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Applying Artificial Neural Networks for analysis of geotechnical problems

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The paper presents a discussion of some applications of Artificial Neural Networks (ANNs) in geo-engineering using the analysis of the following six geotechnical problems, related mainly to prediction and classification purposes: 1) prediction of Overconsolidation Ratio (OCR), 2) determination of potential soil liquefaction, 3) prediction of foundation settlement, 4) evaluation of piles bearing capacity, 5) prediction of compaction parameters for cohesive soils, 6) compaction control of embankments built of cohesionless soils. The problems presented are based on the applications of the Multi-Layered Perceptron (MLP) neural networks.

Keywords: geotechnical problems, artificial neural networks (ANNs), Multi-Layer Perceptron (MLP), Overconsolidation Ratio (OCR), bearing capacity of piles, settlement of foundation, soil liquefaction, compaction control.

1. Introduction

The present study contains a review of selected applications of Artificial Neural Networks (ANNs) in geotechnical engineering, where they appeared to be useful in the analysis of various problems. The literature references indicate that ANNs have been successfully used to solve very important geotechnical problems. From among many problems the following ones were selected: a) 3D material characteristics, b) modelling unsaturated soils behaviour under static and dynamic loadings, c) modelling pressure-deformation curves $\boldsymbol{\sigma}$-$\boldsymbol{\varepsilon}$ for statically and dynamically loaded soils. In particular: ANNs have also been applied in: d) analysis of slope stability assuming a circular or wedge failure mechanism, e) evaluation of the geotechnical parameters on the base of mineral composition for classification of soils referring to their particle size or structure, f) prediction of hydraulic conductivity of cohesive soils, g) density and compaction parameters of various soil types or other properties, for description of suction, collapse potential, and lateral pressure phenomena, h) modelling subsoil-building interaction during mining shocks, i) evaluation of measurement uncertainties, etc. The list of references related to application of ANNs in geotechnics is included in [14].

The aim of the paper is to discuss the possibilities of ANN applications in geotechnics in the analysis of six geotechnical problems, solutions related to prediction and classification purposes, listed in the abstract of this paper. The most representative publications are discussed in [14]. In the present paper all the neural network support applications were related to the Multi-Layered Perceptron (MLP), see Haykin [18], of architecture MLP: D-H-M, where: D – number of inputs, H – number of hidden neurons, M – number of outputs.

2. Measures of errors

The models were evaluated on the basis of the analysis of the following error measures calculated separately for learning and testing data sets:

- Root Mean Squared Error:

$$\mathrm{RMS}_i = \sqrt{\frac{1}{P}\sum_{i=p}^{P}(t_i^{(p)} - y_i^{(p)})^2}, \tag{1}$$

where $t_i^{(p)}$, $y_i^{(p)}$ are target and neurally computed i-th outputs ($i = 1, \ldots, M$) for p-th pattern ($p = 1, \ldots, P$);

- Mean Absolute Error:

$$\mathrm{MAE}_i = \frac{\sum\limits_{p=1}^{P}\left| t_i^{(p)} - y_i^{(p)} \right|}{P}; \tag{2}$$

- Maximum of Absolute Relative Error:

$$\mathrm{MARE}_i = \max(\mathrm{RE}_i^{(p)}); \tag{3}$$

- Relative Error can be defined as:

$$\mathrm{RE}_i^{(p)} = \left| \frac{t_i^{(p)} - y_i^{(p)}}{t_i^{(p)}} \right| 100\%; \tag{4}$$

- Mean Relative Error:

$$\mathrm{MRE}_i = \frac{1}{P}\sum_{p=1}^{P}\mathrm{RE}_i^{(p)}; \tag{5}$$

- Regression coefficient R_i (and determination coefficient R_i^2):

$$R_i = \frac{\sum\limits_{p=1}^{P}(t_i^{(p)} - \overline{t}_i)(y_i^{(p)} - \overline{y}_i)}{\sqrt{\sum\limits_{p=1}^{P}(t_i^{(p)} - \overline{t}_i)^2 \sum\limits_{p=1}^{P}(y_i^{(p)} - \overline{y}_i)^2}}, \tag{6}$$

where $\overline{t}_i$, $\overline{y}_i$ are mean values of sets $\{t_i^{(p)}\}$ and $\{y_i^{(p)}\}$.

