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PEDOTRANSFER FUNCTION FOR DETERMINING SATURATED HYDRAULIC CONDUCTIVITY USING ARTIFICIAL NEURAL NETWORK (ANN)

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Abstract. In the work there were presented two pedotransfer models for determination of saturated hydraulic conductivity, generated by artificial neural networks (ANN). Models were learned based on empirical data obtained in laboratory, on 56 soil samples of differentiated texture. In the first model the input parameters were: characteristic diameters d_{10}, d_{50}, d_{60}, d_{90}, content of sand, silt and clay fractions, total porosity, bulk density and organic matter content. The MLP type of ANN was used. The best fitted model turned out MLP 10-10-1 with satisfactory quality parameters, for learning 0,996, for testing 0,754 and for validation 1,000. Global sensitivity analysis showed that the highest influence on explanation of relationship between saturated hydraulic conductivity in this model had: clay content (absolute influence 37.7%, d_{60} (17.1%), sand content (13.5%), d_{90} (6.0%), bulk density (5.9%) and total porosity (5.7%). The remaining parameters had absolute influence below 5.0%). The next generated ANN model was MLP 6-10-1, with six explaining parameters, of greatest influence. Correlation coefficient attained value 0.989 and 0.955 for the first and the second model. Mean percentage error pointed out underestimation in comparison to laboratory measurement. The values attained 35.9% and 54.8% respectively. Limitation of explaining parameters did not point high deterioration of the ANN model quality.

Key words: saturated hydraulic conductivity, pedotransfer functions, ANN (artificial neural networks)

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INTRODUCTION

Knowledge of water properties of soil has a great significance in natural environment investigations [Saxton et al. 1986, Gòmez-Plaza et al. 2001, Sobieraj et al. 2001, Vukovic and Soro 2006, Tombul 2007, Penna et al. 2009, Sezer et al. 2009, Temimi et al. 2010, Qin et al. 2011, Jia et al. 2013, Klatka et al. 2015, Klatka et al. 2016, Malec et al. 2015, Boroń et al. 2016]. One of the basic property connected with water flow in soil is saturated hydraulic conductivity. The methods for its determination are very differential. They can divided into three groups: laboratory, field and empirical ones [Jabro 1992]. The field method is commonly regarded as the most accurate one. Direct measurement in a field excludes errors, but is very time and cost consuming. On the other hand the laboratory method is usually rapid, but requires complicated devices. The most popular methods are recently the empirical ones [Jabro 1992, Carrier 2003, Odong 2007, Chapuis 2008, Salarashayer and Siosemarde 2012, Parylak et al. 2013]. Their main advantageous is quick result and easier methods for proper data obtaining, usually texture and porosity. At present in literature that methods are commonly called the pedotransfer functions (PTF) [Patil and Singh 2016]. In literature there were presented empirical functions, that may be grouped in three categories. The first one is based only on grains characteristics diameters. The second one apart from grains characteristic diameters regards some physical properties of soil, most often porosity. The third one is based additionally on physical properties of water [Twardowski i Drożdżak 2006]. Recently, in many researches, the artificial neural networks (ANN) for soil properties modeling and their spatial distribution have been used [Minasny et al. 1999, Merdun et al. 2006, Wang et al. 2012, Patil and Singh 2016, Halecki et al. 2017]. In this paper there was used ANN method for determination saturated hydraulic conductivity. The ANN models were learned based on empirical data, measured in laboratory.

