Using of Artificial Neural Networks for Evaluation Soil Water Content with Time Domain Reflectometry

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Abstract

Time Domain Reflectometry (TDR) has become an established method for soil volumetric water content (θ) measurement. TDR exploits the difference in dielectric constant values between the solid phase, air phase and liquid phase. In this paper, we study and evaluate the ability of empirical models to fit TDR calibration data for the soils of different textures, and adopt artificial neural network (ANN) to predict the $K_a - \theta$ relationship using soil physical parameters for ten different heavy texture soil types. The explanatory parameters that gave the most significant reduction in the root mean square error (RMSE) were dielectric constant, bulk density, clay content, silt content, sand content and organic matter content. The $K_a - \theta$ relationship for each soil type was predicted using the other nine soils for calibration purposes. To find the optimum model, various multilayer perceptron (MLP) topologies, having one hidden layer of neurons were investigated.   In this analysis, K_a, bulk density and clay content were selected as input to ANN. The (3-10-1)-MLP, namely a network having 10 neurons in its hidden layer resulted in the best-suited model estimating the soil water content of the heavy texture soils at all soil types. For this topology, R^2 and RMSE values were 0.998 and 0.00433, respectively. A comparative study among ANN models and various empirical models was also carried out. ANN models with RMSE and R^2 of 0.0043-0.0134 ($m^3 m^{-3}$) and 0.923-0.998, respectively, gave better predictions than empirical models. The ANN model performed superior than both empirical and physical models. Since (3-10-1)-MLP outperformed regression models and it uses only one set of weights and biases for all soil types, it should be preferred over empirical and physical models.

Keywords: Soil, Volumetric water content, Dielectric constant, TDR, Artificial neural network

1. Introduction

Time Domain Reflectometry (TDR) has become an established method for soil volumetric water content (SWC) measurement. TDR exploits the difference in dielectric constant values between the solid phase, air phase and liquid phase. At the TDR frequencies, pure liquid water has a dielectric constant of about 80 (depending on temperature and electrolyte solution), air has a dielectric constant of about 1, and the solid phase of about 4 to 16 (Wraith and Or, 1999). A dielectric model is typically used to translate measured dielectric properties (usually the relative constant, ε_r) to SWC (θ) of the composite material. Dielectric mixing models aim to quantify the influence of a range of physical properties on ε_r of a material, and the model may take the form of $\theta(\varepsilon_r)$ or *vice versa*. Thus, in studies where high accuracy is needed, a soil-specific calibration is normally required. This is, however, often an elaborate procedure, even if in some of the recent studies researchers have provided more efficient calibration methods. To avoid such an elaborate, time-consuming procedure, the soil physical

parameters can be used to obtain a relationship between the "apparent" dielectric constant (K_a) and the SWC (θ), i.e., the K_a–θ relationship, without a need for soil-specific calibration Persson et al. (2002).

The use of dielectric properties as an indirect measure of SWC (θ) is widely accepted across a range of disciplines such as the natural sciences, food engineering, timber processing and agriculture. The pioneering work of Nelson et al. (1953) initiated a 50-yr contribution of research relating dielectric measurements to water con tent in vegetables, grains, and other composite porous media. Fellner-Feldegg (1969) suggested the use of TDR for measuring constant, which was taken up in soil science by Hoekstra and Delaney (1974) and in the seminal work by Topp et al. (1980). Persson et al. (2002) used artificial neural network (ANN) methodology to calibrate TDR measurements of light texture soils. They showed that ANN model provided better prediction of the K_a–θ relationship than other commonly used models. A comprehensive review of TDR technology that applies to the measurement of bulk soil permittivity and EC was presented in a review article by Robinson et al. (2003). The authors covered the guiding principles and practical issues, such as TDR probe construction, calibration, and waveform interpretation.

The objectives of this work were to evaluate the ability of existing models to fit TDR calibration data for the soils of different texture and to investigate the use of ANN to understand the K_a–θ relationship from physical parameters of the soil. An attempt was also made to study the influence of different soil physical parameters and mineralogy on the behavior of ANN using sensitivity analysis.

