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APPLICATION OF MODERN METHODS: MODELING OF SEDIMENTARY SOIL ESP CONTENT

Professor Dr. Sorush Niknamian

Board Member of Weston A Price Foundation, Washington DC, USA

ABSTRACT

Knowing the exchangeable sodium percentage (*ESP*) variations and its values in sodic or saline-sodic soils is essential in order to estimate the amount of soil amendments and better land management. *ESP* calculated from cation exchange capacity (*CEC*), and since *CEC* measurement is difficult and time-consuming, *ESP* computation is costly and subject to error. Thus, presenting a method to estimate *ESP* indirectly, by an easily available index is much more efficient and economical. In this study, 296 soil samples collected and analyzed from Sistan plain, southeastern Iran. Soil *ESP* were predicted by using artificial neural networks, comprising radial basis functions (RBFN) and multilayer perceptron (MLP) and adaptive neuro-fuzzy inference systems (ANFIS), and results compared with stepwise linear regression method. Results indicated that the linear regression models performed poorly in order to estimate *ESP* ($R^2 \leq 0.58$ and root mean square error (*RMSE*) ≥ 4.31). Applying fewer inputs (electrical conductivity (*EC*) and *pH*), ANFIS showed better results (R^2=0.80, *RMSE*=2.34), while increasing inputs (clay and organic carbon) decreased the accuracy (R^2=0.82, *RMSE*=4.20). Using more inputs, RBFN resulted in better performance in comparison with other methods (R^2=0.83, *RMSE*=2.85). Sensitivity analysis using the connection weight method demonstrated that *EC*, *pH*, clay percentage and bulk density are the most important variables in order to explain *ESP* variability in the region, respectively. Generally, considering the evaluation criteria and the number of used variables of models, ANFIS (with *EC* and *pH* as inputs) is the most appropriate method for estimating *ESP* in Sistan plain.

Keywords: Saline-sodic soils, Exchangeable sodium percentage, PTFs, Artificial Intelligence, Sistan plain

Introduction

Soil salinity and sodicity are main factors limiting crop growth in irrigated lands. Salinization is the accumulation of solution salts in soil profiles, which limit yield production. When salt accumulation exceeds crop threshold, its importance and effects would reveal. Too amount of salt accumulation in soils is the result of low irrigation and high evaporation rate (Wang et al. 2008).

Currently, near 230 Mha of fields are irrigated worldwide, that 45 Mha of them (20%) affected by salinity (FAO 2008). Sodicity is one of the most important attributes in saline soils, and influences their physical and chemical properties (Farahmand et al. 2011). Sodicity is considerable when exchangeable sodium percentage (*ESP*) exceeds 15% in soil. Soil structure degradation, decreasing hydraulic conductivity, soil aeration and permeability, and increasing *pH* up to 8.5, are main reasons of lowering yield in sodic soils (Richards 1954). Drainage, irrigation and changing crop pattern are some measures to control soil salinity (Cetin and Kirda 2003).

Approximately 10% of soils suffer from saline-sodic problem. Therefore, identifying and managing regions with high salinity limitations are of the most important priorities in agriculture (Barzegar 2001). Exchangeable sodium to other exchangeable cations ratio is one of the most imperative parameters for evaluating soil salinity and sodicity (Rohoades 1968). In this regard, *ESP* usually is the best index.

$$ESP = \frac{Na}{CEC} \times 100 \qquad (1)$$

Where:

ESP = Exchangeable sodium percentage, %

Na = Measured exchangeable *Na* , C mol kg^{-1}

CEC = Cation exchange capacity, C mol kg^{-1}

Knowing the *ESP* variations and its values in sodic or saline-sodic soils, especially in agricultural farms, is essential in order to estimate the amount of soil amendments and better land management. *ESP* computation is time-consuming, costly and subject to error. Errors of *ESP* measurement relate to *CEC* and exchangeable *Na*. Various error sources reported in measuring *CEC* by Bower method (Bower et al. 1952), including remaining excess indicator cations during washing step, and the existence of zeolite mineral in soil which resulted in overestimation of *CEC* and consequently *ESP* would calculate less than its actual value. Moreover, not saturating exchanging parts with indicator cation, in a full manner, soil wasting and hydrolysis of exchangeable indicator cation while washing, not full replacing of sodium by ammonium and solution of gypsum, caused underestimating *CEC* and overestiming *ESP* (Rhoades 1982). On the other hand, *CEC* measurement is time-consuming and costly. When $EC_e \geq 10$ dS m^{-1} (EC_e: EC for saturation extract), exchangeable sodium measurement in soils would prone to errors related to anion expulsion effect. Due to this errors, exchangeable sodium underestimates

(Jurinak et al. 1984). Thus, presenting a method to estimate *ESP* indirectly, by an easily available index is much more efficient and economical way to overcome mentioned problems.

Knowledge of relations and correlations among different soil properties and expressing them by statistical models are one of important issues in soil study. These models called pedo-transfer functions (PTFs) and comprising regression and artificial neural network models (Minasny et al. 2004). PTFs calculate soil attributes which are costly and time-consuming in measurement as function of other properties that easily obtained. Primarily, PTFs used linear regression but gradually it was replaced by nonlinear regression. Statistical regression assumes observations and variables are exact; however, in natural systems such as soils they are not. Thus, it is imperative to use methods for fitting functions that are capable of explaining vague structure of systems and producing actual patterns (Mohamadi and Taheri 2005). Artificial neural networks are a powerful tool for complicated computations and its easy applicability have been led to predictions in various fields (Fortin et al. 2011; Jingwen et al. 2013 and Kurtulmus et al. 2013). In this regard, nowadays artificial neural networks (ANNs) that are inspired in a way that biological nervous systems works, applied widely. An advantage of modeling methods which are based on calculation intelligence compared to regression PTFs is that they do not need to previous information about relations between inputs and outputs, and also their sensitivity to error in input data are less (Agyare and Park 2007). In other words, using minimum measured parameters, these models are able to predict target variables variation, precisely. Sadrmomtazi et al. (2013) demonstrated that intelligent models predicted more accurately than conventional regression models.

There have been developed many PTFs in order to estimate different soil properties till now. For instance, Robbins and Meyer (1990) presented a model to predict *ESP* from *pH* and *EC* in sodic soils of Australia (eq. 2).

$$ESP = [(pH - A) \times (1 + C \times EC)/B]^2 \qquad (2)$$

which *A*, *B* and *C* are soil specific coefficients. Furthermore, they proposed a second-order form equation that its coefficients should modify for different soils. These researchers calculated *A*, *B* and *C* ranges for different soil textures as follows: 4.62-6.95, 0.46-1.20 and 0.004-0.35, respectively. Values of R^2 varies in range of 0.22 to 0.91.

Sistan is one of the interior and flat plains of Iran plateau located in southeastern Iran, with elevation ranging from 475 to 500 meters above sea level and covered by alluvial delta of the Hirmand River and its surrounding floods. Considering dry climate, high groundwater levels, poor annual rainfall, high evapotranspiration rate, and unsuitable water quality which utilized to irrigate agricultural farms, salinity is a serious problem in this region and is expanding. Unfortunately due to vastness of Sistan plain and difficult conditions for field investigations, soil studies and findings in this area are very little. Planning for preventing and solving the problem of salinity in order to improve soil quality and sustainable agricultural development is necessary and inevitable in this area. The purpose of current study is investigating and suggesting relationships and models to predict the amount of soil *ESP* from easily obtained properties of soil. Considering statistical regression methods that have been used in previous studies, computational-intelligence-based methods performance assessed. It was tried to present an accurate model with minimum input variables and acceptable precision that does not need to costly and time-consuming laboratory measurements for estimating *ESP*.

