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ORIGINAL ARTICLES

Investigation Artificial Neural Networks For Point Simulation Of Soil Water Retention Curve

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ABSTRACT

In this research 35 soil samples with Loamy texture were gathered form region near Karaj-Alborz province-Iran. Different points of soil water retention curve (SWRC) in tensions points : 0, 10, 33, 100, and 1500 Kpa as dependent variables have been meseaured using pressure plate and presure membrane. Soil properties organic carbon, bulk density, soil particles size distribution, Caco3, mean and Geometric standard deviation of particle diameter were measured as independent soil peroperties. Independents variables divided into 3 groups of variables. Statistical investigation of pedotransfer functions showed that regression pedotransfer function established with soil particle size distribution, bulk density and organic carbon as dependent variable s resulted in best primary prediction also this pattern of input variables used as input variables of artificial neural networks models with Marquardt-levenburg training algorithm 3 layer procepteron structure with 6 neuron in hidden layer. R2 and RMSR ranged between 0.79- 0.82 and 2.53-1.21 for regression pedotransfer functions. In the other hand R2 and RMSr ranged between 0.85-0.94 and 0.88-1.30 for artificial neural networks. Final Investigation of result showed that artificial neural networks had more precious prediction.

Key words: Point simulation, Soil water retention curve, Regression pedotransfer functions, Artificilal neural networks.

Introduction

Nowadays attention to time consuming and direct measurement of hydraulic soil properties, researchers have focused on indirect measurement of this properties. IN the indirect measurement hydraulic soil properties can be estimated using easy-available properties such as soil size particle distributions organic carbon content, bulk density, cation exchangeable capacity, liquid limit and plastic limit and Caco3. Regression pedotransfer function and Artificial neural networks are two methods that used as estimation and simulation models for prediction of soil water retention curve (SWRC) and saturated or unsaturated hydraulic conductivity (K_s or K_h). Bouma (1989) expressed relationship between soil hydraulic properties and surrogate data such as particle size distribution, Organic matter and bulk density and named regression pedotransfer functions. Nemes and Rawls (2005) could be succeed to achievement acceptable estimation of soil water retention curve using Soil particle size distribution, PSD. Tomesla *et al* (2000) established pedotransfer functions (PTFs) for parametric soil water retention curve in Brazil soils and showed that regression pedotransfer function have more acceptable results rather than traditional and experimental equations and models. Hang and Zhang (2005) used soil particle size distribution as input variables to pedotransfer function and estimated soil water retention curves with R=0.94. Salcho *et al* (1996) estimated field capacity (FC), permanent wilting point(PWP) **,** available water and saturated hydraulic conductivity using Sand, silt, clay, bulk density and organic carbon as input variables. It is considered that method for simulation soil water retention curve divided in to 2 categories: 1- point simulation that simulated moisture content of soli samples at different tensions in soil water retention curve and 2: parametric simulation that estimated parameters of traditional equation of soil water retention curve such as Vangenukhten. Another modern method for modeling and data processing is artificial neural networks that categorized in Intelligence models. Artificial neural networks called briefly ANNs I literature have a data analyzing behavior similar to human brains using generalization and advanced training and learning algorithms and need no pre-determined mathematical models. Many literature showed that ANNs are acceptable method for simulation soil hydraulic properties (Doai *et al* 2005, Minasney and Mcbarteney 2002, Nilson *et al* 2005, Minasney *et al* 2004). Artificial neural networks are intelligence modeling methods can be used for Costly measured soil properties estimation. They have capability of learning complex relationship between multiple input and output variables (Nemes *et al.,* 2002). Artificial neural network is an attempt to build numerical techniques that are supposedly analogous to biological human neural system. Artificial neural network that were used in this research consist of

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an input, hidden and output layer, all containing simple autonomous processing elements (neuron, nodes, units) which are connected by adaptable communication paths called connectors (Minasney *et al*., 2004). Each connector is parameterized with a numeric value (weights) which indicated the strength of the connection between the connected neurons and ability to pass signals (Kralish *et al.*, 2003). The number of neurons in input and output layers correspond to the number of input and output variables of the model. The number of hidden neurons can be varied freely but the optimal number depends on uncertainty and complexity of the modeling problem (Nemes *et al.*, 2002). All input neurons $j = 1...J$ with the input variables $x_1 ... x_J$, are linked to all hidden layer neurons $k = 1...K$ by means of numeric adaptable connectors "weights" (W_{jk}). The input values is multiplied by weights and summed at the hidden neurons (Eq 1). The hidden neurons consist of weighted input and bias (W_{j0}). A bias is simply a weight with constant input of 1 that serves as a constant added to the weights and these are calculated from a set of data through training process. (Minasney & McBartney, 2002; Norgaard, 2002).