MATERIALS AND METHODS

Samples of soil were taken in various places, located on the area of Cracow administrative district, from 0–25 cm soil layer of arable lands. The number of samples was 56 and they had differentiated texture. In this work there were used artificial neural networks (ANN), as pedotransfer models. The ANN models were generated in the Statistica, ver. 12.3 program. There was used the MLP (Multi Layer Perceptron). The input layer consisted of 10 chosen soil parameters: content of clay (C), silt (Si) and sand (S) separates, diameters d_{10}, d_{50}, d_{60} and d_{90} (diameters of particles, which mass with mass of all lower particles composes respectively 10%, 50%, 60% and 90% of soil mass, they were determined based on the cumulative grain size distribution curve), total porosity (n), bulk density (BD) as well as organic matter content (OMC). The input data were divided into learning (50%), testing (25%) and validating (25%) ones. The output layer was the saturated hydraulic conductivity (K_s). Texture was determined by use of the Casagrande's method in the Prószyński modification, according to the PN-R-04032 norm. Content of sand subfractions were determined by the sieve method. Classification of fractions and granular groups was carried out according to the USDA (United States Department of

Agriculture). Total porosity was determined based on bulk density (*BD*) and specific density (*SD*): $n = 1 - \frac{BD}{SD}$, where bulk density was determined using ring method and specific density by use of pycnometer of 100 cm^3 volume and vacuum chamber. Saturated hydraulic conductivity in laboratory was determined by means of apparatus based on Darcy's law with constant water head, in not disturbed samples of 100 cm^3 volume [Lipka et al. 2006], and was standardized for 10°C temperature. Global analysis of networks sensitivity allowed to arrange a percentage influence of the following soil parameters in explanation of saturated hydraulic conductivity Analysis of adjustment of empirical models to experimental data was carried out by means of the following measures [Rahnama i Barani 2005]:

– mean error of prognosis (*MEP*)

$$MEP = \frac{1}{n} \cdot \sum_{i=1}^{n} \left(C_i^m - C^p \right)$$

– root of mean square error (*RMSE*)

$$RMSE = \sqrt{\frac{1}{n} \cdot \sum_{i=1}^{n} \left(C_i^m - C_i^p \right)^2}$$

– mean percentage error (*MPE*)

$$MPE = \frac{1}{n} \cdot \sum_{i=1}^{n} \frac{C_i^m - C_i^p}{C_i^m} \cdot 100 \ \ [\%]$$

– model efficiency (*ME*) [Nash i Sutclife 1970, Tiwari in. 2000]

$$ME = 1 - \frac{\sum_{i=1}^{n} \left(C_i^m - C_i^p \right)^2}{\sum_{i=1}^{n} \left(C_i^m - \overline{C} \right)^2}$$

where:

C_i^m – measured values

C_i^p – simulated values

n – number of data

RESULTS AND DISCUSSION

In analyzed samples prevailed loam (in this: loam (L) in 13 samples, sandy loam (SL) – 14, silty loam (SiL) – 10, clay loam (CL) – 3, sandy clay loam (SCL) – 4). Sand was represented in 8 samples (sand (S) – 2, loamy sand (LS) – 7), silt (Si) in 1, and clay (C) in 1. Diameter d_{10} varied from 0.025 to 1.7 mm, d_{50} between 0.002 and 0.8 mm, d_{60} between 0,0038 and 0,7 mm, while d_{90} between 0,0012 mm and 0,0068 mm. Values of total porosity were between 0,320 and 0,517. Values of saturated hydraulic conductivity K_{s10} for analyzed samples were between $7.00 \cdot 10^{-4}$ and $9.23\ m \cdot day^{-1}$ (Table 1). The best