2. Materials and methods

2.1 Soil Dielectric Constant

The relative dielectric constant (K_r) is expressed as the ratio of the constant of the material K (Fm^{-1}) and the constant of free space (K_0):

$$K_r = \frac{K}{K_0} \tag{1}$$

where K_0 is 8.85×10^{-12} F m^{-1}. In general, K_r is a complex variable given by (Robinson et al., 2003):

$$K_r^* = K_r^{'} - j\left(K_{relax}^{"} + \frac{\sigma_{dc}}{K\omega}\right) \tag{2}$$

where $K_{relax}^{"}$ is the imaginary part of the relative constant due to relaxations, σ_{dc} is the electrical conductivity at zero frequency (S m^{-1}), ω is the angular frequency (2πf) where f is frequency (Hz). The real part accounts for the energy stored in the dielectrics at a given frequency and temperature, while the imaginary part describes the dielectric losses or the energy dissipation. Eq. (2) describes the two processes determining energy losses in wet, porous materials: dipoles relaxations and electrical conductivity. The first is due to the relaxation time required by a dipole to adjust to the orientation of the electromagnetic field, resulting in adsorption of energy by the dipole. The second is due to conduction arising from the material surfaces as a result of electric charges, and from electrolytes in the liquid phase.

From a mechanical standpoint, the velocity v (m s^{-1}) of an electromagnetic wave traveling through a probe of length L(m) is given by $v=2L/t$, where t is time (s). By defining a ratio of the propagation velocity in the material with respect to the propagation velocity in free space, it is easy an easy task to show:

$$K_r = \left(\frac{ct}{2L}\right)^2 \tag{3}$$

Which is the equation used as a basis for TDR analysis. Therefore, to obtain the relative dielectric constant, we only need to measure the travel time, since the probe length and the wave velocity are already known. The primary assumption of TDR-based measurements is that the imaginary part of the complex relative dielectric constant is negligible in comparison to the real part. However, since dielectric losses are always present in a dielectric, the TDR-measured relative dielectric constant is called "apparent" dielectric constant K_a (Topp et al., 1980). The assumption of negligible losses does not hold for soils where surfaces are highly conductive (clay soils) or where high concentrations of electrolyte are present in the soil solution (saline soils).

For a number of soils, the relationship between the soil dielectric constant as measured by TDR, and soil volumetric water content was expressed as (Topp et al., 1980):

$$\theta = (-530 + 292K_a - 5.5K_a^2 + 0.043K_a^3) \times 10^{-4} \tag{4}$$

where K_a is the soil dielectric constant and θ is the soil volumetric water content. This equation fitted well with the experimental data for some soils. However, for organic soils, fine-textured soils and clays the dependence of K_a on θ differed from the one given by Eq. (4) (Dirksen & Dasberg, 1993). This was explained by the increase

in the proportion of confined water with an increase of soil or clay specific surface. The value of 3.2 assumed for the dielectric constant of tightly bound water was much less than that of free water (78.3 at 25°C).

Dielectric mixing models inevitably make simplifying assumptions about many of the loss and combinatorial parameters that are involved in the make-up of a composite material. Looyenga (1965) used a different approach that was in principle, independent of the shape of the particles. Looyenga (1965) expressed the dielectric constants of soils using a three-phase "solid–water–air" mixture:

$$K_a^\alpha = \theta K_w^\alpha + (1 - \varphi)K_s^\alpha + (\varphi - \theta)K_g^\alpha \tag{5}$$

where K_w, K_s and K_g are the dielectric constants of water, solid and gas phases, respectively; and φ is the soil porosity.

Birchak et al. (1974) presented a semi-empirical dielectric mixing model:

$$K_a^\alpha = \theta_{air}K_{air}^\alpha + \theta_s K_s^\alpha + \theta K_w^\alpha \tag{6}$$

where θ_{air} and θ_s are the volumetric content of air and solid particles, and K_{air}, K_s and K_w are the dielectric constant of air, solids and water, respectively.

Malicki et al., (1996) proposed a new general calibration equation that incorporated soil bulk density as:

$$\theta = \frac{(\sqrt{K_a} - 0.819 - 0.168\rho_b - 0.159\rho_b^2)}{(7.17 + 1.18\rho_b)} \tag{7}$$

where ρ_b the bulk density of soil (Mg m^{-3}).

