Computer Assisted Methods in Engineering and Science, **21**: 67–75, 2014.

Prediction of consistency parameters of fen soils by neural networks

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This paper presents application of artificial neural networks (ANNs) for prediction of consistency parameters (plastic limit, liquid limit) of fen soils in comparison with the standard regression analysis. All samples of cohesive soils were retrieved from the Wisłok river floodplain, in the vicinity of Rzeszów, near Lisia Góra (Fox Mountain) reserve. Basic fractions (clay, silt, sand) of fen soils are independent variables in modeling of soil properties. Two regression models and a standard multi-layer back-propagation net have been used.

Keywords: fen soils, granulation, plastic limit, liquid limit, regression, artificial neural networks.

1. Introduction

Determination of the bearing capacity of subsoil requires knowledge of the soil strength parameters. The standard way to determine the soil parameters is the use of direct research methods. In the case of less responsible buildings designed on a subsoil of simple structure it often seems reasonable to adopt basic soil parameters without performing complex analysis. Frequently, the geotechnical parameters are determined on the basis of correlation between physical and mechanical properties of the soil. This is why, it is necessary to research the relationships between different soil parameters in order to make the soil geotechnical identification faster and cheaper. This is very important for design of new structures, and, above all, it also facilitates verification of the substrate quality during execution of construction work.

2. The problem of subsoil diagnosis accuracy

The examination of geotechnical parameters is often costly, complicated and time-consuming. The accuracy of subsoil diagnosis for construction purposes is not always the same. It depends on the classification of the project to an adequate geotechnical category. This classification is based on the type (capability) of the structure to be built and on the complexity of the substrate. In many cases, it is sufficient to determine soil parameters on the basis of correlative relationships. However, these relationships must concern the material of similar genesis and physical characteristics. From the economic point of view it is most reasonable to reduce subsoil diagnosis and the necessary investigations. The range of investigations can be minimized in two ways:

- reduction of the range of types of investigation,
- reduction of the number of tests of the same kind.

Establishing the correlative relationships between the parameters describing the soil is conducive for the first limitation, particularly when the parameters are determined by complex, costly and time-consuming exploration methods. In the second case, it is important to enable the interpolation of intermediate values of the parameters. Values that are predicted for conditions are slightly different than those occurring during the tests. The correlations are not always possible to be described by simple functions. With increased complexity of the equations it becomes more difficult to determine the intermediate parameter values, which often significantly reduces possibility of their application in engineering practice (during the actual construction process). There are also problems with the correctness of the interpolation of the values described by such functions in the ranges for which the input data base was limited or even not existent. Some of the issues described above can be overcome by use of artificial neural networks.

3. Factors influencing on the soil properties

The properties of subsoil depend on many factors present at the time of its formation. It is not possible to describe particular soils with the same parameters, nor are the given parameters equally essential for the characteristics of specific types of substrate. The soil specificity must be considered. In the case of coarse-grained soils, their granulometric composition, having taken into account the density of clastic material, affects almost directly the mechanical parameters. In the case of fine-grained soils, their strength and strain characteristics are decided by more complex dependencies [17]. The factors that have the greatest influence on the parameters of cohesive soils include:

- soil granulation,
- soil natural water content with reference to the water content of consistency limits (particularly liquid limit LL and plastic limit PL),
- genesis and load history (conditions of soil sedimentation and consolidation, or the effect of additional geological processes shaping the substrate, as well as the mineralogical composition).

