi, (2005)
32	37.6	0.82	0.5	Vásárhelyi, (2005)
33	33.7	1.09	0.54	Vásárhelyi, (2005)
34	33.1	0.84	0.84	Vásárhelyi, (2005)
35	35.6	0.89	0.38	Vásárhelyi, (2005)
36	33.8	0.56	0.28	Vásárhelyi, (2005)
37	34	1.13	0.55	Vásárhelyi, (2005)
38	26.1	2.48	2.27	Vásárhelyi, (2005)
39	36.8	1.32	0.86	Vásárhelyi, (2005)
40	42.8	0.8	0.58	Vásárhelyi, (2005)
41	41	0.83	0.52	Vásárhelyi, (2005)

n - porosity in %; σ_{BTdry} - Brazilian indirect tensile strength in dry conditions in MPa; σ_{BTsat} - Brazilian indirect tensile strength in saturated conditions in MPa

Table 1: Input data of modelling (continuation)

No	n	σ_{BTdry}	σ_{BTsat}	References
42	41.6	1.03	0.72	Vásárhelyi, (2005)
43	38.3	0.96	0.63	Vásárhelyi, (2005)
44	42.3	0.68	0.31	Vásárhelyi, (2005)
45	41.8	0.67	0.4	Vásárhelyi, (2005)
46	0.5	3.579	3.219	Čajić, (2015)
47	0.49	4.011	3.412	Čajić, (2015)
48	0.46	4.45	3.946	Čajić, (2015)
49	0.45	4.46	4.474	Čajić, (2015)
50	0.43	4.539	4.607	Čajić, (2015)
51	0.35	5.04	4.734	Čajić, (2015)
52	0.34	5.161	5.303	Čajić, (2015)
53	0.32	6.592	5.305	Čajić, (2015)
54	0.25	6.612	5.948	Čajić, (2015)
55	0.23	7.381	6.233	Čajić, (2015)
x_{min}	0.23	0.07	0.06	
x_{max}	52.2	7.381	6.233	
x_{mean}	29.95	1.96	1.52	
s	15.95	1.86	1.73	

n - porosity in %; σ_{BTdry} - Brazilian indirect tensile strength in dry conditions in MPa; σ_{BTsat} - Brazilian indirect tensile strength in saturated conditions in MPa; x_{min} - minimum value; x_{max} - maximum value; x_{mean} - arithmetic mean of data; *s* - sample standard deviation

3. Results

Based on the collected data, five models for the estimate of the Brazilian indirect tensile strength in saturated conditions were made. The first model is marked SR_1 and is based on the simple regression with porosity (see **Fig.1**). Such a model is defined by the equation (**3**). The evaluation of the model SR_1 is presented in**Table 2**.

$$\sigma_{BTsat} = 4.5665 - 0.1019 \cdot n \tag{3}$$

Where:
σ_{BTsat} – Brazilian indirect tensile strength in saturated conditions (MPa),
n – porosity (%)

Table 2: Evaluation of simple regression models SR_1 and SR_2

	Model SR_1	Model SR_2
R	0.939863	0.971707
R^2	0.883342	0.944215
R^2_{Adj}	0.881141	0.943162
RMSE	0.585059	0.404578

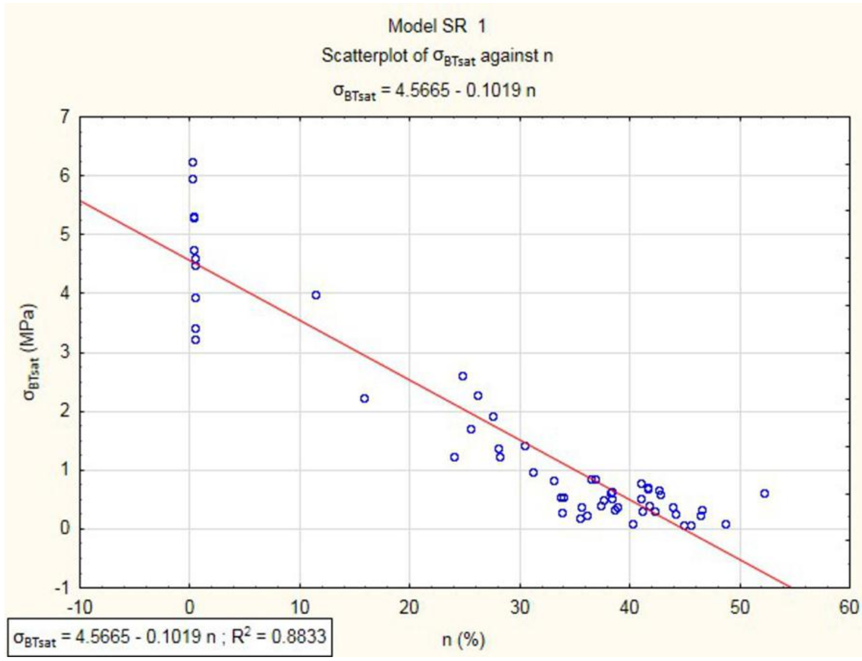

Figure 1: Simple regression with porosity

The second model was made by the simple regression with Brazilian indirect tensile strength in dry conditions and is marked SR_2. It is defined by the equation (**4**). The evaluation of the model SR_2 is presented in **Table 2**.

