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**Review paper**

# Evaluation of the unit weight of organic soils from a CPTM using an Artificial Neural Networks

**G. Straż[1], A. Borowiec[2]**

**Abstract:** This paper discusses the use of mechanical cone penetration test CPTM for estimating the soil unit weight of selected organic soils in Rzeszow site, Poland. A search was made for direct relationships between the empirically determined the soil unit weight value and cone penetration test leading parameters (cone resistance $q_c$, sleeve friction $f_s$. The selected, existing models were also analysed in terms of suitability for estimating the soil unit weight and tests were performed to predict the value soil unit weight of local, different organic soils. Based on own the–regression analysis, the relationships between empirically determined values of soil unit weight and leading parameters cone penetration test were determined. The results of research and analysis have shown that both existing models and new, determined regression analysis methods are poorly matched to the unit weight values determined in laboratory, the main reason may be the fact that organic soils are characterized by an extremely complicated, diverse and heterogeneous structure. This often results in a large divergence and lack of repeatability of results in a satisfactorily range. Therefore, in addition, to improve the predictive performances of the relationships, analysis using the artificial neural networks (ANN) was carried out.

**Keywords:** soil unit weight; artificial neural networks; organic soils; organic content; cone penetration test

[1] PhD., Eng., Rzeszow University of Technology, Faculty of Civil and Environmental Engineering and Architecture Civil Engineering, Powstańców Warszawy 12 Av., 35-959 Rzeszow, Poland, e-mail: gstraz@prz.edu.pl, ORCID: https://orcid.org/0000-0001-5847-0441

[2] PhD., Eng., Rzeszow University of Technology, Faculty of Civil and Environmental Engineering and Architecture Civil Engineering, Powstańców Warszawy 12 Av., 35-959 Rzeszow, Poland, e-mail: artur.borowiec@prz.edu.pl, ORCID: https://orcid.org/0000-0002-9475-3251

# 1. Introduction

The Podkarpackie Voivodeship is an area with an exceptionally varied and complex geological structure, where, especially in the geological profiles of river terraces, interlacing variety of organic soils is very common. Unfortunately, organic soils belong to soft soils characterized by low shear strength and extremely high compressibility, moreover, these layers may have varying thicknesses, from several centimeters to several meters, and very often these occur below the groundwater table, which causes the local conditions for foundation of building objects and engineering constructions are difficult or very difficult. The fact is that the areas they cover are often the only places available for construction in large urban agglomerations, which means that they are increasingly becoming the object of interest and investment of developers. The decision to set up facilities in low-bearing capacity areas brings incomparably higher costs than in the case of foundations on typical mineral soils, but often for logistical or strategic reasons it is necessary. The foundation of building construction in such adverse conditions is of course possible, but requires extremely sensitive and detailed subsoil identification, preferably using different types of penetrometers in situ. No less important are the methods of interpreting the results obtained directly from the research and, consequently, the values of the parameters derived later used at the design stage.

Currently, the assessment of geotechnical parameters and coefficients in the European Union and related countries is mainly based on the EN 1997-1:2004 [1] and EN 1997-2:2007 [2] standards, and among the many methods of subsoil recognition, the Cone Penetration Test is becoming more and more popular. In parallel with the technological modernization of this penetrometer, work is constantly underway on methods of interpreting results obtained directly from research for design purposes. In parallel with the technological modernization of this penetrometer, work is constantly underway on methods of interpretation of results obtained directly from research for the purpose of foundation design and subsoil improvement. The methods of interpreting the results of these soundings generally work very well in the case of substrates with typical mineral soils, but for organic soils considered to be one of the weakest, the results are not conclusive. That is why new methods are constantly being sought and more and more perfect and safe computational models are being developed.

This paper attempts to verify the suitability of existing models for estimating the soil unit weight of organic soils from a selected area of Podkarpacie (Poland). The direct correlations between values measured parameters during the mechanical cone penetration test (CPTM) and desired geotechnical parameters were sought [3]. Were also proposed, and a new tool in the form of artificial neural networks, which is increasingly used to solve geotechnical problems, was used to improve fit quality on a global scale [4–10]. The Polish geotechnics are increasingly using this tool to solve local cases, and their effect is published in the papers [11–18], although at the moment it doesn't concern much organic soils [19, 20]. In the recent past, the authors used the ANN to predict the value of soil unit weight of local organic soils based on their leading parameters: the contents of organic matter and water content [21]. The obtained test results were so promising that it was decided to continue the research using the ANN to determine the soil weight of the soil, but this time based on the results of CPTM tests.

# 2. Methods and materials

## 2.1. Characteristics of the study area at the Rzeszow site

The Podkarpackie Voivodeship is located in the south-eastern part of Poland. From the south is borders with Slovakia and from the east with Ukraine. The region covers three separate physiographic lands, wery varied significantly in terms of geological structure and topography. In the northern part of the Sandomierz Basin is located in the middle of the Carpathian Foothills, Beskidy Mountains in the south, dividing the Bieszczady and Beskid Niski. In the north-eastern part there is a fragment of Roztocze [22]. The study area and data used in this paper come from the site, geologically speaking, is located in the south part of the Carpathian Foredeep, geographically located at the Foothills of Rzeszow, within the macro-region of the Sandomierz Basin and exactly on the area campus of the Theological and Pastoral University in Rzeszow. The site where the recognition was conducted, in terms of morphology, is located in the valley of the Młynówka River and reaches around 206.0 m above sea level [23].

## 2.2. The evaluation of the soil unit weight based on laboratory test

The bulk density of the soil is the mass of soil per unit volume of the material, including any water or gas it contains. The term unit weight, $\gamma_t$, is often used and is calculated by multiplying the bulk density by the acceleration due to gravity [24].

## 2.3. The Cone Penetration Test procedure

The first tests of the cone penetrometer were carried out in 1932. A gas pipe with an external diameter of 35 mm on an internal steel pusher of 15 mm and a cone tip with 10 $cm^2$ projected area and 60° apex angle was applied. Over time, the design of the probe and equipment changed, which also increased its research capabilities. The Delf Soil Mechanics Laboratory used first cone penetration push machine in 1935. A few years later, in 1948, geometry of the original mechanical cone was improved the purpose to prevent soil from entering the gap between the casing and inner rods. The part of basic Dutch mechanical penetrometers with this conical mantle are still in use in some parts of the words. In 1953 Bergmann developed new type cone (CPTM) to include measurement of local sleeve friction and first-time friction ratio was used to classify of kind of soils. The first electric cone was developed by Furgo in 1965. In 1974 were introduced the most modern type of penetrometers that could measure pore pressure (piezocones) especially useful for soft clays. The most commonly used today is the standard cone, where the cross-sectional area of standard cones shall be 1 000 $mm^2$ which corresponds to a diameter of 35,7 mm, but depending on ground conditions, cones with an outer diameter between 25 mm ($A_c$ = 500 $mm^2$) and 80 mm ($A_c$ = 5 027 $mm^2$) are permitted [25].
The mechanical cone penetration test (CPTM), which was used in this study, consists of pushing a cone penetrometer, by means of a series of push rods, into the soil at a constant rate of penetration. During penetration, measurements of cone penetration resistance, total penetration resistance and/or sleeve friction can be recorded [25]. The test results can be used for interpretation of stratification, classification of soil type and evaluation a wide spectrum of geotechnical parameters for example: soil unit weight ($\gamma_t$), liquidity index ($I_L$), relative density (Dr), undrained shear strength ($S_u$), effective friction angle ($\phi'$), effective cohesion ($c'$), constrained modulus ($M$), deformation modulus ($E$), overconsolidation ratio (OCR), coefficient of earth pressure at rest ($K_o$) and many others [26].

