*Original Research Article*

# Prediction of unsaturated hydraulic conductivity of agricultural soils using artificial neural network and c#


## ABSTRACT

**Aims:** The objective of this study was to develop an artificial neural network model and interactive application using C# program to predict unsaturated hydraulic conductivity of soil.

**Study design:** The actual measurements of unsaturated hydraulic conductivity of soil were obtained using the Mini Disk Infiltrometer (Decagon Devices, Inc.).

**Place and Duration of Study:** The study was conducted in laboratory located in Community College, Huraimla, Shaqra University, Saudi Arabia during March-April 2015.

**Methodology:** The experiments were conducted using water having electric conductivity of 2.26 dS/m and sodium adsorption ratio of 4.8. Unsaturated hydraulic conductivity in different soil textures (sand, sandy loam, loam and loamy sand) was determined at suction of -6 cm using Mini Disk Infiltrometer. The soil samples were taken from depth of 0-20 cm and repacked in a plastic 1000 $cm^3$ container.

**Results:** The predicted unsaturated hydraulic conductivity of soils compared favourably with the actual measurements in testing stage, however, mean relative error was 4.184% and coefficient of determination ($R^2$) was 0.9979. In general, artificial neural network model gave considerable results but more data is still necessary. The main equations for C# program were obtained from the trained artificial neural network model.

**Conclusion:** It could be concluded that the developed interactive application is recommended for estimating unsaturated hydraulic conductivity of soil to provide data for water management in Saudi Arabia.



*Keywords: artificial neural network; C#; mini disk infiltrometer; unsaturated hydraulic conductivity of soil.*


## 1.INTRODUCTION

In the field of irrigation agricultural, water management is required to improve the efficiency and sustainability of agricultural systems when water is scarce [1]. One of the tasks of water management is to quantify, to predict and eventually to control water and solute transport into soil. Consequentially, these processes are dependent on soil hydraulic conductivity which needs to be determined in the field or in the laboratory. On the other hand, direct measurement of hydraulic conductivity of soil is difficult, tedious, relatively costly, labour intensive and time-consuming [2-5]. Thus, indirect methods using predictive approaches have been developed for estimation of hydraulic properties of soil from easily measurable soil properties [6-8]. However, predictive approaches of the soil hydraulic conductivity have gained considerable attention and efforts have been made by researchers to improve the power of predictability [9]. The predictive approaches of the soil hydraulic conductivity may be developed by using multiple linear regression, adaptive neuro-fuzzy inference system and artificial neural network models. Such models have been recommended in this field as encourage results of different research papers [10-11] were reported.

Hydraulic conductivity is defined as “the meters per day of water seeping into the soil under the pull of gravity or under a unit hydraulic gradient” [12]. Additionally, hydraulic properties of soil and their applications in the soil water flow models play an important role on solving many water management issues [13].

Hydraulic conductivity is useful to soil and water scientists, land managers, and growers, in knowing how quickly water will infiltrate when applied to a given field or soil type [14].The selection and determination of soil hydraulic parameters is the basis of predicting water movement and solute transfer in soils [15]. The measurements show that the value of unsaturated hydraulic conductivity varies considerably from soil to soil with different water content [16]. Soil hydraulic conductivity

includes saturated hydraulic conductivity and unsaturated hydraulic conductivity [17]. Of all hydraulic properties, the unsaturated hydraulic conductivity is the most difficult to measure. It is considered to be the most important parameter for modelling flow process in unsaturated soil. Furthermore, unsaturated soil hydraulic conductivity is essential to many agriculture and environmental applications [18]. It is considered the most important parameter in soil water flow models [13]. It is a function of soil moisture and its amount will be decreased with going down the soil moisture [19]. It is also one of hydraulic characteristics needed for numerical modelling of water flow and solute transport in the vadose zone [20]. It is also often necessary for solving unsaturated flow problems [21].

Measurement of unsaturated soil hydraulic conductivity is a challenging task and requires costly and skilled experimentation [22]. Therefore, the use of indirect methods has become common to estimate the unsaturated hydraulic conductivity from more easily measured soil properties [23]. Additionally, unsaturated soil hydraulic conductivity could be estimated from air permeability [24] from soil electrical conductivity [25] and from moisture retention data [26].