The de Loor model is a physical model based on the concept that water and air represent disc shaped inclusion in a host medium (solid soil). The de Loor model can be written as (de Loor, 1964):

$$\theta = \frac{3(K_s - K_a) + 2(1 - \theta_s)(K_{air} - K_s) - K_a(1 - \theta_s)\left(\frac{K_s}{K_{air}} - 1\right)}{K_a\left(\frac{K_a}{K_w} - \frac{K_a}{K_{air}}\right) + 2(K_a - K_w)} \tag{8}$$

2.2 Soil sampling

Soils from five different locations were used in this study. Locations are placed in Karaj and Ghazvin in Iran. Samples were taken in summer of 2008. At all five sites, both the topsoil (0–0.3 m depth) and the subsoil (0.3–0.6 m depth) were sampled, Thus, totally ten different soil samples were collected. The bulk density varied between 1.18 to 1.65 Mg m^{-3} and was measured for each sub sample. Soil physical parameters were also determined for each soil texture. These parameters were organic matter, clay, silt, and sand content and mineralogy .Selected properties of the soils are presented in Table 1.

Soil samples were air-dried and ground to pass a 5 mm sieve and then divided into subsamples that were mixed with water. The soil was then packed into PVC cylinders (0.18 m long and 0.19 m in diameter) and TDR measurements were taken using two rod probes connected to a Trace system I, model 6050X1 (Soil Moisture Equipment Corp., Santa Barbara, CA). Then samples were removed from the cylinders, spread in a thin layer again, and brought to the next desired moisture content. The procedure was repeated until the water content was close to saturation. In each subsample, three TDR measurements were taken and averaged. In total, 203 subsamples were analyzed. Gravimetrical determination of water content was carried out by drying the soil at 110°C during 48 h. The range of K_a values was 0.075 to 0.606 (m^3 m^{-3}). All TDR measurements were taken at a constant temperature of (17) °C. Dielectric constants were finally calculated by Eq. (3).

2.3 Artificial Neural networks

An artificial neural network (ANN) is a non-linear model that makes use of a parallel programming structure capable of representing arbitrarily complex non-linear processes that relate the inputs and outputs of any system (Hsu et al., 1995). It provides better solutions than traditional statistical methods when applied to poorly defined and poorly understood complex systems that involve pattern recognition. Although ANN does not provide a model that is readily physically explainable, it is a viable technique to develop input–output simulations and forecast models for situations when the objective is an accurate forecast (Uvo et al., 2000). ANNs are highly interconnected networks of many simple processing units called neurons, which are analogous to the biological neurons in the human brain. Neurons having similar characteristics in an ANN are arranged in groups called layers. The neurons in one layer are connected to those in the adjacent layers, but not to those in the same layer. The strength of connection between the two neurons in adjacent layers is represented by what is known as a 'connection strength' or 'weight'. An ANN normally consists of three layers, an input layer, a hidden layer, and an output layer. In a feed-forward network, the weighted connections feed activations only in the forward

direction from an input layer to the output layer. On the other hand, in a recurrent network additional weighted connections are used to feed previous activations back into the network. The structure of a feed-forward ANN used in this paper is shown in Fig 1.

An important step in developing an ANN model is the training of its weight matrix. The weights are initialized randomly between suitable ranges and then updated using certain training mechanism. There are primarily two types of training mechanisms, supervised and unsupervised. A supervised training algorithm requires an external teacher to guide the training process. This typically involves a large number of examples (or patterns) of inputs and outputs pairs for training in cause variables and outputs are the effect variables of the physical system being modeled. The primary goal of training is to minimize the error function by searching for a set of connection strengths that cause the ANN to produce outputs that are equal to or closer to the targets. A supervised training mechanism called back-propagation training algorithm is normally adopted in most of the engineering applications.

