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Estimating the parameters of Philip infiltration equation using artificial neural network

N. Abrishami-Shirazi*, A. R. Sepaskhah

Department of Irrigation, College of Agriculture, Shiraz University, Shiraz, I. R. Iran

* Corresponding Author: n.abrishami@yahoo.com
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ABSTRACT- Infiltration rate is one of the most important parameters used in irrigation water management. Direct measurement of infiltration process is laborious, time consuming and expensive. Therefore, in this study application of some indirect methods such as artificial neural networks (ANNs) for prediction of this phenomenon was investigated. Different ANNs structures including two training algorithms (TrainLM and TrainBR), two transfer functions (Tansig and Logsig), and different combinations of the input variables such as sand, silt, and clay fractions, bulk density (BD), soil organic matter (SOM), cumulative infiltration (CI) and elapsed time were used to predict sorption coefficient (S) and hydraulic conductivity (A) in Philip equation ($I=S*t^{0.5}+A*t$), which corresponded to 30 soil samples from study areas located in the Agricultural College, Shiraz University, (Bajgah). A two-hidden layer ANNs with two and three neurons in the hidden layers, respectively and TrainLM algorithm performed the best in predicting S when Logsig and Tansig were used. Silt+ clay+ sand+ time+ CI combination was the most basic influential variables for the S prediction. Furthermore, a two-hidden layer ANNs with two and three neurons in the hidden layers, respectively and TrainBR algorithm performed the best in predicting A when Tansig and Tansig were used. Silt +clay +sand +BD + OM+ time+ CI combination was the most basic influential variables for A prediction. Results showed that increasing the hidden layers and input variables significantly improved the ANNs performance. The coefficient of determination (R^2) confirmed that the ANNs predictions for A (84.6 %) fit data better than S (77.5 %).

INTRODUCTION

Water infiltration plays an important role in the hydrological cycle. Estimating the quantity of water infiltration in soil results in proper irrigation management and prevents land, soil and water resources degradation. Different physical and empirical models are provided to quantify the infiltration process such as Philip (1957), Horton (1940), Kostiakov (1932), Holtan (1961) and Green and Ampt (1911). These models can be classified into three categories, i.e. physical models, analytical or semi-empirical models, and purely empirical models. In the first group, one can obtain parameters just from soil-water characteristics without any need to measure the infiltration date (Igbadun et al., 2016). The analytical models are based on mathematical or graphical analysis and utilize the capacity of steady state or asymptomatic infiltration. Empirical methods less depend on soil surface assumptions and their profile condition. In fact, their evaluation conditions play more important roles because their parameters are evaluated by real data of field measurement infiltration (Hillel and Gardner, 1970). However, some researchers simplified the models and verified them well with the experimental measurements (Ogbe et al., 2008).

The important criterion for choosing a model, among others, is the simplicity of its parameter estimation (Mehrabi and Sepaskhah, 2013). There are some coefficients in infiltration models that are dependent on the soil conditions. Some experiments and calibrations are needed to determine these coefficients (Machiwal et al., 2006). Due to rapid spatial variation of infiltration characteristics of soils, simulation of these variations is difficult and a large number of measurements is required. In addition, these measurements are time-consuming and expensive, and using a mean value for this parameter is not accurate (Cosby et al., 1984; Igbadun et al., 2016; Lili, et al., 2008; Saxton et al., 1986). Using indirect methods to measure the infiltration may help to overcome this problem. According to the results of most studies, Philip (1957) model is the best model to describe the spatial characteristics of infiltration in a particular region (Lei et al., 1989; Machiwal et al., 2006; Richter, 1989). In recent decades, techniques based on the soft computing such as artificial neural networks (ANNs) have been used greatly to predict and model various problems effectively. The most important feature of ANNs is the ability to formulate complicated systems without using any correlation (Sablani et al., 1997). Because of this feature and the ANNs ability to predict even noisy, inconsistent and incompatible systems with acceptable accuracy, ANNs have been used widely in agricultural engineering problems (Shaalan et al., 1999).

Using artificial intelligence system is one of the indirect methods to estimate soil hydraulic properties. ANNs are part of this system. This method is a mathematical structure and simulation of the human brain function that is able to show the processes and the nonlinearity of the relationship between inputs and outputs. The hidden relationships between them are found by processing the experimental data.

Pachepsky et al. (1996) evaluated ANNs performance for soil water retention curve estimation. Results showed the same performance of ANNs and the regression models in soil water retention curve estimation. Schaap et al. (1998) used artificial neural networks for estimation of van Genuchten (1980) and Gardner (1958) parameters and significant differences were observed between the measured and predicted values. Minasny and McBratney (2002) conducted similar research for van Genuchten parameters estimation in Australia. They proposed a new objective function for the design of ANNs. Results of this study showed that the provided objective function is acceptable to improve network performance. Moreover, Merdun et al., (2006) used pedotransfer functions and artificial neural network model to estimate van Genuchten (1980) parameters and saturated hydraulic conductivity. Results of this study showed that estimation of the regression models is more accurate than artificial neural network whereas the results were not significantly different. Therefore, possibility of using the new method, i.e., artificial neural networks, as a new option for accurate estimation was proposed.