3. Examples of ANN application in geotechnics

3.1. Prediction of Overconsolidation Ratio (OCR)

The ANN was applied in the analysis of results from studies carried out on clays. The Piezocone Penetration Test (PCPT) was applied in order to model the pressure history in the soil, which was characterized by means of Overconsolidation Ratio (OCR) [6]. The OCR is the ratio of the maximum past vertical effective stress in a soil in the past σ'_p to the existing effective overburden stress in a soil σ'_v. The OCR is a parameter that characterizes the strength, stress-strain behaviour, and the compressibility characteristics of cohesive soils. It is determined in a laboratory during a durable oedometric test using undisturbed soil samples collected in the field.

A set of 195 study results from intact (165 results), and fissured (30 results) clay deposits, in soil ranging from soft, normally consolidated clays to very stiff, heavily overconsolidated clays, were collected. 63% of the data were selected to learn the network, while the remaining 37% were used to test the network. The ANN inputs were composed of variables achieved from the field surveys applying Piezocone Penetration Test basing on the following quantities:

1. q_t – the corrected cone resistance;
2. σ_{v0} – total vertical overburden pressure;
3. u_1 – pore water pressure at the cone tip;
4. u_2 – pore water pressure measured just above the cone base;
5. u_0 – the hydrostatic pore water pressure.

The only output of the ANN is the OCR value from laboratory studies performed in oedometer.

Three neural networks were formulated: MLP1 – network tested by all the data related to intact and fractured clays, MLP2 – trained network, using only data for intact clays, and MLP3 – network using data only for fissured clays. It was found that MLP2 and MLP3 became specialised, i.e. predicted the OCR values. They were specified for intact and fissured clays better than MLP1 that was trained for all data.

The comparison of the OCR prediction quality (within the set of testing data) by neural as well as empirical and theoretical models (developed by various authors on the basis of Piezocone Penetration Testing) is presented in Table 1.

Table 1. Mean OCR values achieved using particular methods [6].

Model	Ratio of OCR value predicted by a model to OCR value from the test			
	Intact clays		Fissured clays	
	Average	Standard deviation	Average	Standard deviation
MLP1 5-8-1	1.07	1.00	1.37	1.46
MLP2 5-8-1	**1.00**	**0.44**	–	–
MLP3 5-5-1	–	–	1.28	1.09
Tumay et al. [17]	2.00	1.77	1.30	0.96
Sully et al. [16]	1.32	0.97	1.61	1.67
Mayne [7]: OCR = $f(u_1)$	2.70	2.49	2.17	2.14
Mayne [7]: OCR = $f(u_2)$	1.52	1.32	2.17	2.60
Chen and Mayne [2]: OCR = $f(u_1)$	1.04	0.97	0.71	0.66
Chen and Mayne [2]: OCR = $f(u_2)$	0.97	0.67	0.80	0.83

It can be seen that for intact clays, MLP2 was the best model. Considering fissured clays on the basis of Chen and Mayne's models [2], the OCR values are predicted with some deficiency in relation to the standards from oedometer test. The MLP3 predicted the OCR values with some excess compared with oedometric standards.

3.2. Determination of potential soil liquefaction

Liquefaction results from seismic vibrations, mainly in loose and hydrated sands. The phenomenon is caused by the loss of compressive strength due to the increase of hydraulic pressure within pores. Prediction of soil liquefaction is difficult because there are many critical factors influencing liquefaction.