In the back-propagation training mechanism, the input data are presented at the input layer, the information is processed in the forward direction, and the output is calculated at the output layer. The target values are known at the output layer, so that the error can be estimated. The total error at the output layer is distributed back to the ANN and the connection weights are adjusted. This process of feed-forward mechanism and back propagation of errors and weight adjustment is repeated iteratively until convergence in terms of an acceptable level of error is achieved. This whole process is called the training of the ANN. The trained ANN is then validated on the testing data set, which it has not seen before. Once an ANN has been trained and tested, it can be used for prediction or modeling the physical system for which it is has been designed. In the current study, the ANN inputs are the dielectric constant, bulk density and clay and the output is the soil volumetric water content (Fig. 1).

Back propagation uses a gradient descent (GD) technique which is very stable when a small learning rate is used, but has slow convergence properties. Several methods for speeding up back propagation have been used including adding a momentum term or using a variable learning rate. In this paper, GD with momentum (GDM) algorithm which is an improvement to the straight GD rule in the sense that a momentum term is used to avoiding local minima, speeding up learning and stabilizing convergence, is used (Omid et al., 2009). The gradient vector is the set of derivatives for all weights with respect to the output error. In the present study, a three-layer feed forward back propagation ANN was used. Before simulation, all data sets were standardized by the software using a linear algorithm. First, the number of nodes in the hidden layer was optimized. This was done by constructing a (6-k-1)-MLP ANN and varying k from 2 to 24. The data set was first separated into a calibration and a validation data set. This was done by randomly selecting 20% of the entire data set as validation data, that is, 40 data points in the validation (testing) data set and 163 in the calibration (training) data set..The value of k=10 that gave the lowest MSE was chosen for the subsequent ANN simulations.

A sensitivity test was performed on the chosen ANNs so that a better understanding of the influence of each input on the output could be examined. Accordingly, the dependency of each of the six inputs (K_a, bulk density, organic matter, clay, silt and sand content) was investigated using the ANN by running sensitivity analysis. Based on the results from the sensitivity analysis we omitted the sand content, silt content and organic matter. Again, various (3-k-1)-MLP ANNs, each having different number of node k in its hidden layer, were trained 20 times and the average output was compared to the test data. Finally, the ANN model was used to predict the K_a-θ relationship for all soil types. As input, the two soil physical parameters and K_a gave the most significant improvement were chosen. The optimum network had k=10. Thus, 3-10-1 ANN was finally selected.

The performance of the trained networks was measured by mean square error (MSE) and coefficient of determination (R^2) on another set of data (testing set), not seen by the network during training and cross-validation, between the predicted values of the network and the target (or experimental) values. The MSE is given as follows (Omid et al., 2009):

$$MSE = \frac{\sum_{j=1}^{N}(\hat{\theta}_{pj}-\theta_{pj})^2}{N} \tag{9}$$

Where $\hat{\theta}_{pj}$ is the network output from observation j, θ_{pj} is the experimental (soil volumetric water content) output from observation j, and N is the total number of data observation.

To design various neural networks, Neuro Solutions (version 5.1) software was used in this study.

