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# Estimate of Uniaxial Compressive Strength and Young's Modulus of the Elasticity of Natural Stone Giallo d'Istria

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**Abstract**

The famous natural stone Giallo d'Istria, is categorized as a thick-bedded biomicritic limestone, is exploited in three locations on the Croatian peninsula of Istria. In order to detect high-quality areas of the existing quarries and some new areas of exploitation as well, models have been developed for the purpose of estimating important physico-mechanical properties of this limestone. The models are based on the results of many laboratory tests. Complex and simple estimation models have been mutually compared. The modelling is based on neural networks and multiple and simple regressions. Special attention was paid to the applicability of the developed models in other sites.



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*Keywords:* Uniaxial compressive strength; Young's modulus of the elasticity; estimation; Giallo d'Istria; neural network; simple regression

## 1. Introduction

Giallo d'Istria (yellow Istrian) is the general name for the natural stone from the Kanfanar, Selina and Korenići quarries which are situated on the Croatian peninsula of Istria. Stratigraphically speaking, Giallo d'Istria is a Lower Cretaceous biomicritic limestone (see Figure 1). These deposits are characterized by a thick-bedded limestone of a yellowish color. The thickness of the individual layers is anywhere from 0.80 to 1.50 m, provided that they are separated with contour lines that define the boundaries and mark the weakly bound contour lines.

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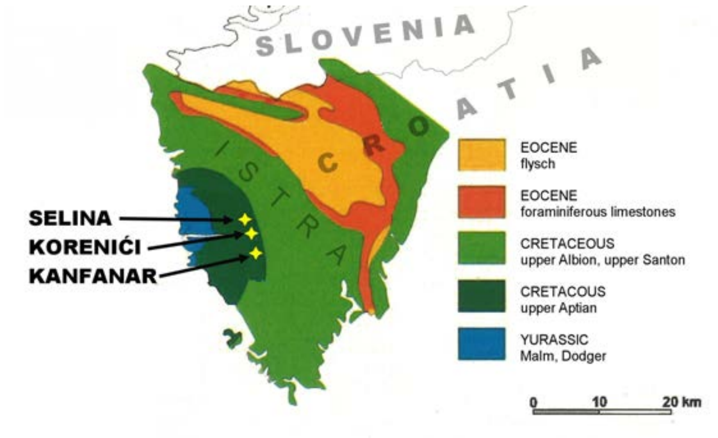


Fig. 1. Position of the quarrys.

The thickness of the overburden is 17 to 25 m, which layers are typically denoted alphabetically as shown in Figure 2, and the exploitation layers have a thickness between 4.8 and 6.8 meters, and sometimes even up to 7.6 m they are marked with Roman numerals I, II, IV, V and VI. The layers differ in appearance and structure, and thus cannot be mixed in the production process. There are also differences in the physico-mechanical properties even within the layers in its strikes and dips, especially in porosity and density. In exploitation, such areas must be rejected, and thus losses in yield occur [1, 2, 3].

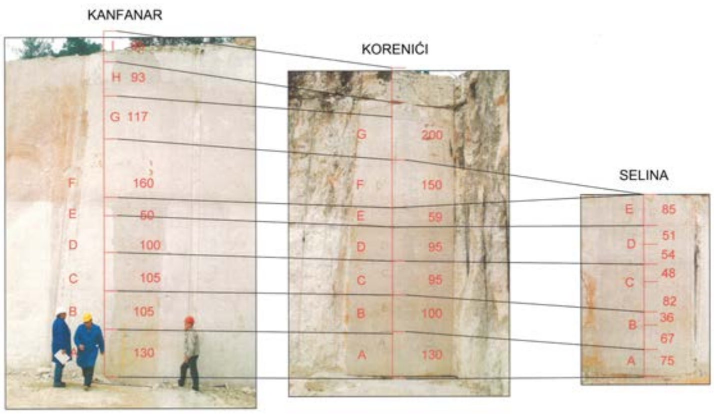


Fig. 2. The spatial distribution of overburden layers in quarries Kanfanar, Korenići and Selina.