Table 1. Values of chosen soil parameters

Nb	Percentage of fraction			Gg	Diameter, mm				n	BD	OMC	K_{s10}
	S	Si	C		d_{10}	d_{50}	d_{60}	d_{90}	–	$Mg \cdot m^{-3}$	%	$m \cdot d^{-1}$
1	53	32	15	L	1.6000	0.1000	0.0280	0.0017	0.403	1.54	2.15	$1.50 \cdot 10^{-3}$
2	52	36	12	L	0.9000	0.0600	0.0270	0.0019	0.423	1.53	1.85	$2.30 \cdot 10^{-3}$
3	49	33	18	L	0.8000	0.0490	0.0190	0.0016	0.412	1.53	1.84	$1.60 \cdot 10^{-3}$
4	79	16	5	LS	1.3000	0.3250	0.2000	0.0080	0.369	1.66	1.45	$3.68 \cdot 10^{-1}$
5	70	18	12	SL	0.9500	0.1800	0.0950	0.0019	0.415	1.55	2.02	$5.50 \cdot 10^{-3}$
6	68	17	15	SL	0.9500	0.1700	0.0850	0.0017	0.407	1.56	1.86	$2.50 \cdot 10^{-3}$
7	10	69	21	SiL	0.0500	0.0075	0.0050	0.0015	0.476	1.31	1.94	$7.00 \cdot 10^{-4}$
8	37	43	20	SiL	0.6000	0.0280	0.0160	0.0015	0.496	1.30	1.54	$2.50 \cdot 10^{-3}$
9	9	69	22	SiL	0.0490	0.0070	0.0045	0.0015	0.504	1.32	1.65	$2.50 \cdot 10^{-3}$
10	65	21	14	SL	1.3000	0.1200	0.0750	0.0017	0.497	1.42	1.78	$6.70 \cdot 10^{-3}$
11	66	16	18	SL	0.7000	0.1600	0.0800	0.0016	0.478	1.43	1.94	$5.40 \cdot 10^{-3}$
12	15	68	17	SiL	0.2000	0.0070	0.0048	0.0016	0.472	1.40	1.66	$7.00 \cdot 10^{-4}$
13	6	86	8	Si	0.0250	0.0065	0.0050	0.0022	0.510	1.42	1.74	$2.40 \cdot 10^{-3}$
14	66	17	17	SL	0.8000	0.1600	0.0800	0.0016	0.468	1.40	1.94	$5.50 \cdot 10^{-3}$
15	68	14	18	SL	0.7800	0.1800	0.1000	0.0016	0.485	1.41	2.12	$8.80 \cdot 10^{-3}$
16	14	65	21	SiL	0.1000	0.0090	0.0052	0.0015	0.506	1.30	1.72	$8.00 \cdot 10^{-4}$
17	22	54	24	SiL	0.2800	0.0100	0.0055	0.0014	0.498	1.31	1.83	$8.00 \cdot 10^{-4}$
18	17	32	51	C	0.2200	0.0020	0.0017	0.0012	0.517	1.31	1.65	$8.00 \cdot 10^{-4}$
19	27	41	32	CL	0.7500	0.0210	0.0060	0.0014	0.527	1.33	1.44	$2.60 \cdot 10^{-3}$
20	22	49	29	CL	0.4800	0.0100	0.0048	0.0014	0.511	1.31	1.58	$4.00 \cdot 10^{-3}$
21	43	19	38	CL	0.7500	0.0350	0.0700	0.0013	0.517	1.32	2.04	$4.20 \cdot 10^{-3}$
22	46	39	15	L	0.9000	0.0400	0.0190	0.0017	0.420	1.52	1.87	$3.50 \cdot 10^{-3}$
23	48	32	20	L	0.7000	0.0450	0.0170	0.0015	0.416	1.53	1.52	$3.50 \cdot 10^{-3}$
24	47	35	18	L	1.0000	0.0390	0.0140	0.0016	0.416	1.53	1.56	$9.50 \cdot 10^{-3}$
25	11	71	18	SiL	0.0700	0.0068	0.0045	0.0015	0.437	1.34	1.68	$7.30 \cdot 10^{-3}$
26	49	35	16	L	0.8000	0.0450	0.0170	0.0016	0.414	1.53	1.86	$2.10 \cdot 10^{-3}$
27	50	21	29	SCL	0.8000	0.0500	0.0260	0.0014	0.404	1.52	2.01	$1.12 \cdot 10^{-2}$
28	52	21	27	SCL	1.0000	0.0580	0.0350	0.0014	0.406	1.52	1.45	$7.30 \cdot 10^{-3}$
29	53	22	25	SCL	0.7000	0.0600	0.0300	0.0014	0.426	1.52	1.65	$6.50 \cdot 10^{-3}$
30	70	15	15	SL	0.8000	0.2000	0.0110	0.0017	0.412	1.57	1.78	$4.34 \cdot 10^{-2}$

Table 1. cont.

