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ORIGINAL PAPER

Developing cation exchange capacity and soil index properties relationships using a neuro-fuzzy approach

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Abstract Artificial intelligence methods are employed to predict cation exchange capacity (CEC) from five different soil index properties, namely specific surface area (SSA), liquid limit, plasticity index, activity (ACT), and clay fraction (CF). Artificial neural networks (ANNs) analyses were first employed to determine the most related index parameters with cation exchange capacity. For this purpose, 40 datasets were employed to train the network and 10 datasets were used to test it. The ANN analyses were conducted with 15 different input vector combinations using same datasets. As a result of this investigation, the ANN analyses revealed that SSA and ACT are the most effective parameters on the CEC. Next, based upon these most effective input parameters, the fuzzy logic (FL) model was developed for the CEC. In the developed FL model, triangular membership functions were employed for both the input (SSA and ACT) variables and the output variable (CEC). A total of nine Mamdani fuzzy rules were deduced from the datasets, used for the training of the ANN model. Minimization (min) inferencing, maximum (max) composition, and centroid defuzzification methods are employed for the constructed FL model. The developed FL model was then tested against the remaining datasets, which were also used for testing the ANN model. The prediction results are satisfactory with a determination coefficient, $R^2 = 0.94$ and mean absolute error, (MAE) = 7.1.

Keywords Artificial intelligence method · Fuzzy logic · Artificial neural network · Clayey soils · Soil index properties · Cation exchange capacity

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Introduction

The quantity of the exchangeable cations needed to neutralize the negative charges in a clay mineral structure (at a given pH) is called the cation exchange capacity (CEC) and it is expressed in milliequivalents (mEq) per 100 g of dried solid (or centimoles of charge of ion per kilogram, cmolc/kg). The CEC of a clayey soil originates primarily in the clay-sized fraction though a small portion of the silt-sized fraction also contributes to the soil's ability to hold on to cations.

In many geotechnical and geoenvironmental engineering applications, it is necessary to have an estimate of the CEC of a soil in order to allow preliminary design estimates. In the literature, it is well documented that the adsorption capacity of a soil is related to its CEC: the greater is the CEC, the greater is the adsorption capacity. It is also reported that CEC is related to the swelling potential of a clayey soil. However, methods for determining the CEC of soils are somewhat cumbersome and time consuming (Manrique et al. 1991). Standard methods of CEC determination involve several steps (e.g. displacement of the saturating cation requires several washings with alcohol). Therefore, there is a need for an efficient and quick method for estimating the CEC of soils for practical engineering applications. In this respect, researchers use parameters that are easy to measure in order to predict parameters that are somewhat cumbersome to obtain.

Several researchers have correlated soil index properties to the CEC and it is reported that the CEC of a soil is closely related to its specific surface area (SSA) (Curtin and Smillie 1976; Cihacek and Bremner 1979; Tiller and Smith 1990; Petersen et al. 1996). Curtin and Smillie (1976) observed in Irish soils that the CEC was strongly correlated with its organic matter content and specific surface area, but not to its clay content. Similarly, Farrar and Coleman (1967) reported that the total surface area and CEC had correlation coefficients of 0.9 or greater for 19 British clayey soils. Farrar and Coleman (1967) concluded that the coefficient of correlation was sufficiently high to correlate both total surface area and Atterberg limits to the CEC. Ohtsubo et al. (1983) studied the relationships between the CEC and clay fraction, liquid limit (LL), plastic limit (PL), and plasticity index (PI) and reported that CEC has highest correlation coefficients with LL and PI parameters. The significant relationship ($R^2 = 0.72$) between the liquid limit and the CEC was also observed by Smith et al. (1985).

Other than these experimental works, few researchers have attempted to employ mathematical tools for the predicition of CEC. In this respect, the neural network models were employed to develop a pedotransfer function for predicting soil cation exchange capacity using the other soil properties (Amini et al. 2005; Fooladmand 2008; Akbarzadeh et al. 2009; Keshavarzi and Sarmadian 2010; Keshavarzi et al. 2011). Akbarzadeh et al. (2009) compared neuro-fuzzy and artificial neural networks (ANN) methods and reported that neuro-fuzzy methods perform better than ANN for predicting CEC.

The benefits of using ANN models are the ease of application and robustness. They are, however, "black box" models. They do not yield an explicit relation between input and output variables, which makes them more difficult to interpret. All that the model offers is a weight matrix that defines the weights of interlayer connections, which are optimized after thousands of iterations. Considering the type of data used in CEC modeling, fuzzy logic (FL) may prove to be a better modeling tool. This is because such data are always associated with some error, which makes the fuzzy approach more suitable. First of all, the fuzzy approach provides possible rules relating input variables to the output variable; hence, it is more in-line with human thought. Therefore, engineers can rapidly develop their own set of rules to test for their fit for the fuzzy model. This makes the fuzzy approach more user friendly.

The objective of this study is to develop a FL model to estimate the CEC of clayey soils by using the most effective parameters. The five different soil index properties were used for better estimation of CEC.