## 2.4. Evaluation of the soil unit weight for existing models from CPT

The source materials on the determination of the soil unit weight of organic soils based on Cone Penetration Test (CPTM) are rare. Therefore, at the initial stage of the work, after analyzing the thematic materials available, an attempt was made to determine the suitability of selected, universally recognized and new calculation models for estimating the soil unit weight of local organic soils. These models were developed for various types of soils, most often for mineral ones, coming from different parts of the world, which gives the study a verification character. The concise characteristics of the models selected for analysis are presented later in the following part of the elaboration.

### 2.4.1. Mayne at al. relationships

Mayne (2006) for saturated soils, based on large data of soils, including soft to stiff clays and silts, loose to dense sands and gravels and as well as mixed geomaterials, proposed correlation depends on both parameters: shear wave velocity and depth (2.1) (coefficient of determination, $R^2$ = 0.808) as follows [27, 28]:

(2.1) $$\gamma_t = 8.32\, log\, V_s - 1.61\, log\, z$$

where:
$\gamma_t$ – soil unit weight, $V_s$ – shear wave velocity, z – depth.

- Mayne (2007) used database contained date for cohesionless soils (loose to dense sands and gravels) and cohesion soils (soft to stiff clays and silts) and proposed relationship between the total unit weight and the sleeve friction from cone penetration test. The relationship was indirectly derived from correlations between the soil unit weight and the shear wave velocity, and between the shear wave velocity with the sleeve friction (2.2) [29]:

(2.2) $$\gamma_t = 2.6\, log(f_s) + 15G_s - 26.5$$

where:
$f_s$ – sleeve friction, $G_s$ – specific gravity of soil solids.

- Mayne et al. (2010) by the multivariable regression analysis were found correlation for the various type of soils (e.g. soft clay, clay till, calcareous clay, natural sand, boulder clay, mine tailing sand, fissured clay, mudstone, stratified soils, etc.) from different, global location such as USA, Japan, UK, Canada, Norway, Ireland, Sweden, Italy, Brazil and North Sea which was described by the formula (2.3) [30]:

(2.3) $$\gamma_t = 11.46 + 0.33\, log(z) + 3.11og(f_s) + 0.7\, log(q_c)$$

where:
$q_c$ – cone resistance.

Mayne (2016) for variety of soil types, mainly clays and sands, found relationship to the sleeve friction ($R^2$ = 0.633). The peats and diatomaceous mudstone were also researched, but these results were not included in the regression analysis formula (2.4) [31]:

$$\gamma_t = \left[1.22 + 0.15\, ln\left(100\frac{f_s}{P_a} + 0.01\right)\right]\gamma_w \quad (2.4)$$

where:

$\gamma_w$ – unit weight of water, $P_a$ – atmospheric pressure.

### 2.4.2. Robertson & Cabal (2010) relationship

Robertson & Cabal (2010) proposed a general relationship for soil unit weight based on parameter from cone penetration tests for clays and silts to sands and gravels based on DMT tests and shear wave velocity in the following form (2.5) [32]:

$$\gamma_t = \left[\left[0.27\, log\, R_f + 0.36\, log\left(\frac{q_c}{P_a}\right) + 1.236\right]\frac{G_s}{2{,}65}\right]\gamma_w \quad (2.5)$$

where:

$R_f$ – friction ratio.

### 2.4.3. Ozer et al. (2012) relationships

Ozer et al. (2012) [33] proposed few models that were performed the method multiple linear regression generally for Lake Bonneville clays (USA). Two relationships with the highest degree of fit were selected by analysis, having: the cone resistance and the friction ratio $R^2$ = 0.80 (2.6), and the sleeve friction and the friction ratio $R^2$ = 0.790 (2.7). Additionally, included the atmospheric pressure and unit weight of water:

$$\gamma_t = 1.27\left(\frac{q_c}{P_a}\right)^{0.148}(R_f)^{0{,}0144}\gamma_w \quad (2.6)$$

$$\gamma_t = 2.495\left(\frac{f_s}{P_a}\right)^{0.147}(R_f)^{-0.132}\gamma_w \quad (2.7)$$

### 2.4.4. Ghanekar (2014) relationship

Ghanekar (2014) [34] used data taken for 16 offshore platform locations from the coast of Mumbai region. Generally, the subsoil was represented calcareous fine-grained soils, often by very soft and soft clays. The single and multi-variable regression analyses were performed on the data using basic parameters. The best, selected results of regression analysis described formula (2.8) ($R^2$ = 0.698):

$$\gamma_t = 4.08 - 0.521og(f_s) + 5.38\, log(q_c) - 2.59\, log(z) \tag{2.8}$$

### 2.4.5. Kovacevic et al. (2018) relationship

Kovacevic et al. (2018) [35] for highly overconsolidated soil come from five different sites in in Northern Croatia based on Mayne et al. [30] model presents new relationship ($R^2$ = 0.850), claiming that effectively reduces the magnitude of the original relationship to more closely approximate reality (2.9):

$$\gamma_t = 11.85 + 0.11\, log(z) + 2{,}591og(f_s) + 0.56\, log(q_c) \tag{2.9}$$

### 2.4.6. Straż (2016) relationship

Straż (2016) [36] for local polish organic soils (Rzeszow city) proposed dependencies based on measured values sleeve friction fs from CPTM, compared with measured values from laboratory tests. The correlations were developed for full spectrum organic soils: from low- to high-organic, according to the actual occurrence in the subsoil. The selected, obtained formula (2.10) ($R^2$ = 0.726) had the following form:

$$\gamma_t = 4.812 f_s^{0.265} \tag{2.10}$$

## 2.5. Artificial Neural Network

One of the most widely used tools for describing dependencies in geotechnics is standard regression. Presently, non-standard methods, including an artificial neural network and a fuzzy logic regression, have also been increasingly used as approximation tools. Moreover, the most common neural networks [37] used for approximation (nonlinear regression) are multi-layer perceptron (MLP), radial basis function (RBF) networks and support vector machines (SVM). The feedforward networks consist of a series of layers (Figure 1). The first layer has a connection from the network input. Each subsequent hidden layer has a connection from the previous layer. The final output layer generates the output from the network.

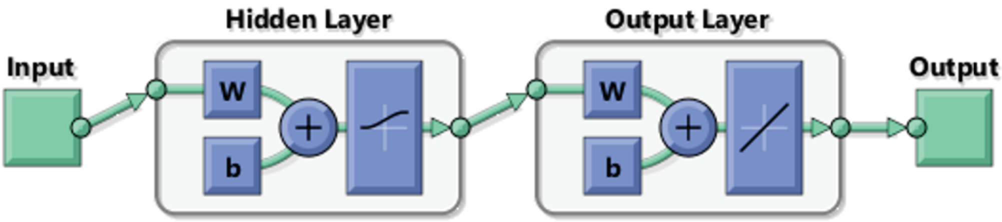



Fig. 1. Scheme of the artificial neural network: w – weights of connections between neurons, b – biases

The training network process requires a set of examples of proper network adjust (relations of parameter inputs and target outputs). The process of training a neural network involves changing the values of the weights and biases of the network to optimize network performance, as defined by the network error function. The default error function for feedforward networks is mean square error.

For training multilayer feedforward networks, any standard numerical optimization algorithm can be used to optimize the error function. Few of them have shown excellent performance for neural network training. These optimization methods use the gradient of the network performance with respect to the network weights or the Jacobian of the network errors with respect to the weights [38].

The Levenberg–Marquardt [39, 40] method generally is the fastest training method. The Broyden–Fletcher–Goldfarb–Shanno (BFGS) quasi-Newton [41] backpropagation method is also quite fast. This algorithm requires more computation in each iteration and more storage than the conjugate gradient methods, although it generally converges in fewer iterations. Both methods tend to be less efficient for large networks (with thousands of weights), since they require more memory and more computation time. The Bayesian regularization [42] algorithm requires more time, but it can result in good generalization for difficult, small or noisy data sets. The architecture of the networks used can be described as I-H-O, where I is the number of inputs, H is the number of neurons in the hidden layer and O is the number of neurons in the output layer. Mostly, the definition of the ANN uses several types of transfer (activation) functions: log-sigmoid, tangent sigmoid, hyperbolic radial basis and some linear.