Material and Methods

Description of the study area

The study area is the Sistan plain located in the southeast of Iran, one of the driest regions of Iran and famous for its "120 day wind", a highly persistent dust storm in the summer which blows from north to south with velocities of nearly 20 knots. The Sistan delta has a very hot and dry climate. In summer, the temperature exceeds 50^{o}C. Rainfall is about 55 mm year^{-1} and occurs only in autumn and winter. Evapotranspiration of the area is 4500 to 5000 mm year^{-1}. Strong winds in the region are quite unique and are an important contributing factor for the high evaporation (Fig. 1).

Field and Laboratory Analyses

Soil samples were collected from 296 points throughout study area. Soil samples were taken in land with a high risk of salinization and/or sodification. Air-dried soil samples were passed through a 2-mm sieve for selected chemical and physical measurements.

The 1:5 and 1:1 soil to water extracts were prepared by adding 20 mL distilled water to 4g and 20g soil in a 100 mL bottles respectively. The bottles were sealed with a stopper, agitated for 15 min on a mechanical shaker (100 r min^{-1}), allowed to stand for 1 h, and then agitated again for 5 min before a sample was obtained by filtration (Chi and Wang 2010). Organic carbon (OC), bulk density (Bd), calcium carbonate equal (CCE), *pH*, *EC*, concentrations of Na^+, Ca^{2+} and Mg^{2+}, *CEC* and soil sample textures were determined (USDA-NRCS 1996). The *ESP* was determined using eq. 1.

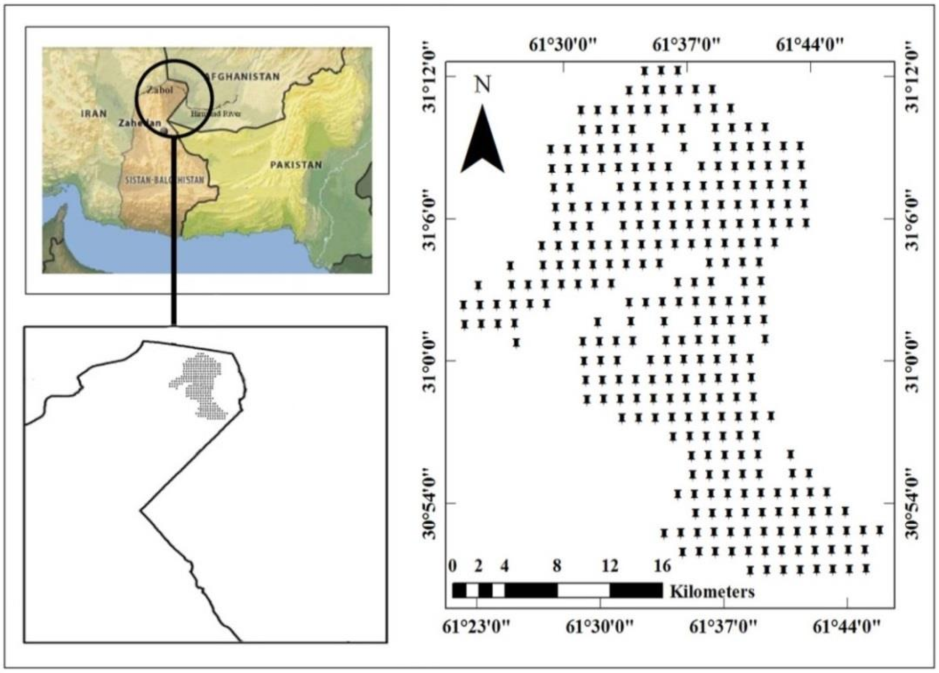


Fig. 1 Map showing the geographical setting of the study area, Sistan plain, Iran

Physical and chemical properties of soil samples were used for modeling *ESP* and evaluating the accuracy of obtained model (Table 1).

Table1 Statistical parameters of soil physical and chemical properties

Variable	Unit	Mean	Minimum	Maximum	SD	Variance	CV
Clay	%	23.2	7.1	49.5	9.20	84.9	39.8
Silt	%	42.5	0.0	82.0	14.6	212	34.2
Sand	%	34.6	2.6	85.0	18.2	330	52.9
Bd	Gr cm^{-3}	1.39	0.8	1.89	0.36	0.13	25.4
OC	%	0.52	0.04	1.26	0.25	0.06	47.7
EC	dS m^{-1}	4.61	0.2	115.8	9.75	95.1	211.5
pH	log[H^+]	8.84	7.7	10.3	0.53	0.28	5.98
Na^+	Cmol kg^{-1}	3.08	1.03	9.32	1.33	1.77	43.3
ESP	Cmol kg^{-1}	23.9	5.86	59.7	9.20	84.5	38.4
CEC	Cmol kg^{-1}	13.3	5.92	34.0	4.47	19.9	33.55

SD: standard deviation, CV: Coefficient of variation, Bd: bulk density, OC: organic carbon, CEC: cation exchange capacity

Stepwise linear regression model

An example of a linear regression model is shown in the equation 3.

$$Y = K_1X_1 + \cdots + K_nX_n + d \qquad (3)$$

Where:

Y: dependent variable, for example, *ESP* of soil samples

X_1 to X_n: independent variables, for example the *EC* of soil samples,

K_1 to K_n : regression coefficient,

d: intercept.

In order to estimate and modeling the *ESP* by *EC* and sodium adsorption ratio (SAR) of soil, a linear regression model was used. Before modeling, 85% of data assigned to simulation and 15% to test the model. all linear regression equations were fitted to the data using the Datafit software and the best regression equations were selected.

Artificial Neural Networks modeling

The artificial neural network (ANN) is useful computational way for predicting and modeling abstruse relationships among parameters, especially when there is no explicit relation among parameters (Smith 1993; Gallant 1993). The ANN comprised of three layers: the input layer that all the data are imported to the network and calculation the weight for each input variables are done, the hidden layer or layers, that data are computed, and the output layer, that the artificial neural network results are obtained. Every single layer includes one or more fundamental section(s) called a node or a neuron (Dreyfus et al. 2011). The problem is the key factor that determines the number of neurons in the layers. The small number of hidden neurons is a limiting factor to learn the process carefully, however, too high number can be very time-consuming and the network may overfit the data (Karunanithi et al. 1994).

In this study, three-layer multilayer perceptron (MLP) networks were constructed for computation of the PTFs. All the computations were performed using the Excel 2003 and MATLAB (Version 7.12, Math Works, Inc., Natwick, MA).