$$\sigma_{BTsat} = -0.2623 + 0.9051 \cdot \sigma_{BTdry} \tag{4}$$

Where:
σ_{BTsat} – Brazilian indirect tensile strength in saturated conditions (MPa),
σ_{BTdry} – Brazilian indirect tensile strength in dry conditions (MPa).

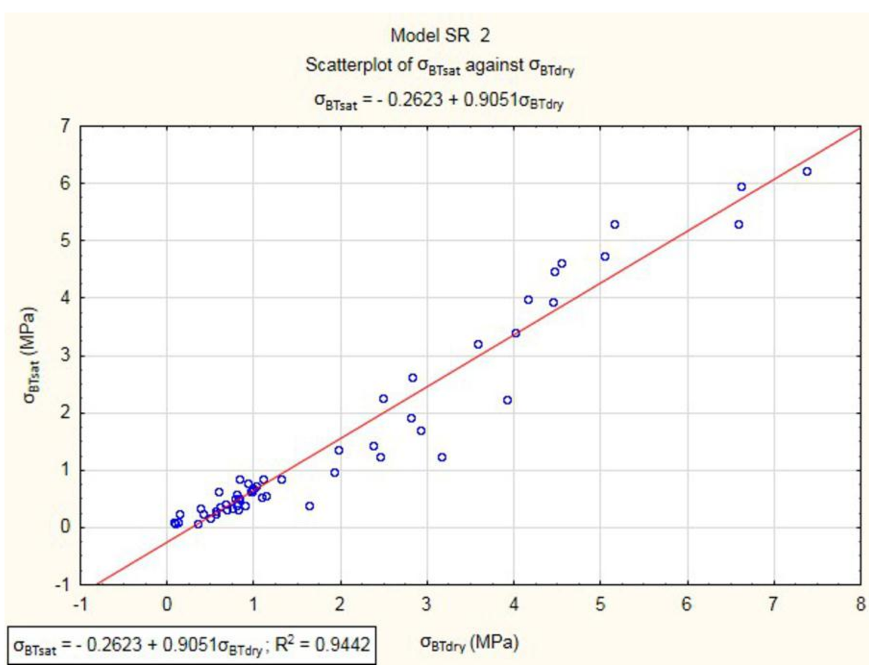

Figure 2: Simple regression with Brazilian indirect tensile strength in dry conditions

The multiple regression model MR consists of independent variables n and σ_{BTdry}, whereas a dependent variable σ_{BTsat} is estimated. The model is of a linear shape and is defined by the equation (**5**). The evaluation of this model is presented in **Table 3**.

$$\sigma_{BTsat} = 0.94624 - 0.02641 \cdot \mathrm{n} + 0.69259 \cdot \sigma_{BTdry} \tag{5}$$

σ_{BTsat} – Brazilian indirect tensile strength in saturated conditions (MPa),
σ_{BTdry} – Brazilian indirect tensile strength in dry conditions (MPa),
n – porosity (%)

Table 3: Evaluation of multi regression model MR

	Model MR
R	0.975469
R Square	0.951540
R^2_{Adj}	0.950626
RMSE	0.377079

Input data from Table 1 was used when creating neural networks. They were divided into three sets. The training set consisted of 70% of the data, validation and test set each have 15% of the total data. All the networks have completely connected perceptrons and were recorded by the one input layer, one hidden layer and one output layer. With the help of training errors, fitting parameters were carried out and the tuning of the parameters was based on the size of validation errors. Test error enabled the assessment of the performance of neural networks. The values of training test and validation errors are relative because they are iteratively adjusted. By means of the software package Statistica 12, 100 models of neural networks of RBF type and 100 models of MLF type were created. The best models were then selected and named NN_RBF and NN_MLP. Their performance is presented in **Tables 4 and 5.** The NN_RB Model has 19 neurons in the hidden layer created by the radial basis function training algorithm (RBFT). The error function used upon training was the sum of squares (SOS), The Model has the Gaussian based activation functions.
The NN_MLP Model has 29 neurons in the hidden layer created by the variant Broyden-Fletcher-Goldfarb-Shanno algorithm (BFGS 94). The error function in this model was also the sum of squares (SOS). This model has the hyperbolic tangent based activation functions.