$$S_k = \sum_{j=0}^{J} (w_{jk} x_j) + w_{j0} \tag{1}$$

The result, S_k is used as a input for a So called activation function such as sigmoid functions yielding the hidden neuron output H_k (Eq 2).

$$H_k = \frac{1}{1 + e^{-S_k}} \tag{2}$$

Then H_k are multiplied by the weights of W_{kl} (Eq 3) and in a same way as H_k , model outputs, Y_l are calculated (Eq 4).

$$Z_l = \sum_{k=0}^{k} (W_{kl} \times H_k) \tag{3}$$

$$Y_l = \frac{1}{1 + e^{z_l}} \tag{4}$$

Artificial neural networks can be used for simulation saturated hydraulic conductivity (Tamari *et al*., 1998; Scha we pp and leij, 1998; Minasney *et al*., 2004), Water retention curve properties (Pachepskey *et al*., 1996; Schapp and leij, 1998) and another soil properties such as soil loss and runoff (Liznar and Nearing, 2003; Rosa *et al*., 1999), soil particle size distribution (Nemes *et al*., 2002), soil dielectric constant (Person *et al*, .2002) and nitrate-nitrogen in drainage water (Sharma *et al*., 2003).

Methodology:

First 35 soil samples with moderate texture from region near karaj were gathered in a random sampling method from 0-20cm depth. Then soil particle size distribution : sand, silt and clay percentage , organic carbon and different water content in different tension point of soil water retention curve included: 0.33, 100, 300, 300,1500 Kpa, bulk density (BD). Mean and geometric standard deviation of particles diameter. For establishment of regression pedotransfer functions we used SPSS 16 for windows and stepwise regression. We divided independent variables into three patterns:

Pattern 1: Particle size distribution (PSD) included Clay%(C), sand% (Sa), silt%(Si), bulk density(BD), organic carbon(OC) and calcium carbonate (Caco3). Pattern1brifely called P_1.

Pattern2: Geometric mean of particle diameter (dg), geometric standard deviation of particles diameter size based on three types :clay, silt and clay.

Pattern3: Geometric mean and standard deviation of particle size distribution based on 9 partitions, bulk density, calcium carbonate and organic carbon.

Dependent variables were soil moisture at tensions 0, 10, 33, 100, 300, 500 and 1500 Kpascal respectively shown briefly in this articles ⍰s, ⍰$_{10}$, ⍰33, ⍰$_{100}$, ⍰$_{300}$, ⍰$_{500}$ and ⍰$_{1500}$ .It is must be considered that after calculate correlation matrices between variables using SPSS we see that there is high intercorellation between Clay and Sand, Silt with sand and finally bulk density with Caco3 so in the input patterns these paired high intercorrelated variables did not ….together. Based on these 3 patterns different regression pedotransfer functions and ANNs established and comprised together based on R2 and RMSR.

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For establishing artificial neural networks we used Neuroslution software and Marquardt-levenburg training algorithm and three layer proceptron structure in ANNs. The number of neuron in hidden layer was determined as 3 neurons based on earlier literature and activation function of hidden and output layer was establishes as a sigmoid tangent function. For Investigation of models performance we used R2 and RMSR. RMSR that explain Root mean square of residuals calculated according to equation5.

$$\mathrm{RMSR} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y_i - Y_i^{/})^2}$$

(5)

That Yi, $Y^{/}$ and n are Measured values of variables I, Predicted value of variable i and number of samples respectively.