In order to ensure a uniform quality of exploited natural stone, it is necessary, and if feasible, as simply as possible, to locate areas where there are distinct changes in the strength and deformability of materials. For this reason, a need arose to find a method which could practically assess the uniaxial compressive strength (UCS) and Young's modulus of elasticity (E) based on easily determined material characteristics. Extensive testing of natural stone for the development and introduction of underground mining in quarries [4] took place and the physical and mechanical properties of the individual layers were tested which advanced the progress in achieving this goal. The implemented tests, among other things, enabled the determination of the interdependence between the various physico-mechanical characteristics. Modelling in this paper was inspired by the methods of assessing physico-mechanical characteristics published in scientific literature. Principally, the most widely used is regression, but recently more sophisticated techniques such as neural networks have frequently been applied as well [5].

Among scientific papers, those which use similar parameters on the basis of which UCS and E are determined should be emphasized: Palchik and Hatzor [6], Tugrul [7], Tziallas et al. [8], Yagiz [9], Moradian, and Behnia [10], Manouchehrian et al. [11], Dehghan [12], Gokceoglu and Zorlu [13], Karakus and Tutmez [14], Yilmaz and Yuksek [15] and Dehghan et al. [16].

## 2. Performed testing

Due to the need of the detailed determination of the physico-mechanical properties of materials from all the representative layers of deposits, laboratory tests were conducted on several occasions during the research period. All basic laboratory tests were carried out according to the recommended methods (Suggested Methods) International Society for Rock Mechanics. The following tests were performed: determining the density and porosity of materials [17]; testing the uniaxial compressive strength (UCS) and deformability of materials [18]; determining the velocity of ultrasonic elastic P-waves (P-velocity) [19]; determining the point load strength index (PLT) [20] and determining Schmidt hammer Rebound Hardness (SRH) [21]. The basic sample preparation was conducted by employees of the company Kamen d.d. (PLC) Pazin, and this preparation consisted of the selection of large blocks at the quarry and preparing smaller blocks and samples at the mill. So they prepared small blocks measuring 23 × 30 × 23 cm layer of overburden F and E from Korenić, D and A from Selina, C and B from Kanfanar where they also extracted samples for testing exploitation layers I, II, IV, V and VI. Laboratory samples were later extracted from such small blocks and analyzed according to the requirements of individual test methods. Sample preparation for individual tests as well as their testing was conducted in the Geomechanical Laboratory at the Faculty of Mining, Geology and Petroleum Engineering, University of Zagreb. Part of the preparation as well as the geological determination of materials was carried out in the Laboratory of Engineering Geology at the Croatian Geological Survey institute in Zagreb [21]. The results of the tests are shown in Table 1.

Table 1. Results of laboratory tests.