Artificial Neural Networks were applied to evaluate the probability of soil liquefaction [4]. They aimed at classifying the soil either as liquefied or non-liquefied one. The probability of soil liquefaction was tested on the basis of sand tests applying Standard Penetration Test (SPT) and adopting the results from other seismic surveys. A set of 85 cases was analysed, including 42 cases representing liquefied soils, while the phenomenon of soil liquefaction was not recorded in remaining cases. The networks were learned and tested using 59 and 26 patterns, respectively.

The best neural network consisted of the following eight inputs:

1. σ_0 – total vertical stress;
2. σ'_0 – effective vertical stress;
3. M – the intensity of earthquake;
4. $(N_1)_{60} - N_1$ is standardised energy for driving energy in drill rods for 60% of the theoretical free-fall energy of a SPT hammer;
5. a/g – peak horizontal acceleration at soil surface;
6. τ_{av}/σ'_0 – equivalent dynamical shear stress;
7. F – percent % of fines content;
8. D_{50} – mean diameter of particles.

Two optional responses were adopted as the outputs: 1 – when the soil was liquefied, or 0 – when no soil liquefaction was recorded. Two error classifications resulted from the tests of the network, which were carried out for the relative error 7.7%. It suggested that neural networks could have a high success ratio at evaluating the potential soil liquefaction.

3.3. Prediction of foundation settlement

The problem of foundation settlement computation is very complex and noised by a great uncertainty. Thus, many authors started with the application of ANNs.

A set of 189 measurements of shallow foundation settlements was completed for the settlement of foundation on non-cohesive soils [13] in order to apply and verify ANNs. 80% and 20% of measurements were selected for the learning and testing data sets, respectively. The following interval data were accepted as input variables in particular ranges:

1. width of foundation footing $B = 0.8$–60.0 m;
2. pressure transferred to the soil by foundation footing $q = 18.3$–697.0 kPa;
3. mean number of hits per 30 cm of the SPT probe to the depth equivalent to $2B$ below the founding level and characterizing the soil compaction $N_{30} = 4$–60;
4. footing geometry $L/B = 1.0$–10.5, where L is foundation footing length;
5. footing embedment $D_f/B = 0.0$–3.4, where D_f is founding depth.

The measured settlement $S_m = 0.0$–121.0 mm was the only network output.

The optimizing process resulted in the MLP: 5-2-1 network. The foundation settlement was calculated according to Meyerhof's [8], Schulze and Sherif's [11], as well as Schmertmann's et al. equations [10]. Comparison of results obtained by MLP vs. traditional equations [8, 10, 11] (within the subset of validation data) revealed quite high predictive quality of the neural network against the formulas used (Table 2 and Fig. 1).

The results demonstrate the prevailing role of the neural model over the traditional methods. It was found that the foot foundation settlement can be predicted by ANN with acceptable precision (MAE = 8.78 mm).

Table 2. Comparison of settlement prediction methods [13].

Error measures	ANN 5-2-1	Meyerhof [8]	Schultze and Sherif [11]	Schmertmann et al. [10]
R^2	0.819	0.160	0.518	0.637
RMS [mm]	11.04	25.72	23.55	23.67
MAE [mm]	8.78	16.59	11.81	15.69