ANNs

ANNs have an ability to identify patterns between input and output variables. In the commonly employed three-layer, feed-forward neural network (FFNN), the input quantities (x_i) are fed into the input layer neurons which, in turn, pass them on to the hidden layer neurons (z_i) after multiplying them by the connection weights (v_{ij}). A hidden layer neuron adds up the weighted input received from each input neuron ($x_i v_{ij}$), associates it with a bias (b_j), and then passes the result (net_j) on through the activation (transfer) function, which can be sigmoid or tangent hyperbolic [tanh (x)] (Govindaraju and Rao 2000; Tayfur 2012).

Similarly, the produced outputs from the inner neurons are passed to the network output neuron. The net information received by the output neuron from the inner neurons is passed through the activation function to produce the network output. The optimal weights are found by minimizing a predetermined error function (E) of the following form (Eq. 1) (ASCE 2000; Tayfur 2012):

$$E = \sum_{P} \sum_{p} (y_i - t_i)^2 \tag{1}$$

where y_i is the component of an ANN output vector Y; t_i is the component of a target output vector T; p is the number of output neurons; and P is the number of training patterns. The gradient-descent method, along with the chain rule of differentiation, is generally employed to modify the network weights as (Eq. 2) (Tayfur 2012):

$$\Delta v_{ij}(n) = -\delta \frac{\partial E}{\partial v_{ij}} + \alpha \Delta v_{ij}(n-1) \tag{2}$$

where, $\Delta v_{ij}(n)$ and $\Delta v_{ij}(n-1)$ are the weight increments between node i and j during the nth and ($n-1$)th pass or epoch; δ is the learning rate; and α is the momentum factor. The details of ANNs can be obtained from ASCE (2000), Govindaraju and Rao (2000), Tayfur (2012).

Overview of FL

A general fuzzy system has basically four components: fuzzification, fuzzy rule base, fuzzy output engine, and defuzzification (Fig. 1).

Fuzzification components form fuzzy sets for input–output variables using membership functions. Fuzzy membership functions may take many forms, but in practical applications, simple linear functions, such as triangular ones, are preferable. Figure 2, for example, presents fuzzy membership functions for temperature in Izmir, Turkey. The key idea in FL is the allowance of partial belongings of any object to different subsets of a universal

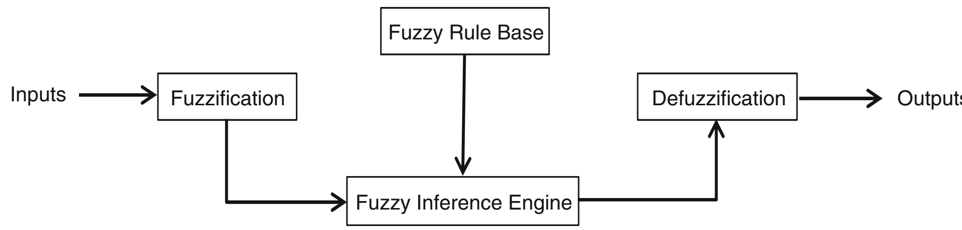

Fig. 1 Schematic representation of the fuzzy system

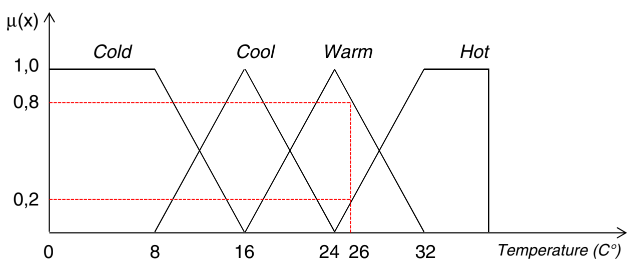

Fig. 2 Fuzzification of temperature for Izmir (Tayfur 2012)