In our numerical research all neural network computation was performed using the Neural Network Toolbox for Matlab [43]. In all the considered examples, a multilayer feedforward network with one hidden layer was applied. In inputs of nets, we consider two parameters, or one of them: the cone resistance $q_c$ and/or the sleeve friction $f_s$. The output of nets was soil unit weight of organic soils $\gamma_t$. In the calculations, five to eight neurons were used in the hidden layers. The Levenberg–Marquardt method was used in the training process. A log-sigmoid transfer function in the hidden layer and a linear function in the output layer were used.

## 3. Results

Based on the analysis of the exploratory research carried out in study area, research program was adopted, which assumed the search for relationships between the basic values measured from the CPTM test (cone resistance, sleeve friction) and the soil unit weight values of organic soils. The values of soil unit weight were verified by testing on undisturbed samples and predicted with existed models. Own solutions based on the results of multi regression and predictions using artificial intelligence were also proposed.

The diagram in Figure 2 presents the interpretation of cone penetration test for selected local soil conditions. The GEO5 program was used to interpret the construction of the subsoil [44].

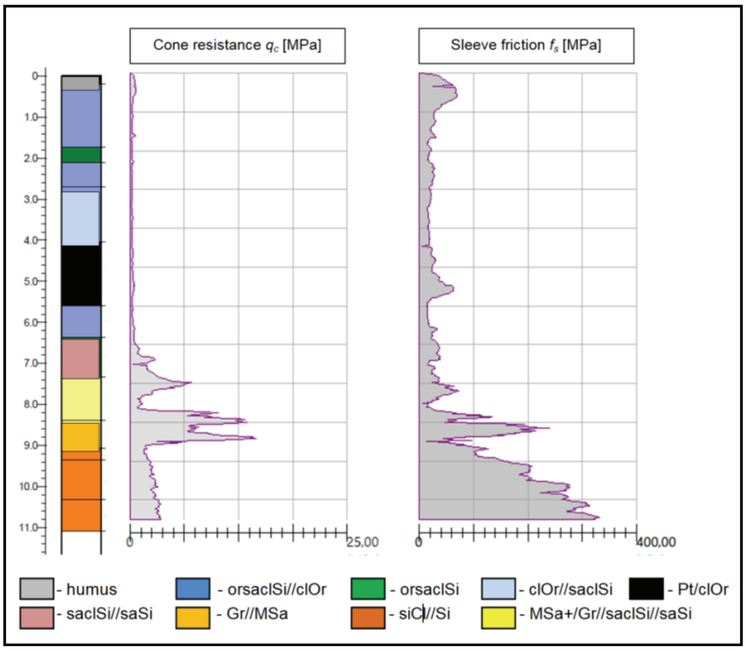



Fig. 2. The examples of results of organic and mineral soils probing with use of cone penetration test CPTM carried out in the selected subsoil of the Rzeszow site

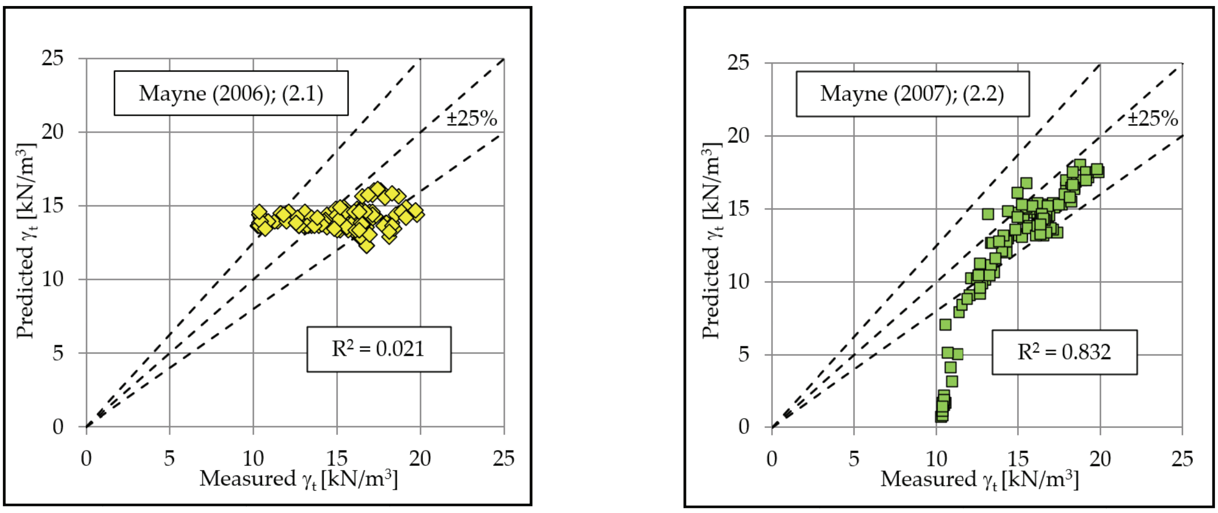
The basic values of parameters for local organic soils at the study at the Rzeszow site were determined and summarized in Table 1.

Table 1. Index properties of organic soils at the Rzeszow site

| Material | Organic Content (%) | Water Content (%) | Bulk Density (t/m$^3$) | Soil Unit Weight (kN/m$^3$) |
|---|---|---|---|---|
| Various organic soils | 5.02–84.93 | 23.52–417.91 | 1.046–2.025 | 10.27–19.86 |

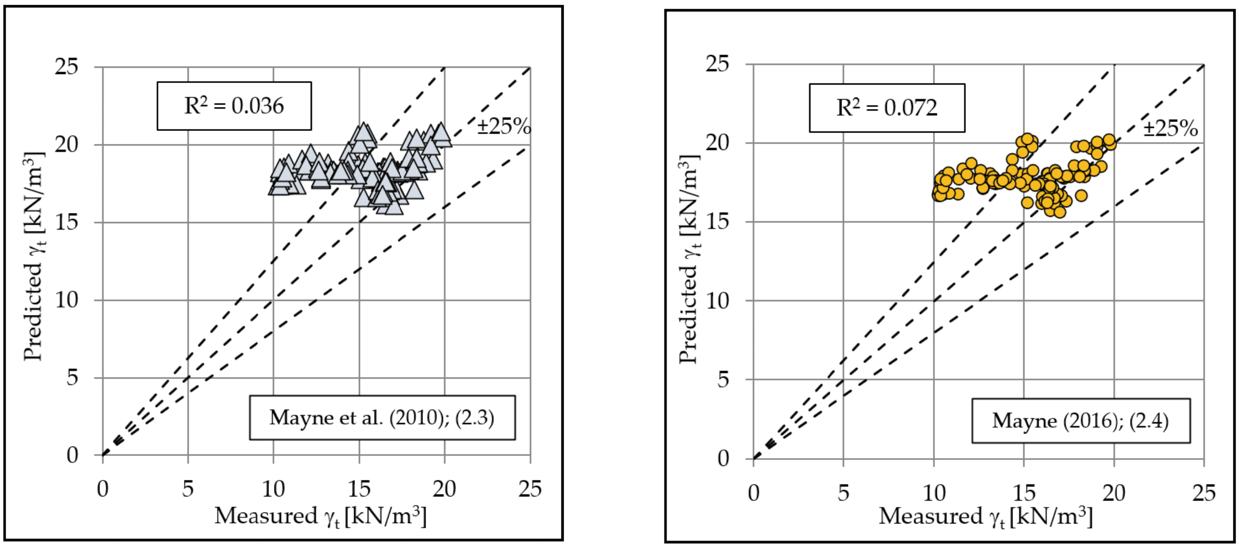
## 3.1. Results evaluation of the soil unit weight based on empirical relationships

The comparisons of the results of the soil unit weight from the regression models are presented in Figures 3–7. Unfortunately, predictive performance of published correlations presented modest relationship to the results of laboratory researches. Also, a kind of surprise was the fact that the results of previously pre-prepared model (Straż, 2016; (2.10)) [36] for selected Polish organic soils were also unsatisfactory (Figure 7b) in this case. The exception is only Robertson and Cabal (2010) model (2.5) presented on Figure 5a, because it fits into the error cone ±25%.