Vereecken et al. [7] measured hydraulic conductivity (saturated and unsaturated) on 127 soil cores, which were taken in different horizons of a wide variety of Belgian soil series. The textural composition in nine fractions, the organic carbon content and the dry bulk density were determined for each of the sample horizons as well. Four different empirical models were evaluated on their performance in describing the measured hydraulic conductivity.

Zhuang et al. [17] estimated the unsaturated hydraulic conductivity of soil according to the main physical properties of the soil and they were the principal characteristics of soil such as density of unsaturated of this research; furthermore, they include soil texture, the hydraulic conductivity of soil, soil water properties and amounts of gypsum and lime precent, actual and apparent the distribution of particle sizes.

Neshat and Farhad [19] carried out an experiment and made calculation for estimating the unsaturated hydraulic conductivity of soil to get suitable relationship between the unsaturated hydraulic conductivity of soil and soil physical properties. Their developed model was as follows:

$$Ku = 41.176\left(\frac{K_S \theta_V \rho_b}{\rho_S}\right)^{2.49} \quad \text{.....(1)}$$

Where $Ku$ is unsaturated hydraulic conductivity of soil, $K_S$ is saturated hydraulic conductivity of soil, $\theta_V$ is volume soil moisture content, $\rho_b$ is apparent density and $\rho_S$ is actual density.

Malaya and Sreedeep [22] investigated the correlation between grain size distribution curve of a soil and unsaturated hydraulic conductivity of soil. They reported that unsaturated hydraulic conductivity of soil could be estimated from grain size distribution curve of a soil.

Amer et al. [27] proposed equation to predict unsaturated hydraulic conductivity as follows:

$$K(\theta) = \frac{\rho_w g r^2 \Delta\theta}{8\eta\theta_s} \quad \text{.....(2)}$$

Where $K(\theta)$ is unsaturated hydraulic conductivity of soil, $\eta$ is water viscosity (0.001kg/m s at 20°C), g is acceleration due to gravity (9.8 m/s$^2$), $\rho_w$ is density of water (988 kg/m$^3$ at 20°C), $\frac{\Delta\theta}{\theta_s}$ is ratio of total volume pores and r is radius of equivalent cylindrical pore size.

Neyshabouri et al. [28] proposed a simplify method to predict unsaturated soil hydraulic conductivity using readily accessible soil. Tests with 51 soils with estimated electrical properties were confirmed good agreement of the developed model for coarse–medium-textured soils (<35–40% clay).

Direct measurement of soil properties is easier and much rapid than unsaturated hydraulic conductivity of soil [29]. There are several studies that have attempted to use artificial neural networks (ANN) for estimating hydraulic conductivity of soil from its physical parameters due to ANN is becoming a common tool for modeling complex input–output dependencies [30]. Ghanbarian-Alavijeh et al. [31] developed ANN model to predict saturated hydraulic conductivity of soil using calculated fractal dimensions, air entry values, bulk density and effective porosity. In the training and testing steps of ANN, 114 and 28 measured soil samples were used, respectively. Coefficient of determination and mean squared error were 0.76 and 0.0028, respectively. Erzin et al. [32] developed ANN model for determining hydraulic conductivity of fine-grained soils. The ANN model exhibits higher prediction performance based on their performance indices. It has been demonstrated that the ANN model developed in their study can be employed for determining hydraulic conductivity of

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compacted fine-grained soils quite efficiently. Ghanbarian-Alavijeh et al. [33] developed an ANN model with back propagation algorithm to estimate saturated hydraulic conductivity from available parameters such as sand and clay contents, bulk density, van Genuchten retention model parameters (i.e. r, θ, α and n) as well as effective porosity functions. The results showed that ANN estimated saturated hydraulic conductivity in a good way. Moosavi and Sepaskhah [34] used sand, silt, clay, bulk density, soil organic matter and initial and saturated volumetric water content to predict the unsaturated hydraulic conductivity by the help of ANN. They showed that silt, clay, sand, bulk density and soil organic matter were the most basic influential input variable for predictions of unsaturated hydraulic conductivity.