MLP description

The multilayer perceptron (MLP) network includes an input layer, hidden layers and an output layer (Fig. 2). In this study, the inputs were *pH* and *EC*. The scaled values have been passed into the input layer and after that propagated from the input layer to the next layer which is called hidden layer, before reaching the output layer (Hussain et al. 2002). Each node in both hidden or output layer acts as a summing junction. Using the following equation, inputs combine and modify from the previous layer (Razavi et al. 2003; Jorjani et al. 2008).

$$Y_i = \sum_{j=1}^{i} X_i W_{ij} + b_j \quad (4)$$

Which:

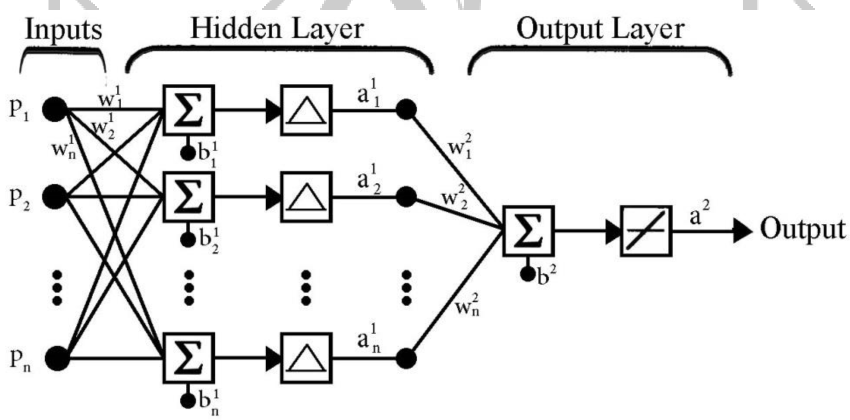
Y_i is the net input to node *j* in hidden or output layer,

W_{ij} is the weight related to neuron *i* and neuron *j*,

X_i is the input of neuron *j*,

b_j is the bias connected to node *j*.

Sigmoidal transfer function usually use for nonlinear relationships (Ghaffari et al. 2006; Torrecilla et al. 2007). The general form of this function is shown below (Jorjani et al. 2008):



$a^1 = \mathrm{Tribas}(w^1{}_i\, p_i + b^1{}_i) \quad a^2 = \mathrm{Purelin}(w^2{}_i\, p_i + b^2{}_i) \quad i=1,2,\ldots,n$

Fig. 1 Schematic representation of the best ANN architecture

$$Z_i = \frac{1}{1+e^{-Y_y}} \quad (5)$$

where:

Z_i: the output of node *j*.

To avoid reduction in network speed and accuracy and to make data values equal, it is necessary to normalize input data (Torrecilla et al. 2007). Normalization was done so that the mean of the data series became 0.5 (Kumar et al. 2002). The following equation is used for normalizing data:

$$x_n = 0.5\left[\frac{x-\bar{x}}{x_{max}-x_{min}}\right] + 0.5 \quad (6)$$

where:
x_n: normalized value,
x: actual value,
$\bar{x}$: mean value,
x_{min}: minimum value,
x_{max}: maximum value of parameter.

MLP network need sample series of input and output data for designing and training. In this study, PTFs have been considered as network inputs and *ESP* as output data. Seventy (70), 15 and 15% of data were used to train, validate and test of MLP model, respectively.

MLP network applied for ANN modeling using MATLAB 7.6 software. Marquardt-Levenberg learning rule and hyperbolic tangent function were used for training (Haykin 1994). Number of neurons in hidden layer was computed by trial-and-error method and finally the best structure for *ESP* was selected considering the greatest R^2 value and the least *RMSE*.

Radial Basis Function (RBFN) model

Radial Basis Function (RBFN) network is based on supervised learning. RBFN networks were independently proposed by many researchers and are a popular alternative to the MLP. RBFN networks are also good at modeling nonlinear data and can be trained in one stage rather than using an iterative process as in MLP and also learn the given application quickly (Venkatesan and Anitha 2006).

The structure of RBFN network is similar to that of MLP. It consists of layer of neurons. The main distinction is that RBFN has a hidden layer which contains nodes called RBF units. Each RBF has two key parameters that describe the location of the function's center and its deviation or width. The hidden unit measures the distance between an input data vector and the center of its RBF. The RBF has its peak when the distance between its center and that of the input data vector is zero and declines gradually as this distance increases. There is only a single hidden layer in a RBFN network with two sets of weights, one connecting the hidden layer to the input layer and the other connecting the hidden layer to the output layer. Those weights connecting to the input layer contain the parameters of the basis functions. The weights connecting the hidden layer to the output layer are used to form linear combinations of the activations of the basis functions (hidden units) to generate the network outputs. Since the hidden units are nonlinear, the outputs of the hidden layer may be combined linearly and so processing is rapid (Foody 2004).

Adaptive neuro-fuzzy inference system (ANFIS)

The advantage of the fuzzy inference system is that it can deal with linguistic expressions and the advantage of a neural network is that it can be trained and also can self-learn and self-improve. Jang (1993) took both advantages, combining the two techniques, and proposed the adaptive neuro-fuzzy inference system (ANFIS). The idea behind neural network and fuzzy inference combination is to design a system that uses a fuzzy logic to represent knowledge in an interpretable manner and has the learning ability derived from a neural network that can adjust the membership functions parameters and linguistic rules directly from data in order to enhance the system performance (Wang et al. 2006). The ANFIS architecture contains a five-layer feed forward neural network (Fig. 3). ANFIS is a hybrid intelligent system which implements a Sugeno fuzzy inference system for a systematic approach to generate fuzzy rules from a given input-output dataset (Negnevitsky 2005).

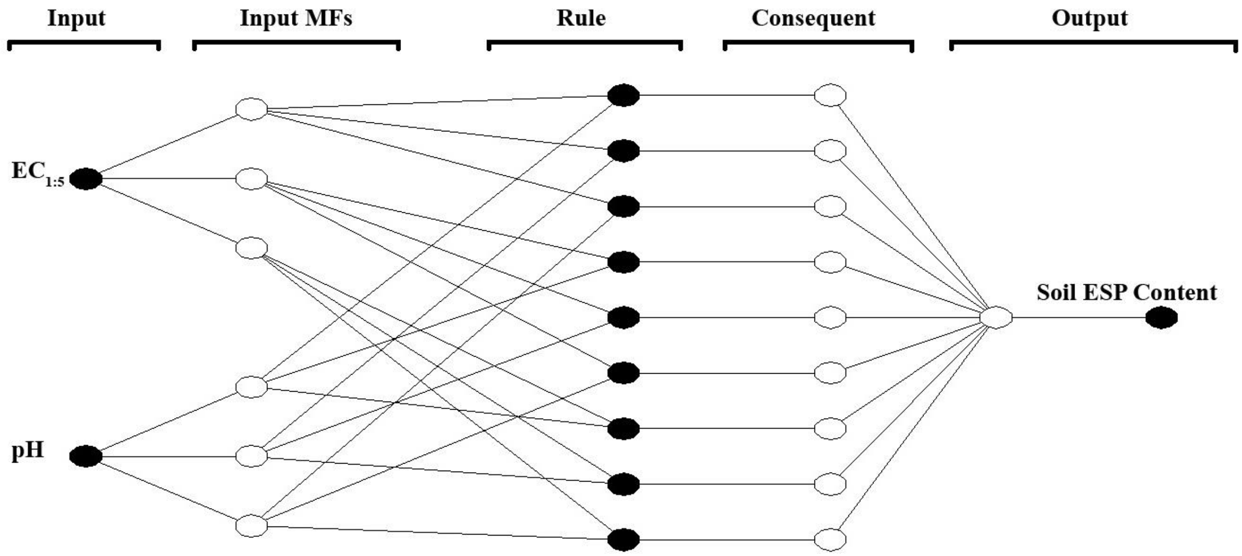


Fig. 2 ANFIS architecture of two input and nine rules

A hybrid ANFIS algorithm based on the Sugeno system improved by Jang (1993) was used for acquiring optimal output data in the study. The algorithm consists of the least-squares method and the back-propagation algorithm. The first method was used for optimizing the consequent parameters, while the second method in relation to fuzzy sets was employed to arrange the premise parameters (Ubeyli and Guler 2005).