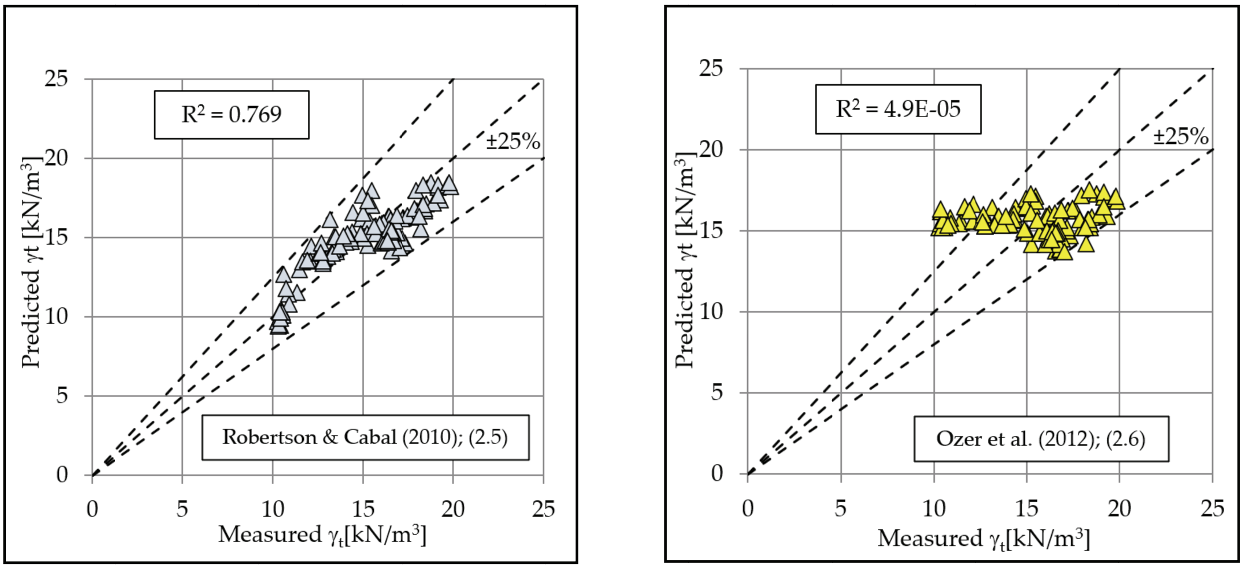

a) b)

Fig. 3. Comparison between measured values of soil unit weight and the values expected based on: a) Mayne, 2006 (2.1) and b) Mayne 2007 (2.2) models



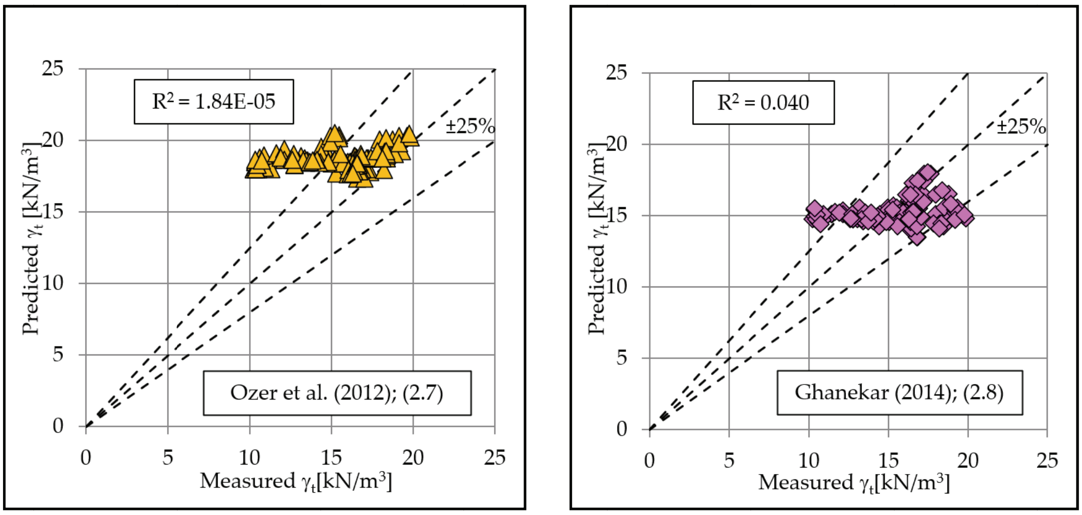

a) b)

Fig. 4. Comparison between measured values of soil unit weight and the values expected based on: a) Mayne et al., 2010 (2.3) and b) Mayne 2016 (2.4) models



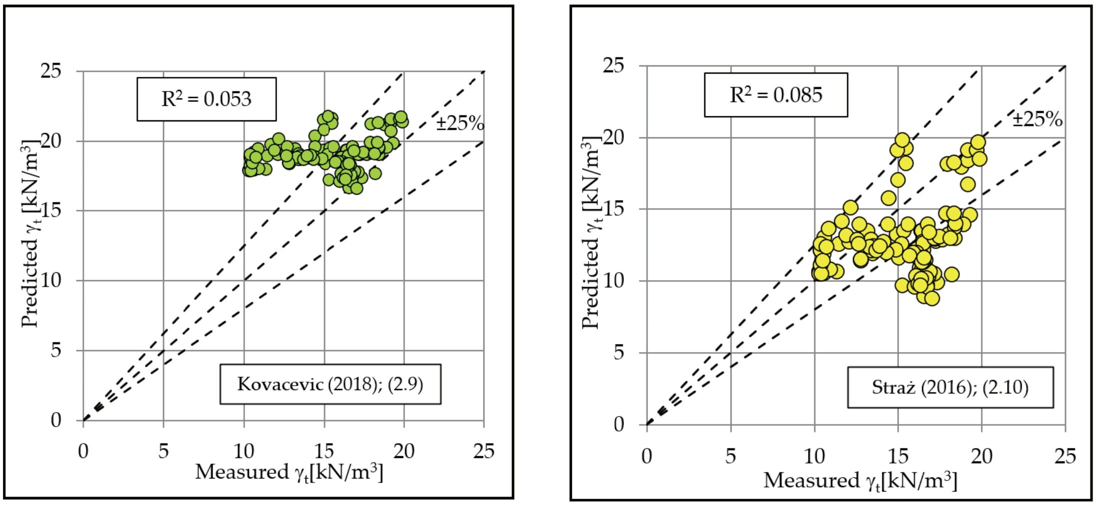

a) b)

Fig. 5. Comparison between measured values of soil unit weight and the values expected based on: a) Robertson & Cabal, 2010 (2.5) and b) Ozer et al., 2012 (2.6) models




a) b)

Fig. 6. Comparison between measured values of soil unit weight and the values expected based on: a) Ozer et al., 2012 (2.7) and b) Ghanekar, 2014 (2.8) models




a) b)

Fig. 7. Comparison between measured values of soil unit weight and the values expected based on: a) Kovacevic et al. 2018 (2.9) and b) Straż, 2016 (2.10) models

The Figures 3–7 shows the values of the determination coefficient $R^2$ for correlation between measured values of soil unit weight and the values expected based on Formulas 2.1–2.10. The best fit, $R^2$ = 0.832, was obtained for Formula 2.2, developed by Mayne (2007) and for Formula 2.5, $R^2$ = 0.769, described by Robertson and Caball (2010). The remaining values of the determination coefficient were very low, ranging from 1.84E-05 to 8.5E-02, which proves the extreme lack of fit for these models used (Formula 2.1, 2.3–2.4, 2.6–2.10) and eliminates them from consideration for the analysis of organic soils.