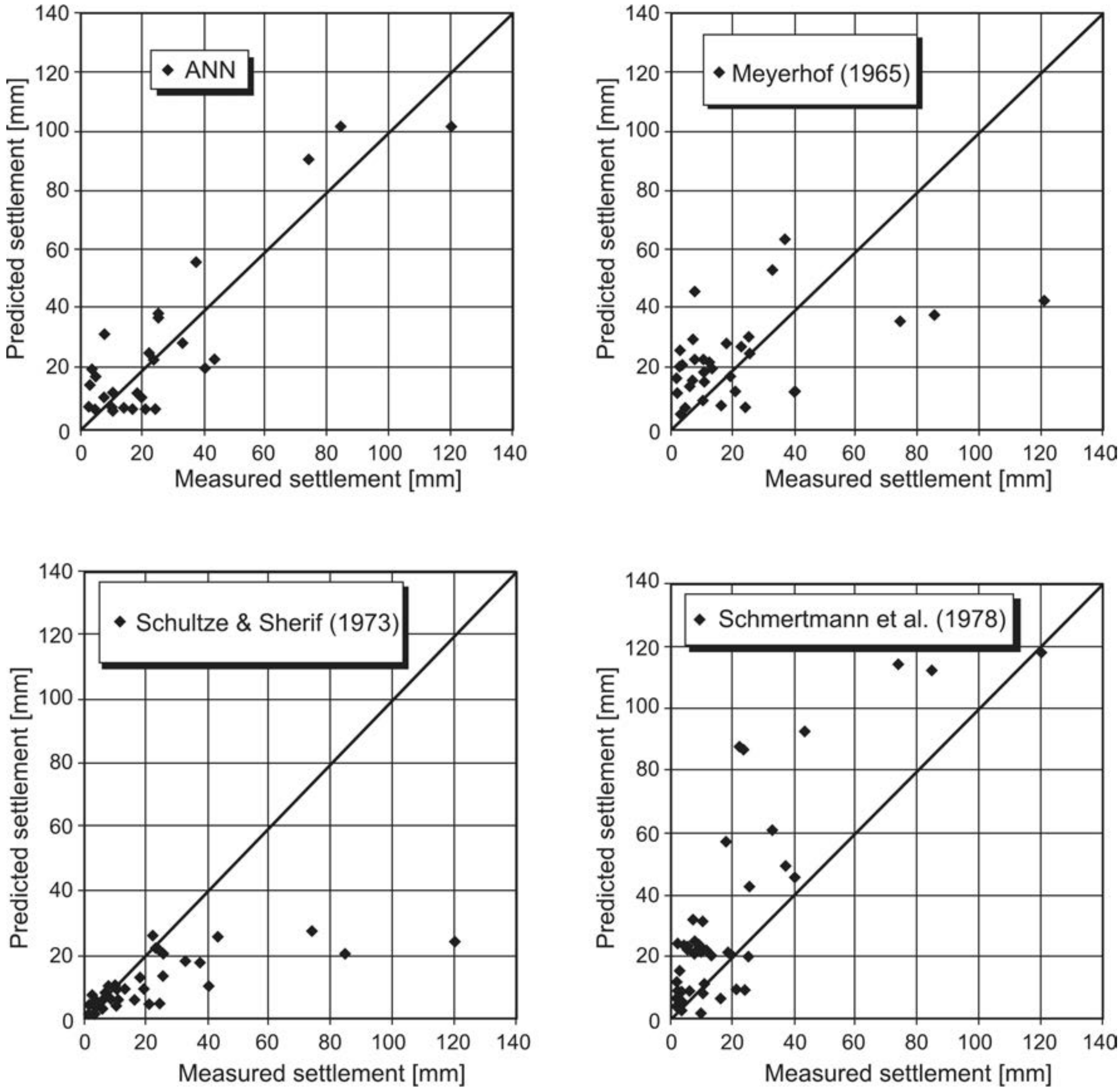

Fig. 1. Settlement values – measured and predicted according to analyzed methods [13].

3.4. Evaluating bearing capacity of piles

From among numerous solutions of pile bearing capacity evaluation, a practical example of neural networks application for the analysis of information obtained from empirical data was presented in [3]. ANNs were applied to evaluate friction capacity f_s on a side surface of timber and steel pipe driven piles. The driven piles were immersed in soft and very soft clays. The following data were collected:

1. embedded pile length $L = 4.7–96.0$ m;
2. pile diameter $D = 13.5–76.7$ cm;
3. vertical component of mean effective stress $\sigma'_v = 19–718$ kPa;
4. undrained shear strength was determined mainly from unconfined compression test or from Vane Shear Test $s_u = 9–335$ kPa;
5. friction capacity from compression tests of piles $f_s = 8.0–192.1$ kPa.