In this study in order to predict *ESP* using MLP and ANFIS, $EC_{1:5}$ and *pH* considered as inputs. MLP had three layers (an input layer, one hidden layer and an output layer) and six neurons in the hidden layer. Furthermore, ANFIS had five layers (input layer, input membership function layer, rules layer, consequent layer and output layer) with three gaussian membership functions (GaussMF) for input function.

Analysis

The R^2, *RMSE* and model efficiency factor (MEF) used to compare models predicted soil *ESP* and measured values and assess the performance of models.

$$R^2 = 1 - \sum_{i=1}^{n}(y_i - y_{di})^2 \Big/ \sum_{i=1}^{n}(y_{di} - y_m)^2 \quad (7)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_{di} - y_i)^2} \quad (8)$$

$$MEF = 1 - \frac{\sum_1^n [y_{di} - y_i]^2}{\sum_1^n [y_{di} - y_m]^2} \quad (9)$$

where:
n: number of points,
y_i: output value got from the neural network model,
y_{di}: experimental value,
y_m: average of the experimental values.

Sensitivity analysis for quantifying variable importance

Prediction accuracy is a major benefit of ANN models, but the ANN models of any physical processes are purely black box models, which do not explain the process being simulated and whose utility is limited, without information regarding the relative importance of the parameters in the system. The development of a method to couple input factors to meaningful outputs in ANN models is of critical importance (Kemp et al. 2007). The data employed for developing ANN models do contain important information regarding the physical process being simulated (Jain et al. 2008).

A connection weight approach was used to evaluate the importance of inputs (soil moisture and salinity) relative to output (crop yield) in ANNs. The connection weight method is to sum the products of the input-hidden and the hidden-output connection weights between each input neuron and output neuron for all input variables (Olden et al. 2004). The relative contributions of the inputs to the output are dependent on the magnitude and direction of the connection weights. When the signs of the input-hidden and hidden-output connection weights are the same (i.e., either both are positive or negative), the input has a positive impact on the output. Contrarily, if the signs of these connection weights are opposite, the specific input has a negative effect on the output. The overall contribution of the input to the output depends on its sum of the positive and negative effect across all different hidden nodes. The larger the sum of the connection weights, the greater the importance of the variable. The relative importance of input variable *i* is determined through the following formula:

$$\mathrm{RI_i} = \sum_{j=1}^{m} \mathrm{W_{ij}W_{jk}} \Big/ \sum_{i=1}^{n}\sum_{j=1}^{m} \mathrm{W_{ij}W_{jk}} \times 100 \qquad (10)$$

where:
RI_i: relative importance of the variable i (i=1,2,3,…,n) in the input layer on the output variable (%),
j: index number of the hidden node (j =1, 2, 3, …, m),
W_{ij}: connection weight between input variable i and hidden node j,
W_{jk}: connection weight between hidden node j and the output node k.
The whole computation was repeated for each output neuron.

Results and Discussion

Descriptive statistics

Descriptive statistics related to *ESP* and other soil properties have calculated (Table 1). Soil *ESP* for study area are high (with an average of 16.3) which demonstrates the necessity for investigating *ESP* variation as sodicity index of soils in Sistan plain. Correlation analysis (Perason coefficient) applied amongst measured attributes and *ESP* using SAS software, and $EC_{1:1}$ and $EC_{1:5}$, clay percentage and soil *pH* were the most correlated variables (Table 2).

Table2 Correlations between organic carbon (OC) and some soil properties

	Clay	CCE	Silt	Sand	Bd	OC	$EC_{1:1}$	$EC_{1:5}$	*pH*
ESP	0.32**	0.14*	0.27**	-0.37**	0.05	-0.05	0.68**	0.70**	0.35**

**: significant at the 0.01 level, *: significant at the 0.05 level

Modifying Robbins and Meyer Equation Coefficients

In this study, *ESP* modeled by the second-order form equation of Robbins and Meyer (1990) and *A*, *B* and *C* coefficients computed for dry alluvial soils of Sistan plain (Table 3).

Table3 *ESP* modeling results by modified equation of Robbins and Meyer (1990) in alluvial soils of Sistan plain

Equation form	*A*	*B*	*C*	*RMSE*	R^2	*MEF*
$ESP = [(pH - A) \times (1 + C \times EC)/B]^2$	7.22	4.28	0.0199	4.53	0.50	0.33

According to statistic parameters of modified equation of Robbins and Meyer (1990), it could be concluded that nonlinear form of this equation is not able to explain *ESP* variation in study area, accurately. This conclusion supported in figure 4.

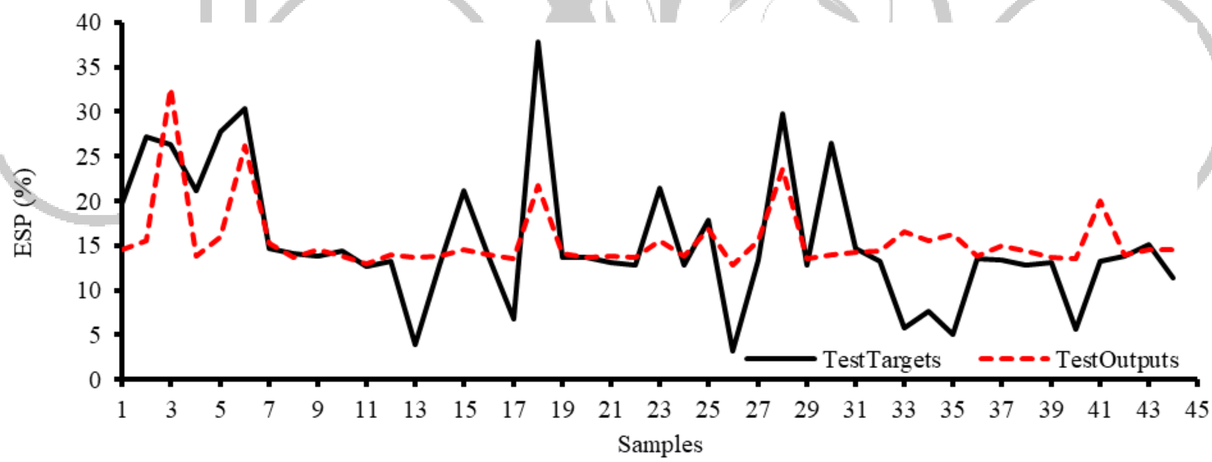


Fig. 4 Measured vs. predicted values of *ESP* using equation of Robbins and Meyer (1990)

Suggested Regression Models to Predict ESP in Dry Alluvial Soils

Table4 The Root Mean Squer Erorr (*RMSE*) of the independent variable, Coefficient of Determination (R^2) and Model Efficiency Factor (*MEF*) of the soil *ESP* pedotransfer function