Result And Discussion

Total of equations derived from P1 were significant at 0.1 (P<0.01). Equations derived P1 showed that sand content was a good predictor of moisture content until 100 Kpa tension in the other hand in the higher levels of tension silt and clay had a more precious effect on prediction because in the higher levels of tensions moisture depends on texture and specific area that determined by silt and clay content. Caco3 was not effective in improvement of PTfs based on P1.(Table 1)Equation derived from P2 were significant at 0.1 (P<0.01). Table2 show that moisture content is very dependent on organic carbon, geometric mean diameter and bulk density. Results indicated that effect of bulk density and geometric mean diameter of soil particles on moisture content in a different tensions(□$_{i}$) is more significant in a low level of tensions rather than high levels. Comparison equation derived from P1 and P2 resulted in there is only significant difference at □$_{10}$ and equations derived P1 had more simple and available dependent input variables so we recommended P1.

Table1: Equations derived form P1 input variables based on regression pedotransfer functions.

Function No.	Dependent variable	Regression functions	r^2_{adj}
1	θ_s	$-22.1 - 0.386Sa + 35BD + 35.2OC$	0.78
2	θ_{10kpa}	$-25 + 0.209C + 0.507Si + 22BD + 7.63OC$	0.79
3	θ_{33kpa}	$-4.23 - 0.323Sa + 19.9BD + 16.9OC$	0.89
4	θ_{100kpa}	$0.5 - 0.257Sa + 15.8BD + 9.29OC$	0.80
5	θ_{300kpa}	$-17.2 + 0.296C + 0.146Si + 11.5BD + 7.46OC$	0.78
6	$\theta_{1500kpa}$	$-12.4 + 0.303C + 0.0418Si + 8.76BD + 5.57OC$	0.80

Table 2: Equations derived form P2 input variables based on regression pedotransfer functions.

Fun ction No.	Depe ndent variable	Regression functions	r^2_{adj}
1	θ_s	$-55.9 + 32.3BD + 36.6OC - 17.00d_g$	0.79
2	θ_{10kpa}	$-13.0 + 15.3BD + 11.0OC - 15.2d_g$	0.72
3	θ_{33kpa}	$-31.9 + 17.3BD + 18.2OC - 13.9d_g$	0.88
4	$_{100kpa}$	$-21.6 + 13.8BD + 10.9OC - 11.81d_g$	0.79
5	$_{300kpa}$	$-17.5 + 11.7BD + 7.4OC - 9.58d_g$	0.79
6	$_{500kpa}$	$-15.9 + 10.7BD + 4.6OC - 7.5d_g$	0.78

Table 3: Equations derived form P3 input variables based on regression pedotransfer functions.

Function No.	Dependent variable	Regression functions	r^2_{adj}
1	θ_s	$-65.8 + 35.6OC + 31.8BD - 19.6d_g$	0.79
2	θ_{10kpa}	$-17.2 + 17.2BD + 9.67OC - 16.3d_g - 0.722$	0.72
3	θ_{33kpa}	$-39.4 - 15.9d_g + 17.5OC + 16.8BD$	0.87
4	θ_{100kpa}	$-27.4 - 12.6d_g + 10.4OC + 13.3BD$	0.79
5	θ_{300kpa}	$-25.7 + 9.62BD + 7.25OC - 11.8d_g + 0.508\sigma_g$	0.79
6	$\theta_{1500kpa}$	$-22.5 + 8.79BD + 4.57OC - 9.32d_g + 0.458$	0.78

After comparison equation derived P1 and P3 we resulted in best performance of P1 exceptionally in θ_0 and θ_{300} but Equation based on P3 had a more complex input variables than P1(Table 3) so we preferred P1 as a best input pattern Variables for predicting soil water retention curve points.

Regarding to comparison regression pedotransfer functions and artificial neural networks in predicting performance of soil water retention curve points, we used best pattern of regression PTFs (P1) as a input variables of artificial neural networks. we established 6 ANNs for 6 points of soil water retention curves. R2 for regression PTFs and ANNs ranged between 0.85-0.94 and 0.79-0.89 and totally statistic significant at 1%. ($P<0.01$).