3. Results and Discussion

3.1 ANN Simulations

For estimating soil water content, beside dialectic constant, the most important physical parameters are bulk density and clay content. Since these parameters are not highly correlated (Table 2), The RMSE values for the 3-k-1 ANNs, with different k values, for the standardized data set are presented in Fig. 2.. This result is in agreement with studies (e.g., Schaap and Bouten, 1996; Persson et al., 2001, 2002). The RMSEs using the non standardized data sets were 0.0071 and 0.0134 m^3 m^{-3} for the calibration and validation data sets, respectively, when $k = 10$, indicating that the model was not overstrained. In all subsequent ANN models, $k = 10$ was used. Since these models contained 3 input nodes, this k value should be sufficient this result is in agreement with the regression analysis for this data set presented in an earlier study (Jacobsen and Schjønning, 1993) and in agreement with Persson (2002). These parameters have also been shown to affect the K_a–θ relationship in other studies (e.g., Malicki et al., 1994; Hook and Livingston, 1996). The bulk density affects K_a since when bulk density is high; porosity is low, leading to that the amount of the mineral phase present in the soil increases. It is expected that soils with high bulk density, or low porosity, will have a larger $\sqrt{K_s}$ value than soils with low bulk density and high porosity. The influence of clay content on θ was probably due to bound water and bulk soil electrical conductivity (EC_b). The polarization of bound water molecules is impeded by high electrostatic attraction from the negatively charged clay particle surface. Reduced polarization will result in much lower dielectric constant. For bound water that is directly attached to the soil particle surface, the dielectric constant is only 3.2, which will lead to a faster propagating velocity and shorter time delay. Therefore, the effect of bound water tends to underestimate soil water content. EC_b consists of soil particle surface electrical conductivity (EC_s) and soil solution conductivity (EC_w). The effect of EC_b on TDR moisture measurement has long been observed (Topp et al. 1980, Malicki et al. 1994, Sun et al. 2000). The elevated EC_b causes dispersion of the reflected signal, resulting in longer rise time, and evidence showed that there is a rise time related measurement error (Hook and Livingston, 1995). Meanwhile the signal is attenuated by energy dissipation through current flow making the detection of final reflection signal very difficult, if it is still possible. The elevated EC_b also increases the apparent dielectric constant (Sun et al. 2000), leading to an overestimated soil water content. Early in 1955, O'Konski described that in a colloid a semi-conducting surface can arise due to a distribution of charge density and induce extra polarization (O'Konski, 1955).

3.2 Comparison of ANN with Other Models

Among soils under study RMSE of T-Gharasan and T-Gharasan were weaker than other soils. Once the soils mineralogy was examined, the results showed that these two soils were different from other soils (about 95 percent smectite). Experimental results suggest that smectite clays exhibit in the high frequency range a more important dielectric dispersion than other clays. However, in our opinion, the microscopic phenomena associated to the dielectric dispersion of clays are still a subject of considerable debate. It is why this aspect, the dielectric dispersion, will not be investigated in this paper but this study shows that effected mineralogy is very significant. The R^2 and the RMSE values for each soil type using the Topp equation, Eq. (4) with parameters for all ten soil types, Birchak model, Eq. (6), Malicki model, Eq. (7), the de Loor model, Eq. (8), with parameters for each soil type and the ANN output are presented in Tables 3 and 4. The RMSE for the calibration data set was about 0.0071 m^3 m^{-3}. From the tables it can be seen that the ANN always outperforms the Topp model, de Loor model, Malicki model and Birchak model. The Topp equation gives poor results with RMSE from 0.0132 to 0.0316 m^3 m^{-3}. This is not surprising since Jacobsen and Schjønning 1993 and persson 2002 showed that the Topp equation gave poor predictions for high volumetric content. The de Loor model gives results comparable with the Malicki and Birchak models. The RMSE and R^2 for the de Loor model presented in Tables 3 and 4 are calculated using an assumed particle density. The other calibrations gave similar RMSEs (0.0151–0.0334 m^3 m^{-3}). For Malicki et al. (1996) RMSE = 0.0167-0.0308 m^3 m^{-3} and for Birchak et al. (1974) RMSE = 0.0124-0.0357 m^3 m^{-3}. These results are in agreement with the detailed calibration by Persson (2002). However, similar RMSE was obtained for Topp (0.019–0.101 m^3 m^{-3}) and De Loor (0.010–0.057 m^3 m^{-3}). In about all soil types expect two soils ANN prediction consistently gives better R^2 and RMSE than the other calibrations. ANN actually performed better than other calibration. The analysis above shows that using ANN, can be avoided without loss in accuracy. Once the ANN is calibrated using different soil types it can be used to predict relationships for new soil types. Only the soil physical parameters (in our case clay content and bulk density) have to be known beforehand (persson 2002). The RMSE values using Eqs. (4)- (8) are, however, high compared with the ANN

4. Conclusions

The relationship between the soil dielectric constant measured by TDR and volumetric water content were expressed. ANNs were used to predict the $K_a-\theta$ relationship using soil physical parameters. All texture the $K_a-\theta$ relationship for 10 different soil textures including sand, loamy sand, sandy loam, sandy clay loam and loam. Besides K_a, five different soil physical parameters (bulk density, clay, silt, sand, and organic matter content) and mineralogy were scrutinized in order to develop ANN models. In this analysis, K_a was used together with bulk density and clay content as input data in a 3-10-1 ANN. It was shown that the ANN provided significantly better prediction of θ than the Topp (1980), de Loor (1964), Birchak et al. (1974), and Malicki et al. (1976) models. Results also show smectites has the highest influence on the Ka-θ relationship. However, in our opinion, the microscopic phenomena associated to the dielectric dispersion of clays are still a subject of considerable debate which must be more investigated.