| Place and layer | Limestone type | Density ($1000\ kg \cdot m^{-3}$) | Porosity (%) | PLT (MPa) | SRH | Vp ($1000\ m \cdot s^{-1}$) | UCS (MPa) | E (GPa) |
|---|---|---|---|---|---|---|---|---|
| Korenići, layer F | Mudstone | 2.164 | 16.46 | 2.1 | 51.4 | 4.424 | 33.1 | 43.647 |
| Korenići, layer F | Mudstone | 2.195 | 18.43 | 2.4 | 51.4 | 4.506 | 56.97 | 30.88 |
| Korenići, layer E | Grainstone | 2.379 | 10.94 | 1.7 | 38.2 | 5.107 | 51.44 | 38.379 |
| Korenići, layer E | Grainstone | 2.376 | 11.25 | 3.8 | 38.2 | 5.261 | 66.48 | 44.338 |
| Selina, layer D | Floatstone | 2.627 | 2.34 | 1.5 | 60 | 5.97 | 74.07 | 45.937 |
| Selina, layer D | Floatstone | 2.626 | 2.61 | 3.24 | 57 | 6.038 | 68.76 | 57.265 |
| Selina, layer D | Floatstone | 2.628 | 2.81 | 3.88 | 61.7 | 6.039 | 82.44 | 56.298 |
| Selina, layer D | Floatstone | 2.623 | 3.27 | 2.68 | 61.3 | 6.044 | 80.12 | 48.805 |
| Selina, layer D | Floatstone | 2.634 | 2.71 | 0.87 | 66.5 | 6.13 | 89.87 | 66.746 |
| Kanfanar, layer C | Wackestone | 2.64 | 3.06 | 4.4 | 63.5 | 5.983 | 129.93 | 58.074 |
| Kanfanar, layer C | Wackestone | 2.634 | 2.43 | 3.6 | 63 | 5.932 | 126.02 | 62.254 |
| Kanfanar, layer C | Wackestone | 2.638 | 2.67 | 3.9 | 68.5 | 5.992 | 136.1 | 57.682 |
| Kanfanar, layer C | Wackestone | 2.634 | 2.82 | 2.1 | 61 | 5.886 | 118.81 | 55.92 |
| Kanfanar, layer C | Wackestone | 2.634 | 2.29 | 3.7 | 59 | 5.88 | 109.75 | 54.787 |
| Kanfanar, layer B | Packstone | 2.652 | 2.12 | 4.77 | 63.5 | 6.098 | 148.39 | 44.862 |
| Kanfanar, layer B | Packstone | 2.652 | 2.49 | 3.76 | 61.1 | 5.976 | 133.41 | 65.552 |
| Kanfanar, layer B | Packstone | 2.653 | 2.3 | 3.91 | 63.5 | 6.067 | 154.2 | 64.756 |
| Kanfanar, layer B | Wackestone | 2.652 | 2.14 | 4.03 | 61 | 6.057 | 122.46 | 65.292 |
| Selina, layer A | Floatstone | 2.635 | 2.81 | 3.2 | 55 | 6.096 | 84.57 | 66.841 |
| Selina, layer A | Floatstone | 2.671 | 3.15 | 2.4 | 58.5 | 6.071 | 89.14 | 52.953 |
| Selina, layer A | Floatstone | 2.635 | 3.48 | 3.2 | 56 | 6.104 | 85.48 | 55.492 |
| Selina, layer A | Floatstone | 2.636 | 2.75 | 2.6 | 70 | 6.123 | 107.61 | 66.878 |
| Selina, layer A | Floatstone | 2.638 | 2.48 | 2.9 | 70 | 6.079 | 102.52 | 63.806 |
| Kanfanar, layer I | Wackestone | 2.675 | 1.75 | 4.64 | 55.5 | 5.884 | 109.68 | 51.835 |
| Kanfanar, layer I | Wackestone | 2.677 | 1.25 | 4.65 | 62.4 | 5.909 | 115.26 | 51.429 |
| Kanfanar, layer I | Wackestone | 2.676 | 1.23 | 3.81 | 66.5 | 5.896 | 121.27 | 52.118 |
| Kanfanar, layer I | Mudstone | 2.674 | 1.15 | 5.42 | 61.8 | 5.958 | 111.3 | 50.405 |
| Kanfanar, layer I | Mudstone | 2.673 | 1.13 | 5.3 | 66 | 5.955 | 121.17 | 55.2 |
| Kanfanar, layer II | Floatstone | 2.65 | 2.07 | 3.6 | 62 | 5.944 | 112.54 | 64.556 |
| Kanfanar, layer II | Floatstone | 2.654 | 2 | 3.2 | 60 | 5.829 | 99.11 | 61.59 |
| Kanfanar, layer II | Floatstone | 2.651 | 2.25 | 3.9 | 61 | 5.984 | 109.31 | 60.941 |

Table 1. Results of laboratory tests - continuation.