The data completed of 45 and 20 tests were selected, respectively, for the training and testing of neural networks.

Prediction results of friction capacity f_s for four best models with a variable number of inputs, three neurons in hidden layer and a single output are shown in Table 3. They are compared with results f_s obtained by means of conventional methods discussed in [1, 12].

Table 3. Comparison of methods for evaluating the f_s values [3].

Model	Input variables of ANN	R		RMS	
		Learning	Test	Learning	Test
MLP2: 2-3-1	s_u, σ'_v	0.985	0.936	1.049	1.267
MLP2A: 2-3-1	s_u, L	0.857	0.944	2.909	2.326
MLP3: 3-3-1	s_u, L, σ'_v	0.981	0.956	1.162	1.278
MLP4: 4-3-1	s_u, L, D, σ'_v	0.985	**0.956**	1.016	**1.194**
Method acc. to Semple and Rigden's [12]	–	0.976	0.885	1.318	1.894
Method β acc. to Burland's [9]	–	0.731	0.704	4.824	3.096

The comparison of f_s values predicted by MLP4 network with the standards from studies is presented in Fig. 2. The figure illustrates that using MLP4 the bearing capacity of piles f_s can be better predicted than applying conventional methods (Figs. 2–4). This is confirmed by a higher regression coefficient and lower value of RMS error, as well as insignificant scatter of results around the $y = x$ diagonal line.

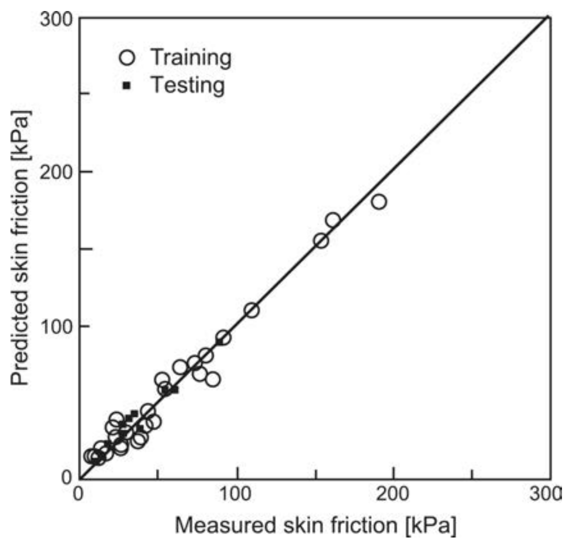

Fig. 2. Skin friction f_s – comparison of values predicted by MLP4 with standards from measurements [3].

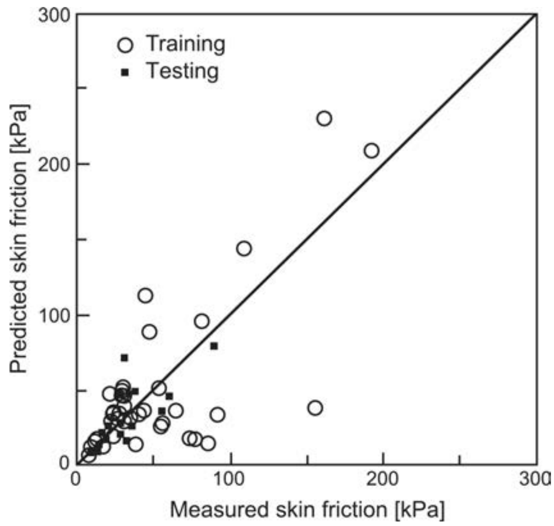

Fig. 3. Skin friction f_s – comparison of values calculated according to Semple and Ridgen's method with standards from measurements [3].