Schaap et al., (1998) calibrated the artificial neural network to predict soil capacity for holding water and saturated hydraulic conductivity by using basic soil characteristics. They concluded that increasing the number of samples improved prediction of the soil capacity for holding water and hydraulic conductivity and high accuracy and flexibility was observed for ANNs by them. Jain et al. (2004) evaluated the ANNs for estimation of soil water retention curve. Results showed acceptable performance of the ANNs in comparison with other methods.

Parasuraman et al. (2006) compared the estimated saturated hydraulic conductivity by two different designs of the ANNs and Rosetta (Parasuraman et al., 2006). Results showed that the ANNs had better performance in comparison with Rosetta to estimate the soil saturated hydraulic conductivity.

Sy (2006) modeled infiltration with multilayer perceptron neural network using rainfall data in the network. It was observed that neural networks had better performance than conventional methods as Philip (1957) and Green and Ampt (1911) and the network performance was improved by the entrance of new variables like rainfall. Furthermore, the artificial neural networks were considered as an acceptable model for estimating the cumulative infiltration at certain times from the beginning of the infiltration process. Holtan (1961) evaluated the artificial neural networks to calibrate the infiltration equations. Results showed that the artificial neural network, especially in situations where data are limited, had higher accuracy than conventional methods such as curve fitting.

Moosavi and Sepaskhah (2011) used the ANNs to predict the unsaturated hydraulic conductivity at six applied tensions and sorptive number at five applied tensions. They stated that the input combination of sand, clay, silt, bulk density, and organic matter was the best influential input variable for predictions of unsaturated hydraulic conductivity and sorptive number at almost all values of applied tensions. Due to obtaining reliable predictions for unsaturated hydraulic conductivity and almost for sorptive number, it is recommended that such artificial intelligence models be used to predict these vital soil hydraulic characteristics (Mehrabi and Sepaskhah, 2013).

Moosavizadeh-Mojarad and Sepaskhah (2011) used the ANNs to determine the soil water retention curve. Two basic neural network structures were considered, including volumetric soil water content prediction and soil matric head prediction. Observations showed that the ANNs estimated the soil water retention curve by acceptable accuracy. Therefore, it was suggested to use such artificial intelligence models to predict the soil hydraulic properties.

In a study by Machiwal et al. (2006), the cumulative infiltration at specific time steps was predicted by using readily available soil data and ANNs. Two types of neural networks were prepared. In the first one, the basic soil properties of the first upper soil horizon were hierarchically used as inputs, and in the second one, models were developed while the available soil properties of the two upper soil horizons were implemented as inputs using principal component analysis technique. Results indicated that the first networks series had the best performance in estimating cumulative infiltration curves at all times. It was concluded that the Kostiakov (1932) model performed better than other infiltration models.

The objective of this study was to estimate two-component Philip equation parameters by ANNs using cumulative infiltration measured in double ring infiltrameter at different times and other soil parameters like percentage of sand, clay, silt, bulk density and organic matter. As explained before, though the Philip equation parameters can be fitted directly, using ANNs can improve the estimation and make the prediction more flexible and more intelligent. It also leads to predicting the parameters with fewer experimental data.

MATERIALS AND METHODS

Theory

Artificial intelligence systems are similar to human brain foundation as simulating human thought, successful response to events, learning and the ability to solve and predict solutions to the problems. These networks are able to process information and solutions even if input data contain errors or defects (Basheer and Hajmeer, 2000). Furthermore, artificial neural networks are able to extract relationships between input and output of a process without any knowledge of their principles. Moreover, they do not require any assumptions about the relationship (linear or nonlinear) between the input and the output (Jain et al., 2004). Although the ANNs has high speed, in fact, they have lower ability in comparison with the biological system of human brain; therefore, the ANNs development requires a longer time (Jain et al., 2004).

Neurons are the most basic part of the networks like the biological nervous system. One neuron is not enough to solve or build an ANNs and multiple neurons operating in parallel ways are needed. The numbers of these neurons, that are called nerve tissues in biological neural networks, transmit information and messages from one part to another. Each layer consists of a matrix of weights and bias, collectors set, boxes of transfer functions and output vectors (Hagan et al., 1996). Weight is multiplied by neuron’s input and is summed with a constant value that is called bias; afterwards, the net input is entered to the function that is called transfer function, by which the net input is converted to the output. Finally, the output neuron is obtained. Weights and biases are variable parameters that improve performance of ANN. All these neurons and layers can be connected in different ways that produce different structures of artificial neural networks.