Nb	Percentage of fraction			Gg	Diameter, mm				n	BD	OMC	K_{s10}
	S	Si	C		d_{10}	d_{50}	d_{60}	d_{90}	–	$Mg \cdot m^{-3}$	%	$m \cdot d^{-1}$
31	36	45	19	L	0.4200	0.0240	0.0120	0.0015	0.426	1.52	1.84	$3.00 \cdot 10^{-2}$
32	39	43	18	L	0.5000	0.0250	0.0130	0.0015	0.414	1.50	1.56	$1.37 \cdot 10^{-2}$
33	71	12	17	SL	1.7000	0.4000	0.1900	0.0016	0.402	1.56	1.54	$9.54 \cdot 10^{-2}$
34	79	14	7	LS	1.7000	0.5000	0.2500	0.0050	0.370	1.67	1.65	$2.47 \cdot 10^{-1}$
35	80	11	9	LS	0.9500	0.5100	0.2400	0.0030	0.366	1.68	1.56	$3.09 \cdot 10^{-1}$
36	72	14	14	SL	1.2000	0.5000	0.2000	0.0018	0.395	1.58	2.06	$6.80 \cdot 10^{-2}$
37	66	18	16	SL	1.5000	0.3400	0.1200	0.0017	0.410	1.58	1.84	$5.96 \cdot 10^{-2}$
38	56	30	14	SL	1.5000	0.1500	0.0400	0.0018	0.410	1.60	1.54	$1.82 \cdot 10^{-1}$
39	83	8	9	LS	1.3000	0.5500	0.4000	0.0050	0.371	1.58	1.78	$1.75 \cdot 10^{-1}$
40	48	36	16	L	0.7000	0.0200	0.0110	0.0017	0.371	1.54	1.96	$3.22 \cdot 10^{-1}$
41	83	6	11	LS	1.7000	0.5500	0.3500	0.0019	0.384	1.67	1.65	$2.50 \cdot 10^{-1}$
42	80	12	8	LS	1.7000	0.6900	0.5500	0.0030	0.369	1.66	1.54	$5.30 \cdot 10^{-1}$
43	68	13	19	SL	1.7000	0.6500	0.4000	0.0015	0.395	1.59	1.65	$7.85 \cdot 10^{-2}$
44	94	4	2	S	1.7000	0.8000	0.7000	0.0680	0.362	1.66	1.66	$9.23 \cdot 10^{0}$
45	81	7	12	LS	1.6000	0.7200	0.6000	0.0019	0.373	1.68	1.51	$1.20 \cdot 10^{0}$
46	90	6	4	S	1.5500	0.7500	0.6200	0.0500	0.348	1.67	1.66	$4.62 \cdot 10^{0}$
47	43	39	18	L	0.0980	0.0290	0.0130	0.0016	0.387	1.49	1.87	$2.68 \cdot 10^{-2}$
48	34	45	21	L	0.5000	0.0110	0.0060	0.0015	0.425	1.53	2.12	$2.40 \cdot 10^{-1}$
49	66	14	20	SL	0.4200	0.0700	0.0600	0.0015	0.466	1.35	1.45	$8.80 \cdot 10^{-3}$
50	26	51	23	SiL	0.3800	0.0090	0.0050	0.0014	0.492	1.32	1.65	$7.00 \cdot 10^{-4}$
51	59	41	0	SCL	1.5000	0.0900	0.0200	0.0035	0.430	1.51	1.75	$2.74 \cdot 10^{-2}$
52	35	43	22	L	0.4000	0.0100	0.0060	0.0015	0.323	1.74	1.87	$2.35 \cdot 10^{-2}$
53	72	10	18	SL	1.5000	0.5000	0.2900	0.0016	0.348	1.63	1.75	$2.50 \cdot 10^{-1}$
54	20	59	21	SiL	0.4000	0.0075	0.0050	0.0015	0.490	1.32	1.87	$7.00 \cdot 10^{-4}$
55	69	15	16	SL	1.6000	0.5500	0.0950	0.0017	0.370	1.62	1.65	$3.76 \cdot 10^{-1}$
56	8	70	22	SiL	0.0350	0.0052	0.0038	0.0015	0.475	1.34	1.73	$4.30 \cdot 10^{-3}$