In the other hand RMSR ranged between 1.21-2.53. Comparison R2 and RMSR showed that ANNs had a better performance than Regression PTFs. (Table4)

For determination relative improvement of ANNs than regression PTFs we used relative improvement (Minasney and MCbarteney. 2002) described as equation 6.

$$RI = \frac{RMSE_{reg.PTF} - RMSE_{ANN}}{RMSE_{reg.PTF}} \times 100$$

(6)

Table 4: R^2 , RMSR and RI of regression pedotransfer functions and ANNs

	(r^2_{adj})		($RMSR$)		RI of ANNs
Moisture point	Reg.PTF	ANN	Reg.PTF	ANN	
θ_s	0.79	0.85	2.53	1.01	%60
θ_{10kpa}	0.81	0.91	1.44	0.98	%30
θ_{33kpa}	0.89	0.92	1.34	0.94	%27
θ_{100kpa}	0.81	0.87	1.47	1.30	%11
θ_{300kpa}	0.80	0.86	2.10	1.28	%39
$\theta_{1500kpa}$	0.82	0.94	1.21	0.88	%27

RI ranged between 0 and 100. RI equal to 100 indicated that ANNs had 100 % better performance than PTFs. In the other hand RI equal to 0 ANNs had no performance than regression PTFs. For example when we use ANNs for predicting θ_{100kpa} estimation performance increased 27 percentage than regression PTFs. This increasing ranged between 11% for θ_{100kpa} and 60% for θ_s .

Our investigation indicated that ANNs had a better performance because of 3 layer procepteron processing function. First In the data processing of ANNs primary pattern entered to network and primary output value calculated. Then network comparised primary predicted values with measured values and finally changed in weights coefficients until there is minimum difference between measured and predicted values. In the other sentences eror values such as RMSR adjusted intelligently but regression PTFs have no such eror decreasing intelligence process. (Minasnet and Mcbarteney 2004). In the other hand data hetrognecis and intercorrelation had no effect in ANNs processing functions and ANNs need no primary mathematical model.(Schap and Leyj,1998).

Figure1 indicated correlation between regression PTFs and ANNS with P1 input variable models for θ_s, θ_{10kpa} , θ_{33kpa}

Figure2 indicated corellatin between regression PTFs and ANNS with P1 input variable models for θ_{100}, θ_{300} , θ_{1500}

Comparison of result showed that both of regression pedotransfer functions and artificial neural networks had a good and acceptable prediction of moisture points of soil water retention curves in the different tensions but because of intelligence error decreasing mechanism of data processing in ANNs models they hade a better performance. ANNs performed for researchers that estimated several independent variables based on one dependent variables that this process is very time consuming.