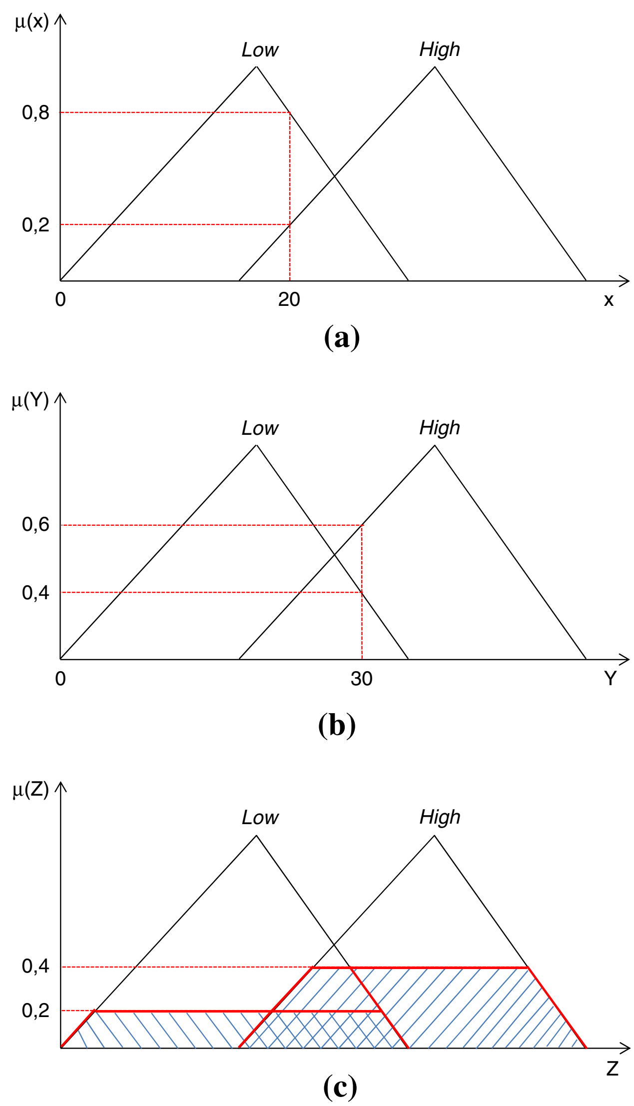

Fig. 3 Schematic representation of fuzzy inferencing **a** $X = 20$, **b** $Y = 30$, and **c** fuzzy output sets for Z

set. For example, four subsets in Fig. 2 form the universal set for the temperature and 26 °C can be, at the same time, a member of hot and warm subsets with 0.2 and 0.8 membership degrees, respectively.

Intuition, rank ordering, and inductive reasoning can be, among many ways to assign membership functions to fuzzy variables. The intuitive approach is instead used commonly because it is simple and derived from the innate intelligence and understanding of human beings. Fuzzification presented in Fig. 2 is an example of the intuitive approach.

The fuzzy rule base contains rules that include all possible fuzzy relations between inputs and outputs. These rules are expressed in the IF–THEN format. In the Mamdani rule system, both antecedent and consequent parts of a rule contain verbal statements. The following is an example of a Mamdani rule:

IF wind (W) is high THEN temperature (T) is low.

The details of the Mamadani rule construction methodology are given elsewhere (Tayfur 2006, 2012).

The fuzzy inference engine takes into account all the fuzzy rules in the fuzzy rule base and learns how to transform a set of inputs to corresponding outputs. To do so, it uses either "min" or "prod" activation operators. In order to illustrate the inferencing methodology, it is considered a simple case presented in Fig. 3, where there are two input variables of X and Y (Fig. 3a, b) and one output variable of Z (Fig. 3c). For this simple system, we also assume the following fuzzy rules:

IF X is low and Y is low THEN Z is high

IF X is high and Y is high THEN Z is low.

As seen in (Fig. 3a), $X = 20$ is a part of '*low*' and '*high*' subsets with membership degrees of 0.8 and 0.2, respectively. Similarly, $Y = 30$ is part of '*low*' and '*high*' subsets with 0.4 and 0.6 degrees of membership, respectively (Fig. 3b). When this input pair is fed into the fuzzy model, the inference engine would trigger the above rules. From the triggered first and second rules, the engine would find, by min operation, fuzzy output subsets of '*high*' and '*low*',

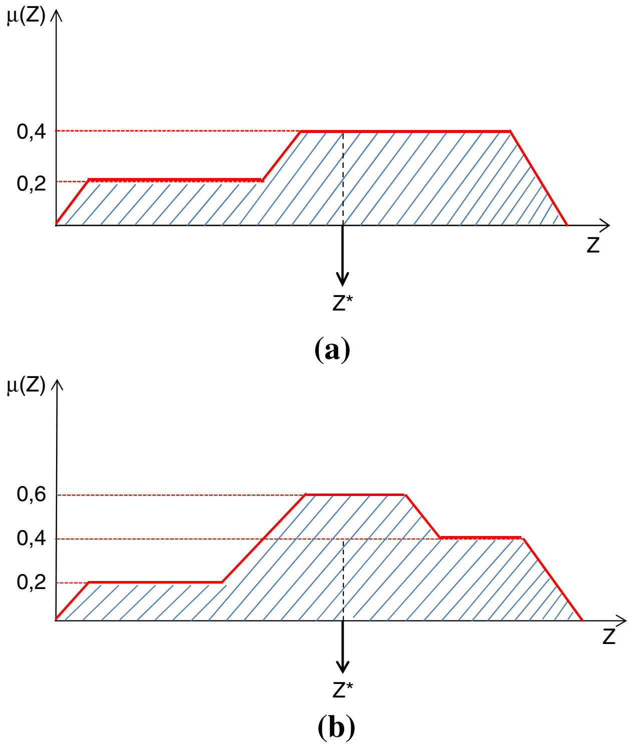

Fig. 4 Schematic representation of **a** max composition and BOA defuzzification (z^* halves the whole set) and **b** sum composition and COG defuzzification (z^* is the abscissa under the centre of gravity of the whole set)

respectively, with different firing strengths (Fig. 3c). One can find the details of the inferencing subprocess in Jantzen (1999) and Tayfur (2012).