Determination of the pre-consolidation stress value is a very difficult problem (if it is at all possible), because the evidence of loads in the past is unknown. Indirect ways of finding this value are the current subject of research of many scientific centers. Similarly, we have no certainty about the formation conditions of the soil and geological processes that have shaped them, etc. Consistency itself does not reflect exactly the properties of cohesive soils, or their physical properties. Consistency limits are nominal water contents, and they allow classification (and unification) of fine-grained material with plastic characteristics [3, 6, 9]. The values of consistency limits mainly depend on soil granulation (especially clay fraction content). Other very important factors are mineralogical composition (also exchangeable ions), particle shapes and possible content of organic matter. In many cases the influence of these additional determinants can be decisive [3, 6]. It should be emphasized, that the complicated relationships between these factors have not so far allowed for an explanation and clear description of their significance. In addition to the above, a significant effect of the methodologies of determining consistency limits and testing material preparation should be indicated [9]. Due to the complexity of the issues presented above, for engineering and scientific purposes, some of the factors, whose significance is difficult to determine and which require intricate study, are disregarded. Then, the conclusions from the performed analysis must be limited to the soils of similar characteristics. The relationships between granulation and consistency limits have been repeatedly the subject of scientific research, obviously in relation to specific soil conditions [1, 6–11, 18]. The publications cited above are often concerned with subsoils of considerable heterogeneity, higher than the material analyzed by the authors. The results of geotechnical investigations have already been presented by the author and published [17]. Therefore the conclusions included in the work will not apply to the geotechnical analysis as such, but will focus on the possibility of using other than standard tools, that is artificial neural networks to describe the dependencies in question.

4. Investigated material

The paper presents the dependencies identified during fen soil testing. The fen substrate is the result of riverine accumulation, i.e., the deposit of disintegrated rock material during floods on the area of floodplain terraces [4, 7]. The test samples of cohesive soils were retrieved from Wisłok river floodplain, in the vicinity of Rzeszów, near Lisia Góra (Fox Mountain) reserve. The samples were excavated from different depths.

The analysis of fen soil granulation has produced an image of a considerable diversity of the subsoil even within a single test site. In the basic research area there were found soils of low and medium cohesion of characteristics shown in Fig. 1. Feret's triangle shows a trend of increasing content of the silty fraction with increasing amounts of clay fraction. The content of organic matter determined by the oxidation method was on average 1.73% [17]. The total of 58 soil samples taken from different depths differed in particle size and water content, and consequently liquidity index IL.

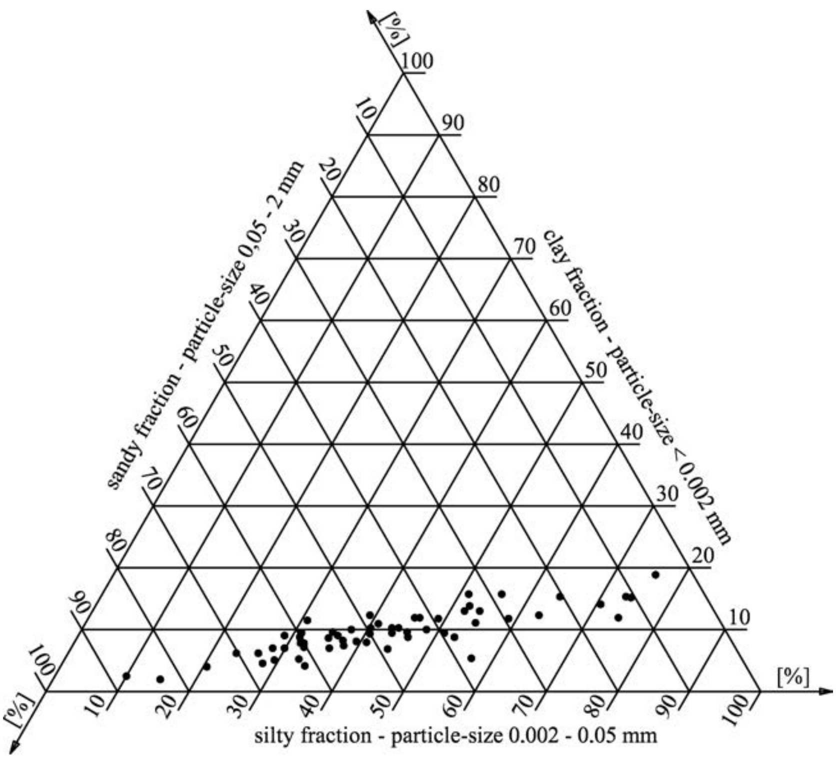

Fig. 1. Granulation of fen cohesive soils from the Wisłok River floodplain in Rzeszow, near Lisia Góra (Fox Mountain) reserve.