Table 4: Performance and evaluation of NN_RBF Model

Net. configuration	Training perf.	Test perf.	Validation perf.	Training error	Test error	Validation error
RBF 2-19-1	0.991499	0.976937	0.979943	0.027605	0.068873	0.042649
Training algorithm	Error function	Hidden activation	R	R^2	R^2_{Adj}	RMSE
RBFT	SOS	Gaussian	0.97547	0.95154	0.95063	0.27881

Table 5: Performance and evaluation of NN_MLP Model

Net. configuration	Training perf.	Test perf.	Validation perf.	Training error	Test error	Validation error
MLP 2-29-1	0.991242	0.988590	0.973099	0.028553	0.041006	0.060950
Training algorithm	Error function	Hidden activation	R	R^2	R^2_{Adj}	RMSE
BFGS 94	SOS	Tanh	0.987348	0.974856	0.974382	0.272791

4. Discussion

First to be discussed is the possibility of creating the model based on the published and newly determined data. The consolidation of the data may be realized if the way of determining the measured values is the same and if the same types of rocks have been investigated. Due to the fact that this paper and the paper by **Vásárhelyi** (**2005**) applied the same recommendation **ISRM** (**1978**) and the same rock types – limestones, it can be concluded that a consolidation of data is possible. It is rather useful that different porous types of limestone were applied in both cases, since this increases the uniqueness on the level of the limestone and widens the ranges within which the created models can function. In order to enable an easier evaluation of the models, **Table 6** presents all the calculated parameters for the estimate of the models.

Table 6: Evaluation of models

	Model SR_1	Model SR_2	Model MR	Model NN_RBF	Model NN_MLP
R	0.939863	0.971707	0.975469	0.975469	0.987348
R2	0.883342	0.944215	0.951540	0.951540	0.974856
R2Adj	0.881141	0.943162	0.950626	0.950626	0.974382
RMSE	0.585059	0.404578	0.377079	0.278810	0.272791

According to all the calculated parameters for the evaluation of the models based on simple regression (see **Table 2**) it can be concluded that the model SR_2 provides a better estimate and that it is better to make estimates of σ_{BTsat} by means of σ_{BTdry} than *n*. The comparison of the model MR and NN_RBF is not so simple due to the fact that R, R^2 and R^2_{Adj} according to **Table 6** have similar values for each investigated model. However, according to the smaller RMSE in the model NN_RBF it can be concluded that the model of the neural network of NN_MLP type has higher values of R, R^2 and R^2_{Adj}, whereas the value of RMSE is similar in both models. Accordingly, the calculation of various parameters enables an easier evaluation of the models, although the same comparison could in this case be carried out by two parameters: R^2_{Adj} and RMSE. The final ranking of the models according to **Table 6** is as follows: the best model is NN_MLP whose diagram of the relation between the desired and the input values is presented in **Figure 3**; followed by the model NN_RBF, the model MR, the model SR_2 and finally the model SR_1.

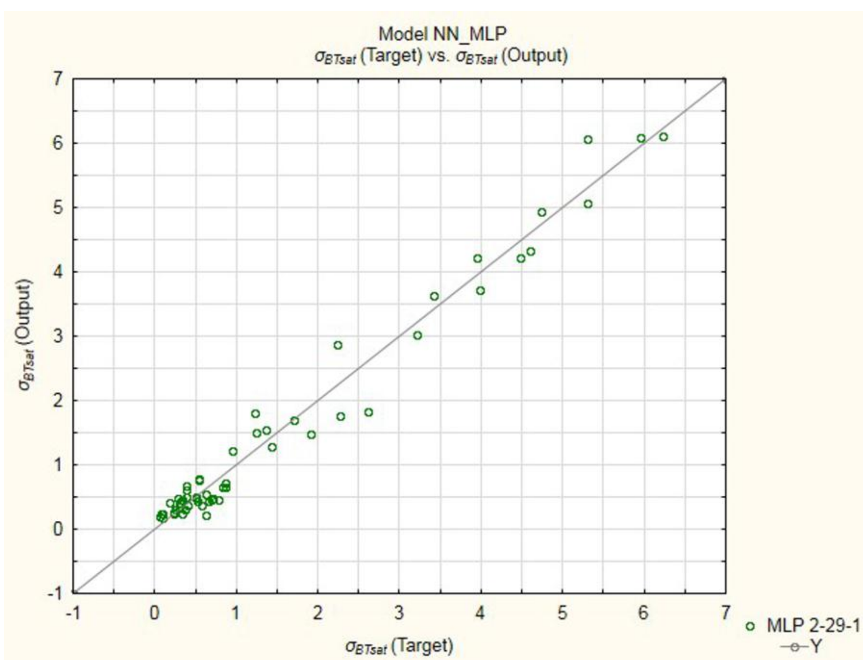

Figure 3: Relation of desired and output values of model NN_MLP

In order to avoid some major errors upon using the models for the estimates σ_{BTsat}, the range of the values of the input parameters *n* and σ_{BTdry} (see **Table 1**) should be considered, on whose base the models were created. Thus the estimate should not be used outside such a range.