The next sub-process in the inferencing engine is the composition where all of the fuzzy output subsets, obtained as a result of the activation operators from the triggered rules, are combined to form a single fuzzy subset for the output variable. For this purpose, there are basically two composition methods, maximization (max) and summation (sum). In max composition, as an example, the two shaded areas in (Fig. 3c) are combined, by taking the point-wise maximum over the two subsets (Fig. 4a). In sum composition, the combined output fuzzy subset is constructed by taking the point-wise sum over all of the fuzzy output subsets (Fig. 4b). The details of the composition subprocess are given elsewhere (Sen 2004; Tayfur 2012).

Defuzzification converts the resulting fuzzy outputs from the fuzzy inference engine to a number. Although there are many defuzzification methods, the centroid method is commonly employed. In the centroid method, the crisp output value is the abscissa under the centre of gravity of the combined fuzzy output subset (z* in Fig. 4b is assumed to be the centroid of the area and be the crisp value). The details of the FL algorithm are available in the literature (Jantzen 1999; Sen 2004; Tayfur 2012).

Materials and methods

Material characterization

In the analyses, 13 from present study and 37 from literature (Cerato 2001) clayey soil samples of different origins and characteristics were used. All soil samples were oven-dried (80 °C–48 h), crushed and sieved through 75 μm. Grain size distribution, specific gravity and CEC of the samples were determined according to ASTM D-422-63 (ASTM 1999), ASTM D-854-92 (ASTM 1999), and the Na method (Chapman 1965), respectively. LL and PL were determined according to ASTM D-4318-98 (ASTM 1999), respectively. The physicochemical properties of the remolded samples are given in Table 1. The SSA of 13 remolded soils were determined using the MB-spot test method (Santamarina et al. 2002). All tests were run in duplicate for accuracy. No treatment was applied on the soil samples before the SSA tests.

ANN and neuro-fuzzy analyses

In this study, five different soil index parameters and their variations were used in the ANN analyses. A total of 50 clayey soil sample data (37 of them compiled from literature) were utilized for this purpose (Cerato 2001; Yukselen 2007). The properties of the 50 clayey soil samples are given in Table 1. NeuroSolutions Version 5.0 was used for the ANN analyses. Fifteen ANN analyses were conducted for different parameter combinations. The number of data used in the analyses was presented in Table 2.

All used data were separated randomly for the testing and the training phases. Eighty percent of the data was used to train the network and the rest to test the accuracy of the developed models. Multilayer perception and a tansig type transfer function were selected for the neural network model. As a result of trials, it was decided to use one hidden layer. Equal momentum and step size values ($\alpha = \delta = 0.01$) were used during the analyses. Maximum epoch number 3,000 and 0.01 (threshold) mean square error restrictions were employed to terminate the training of the network. For the normalization process, Eq. 3 was employed.

$$x_{\text{actual}} = [[1.8((x_i - x_{\min})/(x_{\max} - x_{\min}))] - 0.9] \quad (3)$$

Using ANN analyses, the most effective soil index parameters were determined on the CEC, and then the FL model was developed according to these results. MATLAB Version 7.8 (2009) which contains a fuzzy tool box was used for the FL analyses. The Mamdani Fuzzy Inference System was selected for the fuzzy model. The model was composed of two input parameters [SSA and activity (ACT)] and one output parameter (CEC). Similar to the ANN analyses, for the fuzzy model, the data were separated into the calibration and testing parts. While 80 % of

Table 1 The used clayey soil samples properties

Cation exchange capacity (mEq/100 g)	Specific surface area (m^2g^{-1})	Liquid limit (%)	Plasticity index (%)	Clay fraction (<2 μm)	Activity	References	Testing data
25.1	57.6	58	14.1	32.5	0.43	Yukselen (2007)	
83.7	364.8	113.6	52.9	82	0.65		
60.5	136.8	61.6	11.4	35.5	0.32		
57.2	54	44.9	6.2	32	0.19		
5.9	26.4	24.5	6.45	21	0.31		
67.1	768	330.7	280.8	80	3.51		
26.2	106.8	72.2	37.5	77	0.49		
132.3	753.6	111.5	69.9	56.8	1.23		
6.8	26.4	51.7	9.8	38	0.19		
24	79.2	58.4	23.3	28	0.83		
38.4	168	70	40	75	0.54		
86.1	720	464.8	416.6	90	4.63		Testing
127.9	912	395.8	343.4	90	3.82		
2	15	42	16	36.2	0.44	Cerato (2001)	
0.9	23	60	28	76	0.37	(Artificial clays)	
3.3	26	70	30	67.6	0.44		
2.1	38	65	27	36.2	0.75		Testing
2.1	41	66	29	69.5	0.42		
6.1	61	58	30	63.8	0.47		
17.6	158	33	10	48	0.21		
24.4	224	69	32	42.8	0.75		
60.8	381	64	25	47.4	0.53		Testing
84.4	534	142	98	73.3	1.34		
76.4	637	519	484	60.4	8.01		Testing
67	675	97	50	49.5	1.00		
47.2	704	560	508	95.8	5.30		
120	767	130	72	37.7	1.91		Testing
6.7	31	37	13	37	0.35	Cerato (2001)	
5.9	52	48	19	48.2	0.39	(Natural Clays)	
7.4	53	53	21	56.9	0.37		
8.9	54	46	20	49.8	0.40		
9	70	45	20	57.9	0.35		
9.2	53	38	17	42.2	0.40		
9.6	44	39	19	53	0.36		
15	36	48	21	37	0.30		
18.3	122	35	15	16.4	0.91		
18.5	25	25	8	19.9	0.40		
18.5	29	42	20	56.2	0.36		
22.2	120	42	25	12.4	2.02		
27.5	153	74	55	58.3	0.94		
28.1	149	47	27	44.5	0.61		
31.6	160	54	34	38	0.89		
42.6	169	60	33	60.4	0.55		
43.3	83	56	39	10.2	3.82		
44.9	255	61	33	71.1	0.46		
15.5	11	24	5	22.2	0.23		Testing
13.4	65	74	42	50	0.84		Testing
28.4	101	42	28	25.1	1.12		Testing
17.9	78	64	39	31	1.26		Testing
13.9	75	32	20	21.3	0.94		Testing