All artificial neural networks have the same building. They are formed by three layers including an input layer, middle or hidden layers and the output layer. The input layer is the first layer of the network. Basic information and data are transferred through this layer. The number of neurons in this layer depends on the parameters that are entered to the network. Trial and error is the best way to determine the optimal number of entries (Zhang et al., 1998). The last layer in the network, which produces the final output, is named the output layer. The numbers of neurons in the output layer depend on the nature of the problem, but researchers often use one neuron in the output layer in most cases (Graupe, 2013; Kim, 2017). When more than one neuron is used in the output layer, the network error should be minimized for all outputs and this action reduces the prediction accuracy and network performance. Therefore, it is better to consider a separate network for each prediction. The layers between input layer and output layer are hidden or middle layers. A common method for determining the optimal number of hidden layer neurons is trial and error (Zhang and Hu, 1998). Two-layer or three-layer networks are used in most cases and often the network with more layers will not improve network performance (Hagan et al., 1996). Increasing the number of hidden layers enhances the computing and training time, and also causes overfitting problems. Although networks with more hidden layers are likely to act stronger and two-hidden layers showed better results in some cases, one-hidden layer is preferred in most prediction issues (Gioqinang Zhang and Hu, 1998).

Feedforward Multi-Layer Perceptron (MLP) networks are one of the most important neural networks structures. The network signals are forwarded from input to output and there is no feedback on the network. The output of each layer has no effect on the layer itself and it will be the input for the next layer; then, the next layers produce their output consecutively to reach the last output layer and the final output is achieved (Hagan et al., 1996). The number of neurons for input and output layers is determined by the nature of the problems, but designers specify the number of hidden layers and neurons by trial and error in order to reduce the error value. One hidden layer is usually selected in perceptron network because hidden layers are not directly related to output; layers changes do not affect weight adjustment significantly (Noori et al., 2010).

The most common training algorithm for artificial neural network is back propagation algorithm that is based on error correcting learning rule and subset of supervised training methods. Due to the fast convergence, among different methods of back propagation training algorithm, Levenberg - Marquardt (TrainLM) is usually selected for networks training (Ghobadian et al., 2009; Hagan et al., 1996; Ibn Ibrahimy et al., 2013; Sharma et al., 2016). In addition, the modified Levenberg - Marquardt algorithm, named Bayesian Regularization (BR), is used for training networks.

Methods

Measurement

In this study, required data were obtained from Mehrabi and Sepaskhah (2013). They measured cumulative infiltration in different soils in Agriculture College of Shiraz University farmlands, located at 16 km northeast of Shiraz in Bajgah (Longitude (52º38′), latitude (29º46′) and 1810 m above mean sea level). Infiltration rate and cumulative infiltration were measured by Mehrabi and Sepaskhah (2013) using double ring method in 30 different locations selected randomly in the area (Figure 1). The textures of experimental locations are provided in Table 1. Geographical coordinates (UTM) of these points were recorded by GPS device.

Table 1. Soil texture of experimental locations

Experimental locations	Soil texture
1-7	Clay Loam
8-9	Loam
10-25	Clay Loam
26	Loam
27-30	Clay Loam

As aforementioned, the Philip model is the best model to describe the spatial characteristics of infiltration; therefore, Mehrabi and Sepaskhah (2013) calculated the parameters of Philip equation [Eq. (1)]; sorption coefficient (S) and hydraulic conductivity (A), using least squares (Solver) method for each infiltration test by Excel software.

$$I(t) = St^{1/2} + At \tag{1}$$

Where, t is the time in (min), S is the sorption coefficient in (cm/min$^{-0.5}$), A is the hydraulic conductivity in (cm/min) and I is the cumulative infiltration in (cm).

It should be noted that the values of A were negative in five locations (1, 3, 5, 6 and 30) that could be due to errors resulted from using only two terms of the Philip (1957) analytic solution, or because of the soil heterogeneity or non-uniformity of soil moisture in the lower soil depth. These reasons can be seen clearly in the experimental locations of 1 and 30, because the initial infiltration rate was much higher than other elapsed times due to the fact that the soil moisture was higher in lower soil depth. They used multivariate regression and solved the (A) and (S) equations to fix this problem. Therefore, the Philip parameters values were modified before being used by Mehrabi and Sepaskhah (2013). Other required soil physical properties were measured by the authors in the current study as follows: sand, silt and clay fractions by the hydrometer method (Gee and Bauder, 1986); soil organic matter (SOM) by the wet oxidation method (Nelson and Sommers, 1996) and bulk density (BD) by the core method (Blake and Hartge, 1986). Both disturbed and undisturbed samples were taken at a depth of 0–20 cm in each experimental location in the current study.

Artificial Neural Network Modeling

Afterward, a program was written as m file in MATLAB R2011a (7.12.0.635) to design ANN for estimation and simulation of the parameters of the Philip equation. In order to design and train a neural network, data should be divided to two different sets, training samples and test samples. This data fragmentation is essential for network design (Zhang et al., 1998). Both training data set and test data set were randomly selected from total number of available data. Training sample is a set of inputs and outputs of the network that is used to train network for a specific task. Test sample does not interfere in the network during the training process but is used to determine and draw error and check network performance after training. As the number of samples increased, the network performance improved (Zhang et al., 1998). The total number of measurements in 30 experimental locations is 516, of which 356 (80 percent) were used in the training phase and 160 (about 20%) were used in the test phase.