5. Methodology of soil parameters determination

5.1. Granulation investigation

Grain composition is one of the main factors affecting the physical and mechanical properties of soils as particulate materials. However, the determination of their particle size can be quite a troublesome job, especially if the soils contain a significant amount of undersized fractions. The determination of clay fraction content requires a time-consuming aerometric analysis, or the use of advanced and expensive opto-electronic measuring equipment. But these devices do not fully reflect the shape and size of tested particles, due to only two-dimensional analysis. Areometric analysis is the primary method of testing particle size of cohesive soils. The size of soil particles is here estimated based on the velocity of their fall in water. Soil fine particles form a suspension, whose density decreases with time due to sedimentation of soil particles. The largest particles fall the fastest and the process of sedimentation is longer for smaller particles. Unfortunately, areometric analysis takes more than 24 hours, which is a drawback. Measurements themselves are quite cumbersome and subjective because it is the researcher who takes both the measurements and readings, so they depend on his/her personal intuition. The process of samples preparation for analysis is also very complex. It is therefore clear that the omission of such procedures can be most desirable in many situations.

5.2. Consistency investigation

Another important physical parameter that describes the suitability of cohesive soils for construction subgrade is the liquidity index IL or consistency index IC. The value of these parameters (directly related) can be determined after the consistency limits: plastic limit PL and liquid limit LL, constant for a given soil, have been determined. Methods of investigation of these parameters are relatively simple. The plastic limit PL is determined by a manual method, by rolling a sample (a small ball) of soil. In this way, the soil water content is defined at which the soil loses plasticity features. The moment at which these features are lost (the moment of the soil specimen destruction) is subjectively assessed by the researcher. The liquid limit LL is determined using Casagrande apparatus. In this test, the water content level, at which the edges of the groove previously made in the soil paste are joined, is determined. The soil paste is placed in a special bowl and is shaken after the groove has been made (the bowl hits against the base of apparatus at a given frequency). The liquid limit is the level of water content at which the groove edges are joined following 25 impacts. Determination of this value also partly depends on the manual skill and subjective perception of the researcher. The research methodologies presented previously used for the determination of some soil parameters are unsatisfactory. In these cases, the application of indirect methods is more important. It includes the determination of the functional dependence of correlation between soil parameters, as well as non-standard methods including the use of artificial neural networks. The application of ANNs in modeling the relationship between selected physical properties and particle size of non-cohesive soils was recently investigated by Sulewska [13].

6. Regression analysis

Regression analysis is a statistical tool commonly used for determination of the relationships between variables obtained from experimental investigations. It covers many techniques for modeling and analyzing variables, particularly when the focus is on the dependence between a dependent variable and one or more independent variables which can be measured. First, the linear regression was taken into account. The linear least squares method was used for estimating of the unknown parameters of linear regression.

The analyzed data set was taken from the laboratory results reported in Wilk's Ph.D. dissertation [16]. For all the 58 data sets there were specified basic fractions (clay f_{cl}, silt f_{si}, sand f_{sa}) and corresponding consistency parameters (plastic limit, liquid limit). Next, all data sets were divided into two groups. One group, consisting of 46 sets, was used for the computation of the parameters of regression function. The other 12 sets were used for validation of the accuracy of regression, comparing the forecast results with those actually measured. The division into groups was done randomly. The level of accuracy was checked by root-mean-square error:

$$RMSE = \sqrt{\frac{1}{P}\sum_{p=1}^{P}(t_p - y_p)^2}\,; \tag{1}$$

and determination coefficient R^2 (R – regression coefficient):

$$R = \frac{\sum\limits_{p=1}^{P} \left(t_p - \bar{t}_p\right)\left(y_p - \bar{y}_p\right)}{\sqrt{\sum\limits_{p=1}^{P} \left(t_p - \bar{t}_p\right)^2 \sum\limits_{p=1}^{P} \left(y_p - \bar{y}_p\right)^2}}, \tag{2}$$

where P denotes the number of data, y denotes the predicted results, t denotes the measured values and $\bar{t}$, $\bar{y}$ are mean values. Figure 2 shows one of the possible divisions. Here the regression was used to plastic limit PL estimation based on silt fraction f_{si}. The green line denotes the regression function, the blue circles present the base data while the red triangles show the forecast vales. Figure 3 shows detailed results. The left-hand plot, with the blue line, is related to base data and