Gg – granular groups: L – loam, LS – loamy sand, SL – sandy loam, SiL – silt loam, C – clay, CL – clay loam, SCL – sandy clay loam, Si – silt, S – sand, n – total porosity, BD – bulk density, OMC – organic matter content, K_{s10} – saturated hydraulic conductivity for 10°C determined by laboratory method fitted ANN model with 10 explanation soil parameters, turned out the MLP 10-10-1, with 10 perceptrons in hidden layer (Fig. 1). Analysis of fitting quality and errors (Table 2) showed satisfactory level. Fitting quality attained values: 0.996, 0.754 and 1.000 for learning, test and validation responsibly. The Efficiency measures were quite satisfactory (Table 4). The model underestimates value of K_{s10} in relation to experimental data of maximum 35.9%. The model efficiency attained value 0.998, and correlation coefficient – 0.989. Global sensitivity of ANN showed that the highest influence had: content of clay separate content (C), d_{60}, sand separate content (S), d_{90}, bulk density (BD) and total porosity (n), with absolute influence above 5% (Table 3). Then the next artificial neural model was generated, regarding these parameters (Fig. 2). The best fitted network was MLP 6-10-1, with 10 perceptrons in hidden layer. Analysis of fitting quality and errors (Table 2) gave values: 0.988, 0.751 and 1.000 for learning, test and validation responsibly. Decrease of explaining parameters did not cased deterioration of ANN model quality. Maximum

