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APPLICATION OF COMPUTATIONAL INTELLIGENCE METHODS FOR PREDICTING SOIL STRENGTH

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The aim of this study was to make predictions for soil cone index using artificial neural networks (ANNs), adaptive neuro-fuzzy inference system (ANFIS) and a regression model. Field tests were conducted on three soil textures and obtained results were analyzed by application of a factorial experiment based on a Randomized Complete Block Design with five replications. The four independent variables of percentage of soil moisture content, soil bulk density, electrical conductivity and sampling depth were used to predict soil cone index by ANNs, ANFIS and a regression model. The ANNs design was that of back propagation multilayer networks. Predictions of soil cone index with ANFIS were made using the hybrid learning model. Comparison of results acquired from ANNs, ANFIS and regression models showed that the ANFIS model could predict soil cone index values more accurately than ANNs and regression models. Considering the ANFIS model, a novel result on soil compaction modeling, relative error (ϵ), and regression coefficient (R^2) were calculated at 2.54% and 0.979, respectively.

Keywords: artificial neural network; ANFIS; cone index; modeling; Levenberg-Marquardt algorithm

Soil compaction is an index that displays the soil structure's physical deterioration and is defined as increased soil bulk density or reduced porosity. Certain methods, standards, and indices are used to determine the soil compaction, such as soil color index (compression recognition by means of observation), measurement of soil bulk density, penetrating the soil with radars and evaluation of the soil cone index (Hemmat et al., 2014; Raper et al., 1990; Upadhyaya et al., 1994). In terms of these methods, cone penetrometers were determined as the most reliable (Abbaspour-Gilandeh and Rahimi-Ajdadi, 2016; Clark, 1999; Mulqueen et al., 1977).

The advantage of using an artificial neural network is that it can create a connection between input and output parameters without any theory of predetermined mathematical relations (Goh, 1995; Kushwaha and Zhang, 1998; Levine et al., 1996). The reason for using ANNs and ANFIS for soil cone index predictions in this study is that they show high prediction capability and no mathematical relationship between dependent and independent variables.

Research has demonstrated a correlation between evaluations of the soil cone index and soil bulk density as parameters related to soil compaction and compression (Bayat et al., 2017; Henderson et al., 1988) and between the soil cone index and moisture content (Faure and Da Mata, 1994).

Abbaspour-Gilandeh et al. (2006) reported that soil electrical conductivity (EC) data were highly correlated to soil texture (% clay content) with a correlation coefficient of 0.916 and that there was a strong linear correlation between soil EC and draft force across a field. The soil cone

index could also be a function of soil electrical conductivity (Abbaspour-Gilandeh et al., 2011).

Santos et al. (2012) used statistical analyses and ANNs for predicting soil penetration resistance based on the soil bulk density and water content. Results showed that ANNs architecture 2-2-2-1 presented an RMSE (Root Mean Square Error) of value less than 0.085, an R^2 equal to 0.98 and a global mean error of approximately 6.75%, whereas the model obtained from statistical analyses presented an RMSE of 0.951 and an R^2 of 0.92.

The aim of this study was to develop models based on computational intelligence methods and the regression method for predicting soil cone index. For the purposes of modeling of the soil cone index, artificial neural networks (ANNs), adaptive neuro-fuzzy inference system (ANFIS) and multiple range regression methods were utilized. Finally, performances of these models were compared with each other.

Material and methods

Field experiments

Field experiments were conducted at the Educational and Experimental Farm of the University of Mohaghegh Ardabili, Ardabil, Iran (latitude 38° 19' N, longitude 48° 20' E). Tests were done on three types of soil texture (loam, loamy sand and sandy loam). The effects of three soil moisture content levels (dry, semi-humid and humid), three sampling depths (0–10, 10–20 and 20–30 cm) and three numbers of tractor passes (0, 10 and 20 passes) on soil cone index were

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investigated by application of a factorial experiment based on a Randomized Complete Block Design (RCBD) with five replications using MSTATC Version 2.0.0 statistical software. Considering each test plot, evaluations were made for soil cone index, percentage of soil moisture content, soil bulk density and soil electrical conductivity.