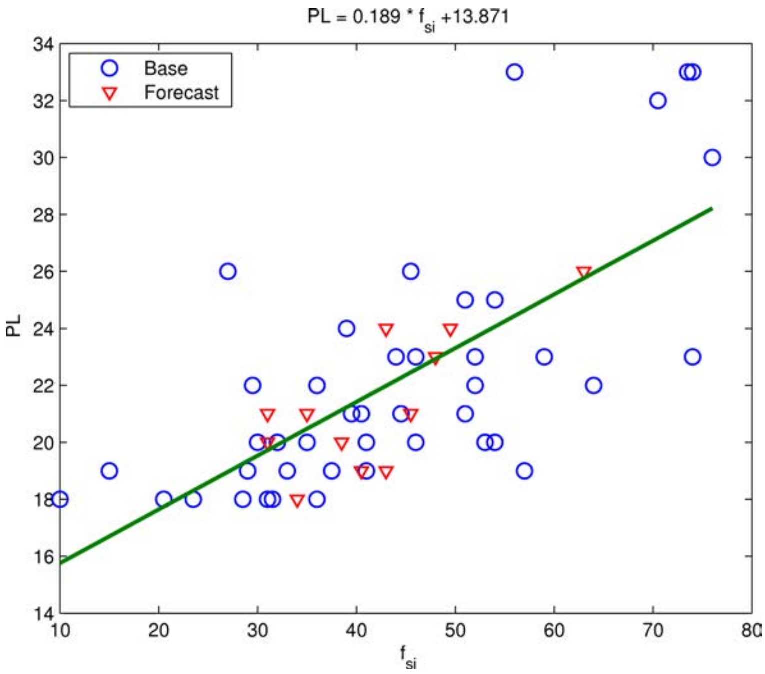

Fig. 2. Linear regression of plastic limit.

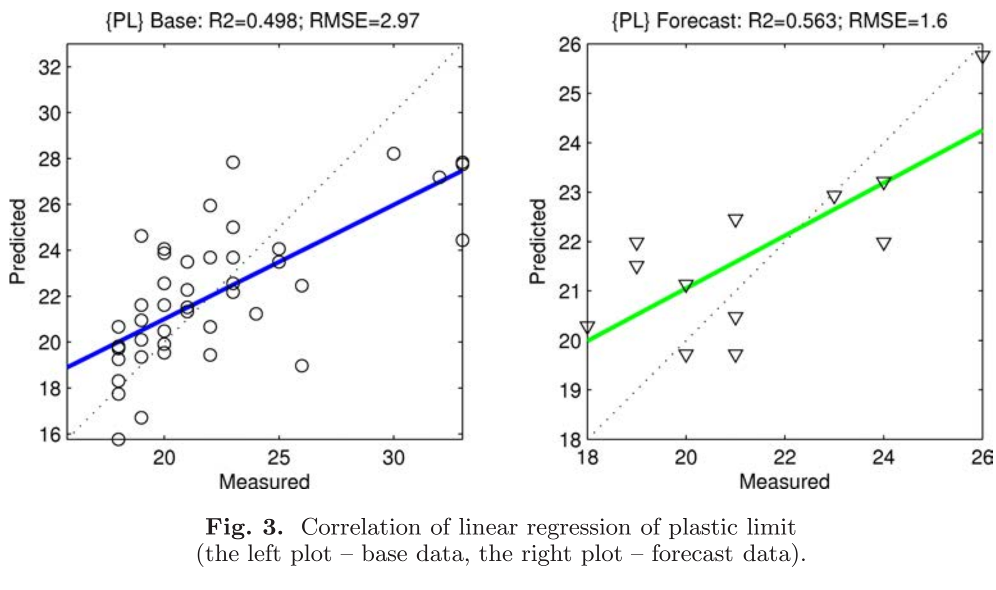

Fig. 3. Correlation of linear regression of plastic limit (the left plot – base data, the right plot – forecast data).

the one on the right, with the green line, is related to the forecast data. All the pairs of variables were verified in regression modeling, respectively: $PL(f_{cl})$, $PL(f_{si})$, $PL(f_{sa})$, $LL(f_{cl})$, $LL(f_{si})$ and $LL(f_{sa})$. The determination coefficients obtained for the linear and polynomial regression have been compared in Table 1. The second order polynomial regressions were used. After the analysis of 120 random sets of data better results were found for the polynomial regression. Generally, the best correlation was obtained using sand fraction.