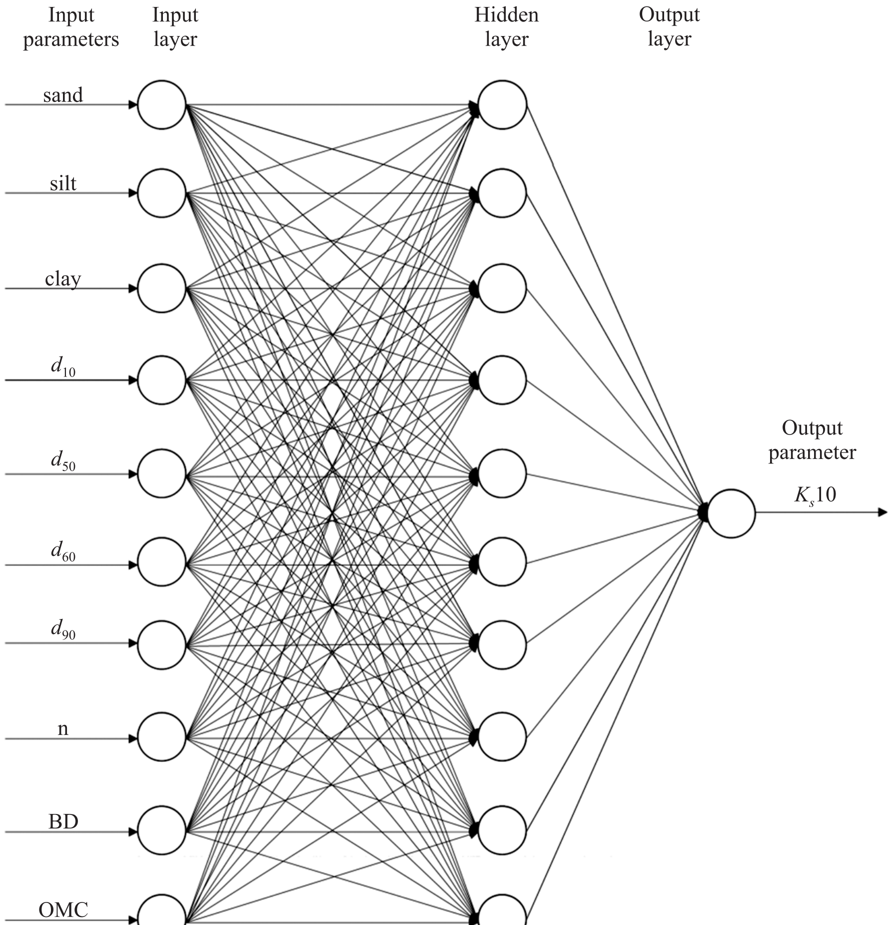

Fig. 1. Scheme of MLP 10-10-1 model

underestimation attains 54.8%. Model efficiency was 0.912 and correlation coefficient – 0.955 (Table 4). Graphical comparison of measured and predicted values for both ANN models are presented in Fig. 3 and 4. Values predicted by two models were compared statistically using the t-Student test. Calculated t parameter was –0.182, while value of t distribution for 0.05 confidence level is 2.021, that is why predicted values do not differ statistically. Ryczek at al. [2017] analyzed 10 pedotransfer functions (Shepard's, Hazen's, USBR, Saxton's et al., Kozeny–Carman's, Krüger's, Terzaghi's, Chapuis's, Sheelheim's, Chapuis', NAVFAC) and compared with laboratory determinations.

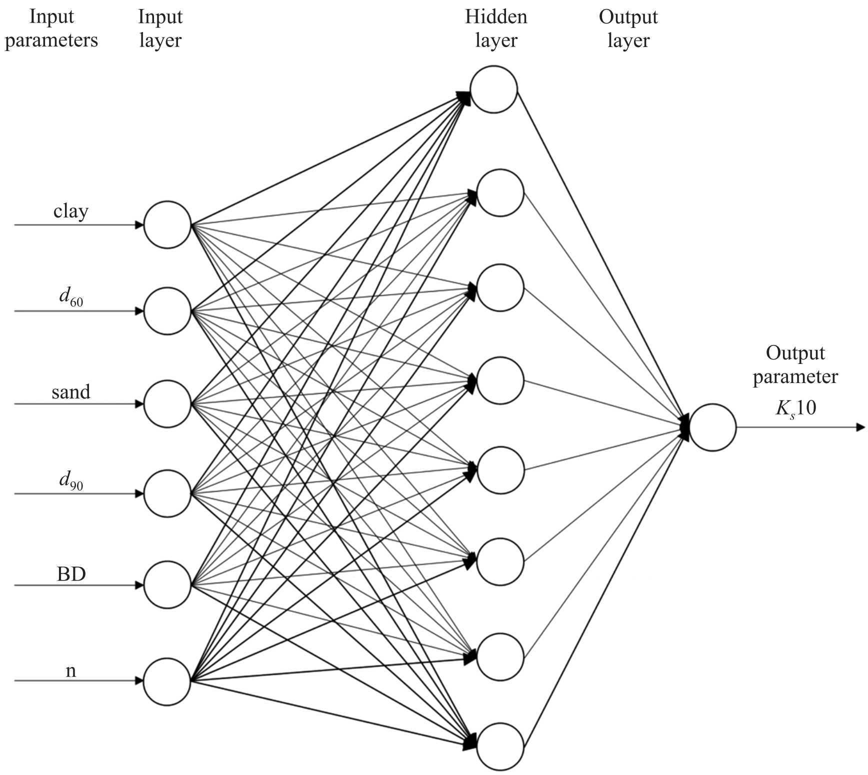

Fig. 2. Scheme of the MLP 6-8-1 model

Table 2. Analysis of fitting quality and errors of MLP models for saturated conductivity coefficient

Network	Network quality			Activation functions		Fitting errors (SOS)		
	learning	test	validation	input	output	learning	test	validation
MLP 10-10-1	0.996	0.754	1.000	linear	exponential	0.00208	0.00106	0.31223
MLP 6-8-1	0.988	0.751	1.000	exponential	exponential	0.00760	0.00435	0.88454