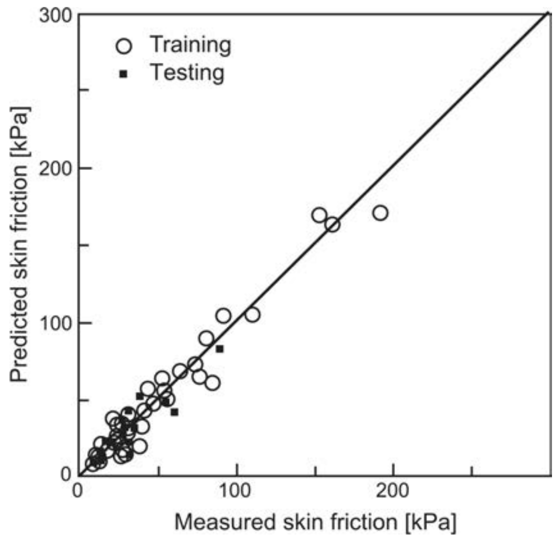

Fig. 4. Skin friction f_s – comparison of values calculated according to β method with standards from measurements [3].

3.5. Prediction of compaction parameters for cohesive soil

It can be stated that in case of cohesive soils evaluation of compaction parameters, i.e. the Optimum Moisture Content (OMC) and the Maximum Dry Density (MDD), by their measurements is highly labour- and time-consuming. Therefore, a simplified approach for evaluating compaction parameters on the basis of empirical models, was investigated in [9] applying ANNs.

Different neural models were analysed in [9] basing on the Standard Proctor's Tests to evaluate the OMC and MDD parameters. The database of laboratory tests for 39 cohesive soils prepared artificially (described by 13 variables) and data from 85 different natural soils surveys (described with 5 variables) was completed. Six and twenty patterns from among the collected data were selected for testing. The best neural models adopted for compaction parameters, corresponding to the most important input variables, as well as their MARE error evaluation corresponding to testing data are presented in Table 4. Evaluation of MLP2: 3-1-2 network for natural soils was presented in Fig. 5. The network exploitation was performed using the new set of 27 data for worldwide natural soils, which confirmed quite high predictive usefulness of the model (Fig. 6).

Table 4. Selected neural models built for artificially prepared and natural soils [9].

Soils	ANN model	Inputs	Outputs	MARE [%]
Artificially prepared	MLP1: 6-4-2	C, S, Sd, G_s, LL, PL	OMC; MDD	11.49; 2.51
Natural	MLP2: 3-1-2	G_s, LL, PL	OMC; MDD	6.26; 2.52

Explanations: C is bentonite content (%), S is silt content (limestone particles with diameter ranging from 0.002 to 0.047 mm) (%), Sd is sand content (sand particles with diameter ranging from 0.074 to 4.76 mm) (%), G_s is specific density solid particles (g/cm^3), LL is liquefaction limit according to Casagrande (%), PL is plasticity limit (%), OMC (%), MDD (pcf, where 1 pcf = 1.016 g/cm^3).

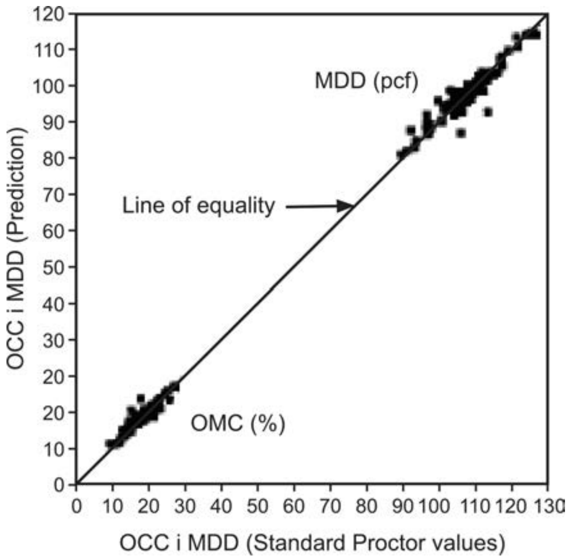

Fig. 5. Comparison of OMC and MDD values tested for 85 natural soils with those predicted by MLP2 [9], where 1 pcf = 0.016018 g/cm^3.