Table 1. Comparison of determination coefficient R^2 for linear and polynomial regression.

Model regressions	Fen soils parameters	Base data			Forecast data		
		f_{cl}	f_{si}	f_{sa}	f_{cl}	f_{si}	f_{sa}
Linear	Plastic Limit	0.548	0.498	0.534	0.380	0.563	**0.602**
	Liquid Limit	0.787	0.655	0.715	0.521	0.528	0.506
Polynomial	Plastic Limit	0.613	0.550	0.605	0.399	0.595	0.601
	Liquid Limit	0.813	0.678	0.750	0.498	0.521	**0.570**

7. Neural network model

In recent years the application of ANNs in structural mechanics and civil engineering including geotechnics [5, 12, 13] has expanded. ANNs have turned out [14, 15] to be an efficient tool in analysis of classification and regression problems. This paper shows application of the ANNs in comparison with standard regression method. All neural networks computation were performed using neural network toolbox for Matlab [2]. In all the examples a standard multi-layer perceptron (MLP) with one hidden layer was applied and the Levenberg-Marquardt algorithm was used in training process. The architecture adopted herein can be described as $I - H - O$, where I is the number of inputs, H the number of neurons in the hidden layer, O their number in the output layer. The number of hidden neurons was obtained as a result of a cross-correlation procedure. In most cases, 4 or 5 neurons in hidden layers were used. The pattern set was taken from the laboratory results [16]. The set of data (pattern) was composed of $P = 58$ patterns on the base of granulation and consistency limits analysis of the fen soils. As in standard regression approach, in each case $L = 46$ patterns ware selected for learning, and the remaining $T = 12$ patterns were considered for testing. In all the examples a comparison of root-mean-square error $RMSE$ and determination coefficient R^2 were made. The input vector covers clay fraction, silt fraction and sand fraction $X = \{f_{cl}, f_{si}, f_{sa}\}$. The output vector of this ANN can be described by plastic limit or/and liquid limit $Y = \{PL, LL\}$.

First, the application of networks with only one element in input and output vector $(1 - H - 1)$ was examined. This approach corresponds to the simple linear regression (one dependent variable and one explanatory variable). The comparison of the determination coefficients obtained for the ANN prediction has been presented in Table 2. In comparison with Table 1, the prediction has improved when based on silt fraction f_{si}. When the focus is on the linear part of regression, a better prediction of liquid limit was obtained by ANNs. Figure 4 illustrates the detailed ANN based results. The left-hand plot, with the blue line, is related to learning data and the one on the

Table 2. Comparison of determination coefficient R^2 for ANN prediction with one element in input vector.

Net arch.	Outputs	Learning			Testing		
		f_{cl}	f_{si}	f_{sa}	f_{cl}	f_{si}	f_{sa}
1-H-1	Plastic Limit	0.659	0.601	0.642	0.450	0.572	**0.588**
1-H-1	Liquid Limit	0.819	0.700	0.754	0.536	**0.599**	0.539