A tractor-mounted cone penetrometer (Abbaspour-Gilandeh et al., 2010) was used to measure the strength of the soil. Calculations for cone index were based on measurements of the force required to press a cone with a 130 mm² base area and 30° point angle into the soil according to the ASAE standard S313.2.

Soil moisture content percentage was measured utilizing Eq. 1; soil samples were extracted from the given depths and subsequently weighed with a precise scale.

$$MC = \left(\frac{W_w - W_d}{W_d} \right) \times 100 \quad (1)$$

where:

W_w – weight of wet matter (g)

W_d – weight of dry matter (g)

To determine the soil bulk density, undistributed soil samples were taken from various depths in the range of 0–30 cm from the test field. Samples were oven dried at 105 °C for 24 hours, weighed and measured for weight of dry soil and soil volume. Then, soil bulk density was determined by dividing the weight of sample by its volume.

An electrical conductivity meter device was used to evaluate electrical conductivity. The electrical conductivity of a solution should be determined at the temperature of 25 °C. Eq. 2 was used to correct the values of soil electrical conductivity (Abbaspour-Gilandeh et al., 2011).

$$EC_{25} = EC_t - 0.02(t - 25) EC_t \quad (2)$$

where:

EC_{25} – electrical conductivity of solution at 25 °C (μS·cm⁻¹)

EC_t – measured electrical conductivity of solution at the actual temperature of the solution (μS·cm⁻¹)

t – actual temperature of the solution (°C)

Design of the Artificial Neural Networks (ANNs) model

A multilayer back propagation network was used for making soil cone index predictions in the network designed in this research. Fig. 1 shows layers and connections of the designed feed-forward back propagating artificial neural network. The three algorithms of descent gradient algorithm with momentum, Levenberg-Marquardt algorithm and scaled conjugated gradient algorithm were used to train the network with MATLAB version R2017a (Matlab, 1994).

Selecting the number of neurons in a middle layer is made by “trial and error”. In this study, selection for the

number of hidden layers and the number of neurons in the middle layers was made by comparing the performance among different networks. Moreover, the type of function used between input and middle layers was sigmoid tangent and linear was used between middle and output layers.

Data were divided into three subcategories including training, validation and testing in such a way that one fourth of data (25%) were considered for testing, 25% for evaluation and half (50%) for training. The best method of training for data and performance of the developed networks was determined by calculating the mean square error (MSE), sum of square errors (SSE), coefficient of determination (R^2), and prediction accuracy (PA) (Gautam et al., 2003; Matlab, 1994).

Design of adaptive neuro-fuzzy inference system (ANFIS)

By combining the fuzzy inference system (FIS) with ANNs that is termed ANFIS, it is possible to acquire both the learning capabilities of a neural network and reasoning capabilities of fuzzy logic for predictions. The goal of ANFIS was to determine a model for correct associating of input values with the target. The ANFIS model proposed in this study was a multilayer neural network-based fuzzy system. Its topology is shown in Fig. 2 and the system had a total of five layers. The hidden layers consisted of nodes functioning as membership functions (MFs) and rules. In this model, to estimate soil cone index, 80% of total data was used for training and 20% of the data was used for validation. Triangular shaped membership functions were used as input variables because of their accuracy. The hybrid learning model was selected for soil cone index prediction with ANFIS.

Fig. 3 shows the data set used to train and check the soil cone index model with ANFIS. Training data were marked with the (○) sign and the check data were indicated with the plus sign (+) in Fig. 3. To initialize FIS using ANFIS, two partition methods were used – grid partitioning and subtractive clustering. The main difference between these two methods is related to how the fuzzy

Fig. 1 Layers and connections of a feed-forward back propagating ANN

Fig. 2 ANFIS architecture for soil cone index prediction

Fig. 3 Loading training and checking data in ANFIS

Table 1 The results of analysis of variance of soil cone index

Variation source	Degree of freedom	Mean square
Replication	4	15,949.515 ^{ns}
Soil texture	2	6,125,782.724**
Moisture content	2	430,853.772**
Texture × moisture	4	555,545.556**
Tractor traffic	2	1,823,290.459**
Texture × tractor traffic	4	32,189.957 ^{ns}
Moisture × traffic	4	43,466.475*
Texture × moisture × traffic	8	107,463.83**
Depth	2	6,029,325.987**
Texture × depth	4	135,206.146**
Moisture × depth	4	57,439.856**
Texture × moisture × depth	8	50,648.257**
Traffic × depth	4	121,767.287**
Texture × traffic × depth	8	161,720.162**
Moisture × traffic × depth	8	58,766.067**
Texture × moisture × traffic × depth	16	79,912.831**
Error	320	14,879.165
Total	404	–