Models	Step	Variable Entered	Partial R-Square	Model R-Square	F Value	Pr > F
Reg Model 1	1	$EC_{1:5}$	0.49	0.49	286.74	<.0001
	2	pH	0.02	0.52	14.01	0.0002
	1	$EC_{1:5}$	0.49	0.49	286.73	<.0001

Reg Model 2	2	Clay	0.04	0.53	20.19	<.0001
	3	pH	0.02	0.56	14.91	0.0001
	4	OC	0.01	0.58	3.65	0.0572

Final Results

Models	Pedotransfer function	*RMSE*	R^2	*MEF*
Reg 1	$ESP = 0.748EC_{1:5} + 1.98pH - 3.858$	4.91	0.52	0.39
Reg 2	$ESP = 0.7EC_{1:5} + 0.155Clay + 1.764pH - 2.161OC - 4.1994$	4.34	0.58	0.50

All variables Entered left in the model are significant at the 0.1000 level

As Robbins and Meyer (1990) used *EC* and *pH* to predict *ESP* in sodic soils of Australia and reported that their model is economic, time-efficient and potentially able to calculate *ESP* from easily obtained data, in current study firstly, all parameters which measured in laboratory (comprising $EC_{1:5}$, *pH*, clay, OC, CCE, Bd, silt and sand) considered as inputs for model. Final model used only $EC_{1:5}$ and *pH* as required data (Table 4).

Although the second regression model (Table 4) used more inputs than the first one, it is not able to explain more than 56% of *ESP* variations. In other words, 44% of *ESP* variability refers to factors that were not considered in regression model. Parts of this discrepancy can ascribe to nonlinear relations among *ESP*, *EC* and other soil properties which linear regression models have not sufficient capability to recognize them.

Comparing measured and predicted values of *ESP* using regression models revealed that variation ranges of outputs in model 1 is narrower than model 2, while results of second model showed some overestimation (Figure 5, 6).

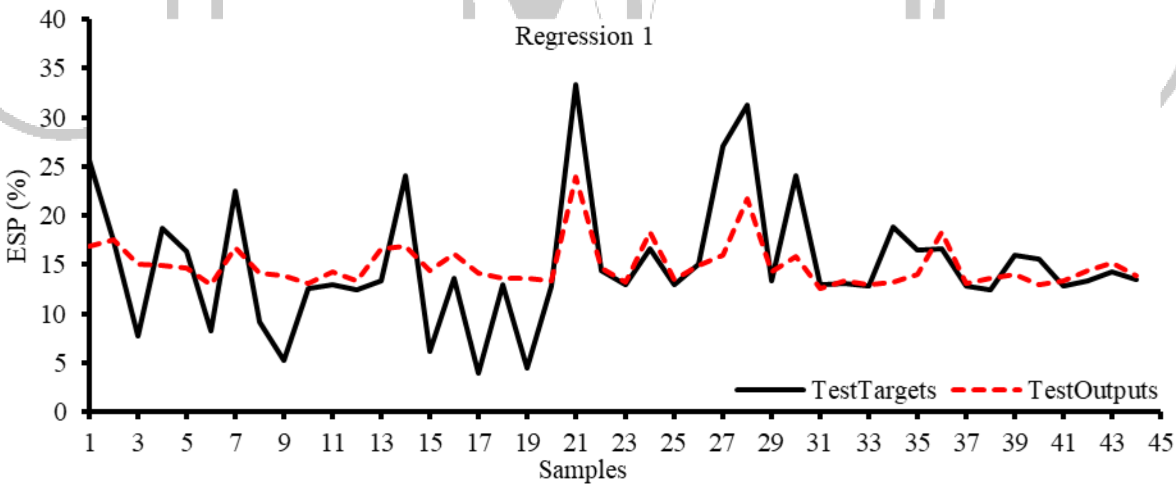


Fig. 5 Measured vs. estimated values of *ESP* using easily obtained soil properties in regression model 1

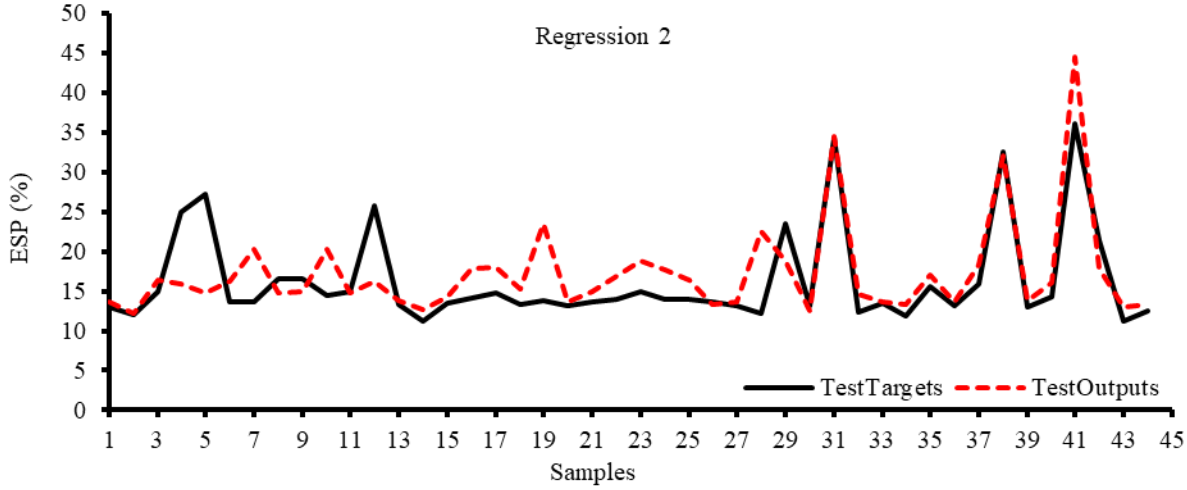


Fig. 6 Measured vs. estimated values of *ESP* using easily obtained soil properties in regression model 2

The purpose of this research was to present a model requiring as low as possible data which are easily obtainable. Since using soil parameters (other than *EC* and *pH*) did not improve model and also these parameters obtained easily, *EC* and *pH* are appropriate inputs for *ESP* estimate.

Regression models obtained, are different from Robbins and Meyer (1990). Therefore, relations between *ESP* and soil attributes are not consistent and influenced by several factors such as *EC* (Jurinak et al. 1984), ionic solution concentration (Shainberg et al. 1980), soil salinity (Frenkel and Alperovitch 1983), and clay minerals and its components (Endo et al. 2002).

The Artificial Neural Networks and ANFIS modeling

In order to predict *ESP* by artificial intelligence methods (MLP, RBFN and ANFIS) using easily-obtained soil properties and comparing results with stepwise linear regression, two models considered. First model comprised *EC* and *pH* as inputs, while in the second one, all measured parameters considered (*EC*, *pH*, clay, OC, CCE, Bd, silt and sand).

During training phase, the best numbers of neurons in hidden layer and the best function in neurons of hidden layer for improving precision of training phase selected by trial and error. Modeling results illustrate in Table 5.