Comparison of the value of soil unit weight of local various, organic soils determined lab method and calculated with using 10 source formulas is shown in Figure 8. The diagram shows the median values, box with 50% all values (25–75%) and range of results from min to max values the soil unit weight determined by different methods are not similar to each other. The calculation results according to the Formulas 2.1, 2.3–2.4, 2.6–2.9 are in the narrowest range, the ranges according to the Formula 2.5, 2.10 and laboratory tests are also comparable. Extremely large discrepancy obtained calculation results were characterized by Formula 2.2.

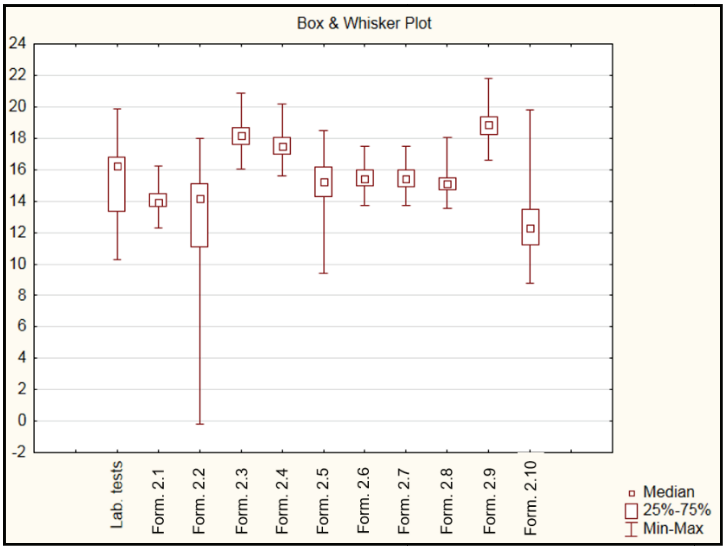



Fig. 8. The values of the median of soil unit weight of soil depending on the determination method by (Statistica 13.3) [45]

## 3.2. Own regression models

The following step after performing laboratory tests was to search for the relationships between the dependent (the soil unit weight $\gamma_t$) from laboratory tests and independent measured variables from cone penetration test (the cone resistance $q_c$, the sleeve friction $f_s$). Aim of our analyses is to compare the results of standard regression to the neural network regression approach in the problem of soil unit mass identification. This combination allows us to compare both regression methods and their approximation error. For this reason, a division of the entire set of 135 measurements into two groups (base – 70%, test – 30%) was assumed. Ninety-four of them were used as basic data to calculate the parameters of the regression fit function. The remaining 41 were used to test the predictions of the soil unit mass from the regression model with measured values. To determine the statistical evaluation during the analysis, the basic data set was randomly selected 250 times. Eight types of standard regression were used to approximate the experimental data. Firstly, four regression models of one variable were used: the two-parameter linear model (3.1), three-parameter polynomial model (3.2), two-parameter power model (3.3) and four-parameter power model (3.4):

$$F1(x) = p_1 + p_2 x \tag{3.1}$$

$$F2(x) = p_1 + p_2 x + p_3 x^2 \tag{3.2}$$

$$F3(x) = p_1 \mathrm{e}^{p_2 x} \tag{3.3}$$

$$F4(x) = p_1 \mathrm{e}^{p_2 x} + p_3 \mathrm{e}^{p_4 x} \tag{3.4}$$

where:

$F(x) = \gamma_t$ and $x = q_c$ or $f_s$

Additionally, the next four regression models of the two variables were used: the three-parameter surface model (3.5), five-parameter surface model (3.6, 3.7) and eight-parameter surface model (3.8):

$$F5(x,y) = p_1 + p_2 x + p_3 y \tag{3.5}$$

$$F6(x,y) = p_1 + p_2 x + p_3 y + p_4 x^2 + p_5 x^2 y \tag{3.6}$$

$$F7(x,y) = p_1 + p_2 x + p_3 y + p_4 y^2 + p_5 x y^2 \tag{3.7}$$

$$F8(x,y) = p_1 + p_2 x + p_3 y + p_4 x^2 + p_5 y^2 + p_6 x^2 y + p_7 x y^2 + p_8 x^2 y^2 \tag{3.8}$$

where:

$F(x) = \gamma_t$ and $x = q_c$ and $y = f_s$.

A total of 3000 models were included in the calculations. The goodness of fit was checked using the coefficient of determination (3.9), mean relative error (3.10) and mean squared error (3.11):

$$R^2 = 1 - \frac{\sum_{p=1}^{n}(d_p - y_p)^2}{\sum_{p=1}^{n}(d_p - \bar{d}_p)^2} = \frac{\sum_{p=1}^{n}(y_p - \bar{d}_p)^2}{\sum_{p=1}^{n}(d_p - \bar{d}_p)^2} \tag{3.9}$$

$$MRE = \frac{1}{n}\sum_{p=1}^{n}\left|\frac{d_p - y_p}{d_p}\right| 100\% \tag{3.10}$$

$$MSE = \frac{1}{n}\sum_{p=1}^{n}(y_p - d_p)^2 \tag{3.11}$$

where:

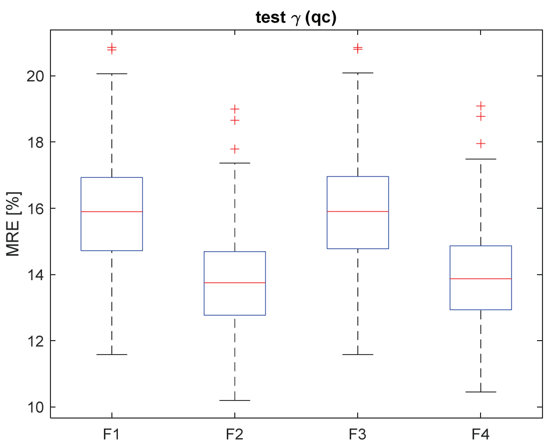
$n$ – number of cases, $d_p$ – measured values, $y_p$ – fitted values (predicted), $\bar{d}_p$ – mean of the measured values and $p = 1,2, ..., n$.

The comparison of the median of the goodness of fit obtained for the regression of the one variable model is presented in Table 2. The median is most important for reliable statistics because it is an outlier-resistant statistic. In our analyses, we do not use minimum error values because outliers may be caused by over-fitting of tested models. The best model obtained in the analyses was the polynomial model $F2$, using cone resistance. It has 13.75% of the median of mean relative error for testing the models. However, it has been shown that there is a very weak relationship between the variables included, as evidenced by the low value of the coefficient of determination ($R^2$). The relationship between the soil unit weight and cone resistance describes the coefficient value 0.167 and for dependence between the soil unit weight and sleeve friction the coefficient is similar an equal to 0.127.