**, * significant at probability levels of 1% and 5%, respectively and ^{ns}: no significant

membership function is selected. Considering the grid partitioning method, type and number of the input membership function vector was determined by the user.

Results and discussion

Analysis of variance of data

Results of Analysis of Variance for the soil cone index are given in Table 1. Results of ANOVA show that the main effects of soil texture, tractor traffic and sampling depth individually had significant impact on soil cone index ($P < 0.01$). Furthermore, interaction effects of moisture content and tractor traffic on soil cone index was significant ($P < 0.05$). However, the interaction effect of soil texture and tractor traffic on soil cone index was determined as not significant. This shows that effects of these two factors on soil cone index were independent of each other. The results of this section indicate that effects of the four parameters – soil texture, moisture content, tractor traffic and sampling depth – should be considered in modeling soil cone index (Varga et al., 2013).

Presenting a regression model for soil cone index

To determine the mathematical model of soil cone index as a dependent variable in relation to the percentage of soil moisture content, data from soil bulk density, electrical conductivity and sampling depth were used as independent variables (Bayat et al., 2017). The multiple-regression model was used for statistical operations. Linear model used as a mathematical model of soil cone index is shown in Eq. 3:

$$CI = 26.2(SD) + 1,298.6(BD) - 28.8(MC) + 133.3(\log EC) - 1,026.6 \quad (3)$$

where:

CI – cone index (kPa)
SD – sampling depth (cm)
BD – bulk density ($\text{g}\cdot\text{cm}^{-3}$)
EC – electrical conductivity ($\mu\text{S}\cdot\text{cm}^{-1}$)

Soil cone index prediction using artificial neural network

Table 2 shows results from the designed neural networks for soil cone

Table 2 Quantitative evaluation standards of made networks by using the Levenberg-Marquardt training algorithm

The number of neurons	Network parameters		Network statistical parameters		Network's determination coefficients			The mean simulation accuracy test (%)	Correlation coefficient
	learning rater	momentum	MSE	SSE	training	validation	test		
28-30	0.3	0.3	0.072	16.2	0.96	0.76	0.83	87.98	0.88
30-30	0.3	0.3	0.0669	15.1	0.97	0.68	0.84	88.04	0.89
30-32	0.3	0.3	0.119	26.7	0.91	0.83	0.85	88.09	0.87
32-32	0.3	0.3	0.0741	16.7	0.94	0.82	0.83	87.76	0.87
32-34	0.3	0.3	0.0895	20.1	0.95	0.74	0.86	88.78	0.88
34-34	0.3	0.3	0.0875	19.7	0.95	0.83	0.85	88.29	0.89

Table 3 Designed networks utilizing 3 training algorithms each having the optimized number of neurons in their hidden layer (layers)

Training algorithm	Transfer function	The optimized structure of network	Mean squares	Determination coefficients of the network			The mean simulation accuracy of the network (%)	Correlation coefficient
				training	evaluation	test		
Scaled conjugate gradient	Sig tan	20 + 1	0.131	0.87	0.86	0.86	88.97	0.86
		12 + 12 + 1	0.128	0.88	0.86	0.85	87.77	0.86
	Sig log	13 + 1	0.137	0.86	0.87	0.86	88.71	0.86
		12 + 12 + 1	0.13	0.87	0.86	0.85	87.97	0.86
Descent gradient with momentum	Sig tan	6 + 1	0.141	0.86	0.85	0.85	88.07	0.85
		6 + 6 + 1	0.14	0.85	0.85	0.84	87.44	0.85
	Sig log	12 + 1	0.126	0.87	0.86	0.85	87.78	0.86
		6 + 6 + 1	0.116	0.88	0.87	0.86	88.37	0.87
Levenberg-Marquardt	Sig tan	25 + 1	0.0974	0.92	0.85	0.85	87.98	0.87
		12 + 13 + 1	0.0981	0.93	0.85	0.87	88.81	0.88
	Sig log	24 + 1	0.102	0.94	0.82	0.87	86.48	0.88
		34 + 34 + 1	0.0875	0.95	0.83	0.86	88.29	0.89