| Place and layer | Limestone type | Density ($1000\ kg\cdot m^{-3}$) | Porosity (%) | PLT (MPa) | SRH | Vp ($1000\ m\cdot s^{-1}$) | UCS (MPa) | E (GPa) |
|---|---|---|---|---|---|---|---|---|
| Kanfanar, layer II | Floatstone | 2.666 | 2.02 | 3.6 | 67 | 5.97 | 136.26 | 68.11 |
| Kanfanar, layer II | Floatstone | 2.651 | 1.61 | 4.3 | 62 | 5.967 | 119.7 | 58.04 |
| Kanfanar, layer IV | Wackestone | 2.684 | 0.64 | 5.5 | 61.5 | 6.149 | 152.37 | 60.884 |
| Kanfanar, layer IV | Mudstone | 2.698 | 0.74 | 5.2 | 61 | 6.145 | 125.64 | 55.797 |
| Kanfanar, layer IV | Mudstone | 2.686 | 0.85 | 5.4 | 68.5 | 6.096 | 178.19 | 61.383 |
| Kanfanar, layer IV | Mudstone | 2.684 | 0.99 | 4.7 | 63.5 | 6.089 | 169.45 | 69.09 |
| Kanfanar, layer IV | Wackestone | 2.688 | 0.84 | 4.6 | 64.5 | 6.136 | 172.93 | 68.997 |
| Kanfanar, layer V | Floatstone | 2.68 | 1.8 | 4.8 | 59.5 | 6.149 | 136.43 | 67.917 |
| Kanfanar, layer V | Rudstone | 2.683 | 1.1 | 4.5 | 63 | 6.229 | 175.24 | 74.153 |
| Kanfanar, layer V | Floatstone | 2.684 | 1.16 | 3.7 | 69.5 | 6.221 | 180.5 | 67.262 |
| Kanfanar, layer V | Floatstone | 2.683 | 0.84 | 4.8 | 60 | 6.178 | 166.31 | 72.322 |
| Kanfanar, layer V | Floatstone | 2.683 | 0.84 | 4.9 | 60 | 6.15 | 168.22 | 68.397 |
| Kanfanar, layer VI | Floatstone | 2.613 | 1.13 | 3.2 | 67 | 5.919 | 107.52 | 61.541 |
| Kanfanar, layer VI | Floatstone | 2.607 | 1.23 | 3.5 | 63.5 | 5.897 | 75.84 | 65.258 |
| Kanfanar, layer VI | Floatstone | 2.601 | 1.5 | 4.8 | 51 | 5.857 | 72.18 | 65.612 |
| Kanfanar, layer VI | Rudstone | 2.629 | 1.28 | 4.3 | 66 | 5.971 | 90.74 | 66.786 |
| Kanfanar, layer VI | Rudstone | 2.624 | 1.15 | 4.8 | 67 | 5.978 | 102.15 | 86.48 |

The results of descriptive statistics of the set presented in Table 1 are given in Table 2. According to the size of the standard deviation, it is visible that the largest dispersion of data was given by the UCS test results, while on the other hand, the least dispersion of data was during the testing of the density and velocity of P waves. However, if we want to compare the dispersion of data for different values with different units of measurement, then the Coefficient of variation is accurate. It shows the greatest dispersion with porosity, and two property groups have approximately the same dispersion. The first group consists of UCS and PLT, and the second group consists of density, SRH and P-velocity.

Table 2. Descriptive statistics of the surveyed materials Giallo D Istria.

| Comparative tests conducted | Mean value | Minimum value | Maximum value | Standard deviation | Coefficient of variation (%) |
|---|---|---|---|---|---|
| Density ($1000\ kg\cdot m^{-3}$) | 2.6215 | 2.1640 | 2.6980 | 0.11112 | 4.239 |
| Porosity (%) | 2.9242 | 0.6400 | 18.4300 | 3.66629 | 125.378 |
| Point load test – PLT (MPa) | 3.7867 | 0.8700 | 5.5000 | 1.09370 | 28.883 |
| Schmidt Rebound Hardness - SRH | 61.0208 | 38.2000 | 70.0000 | 6.63633 | 10.876 |
| P-wave velocity ($1000\ m\cdot s^{-1}$) | 5.9234 | 4.4240 | 6.2290 | 0.36506 | 6.163 |
| Uniaxial compressive strength – UCS (MPa) | 114.1865 | 33.1000 | 180.5000 | 35.86063 | 31.405 |
| Young's modulus of elasticity – E (GPa) | 59.4489 | 30.8800 | 86.4800 | 9.99195 | 16.808 |

The correlation dependence of individual tests is shown in Table 3. Porosity has a negative correlation with all other properties, which means an increase in the porosity results in a reduction in all other values. According to Evans' interpretation [22] the strength of interdependencies can be described by size, as shown in Table 3.

Table 3. Correlations between tests performed.

| Comparative tests conducted | Density ($1000\ kg\cdot m^{-3}$) | Porosity (%) | PLT (MPa) | SRH | Vp ($1000\ m\cdot s^{-1}$) | UCS (MPa) | E (GPa) |
|---|---|---|---|---|---|---|---|
| Density ($1000\ kg\cdot m^{-3}$) | 1.000000 | -0.975333 | 0.459429 | 0.640282 | 0.965444 | 0.649812 | 0.594591 |
| Porosity (%) | -0.975333 | 1.000000 | -0.482353 | -0.653525 | -0.942704 | -0.600888 | -0.652219 |
| PLT (MPa) | 0.459429 | -0.482353 | 1.000000 | 0.222391 | 0.384955 | 0.603924 | 0.336280 |
| SRH | 0.640282 | -0.653525 | 0.222391 | 1.000000 | 0.628970 | 0.561293 | 0.543868 |
| P-velocity ($1000\ m\cdot s^{-1}$) | 0.965444 | -0.942704 | 0.384955 | 0.628970 | 1.000000 | 0.621141 | 0.646761 |
| UCS (MPa) | 0.649812 | -0.600888 | 0.603924 | 0.561293 | 0.621141 | 1.000000 | 0.522603 |
| E (GPa) | 0.594591 | -0.652219 | 0.336280 | 0.543868 | 0.646761 | 0.522603 | 1.000000 |