Fig. 1. The **view of the area and measurement locations.**

Network accuracy and speed is reduced by importing raw data to the network. Therefore, input and output data should be in the range of the transfer function to increase network training efficiency and maintain data uniformity. Therefore, Preprocessed (data normalization), which is usually done before training network, means applying some changes in the inputs and outputs of the network to locate them in a specific range. After the training process finished and the results turned out, the network output was converted to its original form, which is called post-processing. According to previous studies, data normalization should be done so that the data are close to 0.5 (Kumar et al., 2002). Therefore, a program was developed in MATLAB R2011a (7.12.0.635) to normalize the data linearly before the training process as follows:

$$x_n = \frac{x + a}{b} \qquad (2)$$

where x is the observed value, and x_n is the normalized observed value, a and b are constants and calculated as follows:

$$b = \frac{x_{\max} - x_{\min}}{x'_{\max} - x'_{\min}} \qquad (3)$$

$$a = x'_{\min} \times b - x_{\min} \qquad (4)$$

where x_{min} and x_{max} are the minimum and maximum values of data, respectively, x'_{min} and x'_{max} are the minimum and maximum values of the normalized data.

Furthermore, another program was prepared to reverse the pervious action and restore the result into an original state. Total inputs for each experimental location are infiltration value that are related to each elapsed time as the constant input and the percentage of sand, silt, clay and organic matter (OM) and bulk density (BD) as the variable input (Table 2). Based on the input parameters, various networks with different input parameters and different structures (variable number of neurons and layers) were defined for estimating sorption coefficient (S) and hydraulic conductivity (A) in Philip equation. Two trainings, TrainLM and TrainBR, were used to train the network. The most common type of transfer functions are sigmoid functions, logarithm- sigmoid and tangent-sigmoid that are considerable because of the uniformity and non-linear performance (Brown and Chris, 1994). After selecting the appropriate algorithm, the transfer function of each layer, the number of hidden layers, the number of neurons needed for each layer and other parameters were provided to the network. After network training was finished, the test data set was used in the network for evaluating the results.

Accuracy Analysis

Ultimately, the network was evaluated with statistical parameters, Normalized Root Mean Square Error (NRMSE), Mean Absolute Error (MAE), index of agreement (d) and the coefficient of determination R^2 as follows:

$$NRMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(A(or)S_{sim} - A(or)S_{obs}\right)^2}{\sum_{i=1}^{n} A(or)S_{obs}^{\ 2}}} \qquad (5)$$

(6)

$$d = 1 - \left[\frac{\sum_{i=1}^{n}\left(A(or)S_{sim} - A(or)S_{obs}\right)^2}{\sum_{i=1}^{n}\left(\left|A(or)S_{sim} - \overline{A(or)S_{obs}}\right| + \left|A(or)S_{obs} - \overline{A(or)S_{obs}}\right|\right)^2}\right] \qquad (7)$$

Where *A(or)S* is the simulated value of *A(or)S* by ANNs; *A(or)S* is the observed value of *A(or)S* and n is the number of observations.

RESULTS AND DISCUSSION

Different ANN structures and input combination and specific scenarios were considered and after several trial and errors, the best combination of input parameters and the best structure of the neural network were chosen. Try and error method and selecting criteria were described in previous sections. Thereafter, the Philip equation parameters were estimated by including and excluding the cumulative infiltration and elapsed time in input combinations. The lowest values of NRMSE and MAE and the maximum values of d and R^2 are shown in Tables 3, 4, 5, 6 for different ANNs' input combinations. Afterwards, the comparison of the measured and estimated values and their linear relationships are shown in figs. 2 and 3

Determination of the Optimal Number of Hidden Layers for the Network

All available inputs (elapsed time and cumulative infiltration, percentage of sand, silt, clay, organic matter, and bulk density) were used to determine the optimal number of hidden layers. Therefore, the neural networks with one, two and three hidden layers were designed to estimate S and A.

The optimal mode was selected by trial and error. Comparison of the results in Table 3 indicated that S was estimated with relatively higher accuracy by ANNs with three hidden layers than the networks with one or two hidden layers; however, different results observed for A estimation and ANNs with three hidden layers had poor accuracy. Also, as a general principle in artificial neural networks, when the simpler networks that adequately represent the learning data are available, the complex networks are not preferred. In addition, the numbers of neurons are significantly increased in the neural networks with three hidden layers compared with one and two hidden layers networks. This event not only caused network complexity, but also made difficulty in the network generalization. Networks should be trained so that the prediction is done correctly; in other words, it should not be over-trained by the learning data. This situation occurs when a large number of neurons in the hidden layer is selected. On this basis, neural networks with two hidden layers were preferably selected and they were considered for other models with different inputs and special scenarios (Fig. 2).