Table 2 R^2 and MAE values for the combinations

	R^2	MAE	Data number
1st Combination set			
SSA-LL-PI-CF	0.986	14.17	50
SSA-LL-PI	0.960	13.64	50
SSA-LL-CF	0.951	15.14	50
SSA-CF-PI	0.946	14.24	50
LL-PI-CF	0.050	28.49	50
2nd Combination set			
SSA-LL-PI-ACT	0.978	9.44	50
SSA-LL-PI	0.949	10.40	50
SSA-LL-ACT	0.939	11.15	50
SSA-ACT-PI	0.946	11.53	50
LL-PI-ACT	0.264	24.75	50
3rd Combination set			
SSA-LL-CF-ACT	0.903	21.47	50
SSA-LL-CF	0.870	22.70	50
SSA-LL-ACT	0.946	21.32	50
SSA-ACT-CF	0.894	20.45	50
LL-ACT-CF	0.334	35.45	50

the data was used for the establishment of the fuzzy rules, 20 % of the data was assigned randomly to test the accuracy of the FL model. The testing data is shown in Table 1.

Results and discussions

CEC predication by ANNs

Five clayey soil index parameters were investigated by combining four and three parameters separately so as to find the parameters with the greatest effect on the cation exchange capacity. In the first combination SSA-LL-PI-CF parameters were used. While 40 datasets were used in network training, 10 datasets were reserved for the network testing. The results of the first combination are presented in Table 2. Table 2 shows that SSA has a significant influence on the CEC.

In the second combination, the ACT parameter was used instead of CF. All ANN analyses were conducted for the same datasets with the same model features. As for the first combination, four sub-combinations were also investigated for the second combination parameters. The results are presented in Table 2. When the SSA parameter is included in the combination, the determination coefficients are higher for the case where the SSA parameter is excluded (LL-PI-ACT). The first two combinations (SSA-LL-PI-ACT and SSA-LL-PI-CF) and their sub-combinations show that there is a very strong relationship between SSA and CEC parameters (Table 2). The results of the first two combinations in Table 2 indicate that the ACT is more effective than the CF parameter on CEC. In the third combination, SSA, LL, CF, and ACT parameters were used and the PI parameter was eliminated. The ANN testing results for this case are also summarized in Table 2. This shows that SSA is the most effective parameter, followed by ACT.

As a result of ANN sensitivity analyses results (Table 2), it was found that SSA and ACT are the most effective parameters for the prediction of CEC. The model closely predicts the measured values with $R^2 = 0.92$, MAE = 9.11, and MSE 114.94. Therefore, these parameters were employed for the construction of the fuzzy logic model.

CEC prediction by neuro-fuzzy analyses

As a result of the ANN analyses, the most effective soil index parameters were determined on the cation exchange capacity, and then the fuzzy logic model was developed according to these results. The model was composed of two input parameters [SSA and ACT] and one output parameter (CEC). By looking at the distribution of the available data for each variable, it was decided that the number of subsets and corresponding ranges for each variable. This is well applied methodology in fuzzy modeling. Following the data clustering for each variable (Fig. 5), related fuzzy subsets were created, as presented in Fig. 5. Each variable (two input and one output) was then designed to have five fuzzy subsets with the triangular and trapezoidal membership functions (Fig. 5).

With the help of an excel worksheet, the model rules were constituted following the rule-construction procedure in Tayfur (2012). The possible rules constituted using the calibration data set were then subject to the expert's interpretations, consistency of the rules and weight of the rules. In the end, a total of nine optimal Mamdani type fuzzy rules were obtained, as summarized in Table 3.