Porosity has a very strong interdependence with density and P-velocity. UCS has a strong correlation with density, porosity, PLT and P-velocity. E has a strong correlation with porosity and P-velocity, a weak interdependence with PLT, and it has a moderate relationship with the rest of the properties. The geological determination of samples shows that the test samples were mostly with mud and matrix supported and belonging to madstone, wackstone and floatstone types per Dunham's classification limestone [23]. The appearance of grain-supported in the form of grainstone and packstone types occur in two layers of overburden, but also in the deepest layers marked V and VI where there were three samples of the rudstone type.

## 3. Modelling estimates

The most accessible method for assessing UCS and E are simple and multiple regression as well as neural networks and so modelling in this paper was based on those procedures. For modelling complex assessments, the software package Statistica 12 was used, which offers the possibility of creating regression models and the models of artificial neural networks such as Multiple Layer Perceptron (MLP). This type of network was chosen because it performed better than the other type which Statistica 12 can produce, i.e. Radial Basis Function (RBF).

### *3.1. Simple regression models*

Simple regression equations comprise relations defined for the estimation of UCS and E values as dependent variables based on the tested value of another property that constitutes an independent variable [24]. In this paper, the independent variable was represented by one of the values for testing density, porosity, PLT, SRH and P-velocity. The success of the model is usually determined through the coefficient of determination $R^2$. The modelling results are shown in Table 4. Among all the performed simple models, the best models for estimating UCS are shown in equations (1) (2) and (3) which used density, porosity and SRH as independent variables. The best models for estimating E are shown in equations (4) and (5) which used porosity and P-velocity as independent variables.

$$UCS = 0{,}1724 \cdot e^{2{,}4567 \cdot \rho} \tag{1}$$

$$UCS = 139{,}63 \cdot n^{-0{,}36} \tag{2}$$

$$UCS = 1{,}5991 \cdot e^{0{,}7112 \cdot v_p} \tag{3}$$

$$UCS = 65{,}025 \cdot e^{-0{,}036 \cdot n} \tag{4}$$

$$UCS = 7{,}1465 \cdot e^{0{,}3551 \cdot v_p} \tag{5}$$

where is: *UCS* - uniaxial compressive strength in MPa, *E* - Young's modulus of elasticity in GPa, $\rho$ - density in 1000 kg·m$^{-3}$, $n$ – porosity in %, $v_p$ - P-wave velocity in 1000 m·s$^{-1}$.

Table 4. Simple models for estimation UCS and E.

| Dependent variable | Independent variable | Coefficient of determination $R^2$ |
|---|---|---|
| UCS | Density | 0.5959 |
| UCS | Porosity, | 0.5703 |
| UCS | PLT | 0,3711 |
| UCS | SRH | 0,3885 |
| UCS | P velosity | 0.5391 |
| E | Density | 0.4427 |

Table 4. Simple models for estimation UCS and E- continuation.

| Dependent variable | Independent variable | Coefficient of determination $R^2$ |
|---|---|---|
| E | Porosity | 0.5201 |
| E | PLT | 0.1226 |
| E | SRH | 0.3271 |
| E | P-velocity | 0.5045 |

### 3.2. Multi regression models

Multiple regression models are represented by the equation (6).

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_i X_k + \varepsilon \quad (6)$$

where is: $Y$ - dependent variable, $X_1$, $X_2$, …, $X_k$ - independent variables, $\beta_i$ - denotes contribution of the independent variable $X_i$, $\varepsilon$ - random error.

According to Table 5, which presents the results of modelling, the model that included porosity, PLT, SRH and P-velocity proved to be the best for estimating UCS. The estimation of E using this type of model did not show greater success than the model based on single regressions.