Table 3. Analysis of global sensitivity of the MLP models

Nb	Parameter	Relative sensitivity, –	Absolute influence, %
1	Clay content (C)	608.600	37.7
2	Diameter d_{60}	275.204	17.1
3	Sand content (S)	218.437	13.5
4	Diameter d_{90}	96.538	6.0
5	Bulk density (BD)	95.570	5.9
6	Total porosity (n)	91.979	5.7
7	Diameter d_{50}	77.717	4.8
8	Silt content (Si)	77.562	4.8
9	Diameter d_{10}	36.622	2.3
10	Organic matter content (OMC)	34.370	2.1

Table 4. Model efficiency measures

ANN model	Efficiency measures				
	MEP, $m \cdot d^{-1}$	RMSE, $m \cdot d^{-1}$	MPE, %	ME, –	*r*, –
MLP 10-10-1	0.036	0.104	35.9	0.998	0.989
MLP 6-8-1	0.079	0.208	54.8	0.912	0.955

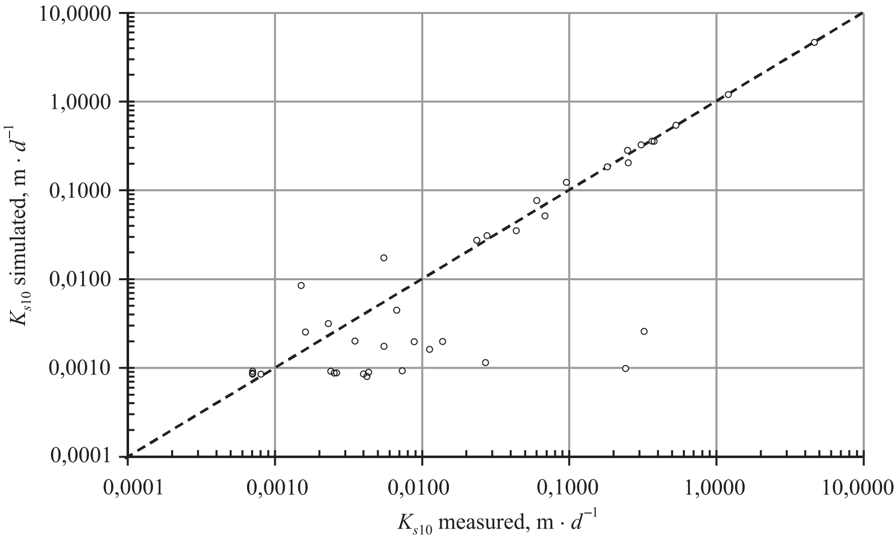

Fig. 3. Saturated hydraulic conductivity simulated vs measured for the MLP 10-10-1 model

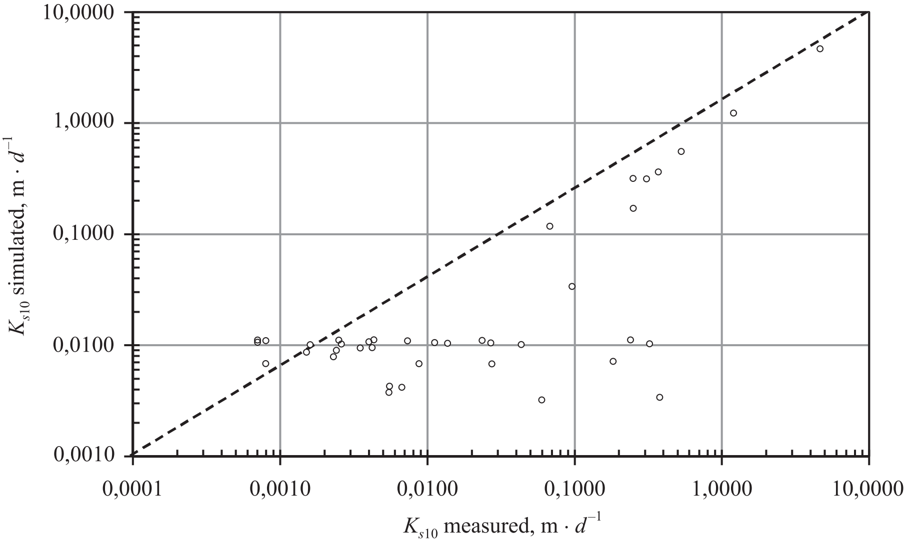

Fig. 4. Saturated hydraulic conductivity simulated vs measured for the MLP 6-10-1 model