Table5 Properties of resulted MLP, RBFN and ANFIS models

Model	Input	Layer No.	Neurons in hidden layer	HLF*	OLF*	RMSE	R^2	MEF
		MLP						
1	$EC_{1:5}$+pH	3	4	tribas	Purelin	3.95	0.74	0.69
2	8 parameters**	3	6	tansig	Purelin	3.65	0.76	0.75
		RBFN						
Model	Input	Spread	Neurons in hidden layer	HLF*	OLF*	RMSE	R^2	MEF
1	$EC_{1:5}$+pH	0.7	5	gaussian	Liner	3.55	0.77	0.74
2	8 parameters**	1	10	gaussian	Liner	2.85	0.83	0.80
		ANFIS						
Model	Input	Layer No.	Rules	IMF*	OMF*	RMSE	R^2	MEF
1	$EC_{1:5}$+pH	5	9	gaussMF	liner	2.34	0.80	0.81
2	8 parameters**	5	4	gaussMF	liner	4.20	0.82	0.71

*HLF: hidden layer function, OLF: output layer function, IMF: input membership function, OMF: output membership function, LIF: input layer function
** 8 parameters: $EC_{1:5}$, *pH*, clay, silt, sand, organic carbon, carbonate calcium equivalent, density

Results showed that aiming at estimating *ESP* by model 1 (inputs: *EC* and *pH*), ANFIS is the most efficient model (R^2=0.80, *RMSE*=2.34 and *MEF*=0.81). MLP and RBFN are suitable, too, however, as shown in Figure 7, ANFIS outputs are more comparable with input data and *ESP* predicted better. Generally, artificial intelligence methods (MLP, RBFN and ANFIS) were more capable to predict *ESP* from *EC* and *pH* (model 1). Erzin and Gunes (2011) estimated swell percent and swell pressure of soil by using ANN and multiple regression analysis (MRA) and reported that ANN performed significantly better than MRA. They presented ANN as an inexpensive and rapid alternative for laboratory methods to predict swell percent and swell pressure of soil. Estimating soil parameters from more readily available soil data in Ziyaran region, Keshavarzi et al. (2010) concluded that the ANN model with five neurons in hidden layer gives better estimates of field capacity and permanent wilting point than the multivariate regression model. Singh and Deo (2007) in their study to forecast daily river flows along river Narmada in India, using ANFIS, generalized regression neural network (GRNN) and RBFN, found out ANFIS and RBFN are more precise than GRNN and MLP. Amutha and Prochelvan (2011) after studying the seasonal ground water levels in Malattar sub-watershed, located in Vellore district, Tamilnadu, India, assessed performances of ANFIS and RBFN. Both models had 3 inputs. The results showed that the ANFIS is better when compared to RBFN.

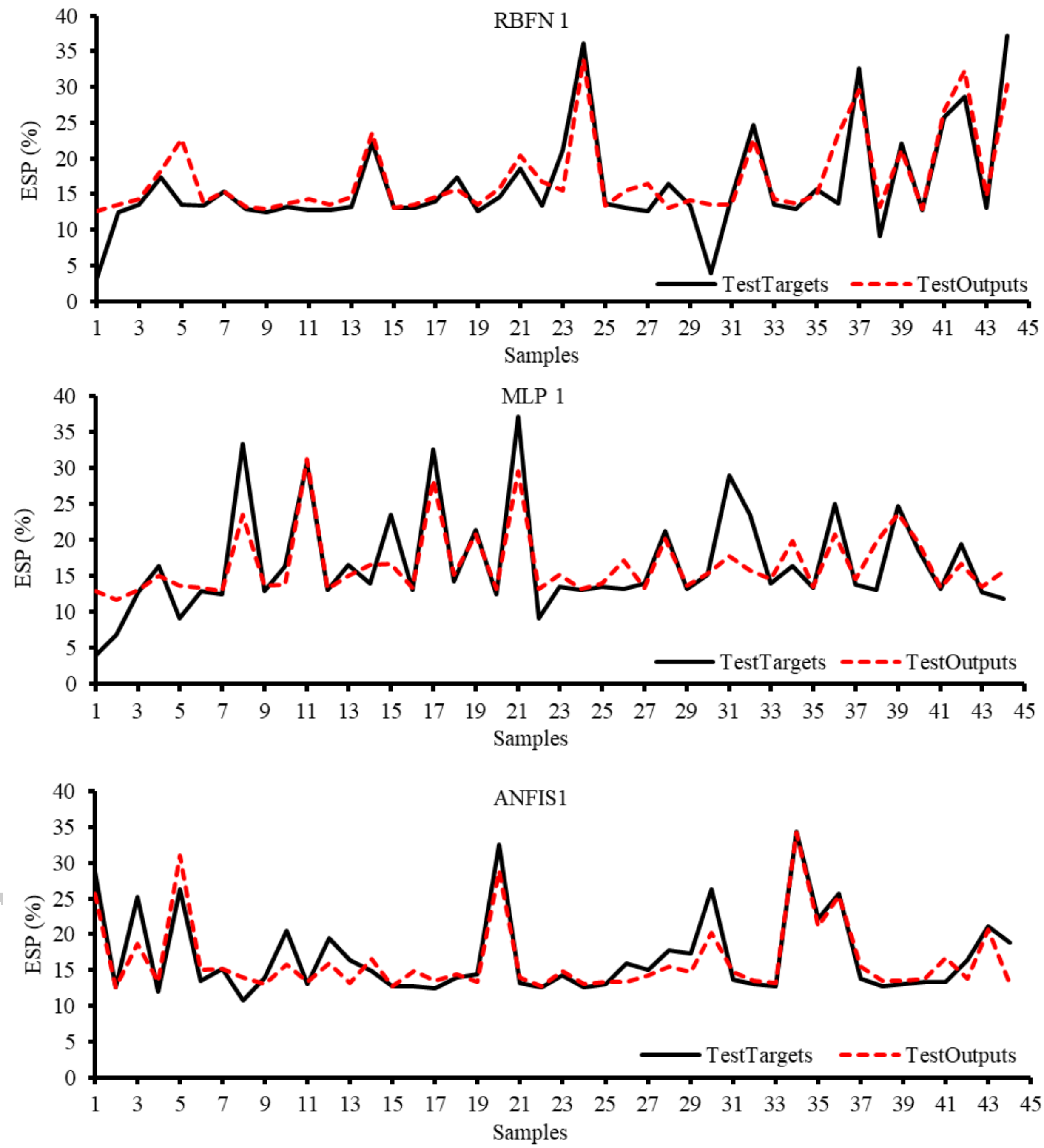


Fig. 7 Measured vs. estimated values of *ESP* using easily obtained soil properties in model 1 by RBFN, MLP, ANFIS

Increasing inputs changed results in which RBFN has better outcomes in comparison with ANFIS and MLP (R^2=0.83, *RMSE*=2.85 and *MEF*=0.80). Outputs of RBFN are more consistent with input data and *ESP* predicted better (Figure 8). Yilmaz and Kaynar (2011) in order to determine the swell potential of clay soils, applied MLP, RBFN, ANFIS and multiple regression (MR) models. They reported that MLP and ANFIS have quite the same results and RBFN is the best model. Increasing inputs in ANFIS resulted in increasing error, however, for MLP and RBFN this was vice versa, and although R^2 improved to some extent, *RMSE* improved significantly (Table 5).