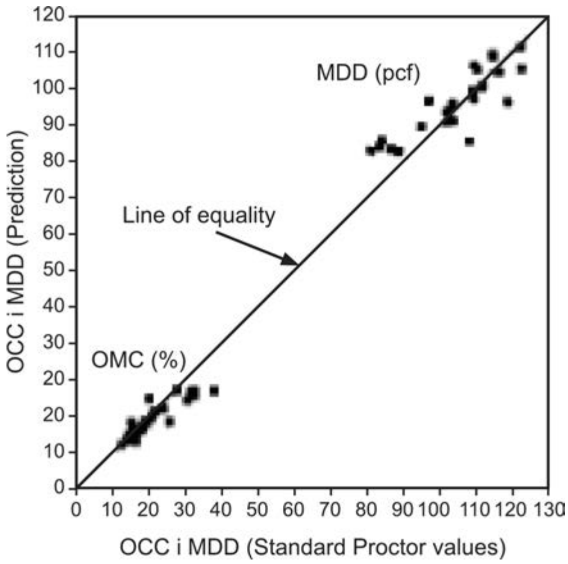

Fig. 6. Comparison of OMC and MDD values tested and predicted by MLP2 for new set of 27 natural soils [9].

3.6. Compaction control of embankments built of non-cohesive soils

The Light Falling Weight Deflectometer (LFWD) is one of the field instruments for controlling the compaction of non-cohesive soils built into the surface layers of embankments. It is applied to determine the dynamic deformation modulus E_D. In order to determine the quality of embankment compaction applying LFWD, earlier prepared curves of the instrument calibration are used (i.e. dependence between E_D vs. soil compaction measures such as: density index I_D or degree of compaction I_s).

Non-linear dependence of E_D vs. I_D and I_s, as well as the bulk density of soil ρ was studied by means of the data set completed of 36 measurements for medium sand and 45 measurements for gravel and sandy gravel [5]. In order to solve the problem, neural network MLP: 3-5-1 architecture was applied and the results were compared with those from simple linear regression approach, quoted in [15]. The comparison of E_D prediction for medium sand, MLP and regression results is presented in Figs. 7 and 8.

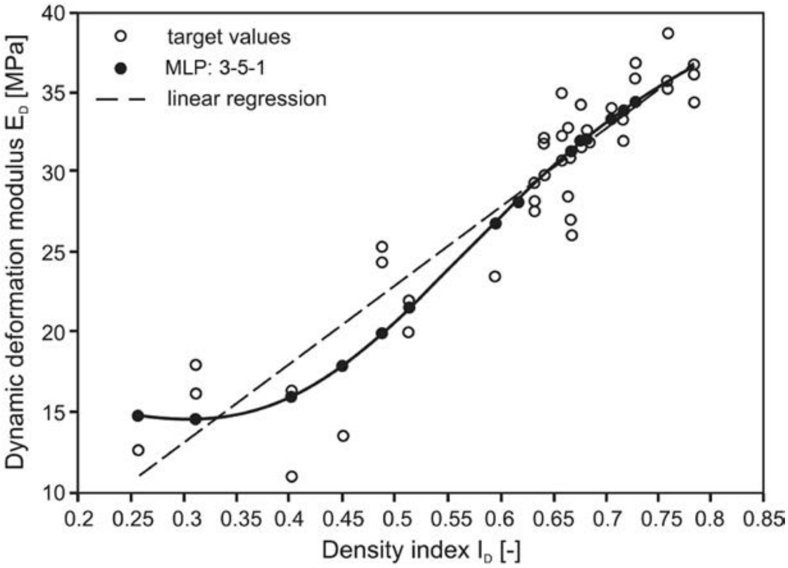

Fig. 7. Dependence $E_D = f(I_D)$ for medium sand [5].