Values of correlation coefficient *r* fluctuated between 0.654 and 0.946. All were essential for confidence level 0,05. ME were between –0.001 and 0.830. Results obtained for MEP varied between –0.074 and 11.3, MEP showed that maximum overestimation attained 49.6%. In conclusions authors stated, that analyzed pedotransfer functions are not universal for every granular group. The models analyzed in this work showed satisfactory results for the data used.

CONCLUSIONS

1. The highest influence on explanation of saturated hydraulic conductivity had the following soil parameters: clay separate content, d_{60}, sand separate content, d_{90}, bulk density and total porosity.
2. Limitation of explaining parameters to six did not deteriorate to a high degree quality of the MLP model in comparison to the one with ten parameters. Test t-Student's did not show statistically essential difference between predicted values of saturated hydraulic conductivity.
3. The analyzed ANN-based pedotransfer functions are universal for various granular groups and show better estimation of saturated hydraulic conductivity.
4. For better quality of fitting there are necessary further investigations on soil with higher differentiation regarding texture.

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FUNKCJE PEDOTRANSFEROWE DO OZNACZANIA PRZEWODNICTWA HYDRAULICZNEGO NASYCONEGO PRZY WYKORZYSTANIU SZTUCZNYCH SIECI NEURONOWYCH (SSN)

Streszczenie. W pracy przedstawiono dwa modele pedotransferowe do oznaczania przewodnictwa hydraulicznego w strefie nasyconej gleby, skonstruowane przy pomocy sztucznych sieci neuronowych (SSN). Modele zostały nauczone w oparciu o dane empiryczne otrzymane w laboratorium, przeprowadzone na 56 próbkach gleby o zróżnicowanym składzie granulometrycznym. W pierwszym modelu danymi wejściowymi były: średnice charakterystyczne d_{10}, d_{50}, d_{60}, d_{90}, zawartość frakcji piasku, pyłu iłu, porowatość ogólna, gęstość objętościowa i zawartość materii organicznej. Wykorzystano rodzaj MLP (perceptron wielowarstwowy) SSN. Najlepiej dopasowanym modelem okazał się model MLP 10-10-1 z satysfakcjonującymi wartościami parametrów jakości: dla próbki uczącej 0.996, for testowej 0.754 a dla walidacyjnej 1.000. Globalna analiza wrażliwości wykazała, że największy wpływ na wyjaśnienie relacji z przewodnictwem hydraulicznym w strefie nasyconej w tym modelu miały: zawartość frakcji iłu (wpływ absolutny 37.7%, d_{60} (17.1%), zawartość frakcji piasku (13.5%), d_{90} (6.0%), gęstość objętościowa (5.9%) i porowatość ogólna (5.7%). Pozostałe parametry miały absolutny wpływ poniżej 5.0%. Następny wygenerowany model SSN był typu 6-10-1, z sześcioma wyjaśniającymi parametrami o największym wpływie. Współczynnik korelacji osiągną wartość 0.989 i 0.955 dla pierwszego i drugiego modelu odpowiednio. Średni procentowy błąd wskazał na niedoszacowanie wartości wyjaśnianej przez model w stosunku do wartości uzyskanych w laboratorium. Wartości błędu osiągnęły 35.9% i 54.8% odpowiednio. Ograniczenie ilości parametrów wyjaśniających nie wykazało dużego pogorszenia jakości modelu SSN.

Słowa kluczowe: przewodnictwo hydrauliczne nasycone, funkcje pedotransferowe, SSN (sztuczne sieci neuronowe)

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