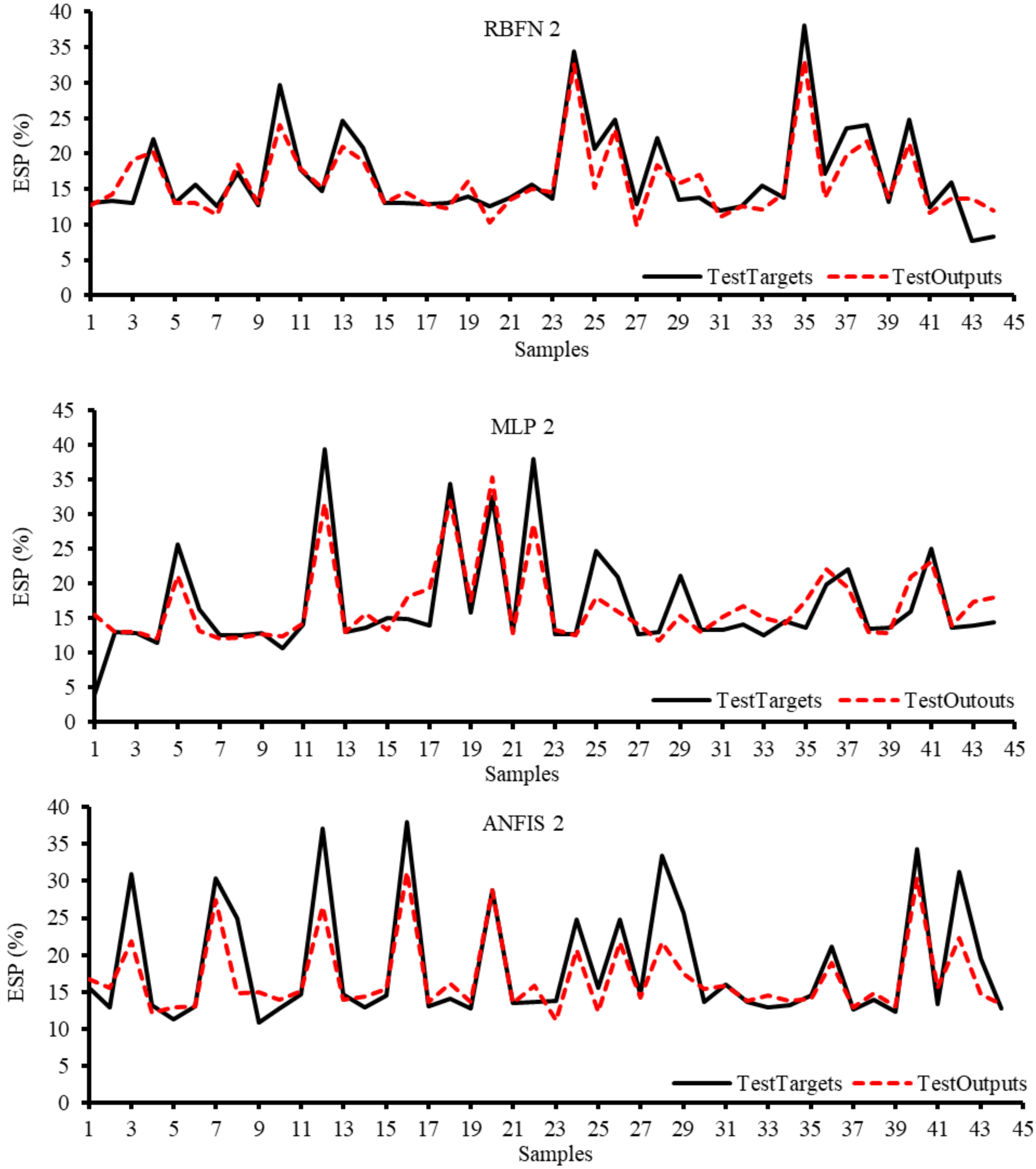


Fig. 8 Measured vs. estimated values of *ESP* using easily obtained soil properties in model 2 by RBFN, MLP, ANFIS

General comparing among artificial intelligence methods aiming at *ESP* modeling, implied that ANFIS outperforms RBFN and MLP. Despite the fact that statistical parameters showed good performance of RBFN (model 2), ANFIS (model 1) is more desirable because of lesser inputs (compared with 8 inputs in RBFN 2 which required more time and cost to determine), easy measurement and obtaining. Karami and Afiuni-Zadeh (2012) for modeling of sizing of rock fragmentation due to bench blasting by estimation of 80% passing size (K80) of Golgohar iron ore mine of Sirjan, Iran, found out that ANFIS is superior to RBFN.

They expressed that using only two input parameters in ANFIS is the reason of its superiority over RBFN with seven inputs.

Investigating histogram curves for the best models of *ESP* prediction shows better estimates of ANFIS (model 1) using *EC* and *pH* as inputs and RBFN (model 2) using all parameters (Figure 9). Frequencies of error percent in RBFN (model 2) is closer to zero and has the least variation range and also *SD* (5.76), which implies its ability for modeling *ESP* employing more inputs, compared to other models. Furthermore, regression model has the widest curve and the most error variations (Figure 9), however, *SD* for ANFIS (model 1) (2.62) is lesser than others that resulted to lesser error (*RMSE*=2.34) and more accuracy to estimate *ESP* (Figure 9-d).

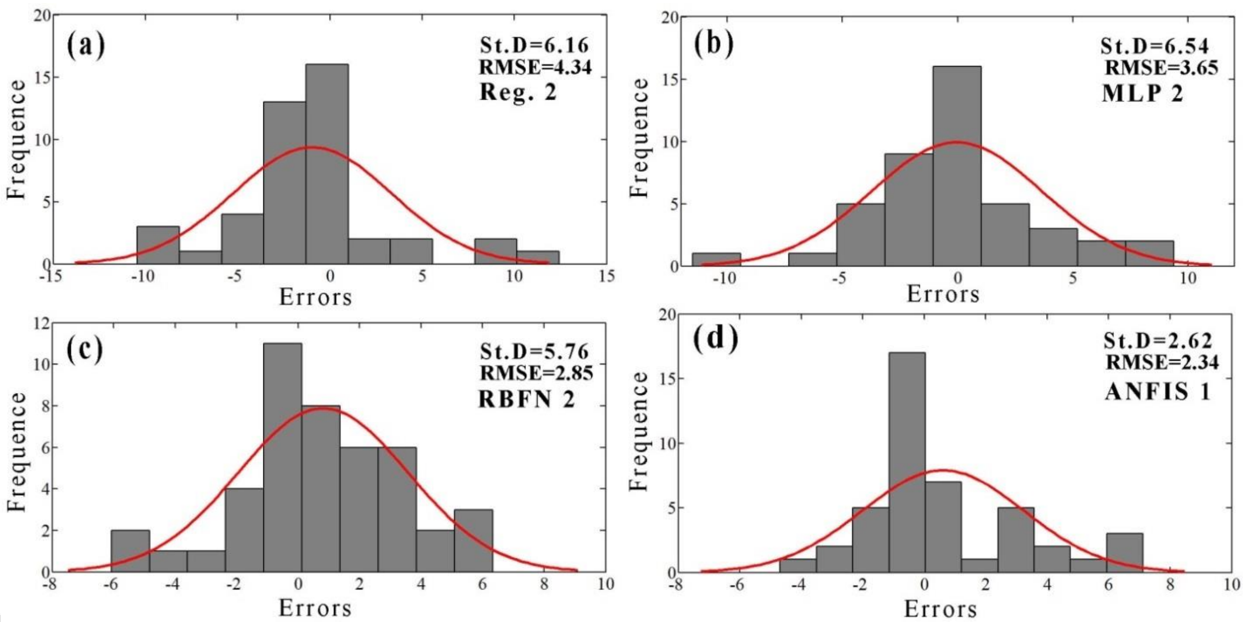


Fig. 9 Histogram curves of the best models: (a) Regression 2, (b) MLP 2, (c) RBFN 2 and (d) ANFIS 1 (St.D: standard deviation)