5. Conclusion

After collecting the data, their consolidation was successfully completed according to the method of investigation and types of material. The neural network model of the type Multiple Layer Perceptron was estimated as the best one among all the created models. However, in view of the possibility of a wide application, the model of multiple regression is the most promising one due to the fact that its application does not require complicated software packages.

The models should be used only if the input parameters are in the range from 0.07 to 7.381 MPa for the Brazilian indirect tensile strength in dry conditions.

Future research works should be aimed at the investigation and collection of data on various types of limestone, in order to enable the creation of high quality models, which should result in the possibility to estimate the limestone material better.

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Sažetak

Modeli za procjenu neizravne čvrstoće vapnenca u saturiranom stanju

Potreba za procjenom neizravne vlačne čvrstoće koju inače određujemo brazilskim testom može se javiti pri idejnim rješenjima podzemnih radova u sredinama gdje je prisutna podzemna voda. Pregledom dostupne literature iz relevantnih izvora, koja se bavi utjecajem zasićenja na neizravnu vlačnu čvrstoću stijena koja se određuje brazilskim testom, utvrđeno je da se samo nekoliko radova bavi procjenom neizravne vlačne čvrstoće kod vapnenaca i pri tome se ne bave zasićenjem vodom. Isto tako, autori ovoga rada pregledom dostupne literature iz relevantnih izvora nisu naišli na rad koji bi se bavio procjenjivanjem neizravne vlačne čvrstoće vapnenca pomoću neuronskih mreža koje bi primjenjivale samo dva ulazna parametra, neizravnu vlačnu čvrstoću u suhome stanju i/ili šupljikavosti, stoga je bio razumljiv znanstveni interes za izradu i primjenu modela takva tipa. Skup podataka na temelju kojega je modelirano izrađen je jednim djelom od prikupljenih podataka iz objavljene literature gdje su navedeni rezultati ispitivanja poroznosti, indirektne vlačne čvrstoće u suhome i zasićenome stanju miocenskoga vapnenca, a drugi dio početnoga skupa bazira se na istraživanjima koja su provedena u Geomehaničkome laboratoriju RGN fakulteta u Zagrebu na vapnencima iz kamenoloma „Podberam" kod Pazina. U obama slučajevima ispitivanja su obavljena prema preporuci Međunarodnoga društva za mehaniku stijena pa je objedinjavanje bilo moguće. Na temelju prikupljenih podataka pomoću programskoga paketa Statistica 12 ukupno je napravljeno pet modela za procjenu neizravne vlačne čvrstoće. Modeli jednostruke regresije nose oznaku SR_1 (temelji se na jednostavnoj regresiji s poroznošću) i SR_2 koji je napravljen pomoću neizravne vlačne čvrstoće u suhome stanju. Model višestruke regresije nazvan je MR, a u njemu su nezavisne varijable šupljikavosti i neizravne vlačne čvrstoće u suhome stanju. Model neuronskih mreža s radijalnom baznom funkcijom nazvan je NN_RBF, a model tipa višeslojna mreža nosi oznaku NN_MLP. Uobičajeno se izrađeni modeli evaluiraju pomoću niza koeficijenata koji služe u tu svrhu: koeficijent koleracije (R), koeficijent determinacije (R^2), korigirani R^2 (R^2_{Adj}) i korijen srednje kvadratne pogreške (RMSE). Prema parametrima ocjene najbolji je model NN_MLP, zatim slijedi model NN_RBF pa model MR te model SR_2 i na kraju model SR_1. Iako model NN_MLP najbolje procjenjuje neizravnu vlačnu čvrstoću u saturiranome stanju jer ima R = 0,987348; R^2 = 0,974856; R^2_{Adj} = 0,974382 i RMSE = 0,272791, ipak prema mogućnosti šire primjene u inženjerskoj praksi model višestruke regresije najviše obećava jer za njegovu primjenu nisu potrebni složeni programski paketi.

Modele iz ovoga rada treba primjenjivati samo kada su ulazni parametri u rasponu za indirektnu vlačnu čvrstoću u suhome stanju od 0,07 do 7,381 MPa.

Ključne riječi

procjena, neizravna vlačna čvrstoća, saturacija, vapnenac, mehanika stijena