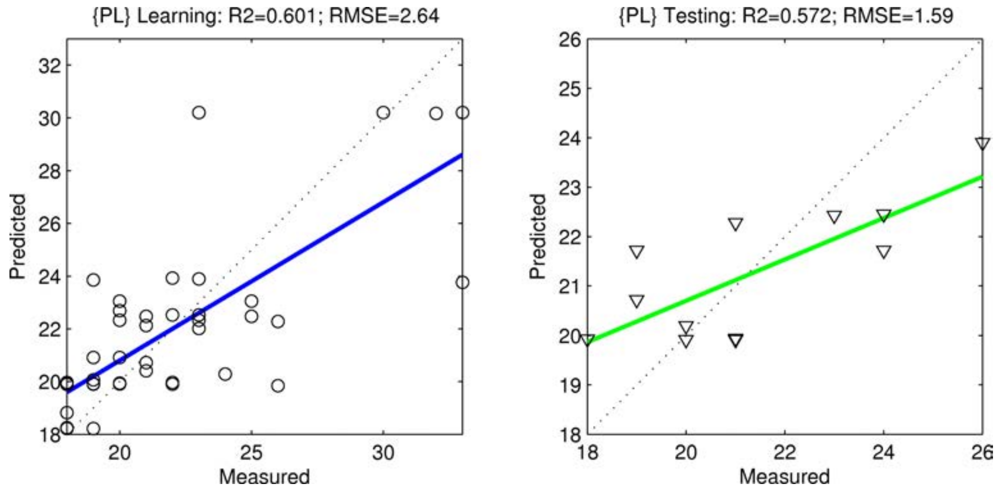

Fig. 4. Correlation of ANN prediction of plastic limit (the left plot – learning data, the right plot – testing data).

right, with the green line, is related to the testing data. The results may be compared to the results shown in Fig. 3 based on regression. The obtained results were very similar.

Next, the application of networks with two elements in input vector and one or two elements in output vector $(2 - H - 1(2))$ was checked. This approach corresponds to the multiple regression. This approach clearly shows (see Table 3) an improvement of neural network based prediction of fen soil parameters. The two last lines of the table show the results of one network for two separate outputs. The majority of results were improved compared with those in the previous table. The best results were obtained using input vector $X = \{f_{cl}, f_{sa}\}$.

Table 3. Comparison of determination coefficient R^2 for ANN prediction with two elements in input vector.

Net arch.	Outputs	Learning			Testing		
		$\{f_{cl}, f_{si}\}$	$\{f_{cl}, f_{sa}\}$	$\{f_{si}, f_{sa}\}$	$\{f_{cl}, f_{si}\}$	$\{f_{cl}, f_{sa}\}$	$\{f_{si}, f_{sa}\}$
2-H-1	{Plastic Limit}	0.770	0.782	0.708	0.479	0.534	0.556
2-H-1	{Liquid Limit}	0.928	0.854	0.884	0.633	0.624	0.560
2-H-2	{Plastic Limit,	0.749	0.722	0.753	0.604	**0.625**	0.603
2-H-2	Liquid Limit}	0.882	0.851	0.844	0.638	**0.650**	0.600

Finally, a network with three element in input and one or two elements in output vector $(3 - H - 1(2))$ was verified. The comparison of the determination coefficient R^2 obtained for the ANN prediction has been presented in Table 4. The two last lines of the table show the results of one

Table 4. Comparison of determination coefficient R^2 for ANN prediction with three elements in input vector.

Net arch.	Outputs	Learning	Testing
		$\{f_{cl}, f_{si}, f_{sa}\}$	$\{f_{cl}, f_{si}, f_{sa}\}$
3-H-1	{Plastic Limit}	0.725	**0.552**
3-H-1	{Liquid Limit}	0.890	**0.665**
3-H-2	{Plastic Limit,	0.811	0.520
3-H-2	Liquid Limit}	0.850	0.635

network for two separate outputs. In this approach, the prediction of liquid limit was found improved while the prediction of plastic limit was found worse.

8. Conclusions and final remarks

On the basis of the performed analysis it can be stated that:

- trained artificial neural networks are able to predict consistency parameters of fen soils with acceptable error,
- parameter prediction based on ANNs is improved in comparison with that based on standard linear regression,
- generally, liquid limit was better predicted by ANNs,
- the approach with two inputs and outputs net $(2 - H - 2)$, which produced the most favorable results, seems very promising.

Obviously, future works should take into account robust regression and rejection of outlier data, which in geotechnical exploration is justified in view of subgrade non-homogeneous structure.

Acknowledgements

Numerical experiments were conducted with the use of MATLAB application, purchased during the realization of project no. UDA-RPPK.01.03.00-18-003/10-00 "Construction, expansion and modernization of the scientific-research base at Rzeszów University of Technology" co-financed by the European Union from the European Regional Development Fund within Regional Operational Programme for the Podkarpackie Region for the years 2007–2013, I. Competitive and innovative economy, 1.3 Regional innovation system.

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