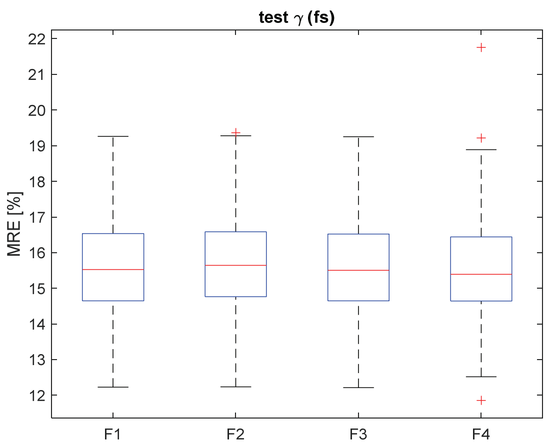
Table 2. The median of the goodness of fit for regression of the one variable models

| Soil parameter | | F1 | | F2 | | F3 | | F4 | |
|---|---|---|---|---|---|---|---|---|---|
| | | base | test | base | test | base | test | base | test |
| $\gamma_t (q_c)$ | $R^2$ | 0.001 | 0.009 | 0.182 | 0.167 | 0.002 | 0.009 | 0.181 | 0.161 |
| | MRE [%] | 15.57 | 15.90 | 13.43 | 13.75 | 15.57 | 15.90 | 13.51 | 13.87 |
| | MSE | 6.673 | 6.816 | 5.441 | 5.737 | 6.672 | 6.843 | 5.447 | 5.764 |
| $\gamma_t (f_s)$ | $R^2$ | 0.096 | 0.133 | 0.098 | 0.121 | 0.095 | 0.132 | 0.119 | 0.127 |
| | MRE [%] | 15.63 | 15.53 | 15.64 | 15.64 | 15.63 | 15.50 | 15.32 | 15.39 |
| | MSE | 6.054 | 5.946 | 6.046 | 6.034 | 6.056 | 5.963 | 5.868 | 5.958 |

The comparison of the MRE models, included in Table 2 for laboratory data, is presented using box-and-whisker diagrams in Figure 9. On each box, the central mark is the median, the edges of the box are the 25th and 75th percentiles, the whiskers extend to the most extreme data points, which are not considered outliers, and outliers are plotted individually.




a)




b)

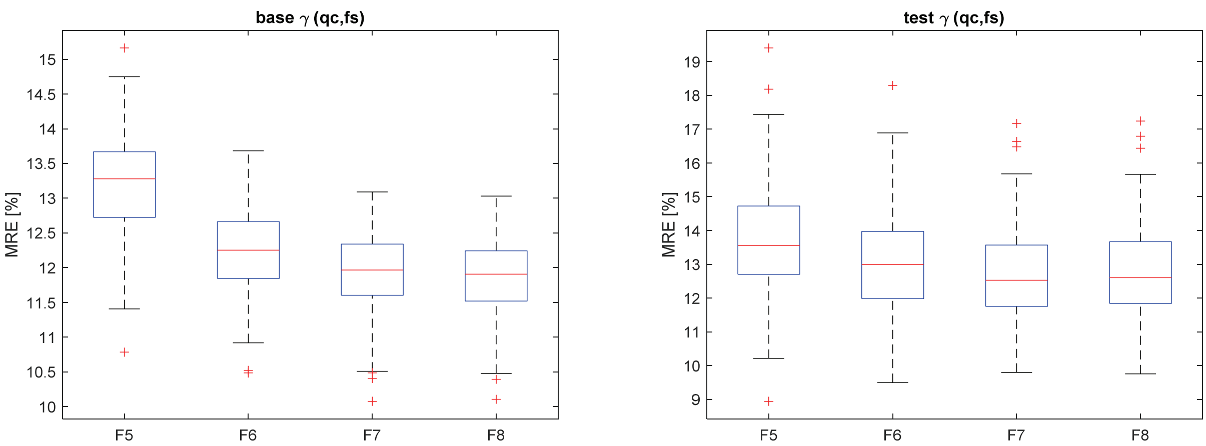
Fig. 9. Comparison of the MRE tested models ($F1$–$F4$): a) $q_c$ and b) $f_s$

Generally, better results using cone resistance were obtained. Table 3 presents a comparison of the median of the goodness of fit obtained for the two variables regression models (*F*5–*F*8). The best result was obtained for the *F*7 regression model. The multiple regression analysis developed in this study has proven that the models (*F*1–*F*4) and model (*F*5–*F*8) gave very similar value but didn't provide sufficiently accurate predictions of the soil unit weight value in relation to the results of laboratory tests for organic soils.

Table 3. The median of the goodness of fit for the regression of the two variables models

| Soil parameter | | *F*5 | | *F*6 | | *F*7 | | *F*8 | |
|---|---|---|---|---|---|---|---|---|---|
| | | base | test | base | test | base | test | base | test |
| $\gamma_t\,(q_c, f_s)$ | $R^2$ | 0.263 | 0.254 | 0.353 | 0.302 | 0.395 | 0.351 | 0.400 | 0.337 |
| | MRE [%] | 13.28 | 13.56 | 12.25 | 12.99 | 11.97 | 12.53 | 11.91 | 12.60 |
| | MSE | 4.908 | 5.223 | 4.334 | 4.807 | 4.047 | 4.393 | 4.017 | 4.514 |

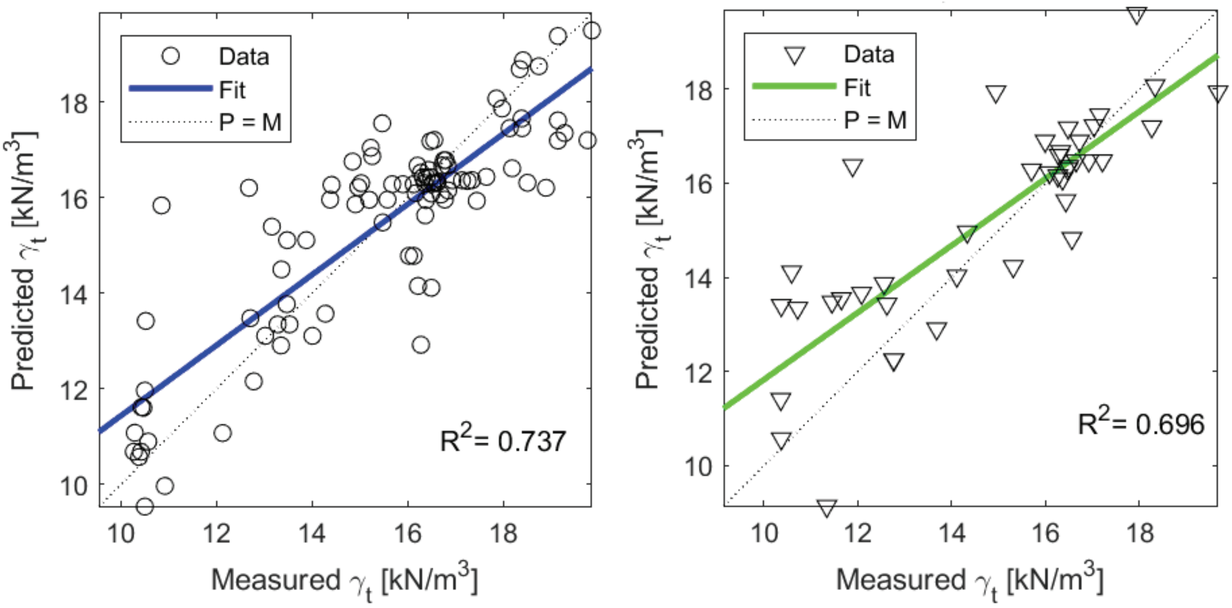
The comparison of the test results from the MRE of models are included in Table 3 for two laboratory parameters ($q_c$, $f_s$) are presented in Figure 10. The Figure 10a compares the results for the base data used to compute the regression fit parameters. Obtained medians of mean relative errors of base data were in the range of 11.91–13.28%. Respectively, the medians of MRE of test data were in the range of 12.53–13.56%. The Figure 10b shows the comparison statistical results of predictions of the soil unit weight. The model F6 had the least outliers.




a) b)

Fig. 10. Comparison of the MRE tested models (*F*5–*F*8): a) base $\gamma_t\,(q_c, f_s)$ and b) tested $\gamma_t\,(q_c, f_s)$

Figure 11 shows detailed results from the *F*7 model with two variables ($q_c$, $f_s$). The left-hand plot (Figure 11a), with the blue line, is related to the base data, and the right-hand plot (Figure 11b), with the green line, is related to the test data. The best prediction of standard regression had coefficients of determination equal 0.696.




a) b)

Fig. 11. Regression of the F6 model of soil unit weight ($q_c$, $f_s$): a) base data and b) test data

The evoked results excluded direct relationship between the measured and expected values and can't be used to estimate the desired of geotechnical parameter for foundation buildings or structures. Other alternative estimation methods should be tested to improve the match and reliability of results.