Table 2. Different ANNs' input combinations

Output parameter	Input parameters	Name of ANN
Hydraulic conductivity (A)	Sand%, Silt%, Clay%, BD*, OM**, T***, CI****	ANN^A_1
	Sand%, Silt%, Clay%, OM, T, CI	ANN^A_2
	Sand%, Silt%, Clay%, BD, T, CI	ANN^A_3
	Sand%, Silt%, Clay%, T, CI	ANN^A_4
	BD, OM, T, CI	ANN^A_5
Sorptivity (S)	Sand%, Silt%, Clay%, BD, OM, T, CI	ANN^S_1
	Sand%, Silt%, Clay%, OM, T, CI	ANN^S_2
	Sand%, Silt%, Clay%, BD, T, CI	ANN^S_3
	Sand%, Silt%, Clay%, T, CI	ANN^S_4
	BD, OM, T, CI	ANN^S_5

* Bulk Density ** Organic Matter *** Time **** Cumulative Infiltration

Table 3. Optimal results of different ANNs' structures for determining the number of hidden layers

Inputs	Outputs	Number of hidden layers	Number of neurons	Transfer function	Training algorithm	Step	R^2	NRMSE	MAE	d
Sand% Silt% Clay% BD OM T CI	S	1	1	Tansig	BR	Train	0.560	0.304	0.162	0.684
						Ttest	0.622	0.281	0.153	0.742
		2	2-3	Tansig-tansig	BR	Train	0.685	0.328	0.170	0.714
						Test	0.676	0.324	0.167	0.719
		3	10-11-10	Logsig-logsig-tansig	LM	Train	0.992	0.005	0.002	0.998
						Test	0.812	0.395	0.173	0.828
	A	1	2	Llogsig	BR	Ttrain	0.805	0.371	0.024	0.875
						Test	0.827	0.389	0.025	0.867
		2	2-3	Tansig-tansig	BR	Train	0.820	0.344	0.021	0.905
						Test	0.846	0.392	0.024	0.882
		3	8-10-10	Tansig-logsig-tansig	LM	Train	0.994	0.019	0.002	0.999
						Test	0.816	0.554	0.077	0.882

Table 4. Optimal results of different ANNs' input combinations

Outputs	Iinputs	Number of hidden layers	Number of neurons	Transfer function	Training algorithm	Step	R^2	NRMSE	MAE	D
S	Sand% Silt% Clay% CI	2	2-3	Logsig-tansig	LM	S	Train	0.808	0.214	0.097
							Test	0.775	0.269	0.144
A	Sand% Silt% Clay% BD OM T CI	2	2-3	Tansig-tansig	BR	A	Train	0.820	0.344	0.021
							Test	0.846	0.392	0.024

Table 5. Optimal results of different ANNs by excluding the infiltration and elapsed time from input combinations

Outputs	Inputs	Number of hidden layers	Number of neurons	Transfer function	Training algorithm	Step	R^2	NRMSE	MAE	D
S	Sand% Silt% Clay% BD OM	2	7-10	Logsig-tansig	LM	Train	0.994	0.054	0.022	0.996
						Test	0.706	0.444	0.143	0.956
A	Sand% Silt% Clay% BD OM	2	9-11	Tansig-logsig	LM	Train	0.989	0.125	0.013	0.994
						Test	0.609	0.887	0.085	0.739

Table 6. Optimal results of different ANNs by excluding the infiltration and elapsed time from input combinations

Outputs	Inputs	Number of idden layers	Number of neurons	Transfer function	Training algorithm		Step	R^2	NRMSE	MAE	D
S&A	Sand% Silt% Clay% BD OM T CI	2	10-12	tansig-logsig	BR	S	Train	0.997	0.001	0.002	0.997
							Test	0.612	0.370	0.205	0.749
						A	Train	0.988	0.010	0.003	0.992
							Test	0.253	0.850	0.091	0.465