The constructed FL model, as a result of the calibration dataset, was first subject to predict CEC measured values as a function of the SSA and ACT in the calibration data set to check the optimality of the calibration procedure. For this stage, R^2 is obtained 0.91, MAE = 9.34, MSE = 130.76 (training) and the prediction of the measured data is presented in (Fig. 6a, b). As seen, the model closely simulates the measured data. It neither over nor under-predicts measured values. These calibration results imply that the constructed FL model (Fig. 5) with nine rules (Table 3) is satisfactory.

The calibrated FL model was then tested against the validation datasets. Figure 7a and b show measured versus predicted results. As seen, the model closely predicts the measured values with $R^2 = 0.93$,

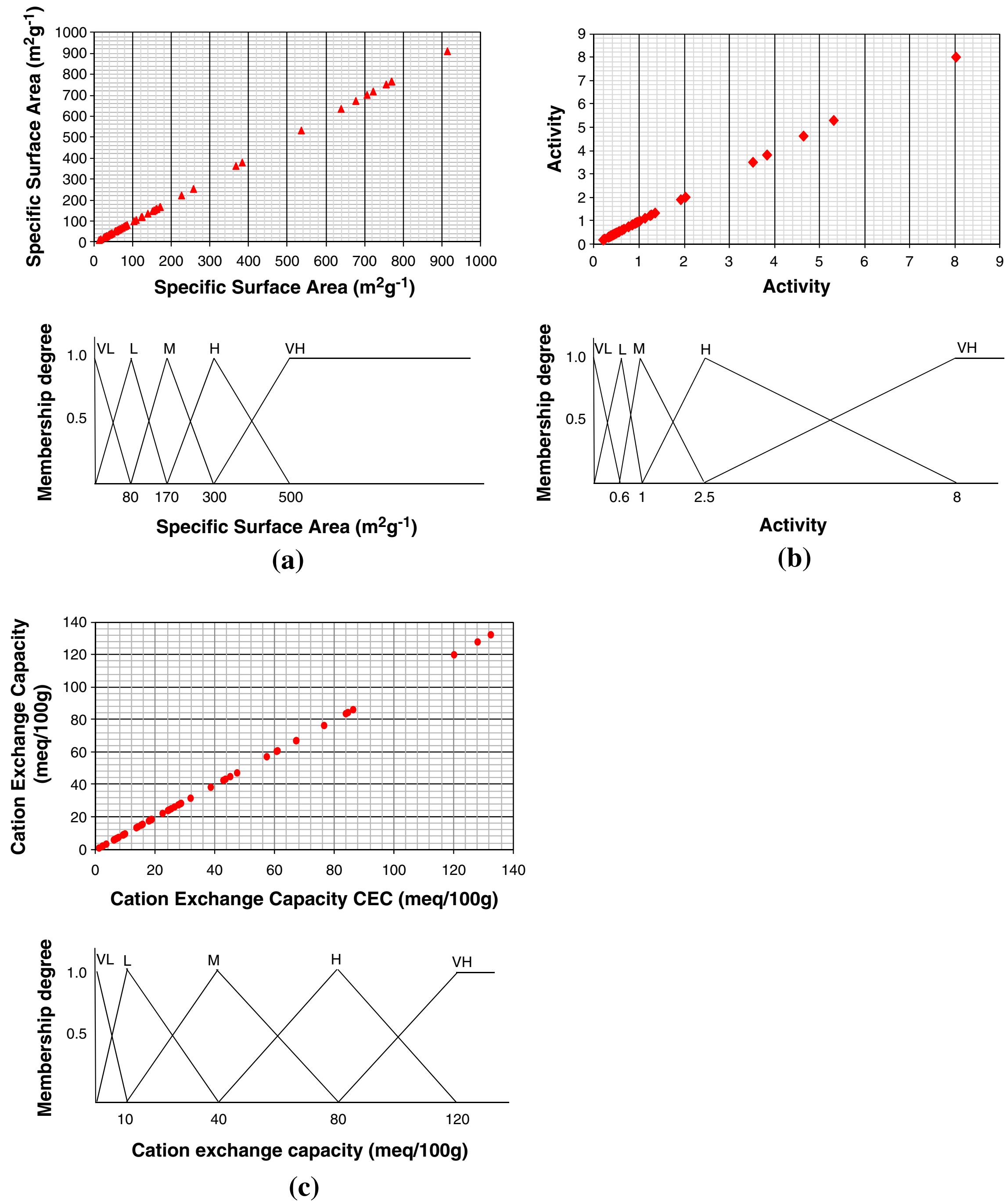

Fig. 5 Data clustering and universal fuzzy sets for **a** SSA, **b** ACT and **c** CEC

MAE = 7.12, and MSE = 98.74 (testing). Note that MAE value of 7.12 may be considered to be high for low measured values. This may imply that ANN and FL models make over-predictions of very low measured values used in this study. However, similar model performances can be commonly encountered in a wide spectrum of research area in the literature, especially when the employed range of the dataset is too large (Tayfur 2012). Hence, performance of a model is evaluated overall, not just based upon low (or high) values. In that sense, it can be stated that the developed soft computing methods in this study performed overall satisfactorily.