Acknowledgments

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Table 1. Properties of the different soils investigated in this study

Location	Depth	Clay%	Silt%	Sand%	OM%	BDMg M^{-3}	Textural class*
Takestan	Topsoil (0-30)	28.6	29.2	41.2	2.23	1.29	Clay loam
	Subsoil (30-60)	56.6	25.2	18.1	1.93	1.52	Clay
Tape	Topsoil (0-30)	31.6	17.2	46.6	1.86	1.44	Sandy clay
	Subsoil (30-60)	39.1	24.2	36.6	1.34	1.45	Clay loam
Shal	Topsoil (0-30)	61.6	25.7	12.6	1.86	1.18	Clay
	Subsoil (30-60)	57.6	24.7	17.6	1.26	1.58	Clay
Gharasan	Topsoil (0-30)	31.8	35.2	26.6	1.49	1.38	Clay loam
	Subsoil (30-60)	39.6	41.7	18.6	0.67	1.49	Silty clay
M. Danesh	Topsoil (0-30)	26.0	48.0	26.0	2.33	1.41	Loam
	Subsoil (30-60)	26.0	40.0	34.0	1.12	1.65	Loam

*   Textural classification was based on the USDA classification system.

Table 2. Correlation coefficient between the different data inputs

Inputs	Bulk density	Dielectric constant	Organic matter	sand	silt
clay	-0.198	-0.030	-0.085	-0.714	-0.539
silt	0.176	-0.039	-0.081	-0.206	1
sand	0.083	0.068	0.166	1	
Organic matter	-0.548	0.082	1		
Dielectric constant	0.062	1			
Bulk density	1				

Table 3. The RMSE values of different models for the ten soil types

Location	ANN 3-10-1	De Loor (1964)	Birchak et al. (1974)	Topp et al. (1980)	Malicki et al. (1996)
T-Takestan	0.0057	0.0238	0.0236	0.0246	0.0240
S-Takestan	0.0071	0.0219	0.0334	0.0236	0.0238
T-Tape	0.0043	0.0151	0.0170	0.0173	0.0167
S-Tape	0.0125	0.0289	0.0306	0.0296	0.0308
T-Shal	0.0129	0.0212	0.0209	0.0192	0.0209
S-Shal	0.0061	0.0130	0.0124	0.0132	0.0128
T-Gharasan	0.0109	0.0225	0.0221	0.0217	0.0226
T-Gharasan	0.0134	0.0289	0.0286	0.0278	0.0293
T-M.danesh	0.0232	0.0340	0.0357	0.0316	0.0356
S-M.danesh	0.0058	0.0167	0.0194	0.0204	0.0192

Table 4. The R^2 values of different models for the ten soil types

Location	ANN 3-10-1	De Loor (1964)	Birchak et al. (1974)	Topp et al. (1980)	Malicki et al. (1996)
T-Takestan	0.996	0.967	0.971	0.963	0.970
S-Takestan	0.994	0.970	0.923	0.971	0.971
T-Tape	0.998	0.988	0.987	0.984	0.988
S-Tape	0.984	0.956	0.957	0.953	0.957
T-Shal	0.988	0.972	0.975	0.976	0.975
S-Shal	0.993	0.967	0.976	0.972	0.975
T-Gharasan	0.961	0.919	0.937	0.932	0.934
T-Gharasan	0.923	0.876	0.901	0.896	0.896
T-M.danesh	0.947	0.936	0.937	0.944	0.938
S-M.danesh	0.996	0.977	0.974	0.969	0.975

Figure 1. The structure of a feed-forward ANN

Figure 2. RMSE using standardized data for different number of hidden nodes during training of ANNs