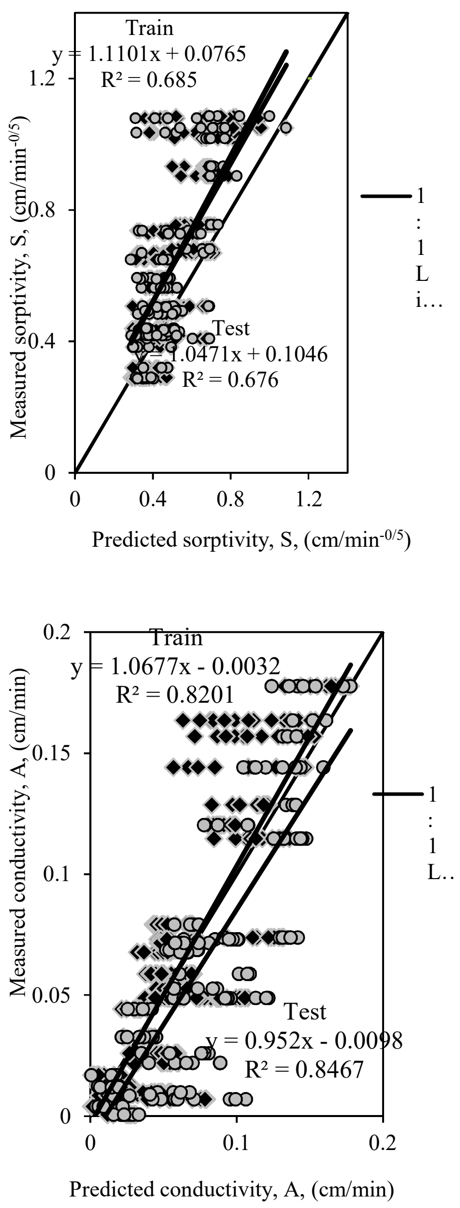


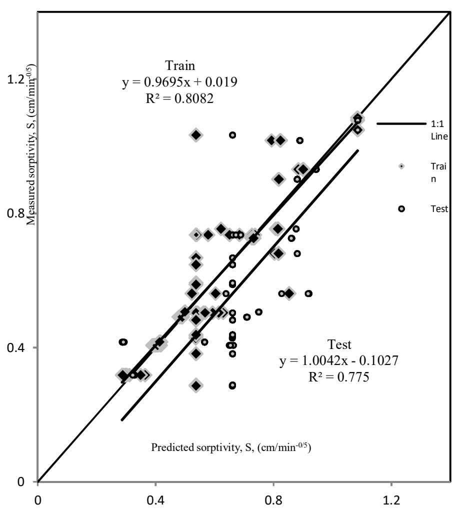
Fig. 2. Relationship between the predicted value of (a) sorption coefficient (b) hydraulic conductivity and the measured values by two hidden layers network with the input combination including elapsed time and cumulative infiltration, percentage of sand, silt, clay, organic matter, and bulk density

Determination of the Optimal Input Combination for the Network

Based on the mentioned factors, the artificial neural network with two hidden layers was chosen; then, various types of training algorithms and transfer functions, and different numbers of neurons were used to design the networks. It should be noted that since no other correlations were used in the current research, it is preferred to study the effect of each parameter individually on the performance of the network to increase the accuracy of the study. Therefore, various combinations of the input parameters were tested. The best network structure and input combinations for S estimation were achieved when the percentage of sand, silt, clay, elapsed time and cumulative infiltration were used as inputs. Furthermore, this model with 5-2-3-1 neuron structure, the logarithm sigmoid (log-sig) as transfer function for the first hidden layer and tangent sigmoid (tan-sig) as transfer function for the second hidden layer, and Levenberg-Marquardt algorithm as training algorithm showed the closest result to the measured data (Table 4). The regression equations for the relationship between the predicted and measured output for testing and training stages, derived from the best choice of neural network, are given in Figure 3a. The best network structure and input combinations for A estimation were achieved when the percentage of sand, silt, clay, bulk density, organic matter, elapsed time and cumulative infiltrations were used as inputs. Furthermore, this model with 7-2-3-1 neuron structure, the tangent sigmoid (tan-sig) as transfer function for both hidden layers, and Bayesian Regularization (TrainBR) as training algorithm showed the closest result to the measured data (Table 4). The regression equations for the relationship between the predicted and measured output for testing and training stages, derived from the best choice of neural network, are given in Fig. 3b.

Estimation of Philip Equation Parameters by Excluding the Cumulative Infiltration and Elapsed Time from Input Combinations

All of the available inputs including the elapsed time and cumulative infiltration, percentage of sand, silt, clay, organic matter, and bulk density were used in networks in the previous results.



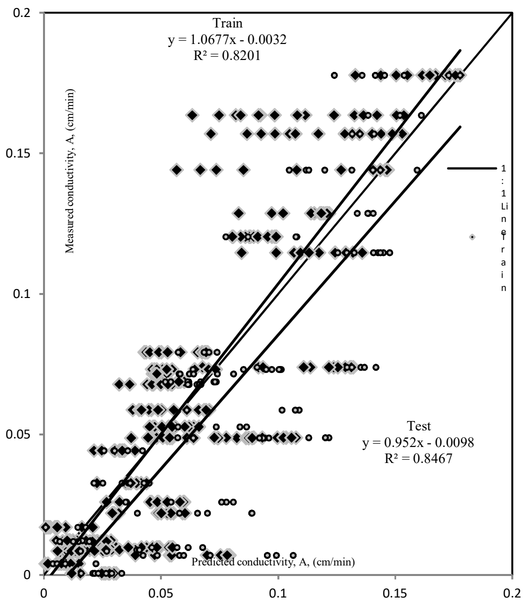


Fig. 3. Relationship between the predicted value and the measured values for optimal result by two hidden layers network for(a) sorption coefficient with the input combination including elapsed time and cumulative infiltration, percentage of sand, silt and clay (b) hydraulic conductivity with the input combination including elapsed time and cumulative infiltration, percentage of sand, silt, clay, organic matter, and bulk density