Investigation of soil properties such as CEC has an important role in studies concerning pollution prevention and crop management. Since laboratory procedures for

Table 3 Constructed fuzzy rules

SSA	ACT	CEC
VL	L	VL
L	L	L
M	VL	L
M	L	M
M	M	M
H	M	H
VH	M	H
VH	H	VH
VH	VH	VH

VL very low, *L* low, *M* medium, *H* high, *VH* very high

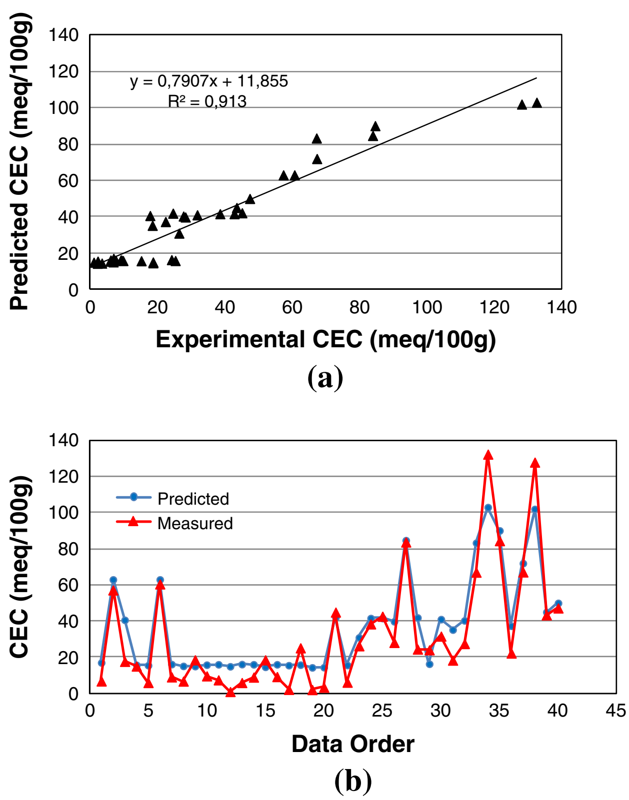

Fig. 6 **a** Comparison between measured CEC versus FL predicted CEC with training data. **b** Comparison between measured CEC and FL predicted CEC against data order (training data)

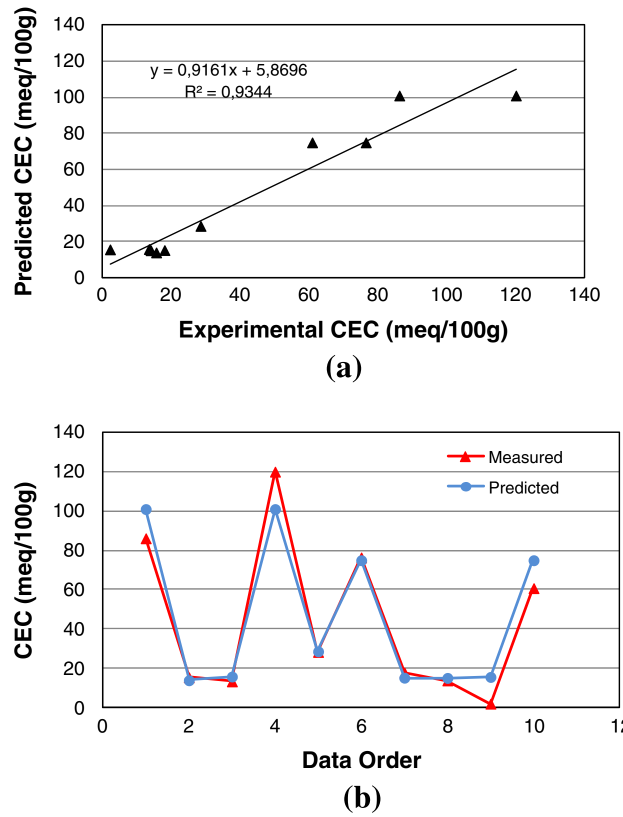

Fig. 7 **a** Comparison between measured CEC versus FL predicted CEC with testing data. **b** Comparison between measured CEC and FL predicted CEC against data order (training data)

estimating CEC are cumbersome and time-consuming, it is necessary to develop an indirect approach such as neuro-fuzzy models for prediction of this parameter from other soil data. Therefore, in this study indirect methods have been used to estimate cation exchange capacity for preliminary assessments. A total of fifty soil samples were collected from two different studies, and therefore, the soil samples have widely different properties with CEC values determined by different operators. According to the overall results of this study, the most related soil index parameters to CEC are SSA and ACT. If SSA and ACT are known, the CEC value can be estimated using the neuro-fuzzy model equation which was derived in this study. CEC can be determined by performing only a limited number of test operations, thus saving engineering effort, time, and funds.