Table 5. Multiple regression models.

| Dependent variable | Independent variable | Coefficient of determination $R^2$ |
|---|---|---|
| UCS | Density, PLT, SRH | 0.5918 |
| UCS | Porosity, PLT, SRH | 0.5656 |
| UCS | PLT, SRH, P-velocity | 0.5952 |
| UCS | Density, PLT | 0.5405 |
| UCS | Density, SRH | 0.4580 |
| UCS | Porosity, PLT | 0.4896 |
| UCS | Porosity, SRH | 0.4107 |
| UCS | PLT, P-velocity | 0.5421 |
| UCS | SRH, P-velocity | 0.4340 |
| E | Density, PLT, SRH | 0.4075 |
| E | Porosity, PLT, SRH | 0.4518 |
| E | PLT, SRH, P-velocity | 0.4593 |
| E | Density, PLT | 0.3586 |
| E | Density, SRH | 0.3987 |
| E | Porosity, PLT | 0.4260 |
| E | Porosity, SRH | 0.4495 |
| E | PLT, P-velocity | 0.4273 |
| E | SRH, P-velocity | 0.4494 |

### 3.3. Neural network models

The success of neural network models is shown in Table 6, where the best performance estimate of UCS is shown in the model in the first row of the table which has the largest number of available predictors. Based on performance, the second place model is the model in which the predictors were density, porosity, PLT and SRH, and in third place is the model with the density and porosity predictors. Predictors of the third model can be determined by one simple procedure and so from that point of view, this model is very suitable for the estimation of UCS.

Table 6. Neural networks models.

| Estimates target | Input parameters | Coefficient of determination $R^2$ |
|---|---|---|
| UCS | Density, porosity, PLT, SRH, P-velocity | 0.8565 |
| UCS | Density, porosity, PLT, SRH | 0.8015 |
| UCs | Density, porosity, SRH | 0.7755 |
| UCS | Porosity, PLT, SRH, | 0.7546 |
| UCS | Density, porosity | 0.7828 |
| UCS | Density, SRH | 0.7323 |
| UCS | Density, PLT | 0.7183 |
| E | Density, porosity, PLT, SRH, P velocity | 0.6406 |
| E | Density, porosity, PLT, SRH | 0.5705 |
| E | Density, porosity, SRH | 0.4912 |

## 4. Discussion

Due to the need for more accurate and easier detection of areas of exploitation layers that have unfavorable physico-mechanical properties, models to estimate UCS and E were developed based on laboratory tests. It was necessary to find a simple and sufficiently versatile model that would be based on simple, achievable tests. Tests on density, porosity and SRH can be easily evaluated, so it is understandable that they are the preferred parameters on the basis of which UCS and E are estimated.

The best model for the estimation of UCS based on single regression is the one with density as the independent variable that has a $R^2$ of 0.5959, and the best model of its kind to estimate E is the one with an independent variable porosity with a $R^2 = 0.5201$. More complex models can be considered more successful only if they have a higher $R^2$ value than the aforementioned values.

While modelling with the method of multiple regression, it was necessary to take into account that the tested independent variables used are not interdependent. According to Table 3, there is a large interdependence between density, porosity and P-velocity and so combinations of these values are not used in modelling. Table 5 shows that no combination of independent variables can achieve a higher $R^2$ than those achieved in single regression models. Simple models have a non-linear form and this is the reason why they are better than multiple regression models.

Neural network models have a higher estimate success rate, as expected, and the advantage of this type of model is that you are not limited in terms of the combination of predictor values. Table 6 shows that the largest $R^2$ values are achieved by models estimating UCS and E where the predictors include all the available values. However, since the implementation of the P-velocity test cannot be regarded as a simple test, this characteristic is omitted from the list of predictors. Therefore, it can be determined that the best estimate with the application of all essential criteria for a successful estimate is achieved by models which have density, porosity, PLT and SRH as predictors. In the case of UCS estimates, these models have a $R^2 = 0.8015$ whereas in the case of E estimates, $R^2$ is 0.5705.

## 5. Conclusion

When modelling estimates are performed in the mining industry, the possibilities of the easiest application of the model in the field must be taken into account. Therefore, single regression methods should not be neglected even though their parameters of success do not give better results than neural networks, but they have the advantage of application simplicity.

Simple regression methods that have a non-linear shape proved to be more successful than the linear generalized form of multiple regression. Therefore, future modelling using multiple regression should focus more on non-linear forms of multiple regression.

The rapid rise of computer technology makes models of neural networks more accessible, so such complex models become practically applicable and contribute to the greater security of estimated results

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