The total number of data was 516 for these combinations of inputs in 30 experimental locations; however, it was reduced to 30 by excluding the elapsed time and cumulative infiltration from the input combination. Therefore, the total numbers of data were 30 for 30 locations in the new scenario. The best network structure for inputs combination including percentage of sand, silt, clay, organic matter, and bulk density for hydraulic conductivity (A) estimation were achieved when the tangent sigmoid (tan-sig) was used as transfer function for the first hidden layer and logarithm sigmoid (log-sig) was used as transfer function for the second hidden layer, TRAINLM was used as training algorithm with 5-9-11-1 neuron structure.

The best network structure for the same inputs combination for sorption coefficient (S) estimation was achieved when the logarithm sigmoid (log-sig) was used as transfer function for the first hidden layer and tangent sigmoid (tan-sig) was used as transfer function for the second hidden layer, TrainLM was used as training algorithm with 5-7-10-1 neuron structure (Table 5). Learning datasets should be large enough because of desirable networks generalization. Therefore, due to inadequate data for use in artificial neural network, it does not give acceptable results in this part. Almost among all studies, the linear transfer function was recognized as the best function for output layer in different neural network structures, but because of inadequate data, tangent- sigmoid transfer function was used for the output layer in the acceptable results.

Simultaneous Estimation of the Philip Equation Parameters in a Network

In another case, a network was designed to estimate both output i.e., S and A simultaneously by some little changes in the program. Soil parameters including the elapsed time and cumulative infiltration, percentage of sand, silt, clay, organic matter, and bulk density were used as inputs. According to the results, the network did not estimate S and A with acceptable accuracy (Table 6). As the network must accommodate errors with two outputs, this method of network design was not acceptable.

Comparison between the Measured and Predicted Value of Philip Equation

For further evaluation of the result of neural network, the measured and predicted Philip equations in three experimental locations were compared (Fig. 4). Results showed acceptable agreement between the measured and predicted Philip equation. Therefore, it is indicated that neural networks are able to estimate the Philip equation with high accuracy.

It should be noted that based on the reported values of the statistical parameters, the performance of the ANNs is not very excellent. This is because the experimental data set used for the training and prediction processes are scattered. This makes prediction or fitting of the Philip equation parameters with higher accuracy impossible. On the other hand, estimation of these parameters for the current case study based on the curve fitting method showed similar errors (Mehrabi and Sepaskhah, 2013). Therefore, ANNs can be used successfully to describe the current phenomena as illustrated in Fig. 4. In addition, by using the neural network, prediction of the parameters does not require hard, time-consuming and costly workouts.

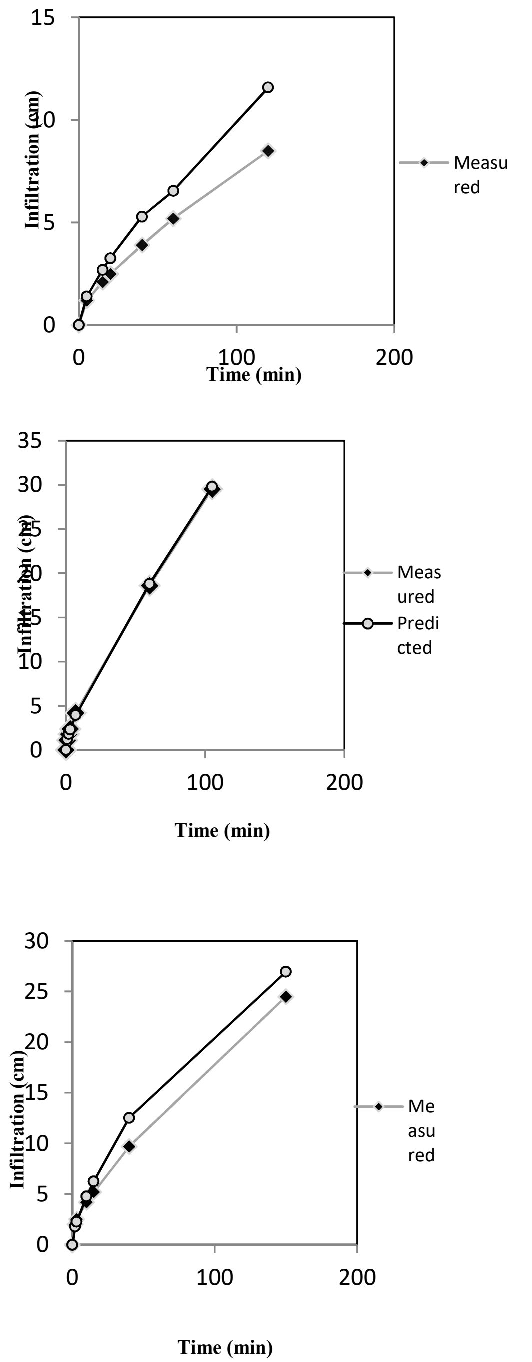


Fig.4. Comparison between the measured and predicted Philip infiltration equation for three experimental locations: (a) location Num. 8 (b) location Num. 12 (c) location Num.23