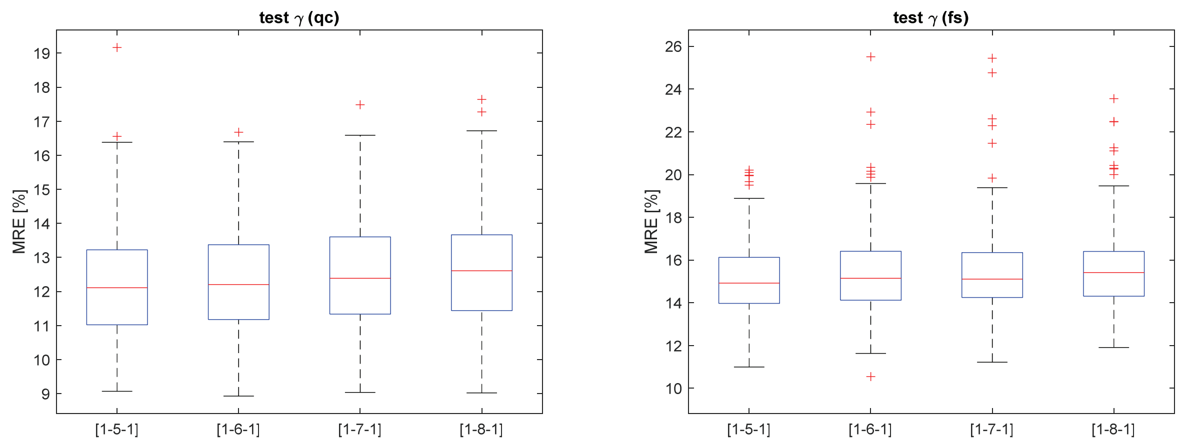
### 3.3. Artificial Neural Networks analysis

Next, a neural regression model was applied. In all the examples, standard multi-layer perception with one hidden layer was applied. In this case, the nets have only one element in the output vector (soil unit weight). The number of hidden neurons is obtained from a cross-correlation procedure. In the calculations, five to eight neurons were used in the hidden layers. The same pattern divided as that for the standard regression was used to learn and test the networks. The comparison of the median of the goodness of fit, obtained for a few architectures, is presented in Table 4.

Table 4. The median of the goodness of fit of the ANN models with one input

| Soil parameter | | [1-5-1] | | [1-6-1] | | [1-7-1] | | [1-8-1] | |
|---|---|---|---|---|---|---|---|---|---|
| | | learn | test | learn | test | learn | test | learn | test |
| $\gamma_t$ ($q_c$) | $R^2$ | 0.343 | 0.232 | 0.360 | 0.227 | 0.368 | 0.203 | 0.375 | 0.188 |
| | MRE [%] | 10.82 | 12.11 | 10.65 | 12.21 | 10.52 | 12.39 | 10.42 | 12.61 |
| | MSE | 2.092 | 2.319 | 2.066 | 2.344 | 2.053 | 2.372 | 2.038 | 2.413 |
| $\gamma_t$ ($f_s$) | $R^2$ | 0.262 | 0.140 | 0.283 | 0.120 | 0.299 | 0.121 | 0.311 | 0.104 |
| | MRE [%] | 13.38 | 14.92 | 12.92 | 15.15 | 12.73 | 15.11 | 12.51 | 15.42 |
| | MSE | 2.214 | 2.441 | 2.177 | 2.495 | 2.156 | 2.518 | 2.138 | 2.565 |

The presented results include the median obtained parameters for one element in the input vector. During the calculation of the values, 20 repetitions of the network training were considered for each of the 250 pattern divisions. In this way, 1000 nets learning results were performed for each ANN model. Better prediction was obtained, like that in the standard regression for cone resistance, in the input vector. A comparison of the MRE of the tested nets, included in Table 4, is presented in Figure 12.




a) b)

Fig. 12. Comparison of the MRE of the tested nets with one element in the input vector: a) $q_c$ and b) $f_s$

In this case, the network architecture does not affect the accuracy of approximation. Obtained medians of mean relative errors of testing using cone resistance were in the range of 12.11–12.61%. Respectively, the medians of MRE of testing using natural sleeve friction were in the range of 14.92–15.42% and had more outliers. In Table 5, the comparison of the median result, obtained for the nets with two elements in the input vector, is presented. In that approach, a better result was also obtained, like that in the standard regression with two independent variables. The medians of mean relative errors of testing using two parameters were in the range of 8.84–9.01%.

Table 5. The median of the goodness of fit of the ANN models with two input

| Soil parameter | | [2-5-1] | | [2-6-1] | | [2-7-1] | | [2-8-1] | |
|---|---|---|---|---|---|---|---|---|---|
| | | learn | test | learn | test | learn | test | learn | test |
| $\gamma_t\,(q_c, f_s)$ | $R^2$ | 0.705 | 0.564 | 0.739 | 0.550 | 0.767 | 0.541 | 0.783 | 0.532 |
| | MRE [%] | 6.92 | 8.97 | 6.37 | 8.84 | 6.04 | 8.94 | 5.70 | 9.01 |
| | MSE | 1.409 | 1.756 | 1.314 | 1.776 | 1.250 | 1.795 | 1.195 | 1.834 |

The comparison test results from the MRE of models, included in Table 5 for two laboratory parameters $\gamma_t$ ($q_c$, $f_s$), are presented in Figure 13. The left one (Figure 13a) compares the results for the learning nets. There is a visible improvement in the quality of learning for bigger networks in the range of 6.92–5.70%. The right one (Figure 13b) shows the results for the testing. There is no clear difference in the results. The obtained results for the two inputs are a little better, which is the opposite case for the nets with one input. The smallest median of mean relative error test of the ANN was equal to 8.84%.