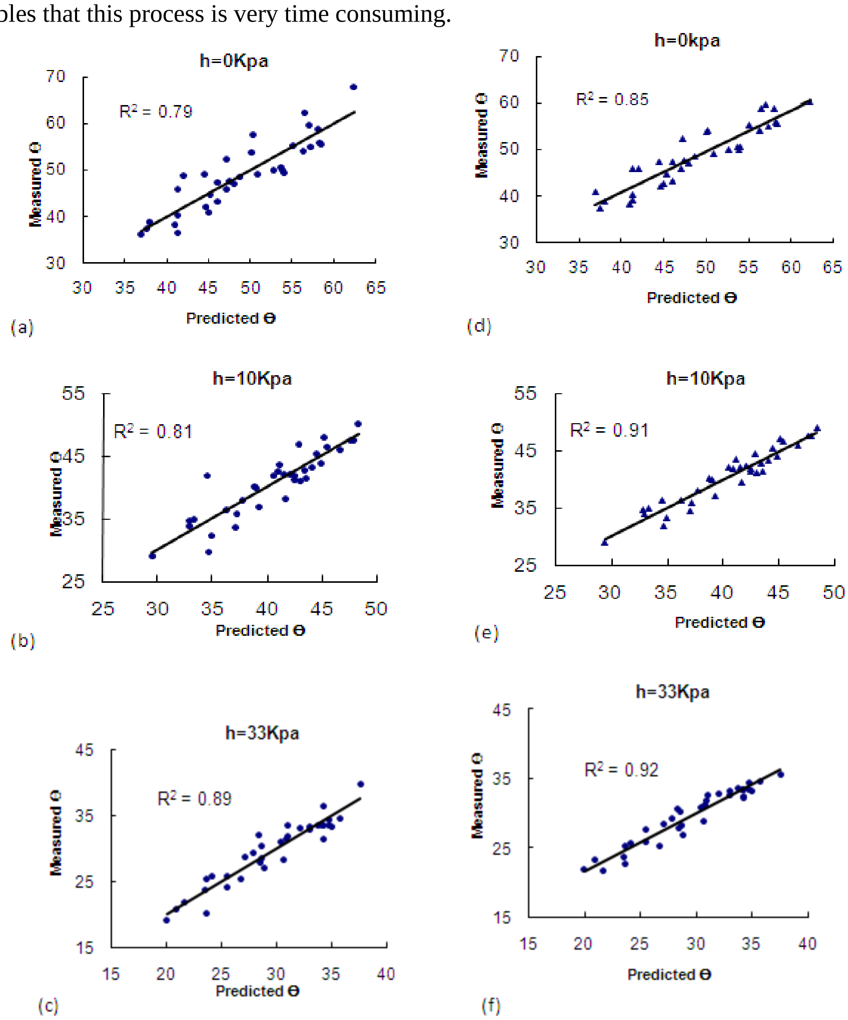

Fig. 1: corellatin graphs between regression PTFs (a,b,c) and ANNS (d,e,f) with P1 input variable models for θ_s, θ_{10kpa} , θ_{33kpa}

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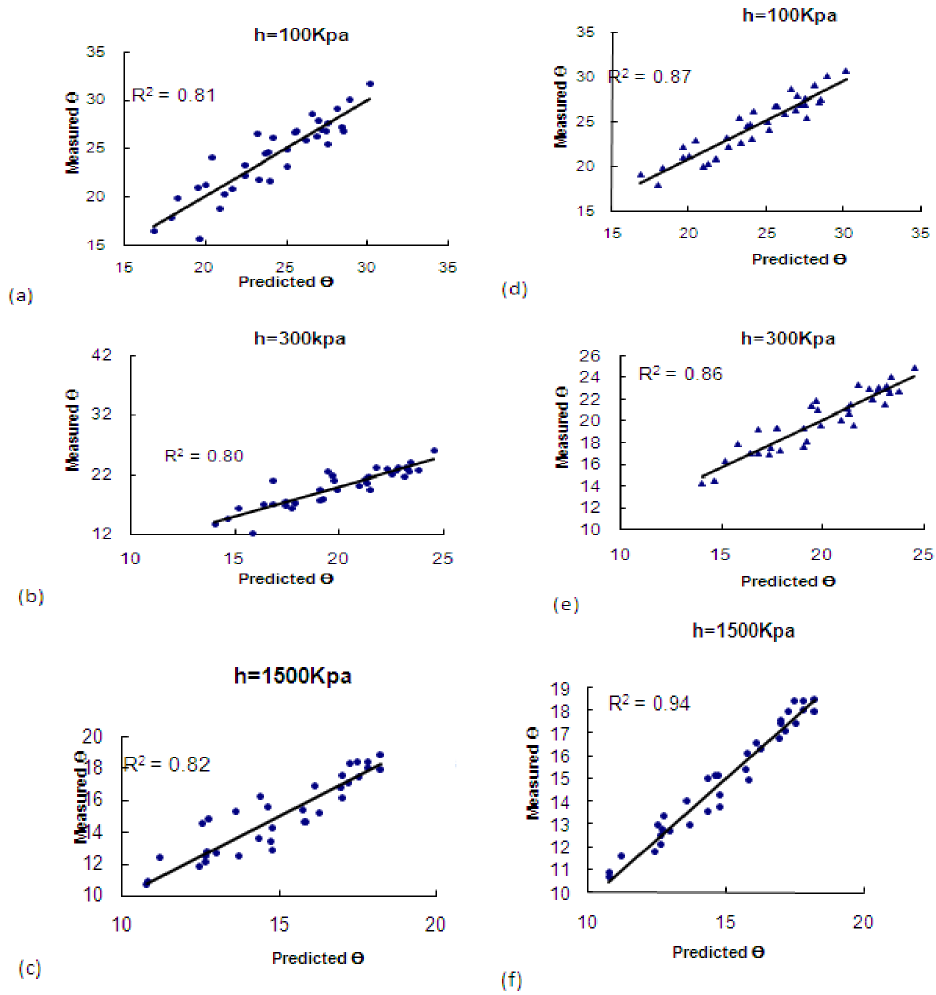

Fig. 2: corellatin graphs between regression PTFs (a,b,c) and ANNS (d, e, f) with P1 input variable models for θ_{100}, θ_{300}, θ_{1500}

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