In order to find the importance of used variables, the best model including all inputs (RBFN 2) considered. Then, connection weights between input variables and hidden nodes (W_{ij}) and connection weights between hidden nodes and the output nodes (W_{jk}) derived (Table 6). Finally, sensitivity of all inputs of RBFN 2 calculated using equation 9 (Figure 10). This figure illustrates that $EC_{1:5}$, *pH*, clay percent and Bd, sort by relevance, are the most important parameters regarding *ESP* estimation in alluvial soils of Sistan plain.

Table6 Neuron weights used for sensitivity analysis

Input weight										
	Neuron1	Neuron2	Neuron3	Neuron4	Neuron5	Neuron6	Neuron7	Neuron8	Neuron9	Neuron10
CCE	0.4814	0.591	0.6458	0.4745	0.454	0.4951	0.4198	0.2622	0.4951	0.3855
Bd	0.7087	0.7087	0.4655	0.4334	0.6674	0.6903	0.3555	0.6353	0.4472	0.6444
OC	0.4324	0.4404	0.4598	0.4657	0.5221	0.4316	0.509	0.6081	0.4689	0.6368
Clay	0.7059	0.6163	0.3757	0.4182	0.4418	0.3686	0.4182	0.5125	0.4076	0.5019
Silt	0.5875	0.5631	0.4351	0.4656	0.5814	0.679	0.4107	0.3497	0.5326	0.4351
Sand	0.3065	0.3769	0.6281	0.576	0.4485	0.3891	0.6306	0.6427	0.5147	0.5632
$EC_{1:5}$	0.6792	0.5089	0.4616	0.5025	0.4651	0.815	0.4588	0.6624	0.4661	0.4598
pH	0.7391	0.6741	0.4832	0.5127	0.5009	0.4635	0.4969	0.5521	0.493	0.5127
Layer weight										
	Neuron1	Neuron2	Neuron3	Neuron4	Neuron5	Neuron6	Neuron7	Neuron8	Neuron9	Neuron10
	2.0593	-0.6136	3.8075	-18.0898	-0.6824	0.5658	5.564	4.4402	8.4618	-4.3618

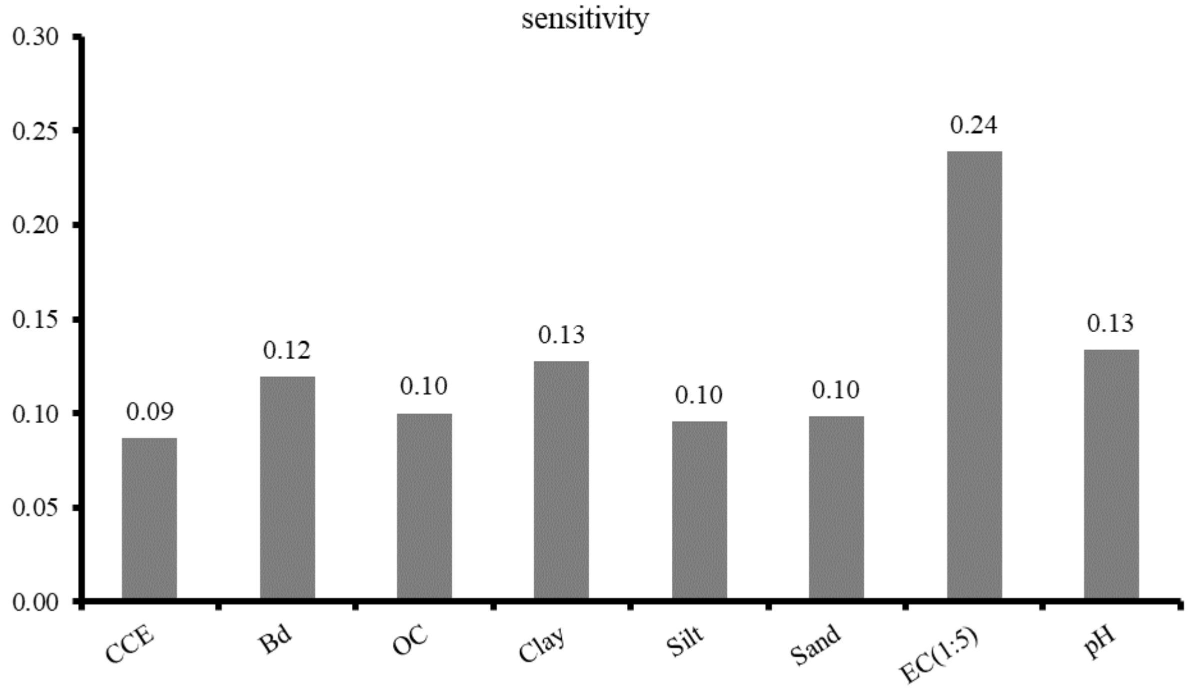


Fig. 10 Sensitivity coefficients histogram for some soil properties

Conclusions

In this study, the feasibility of predicting *ESP* by soil easily-obtained properties assessed using different methods. *ESP* estimated by regression models and results implied that they have not acceptable performance (R^2 ≤ 0.58, *RMSE* ≥ 4.31 and *MEF*≥39). However, using more inputs improved estimation in regression model 2 and partial R^2 values showed the effect of *EC*, clay, *pH* and OC, sort by relevance, in approximating *ESP*. Then, artificial intelligence models utilized with the same inputs, which demonstrated better results than regression.

When used less inputs (model 1), ANFIS are the most efficient model (R^2=0.80, *RMSE*=2.34, *MEF*=0.81 and *SD*=2.62), while increasing inputs (model 2) lowered the accuracy (R^2=0.82, *RMSE*=4.20 and *MEF*=0.71).

Increase in number of input data beside control number of neurons in middle layer, made the RBFN (model 2) the most powerful model (R^2=0.83, *RMSE*=2.85 and *MEF*=0.80). Results showed that RBFN, ANFIS and MLP are able to predict *ESP* fro easily-obtained properties of soils, accurately.

Considering results of suggested models (1 and 2) for estimating *ESP* and according to number of input data beside evaluation criteria, model 1 (inputs: *EC* and *pH*) proposes. ANFIS reported the best estimates by this model. Moreover, the other advantage is less inputs that require less time and cost to obtain compared to required data in model 2. Sensitivity analysis results for applied variables regarding *ESP* estimation revealed that *EC*, *pH*, clay percentages and bulk density are the most important data.

In total, due to superiority of artificial intelligence models compare to linear regression, it is possible to use soil easily-obtained properties such as *EC* and *pH* to estimate *ESP*. It is imperative to conduct similar researches in different soils.

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