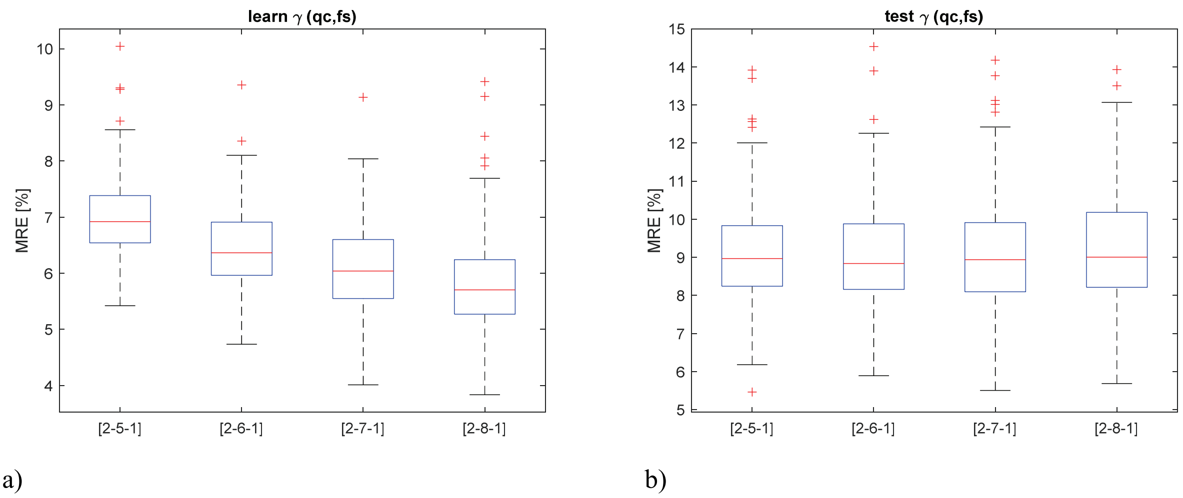
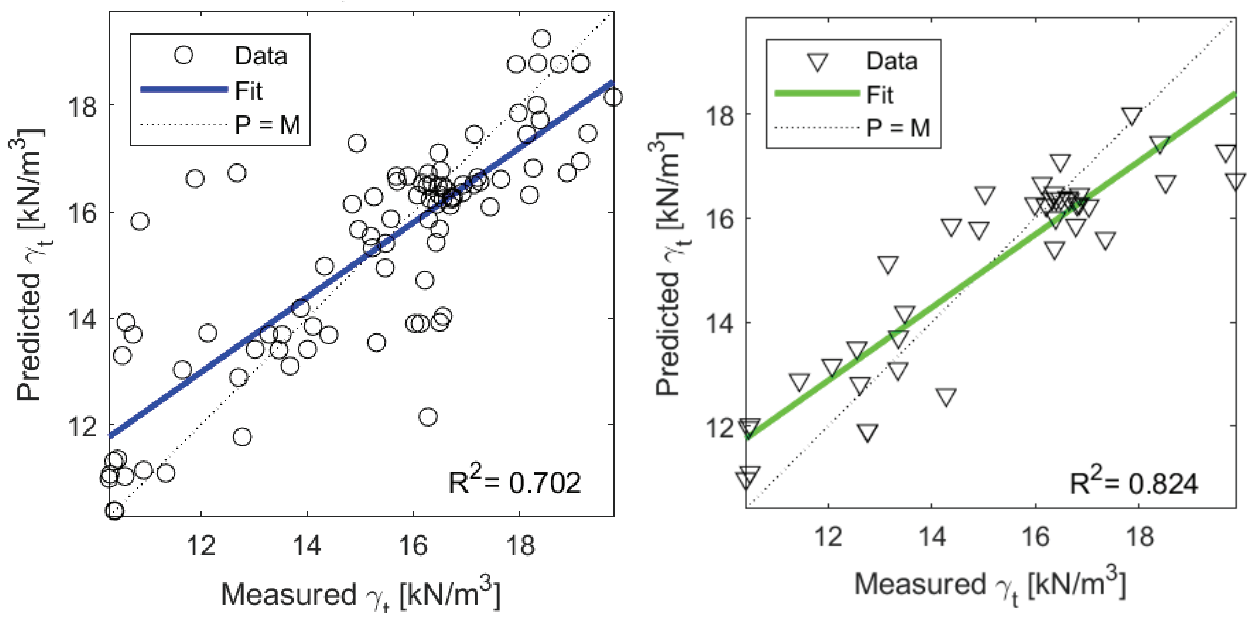



Fig. 13. Comparison of the MRE of the nets with two elements in the input vector: a) learned $\gamma_t\,(q_c, f_s)$ and b) tested $\gamma_t\,(q_c, f_s)$

Figure 14 shows detailed results for the ANN's prediction of the soil unit weight using two variables ($q_c$, $f_s$) in the input vector for one of the best predictions. Figure 14a shows learning data and Figure 14b shows the testing data. The coefficients of determination of testing was quite high 0.824 and the mean relative error of testing was 5.90% in this case.




a) b)

Fig. 14. Regression of the ANN prediction of soil unit weight $\gamma_t$ ($q_c$, $f_s$): a) learn data and b) test data

Generally, the use of neural networks has allowed the soil unit weight values to be predicted based on laboratory tests with poor accuracy. The ANN regression models are better than in the considered regression models. There were no clear difference results in respect the architecture of nets used. The best prediction neural networks were determined based on the lowest medians of mean relative error.

## 4. Conclusions

The results of prediction of values of the soil unit weight based on basic parameters of the mechanical cone penetration test (CPTM) carried out on existing models in the literature and standard regression models developed for the purposes of this study for Polish, local organic soils from the vicinity of Rzeszów were unsatisfactory and showed their low usefulness. Therefore, the use of standard neural networks was verified. Comparison of standard regression and neural networks to predict soil unit weight from the results of the cone penetration test indicates the neural networks are more accurate. The maximum median values of the coefficient of determination obtained were equal, respectively, to 0.353 and 0.564. The result of using neural networks is not satisfactory but very promising. The levels of predictive errors in geotechnics obtained in the analyses ware not such big, especially for very different organic soils. However, all methods of studying the geotechnical parameters of organic soils are burdened with large measurement uncertainties.

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## Wyznacznie ciężaru objętościowego gruntu organicznego na podstawie badań CPTM z zastosowaniem sztucznych sieci neuronowych

**Słowa kluczowe:** ciężar objętościowy gruntu, sztuczne sieci neuronowe, grunty organiczne, sonda stożkowa statyczna CPTM

### Streszczenie:

W artykule zaprezentowano możliwości zastosowania wyników badań terenowych uzyskanych za pomocą stożkowej sondy statycznej CPTM (ze stożkiem mechanicznym) do wyznaczania ciężaru objętościowego wybranych gruntów organicznych zlokalizowanych na terenie Rzeszowa. Głównym celem prowadzonych badań było poszukiwanie bezpośrednich zależności pomiędzy między wyznaczonymi w warunkach laboratoryjnych wartościami ciężaru objętościowego gruntu $\gamma_t$ a parametrami wiodącymi dla badania sondą statyczną CPTM, którymi są: opór gruntu podczas zagłębiania stożka $q_c$ oraz opór tarcia na tulei ciernej $f_s$. Testy laboratoryjne wykonano na próbkach o nienaruszonej strukturze, pobranych z otworów kontrolnych umiejscowionych w bezpośrednim sąsiedztwie punktów sondowania, co pozwoliło na pozyskanie reprezentatywnych próbek gruntów o szerokim spectrum zawartości części organicznych od 5,02 do 84,93%.

Wykorzystując metodę standardowej analizy regresji określono zależności między empirycznie wyznaczonymi wartościami ciężaru objętościowego badanych gruntów organicznych, a parametrami wyznaczonymi za pomocą sondy statycznej w warunkach *in situ*. Wykorzystano również szereg modeli literaturowych, opracowanych przez prezentujących je badaczy dla różnych ośrodków gruntowych i parametrów wiodących. Niestety, analiza regresji wykazała, że zarówno istniejące modele, jak i nowe są słabo dopasowane do wartości ciężaru objętościowego wyznaczonych w laboratorium. Głównym powodem może być fakt, że grunty organiczne charakteryzują się niezwykle skomplikowaną budową, różnorodną i niejednorodną strukturą, a przede wszystkim bardzo zróżnicowaną zawartością części organicznych, które mogą lokalnie różnić się genezą czy składem chemicznym. Czynniki te mają wpływ na wyjątkowo dużą rozbieżność i brak powtarzalności uzyskiwanych wyników w zadowalającym zakresie. Dlatego, dodatkowo, aby poprawić predykcyjne działanie zależności, przeprowadzono analizę z wykorzystaniem sztucznych sieci neuronowych (SSN).

Porównanie wyników zastosowania standardowej regresji i sieci neuronowych w celu prognozowania ciężaru objętościowego wybranych gruntów organicznych na podstawie wyników sondowania statycznego wykazało, że sieci neuronowe są dokładniejsze. Maksymalne wartości median uzyskanych w analizach statystycznych współczynników determinacji ($R^2$) testowanych modeli wynosiły odpowiednio 0,353 i 0,564. Wynik wykorzystania sieci neuronowych nie jest zadowalający, ale bardzo obiecujący. W związku z tym, planowana jest kontynuacja prac z wykorzystaniem analizy za pomocą sztucznych sieci neuronowych, lecz z zastosowaniem różnych kryteriów kategoryzowania lokalnych gruntów organicznych.

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