Fig. 4 The regression chart for evaluation step of the network to predict the soil cone index quantities

index prediction using the Levenberg-Marquardt algorithm with a middle layer (middle layers) and a different number of neurons in the middle layer (layers). The sigmoid tangent function was used between the input and middle layers and a linear type was used between the middle layers and the output layer. As shown in Table 2, the network containing 34 neurons in each middle layer for predicting the soil cone index quantities had the lowest value for mean square error, the least sum of squares error, the highest correlation coefficient, the maximum simulation accuracy and the highest determination coefficient. Therefore, this topology was selected for the network design.

A diagram indicating the best fitted line between real data (T) and predicted data by the network (Y) is shown in Fig. 4. The regression coefficients for soil cone index prediction between the data groups were extracted by as much as 0.94 for the built network with 34 neurons in each middle layer for predicting soil cone index quantities. The highest gradient and the maximum correlation coefficient were extracted for this structure. These quantities for prediction of the soil cone index were 0.9195 and 0.9419, respectively.

Table 4 Characteristics of ANFIS model and its evaluation based on statistical parameters

Type of membership functions		Number of membership functions		Learning method	RMSE	ϵ (%)	R^2
input	output	input	epoch				
triangular	linear	5	30	hybrid	0.621	2.54	0.979

Fig. 5 Changes in the training and checking data error **Fig. 6** Comparison of predicted data with training data **Fig. 7** Comparison of predicted data with checking data

Table 3 shows a summary of the results of built networks utilizing the 3 aforementioned training algorithms and a comparison of their statistical parameters and accuracy. As shown in Table 3, Levenberg-Marquardt training algorithm presented better results in simulation and training of the artificial neural network compared with the other training algorithms. The Levenberg-Marquardt training algorithm associated to sigmoid logarithm transfer function containing 2 hidden layers and 34 neurons in each hidden layer had a lower mean square and higher determination of coefficients in training, validation

and test steps of the network in comparison to the similar single-layer network.

Prediction of soil cone index using ANFIS

Fig. 5 shows the relationship between the root mean square error (RMSE) and epochs for training and checking data. Training data error and checking data error are marked with (*) and (♦), respectively. Fig. 5 shows how the training and checking error decreased to a certain point. After training and checking the ANFIS model, predicted values of model were obtained and compared with the training and checking data. Results are shown in Figs. 6 and 7. Root Mean Square Errors were obtained at 0.621 and 0.436 for training and checking, respectively.

Table 4 shows characteristics of the model and its evaluations based on statistical parameters of RMSE, percentage of relative error (ϵ) and coefficient of determination (R^2). These results show that the ANFIS model was capable of estimating and predicting soil cone index with high accuracy.

Conclusion

The Analysis of Variance of soil cone index revealed that effects of the four parameters of soil texture, soil moisture content, tractor traffic and sampling depth were significant on soil cone index and should be taken into account in soil cone index modeling using artificial neural networks or a multiple-regression modeling (Ozoemena et al., 2018; Varga et al., 2013). The developed multiple-regression model was evaluated by normality assumption, assumption of constant variance and the Leverage index. Acceptable results were obtained from the multiple regression models to predict soil cone index values. The effects of independent variables had significant impact on soil cone index as a dependent variable ($P < 0.01$). Multilayer network back propagation with Levenberg-Marquardt algorithm showed better results in comparison to other algorithms utilized in data simulation and training of artificial neural networks. In terms of ANFIS model for the soil cone index estimation, novel result on soil cone index modeling, relative error (ϵ), and regression coefficient (R^2) were calculated at 2.54% and 0.979, respectively. Comparison of the results achieved by ANFIS model with ANNs and regression models showed that ANFIS managed to model the soil cone index with high accuracy (Abbaspour-Gilandeh and Abbaspour-Gilandeh, 2019).

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