CONCLUSIONS

It is concluded that increasing network inputs and the number of hidden layers to two layers improved the network performance and showed a significant effect on results. The most appropriate artificial neural network structure for sorption coefficient (S) estimation is ANN^S_4 model with five inputs (elapsed time, cumulative infiltration, percentage of sand, silt, and clay). It has two hidden layers with two neurons in the first layer and three neurons in the second one (5-2-3-1). Logarithm-sigmoid and tangent-sigmoid are the transfer functions for the first and the second hidden layers, respectively. The training algorithm is TrainLM. The values of R^2, NRMSE, MAE and d are 0.775, 0.269, 0.144, 0.820, respectively in the test stage. Also, the most appropriate ANNS structure for hydraulic conductivity for A estimation was ANN^A_1 model, with seven inputs (elapsed time and cumulative infiltration, percentage of sand, silt, clay, organic matter, and bulk density). It has two hidden layers with two neurons in the first layer and three neurons in the second layer (7-2-3-1). Tangent-sigmoid is the transfer functions for both hidden layers. The training algorithm is TrainBR. The values of R^2, NRMSE, MAE and d are 0.846, 0.392, 0.024, 0.882, respectively in the test stage. It is noteworthy that the network structure with Levenberg-Marquardt training algorithm and sigmoid transfer functions in hidden layers and tangent-sigmoid transfer function in the output layer showed the best performance when the number of data is less than adequate (although it was not acceptable). However, the network with Bayesian Regularization (TrainBR) as training algorithm and sigmoid transfer functions in middle layers and linear transfer function in the output layer showed a better result by using an adequate number of data. Also, it is observed that the proposed network is able to predict only one output (i.e. S or A) with good accuracy and it is not acceptable to estimate several outputs (i.e. S and A) in a network simultaneously. Besides, it was confirmed that using ANNs simplifies the prediction process by decreasing the number of experimental data needed for the network training.

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کاربرد شبکه عصبی مصنوعی برای تخمین پارامترهای معادله نفوذ فیلیپ

نازنین ابریشمی شیرازی*، علیرضا سپاسخواه

بخش مهندسی آب ، دانشکده کشاورزی، دانشگاه شیراز، شیراز، ج. ا. ایران

*نویسنده مسئول

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چکیده- نفوذپذیری آب در خاک یکی از مهم‌ترین پدیده‌های فیزیکی خاک است. روش‌های تجربی تعیین معادله‌های نفوذ، نیازمند انجام آزمایش‌های زمان بر و پرهزینه است، لذا در این پژوهش از روش غیرمستقیم شبکه عصبی مصنوعی برای تخمین مقادیر ضریب جذب (S) و فاکتور انتقال(A) معادله فیلیپ استفاده شد. ساختارهای مختلف شبکه عصبی مصنوعی متشکل از الگوریتم های آموزش TrainLM و TrainBR و توابع انتقال لوگ سیگموئید و تانژانت سیگموئید برای لایه‌های میانی و تابع تبدیل خطی برای لایه خروجی و ترکیبات متفاوتی از ورودی‌ها، شامل مقادیر نفوذ تجمعی و زمان‌های مربوط به هرکدام، به‌عنوان ورودی ثابت و درصد شن، درصد سیلت، درصد رس، چگالی ظاهری و ماده آلی به عنوان ورودی‌های متغیر، برای ۳۰ نقطه در دانشکده کشاورزی واقع در منطقه باجگاه بررسی گردید. برای تخمین ضریب جذب بهترین ساختار دارای دو لایه مخفی و ۳ ورودی (درصد شن، درصد سیلت و درصد رس) با دو نرون در لایه اول و سه نرون در لایه دوم و الگوریتم آموزش TrainLM بود. برای تخمین فاکتور انتقال بهترین ساختار دارای دو لایه مخفی و ۵ ورودی (چگالی ظاهری، مقدار ماده آلی، درصد شن، درصد سیلت و درصد رس) با دو نرون در لایه اول و سه نرون در لایه دوم و الگوریتم آموزش Train BR بود. افزایش تعداد لایه‌های مخفی و تعداد ورودی‌ها تاثیر به سزایی در بهبود نتیجه داشت و شبکه عصبی در تخمین مقادیر فاکتور انتقال عملکرد بسیار بهتری نسبت به ضریب جذب را نشان داد. مقدار ضریب تعیین (R^2) نشان داد که پیشبینی های شبکه عصبی برای A (٪ ۸۴/۶) بهتر از S (٪ ۷۷/۵) می‌باشد.