Conclusions

In the first part of the study, the relationships between the soil properties (SSA, LL, PI, CF, and ACT) and CEC were investigated by using ANN analyses. Three main combinations and 12 sub-combinations were constituted by using five soil properties (SSA, ACT, LL, CF, PI). The determination coefficients and MAE values were obtained from 15 ANN analyses. In light of these results (R^2 and MAE), the SSA parameter was found to be the parameter with most effect on the CEC. Moreover, as a result of the analyses conducted, it is also observed that the ACT parameter has more effect than the CF and PI parameters. As a result of the ANN analyses, in the end, the SSA and ACT parameters were selected as the most influential parameters on the CEC. The ANN performance in predicting CEC was found to be satisfactory.

In the second part of the study, a FL model was used to constitute a connection between CEC and effective parameters (SSA-ACT). The FL model's performance revealed that five subsets for each variable with nine optimal fuzzy rules are sufficient to perform satisfactorily. The FL model performed as well as the ANN. The prediction results are found to be satisfactory with a determination coefficient (R^2) 0.94, mean absolute error (MAE) 7.1, and mean square error (MSE) 98.7. These results reveal that FL models can be used to predict CEC as a function of SSA and ACT. However, it should be noted that the models, while they satisfactorily predict the high values, tend to over predict the very low values.

References

Akbarzadeh A, Mehrjardi RT, Lake HR, Ramezanpour H (2009) Application of artificial intelligence in modeling of soil properties (case study: roodbar Region, North of Iran). Env Res 3(2):19–24

Amini M, Abbaspour KC, Khademi H, Fathianpour N, Afyuni M, Schulin R (2005) Neural network models to predict cation exchange capacity in arid regions of Iran. European J of Soil Sci 56:551–559

ASCE Task Committee (2000) Artificial neural networks in Hydrology. I: preliminary concepts. J Hydrol Eng 5(2):115–123

ASTM (1999) American Society of Testing Materials, Annual book of the ASTM standards. ASTM International, 04-08, West Conshohocken

Cerato AB (2001) Influence of specific surface area on geotechnical characteristics of fine-grained soils. MSc. Thesis, Massachusetts University, Amherst, USA

Chapman HD (1965) Cation exchange capacity. In: Black JA (ed) Methods of soil analysis. Agronomy, vol 9. American Institution of Agronomy, Madison, pp 891–901

Cihacek LJ, Bremner JM (1979) A simplified ethylene glycol monoethyl ether procedure for assessment of soil surface area. Soil Sci Soc Am J 43:821–822

Curtin D, Smillie GW (1976) Estimation of components of soil cation exchange capacity from measurements of specific surface and organic matter. Soil Sci Soc Am J 40:461–462

Farrar DM, Coleman J (1967) The correlation of surface area with other properties of nineteen British clay soils. J Soil Sci 18(1):118–124

Fooladmand HR (2008) Estimating cation exchange capacity using soil textural data and soil organic matter content: a Case Study for the South of Iran. Archi Agro Soil Sci 54(4):381–386

Govindaraju RS, Rao AR (2000) Artificial neural networks in Hydrology. Water science and technology library, vol 36. Kluwer, Dordrecht

Jantzen J (1999). Design of fuzzy controllers, Technical Report, No:98-E864, Department of Automation,Technical University of Denmark

Keshavarzi A, Sarmadian F (2010) Comparison of artificial neural network and multivariate regression methods in prediction of soil cation exchange capacity. World Acad Sci Engand Tech 72:495–500

Keshavarzi A, Sarmadian F, Labbafi F, Vandechali MR (2011) Modeling of soil cation exchange capacity based on fuzzy table look-up scheme and artificial neural network approach. Modern Appl Sci 5(1):153–164

Manrique LA, Jones CA, Dyke PT (1991) Predicting cation exchange capacity from soil physical and chemical properties. Soil Sci Soc Am J55:787–794

Ohtsubo M, Takayama M, Egashira K (1983) Relationships of consistency limits and activity to some physical and chemical properties of Ariake marine clays. Soils Found 23(1):38–46

Petersen LW, Moldrup P, Jacobsen OH, Rolston DE (1996) Relations between specific surface area and soil physical and chemical properties. Soil Sci 161(1):9–21

Santamarina JC, Klein KA, Wang YH, Prencke E (2002) Specific surface: determination and relevance. Canadian Geotech J 39:233–241

Sen Z (2004) Fuzzy logic and system models in water sciences. Turkish Water Foundation, Istanbul

Smith CW, Hadas A, Dan J, Koyumdjisky H (1985) Shrinkage and Atterberg limits in relation to other properties principal soil types in Israel. Geoderma 35:47–65

Tayfur G (2006) Fuzzy, ANN, and regression models to predict litudinal dispersion coefficient in natural streams. Nord Hydrol 37(2):143–164

Tayfur G (2012) Soft computing in water resources engineering. WIT Press, Southampton

Tiller KG, Smith LH (1990) Limitations of EGME retention to estimate the surface area of soils. Aus J Soil Res 28:1–26

Yukselen Y (2007) Specific surface area and pore size distribution effect on engineering properties of fine-grained soils. PhD Thesis, Dokuz Eylül University, Izmir, Turkey