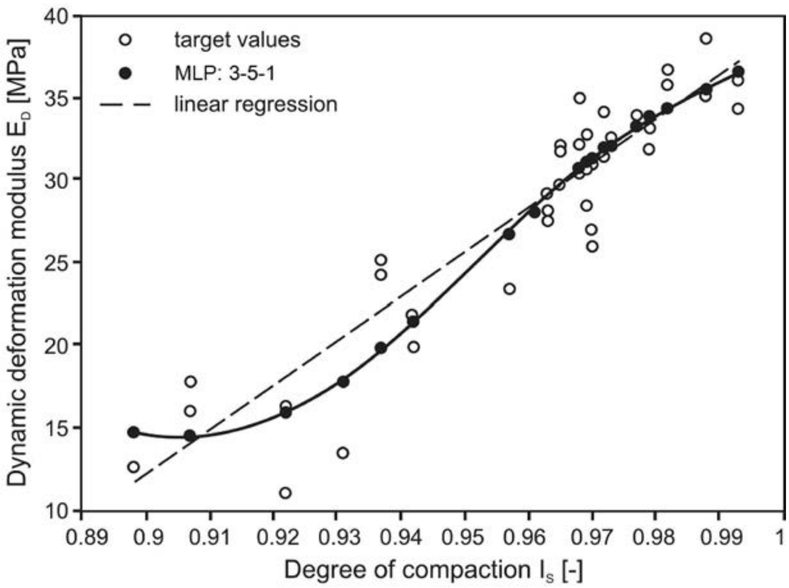

Fig. 8. Dependence $E_D = f(I_s)$ for medium sand [5].

The evaluation of the quality of particular prediction methods is illustrated in Table 5. It shows that the precision of E_D prediction by means of ANN is superior to the linear regression method.

Table 5. The error measures for Artificial Neural Network and regression method [5, 15].

Error measures	MLP: 3-5-1	Regression method		
	$E_D = f(I_s, I_D, \rho)$	$E_D = f(I_s)$	$E_D = f(I_D)$	$E_D = f(\rho)$
MRE [%]	9.094	10.794	10.521	14.474
MARE [%]	46.033	65.380	64.874	109.494
R	0.937	0.923	0.925	0.861

4. Conclusions

1. All the examples described above prove that Artificial Neural Networks can be efficiently applied for solving many geotechnical problems.

2. ANNs approach can be recommended particularly for cases when theoretical process modelling does not yield expected results, or when some difficulties arise in the application of the statistical standard methods.

3. Contemporary methods of theoretical modelling have their constraints resulting from incomplete knowledge of the process or phenomenon understanding. This can affect the complexity or defects of theoretical analytical tools. Some parameters, influences or effects are neglected in theoretical models, which is a consequence of simplifications and idealisation of the phenomena described. In turn, data sets for statistical analysis have to be as large as possible and should be characterised by their high quality. Sets of data and statistical analyses have to meet many assumptions, e.g. related to variable distribution normality, however, they are not always met.

4. ANNs are empirical models that have to adopt not so strong assumptions as standard statistical methods. New and original solutions obtained by means of ANNs applications are constantly growing. However, an insufficient number of cases for training and testing the ANN can be a remarkable limitation for ANNs applications.

5. The number of regression type problems in geotechnics, successfully analysed by ANNs, is constantly increasing. In the paper, only the Multi-Layered Perceptron type neural networks are discussed. There are many problems for which other standard ANNs can be successfully applied. The application of fuzzy-neural networks and the Bayessian inference methods seem to be very promising in the future analysis of geotechnical problems, cf. supplementary paper [19].

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