In spite of the cited studies carried out for estimating unsaturated hydraulic conductivity from soil properties, but in semi-arid regions like Saudi Arabia, water management is vital goal to improve the efficiency and sustainability of agricultural systems as water is scarce. So, the objective of this study was to use artificial neural network technique to create a model for unsaturated soil hydraulic conductivity predictions based on sand, silt, clay contents, soil electric conductivity, soil adsorption ratio, soil organic matter, initial soil moisture content and soil bulk density to be used as a method for creating a database collection about soil hydraulic conductivity for agricultural soils in Saudi Arabia.

## 2.MATERIALS AND METHODS

### 2.1Soil and water samples characteristics

Experiments were conducted in laboratory scale in Community College, Huraimla, Shaqra University, Saudi Arabia during March-April 2015. Three samples of soil were taken from the top 20 cm of representative sites. Textural analyses showed that the samples could be classified as sand, sandy loam, loam and loamy sand. The initial soil water content (dry base) of the samples was measured by the help of electric oven for 24 h at 105°C. The soil was carefully repacked in a plastic container with capacity of 1000 $cm^3$ with almost volume of 600 $cm^3$.

Sodium adsorption ratio (SAR) is a measure of the sodicity of soil, as determined from analysis of water extracted from the soil. The formula for calculating sodium adsorption ratio is [35]:

$$SAR = \frac{Na^{+}}{\sqrt{\frac{1}{2}\left(Ca^{++} + Mg^{++}\right)}} \quad \text{.....(3)}$$

Where $Na^{+}$, $Ca^{++}$, and $Mg^{++}$ represent concentrations expressed in milliequivalents per litre (meq/L). The characteristics of water used in the laboratory experiments are shown in Table 1.

**Table 1. The characteristics of water used in the laboratory experiments.**

| pH | $EC_{water}$ | $SAR_{water}$ | $HCO_3$ | $SO_4$ | Cl | Na | K | Ca | Mg |
|---|---|---|---|---|---|---|---|---|---|
| (---) | (dS/m) | | | | | (meq/L) | | | |
| 7.7 | 2.26 | 4.8 | 8 | 5.8 | 22 | 15.3 | 0.3 | 15 | 5.2 |

### 2.2 Mini disk infiltrometer

Mini disc infiltrometer (Decagon Devices, Inc.) measures soil hydraulic conductivity quickly and easily in any soil type. The infiltrometer as shown in Fig. (1) is constructed of a polycarbonate tube with a semi-permeable stainless steel sintered disk on the bottom. An adjustable steel tube above the sample chamber regulates the discharge rate. The top and bottom chambers are both filled with water. The top chamber controls the infiltrometer's suction. The lower chamber contains the water that will infiltrate into the soil and is marked like a graduated. It can measure the hydraulic conductivity in the unsaturated medium (close to near saturation) for adjustable suction ranging from -0.5 cm to -7 cm. At time zero, the infiltrometer is placed on the soil surface. The volume of water that infiltrate into the ground has been recorded as a function of time, based on which infiltration and permeability characteristics is determined.

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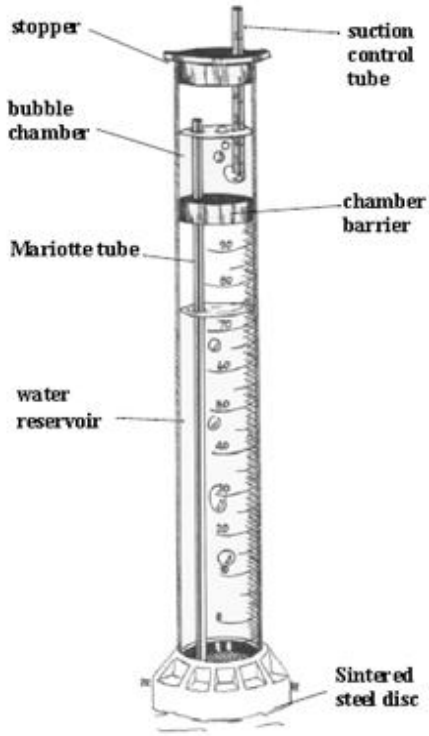


**Fig. (1). Mini disk infiltrometer (Decagon Devices, Inc.).**

## 2.3 Calculating hydraulic conductivity

A number of methods are available for determining soil hydraulic conductivity [36]. The method proposed by Zhang [37] is quite simple and works well for measurements of infiltration into dry soil from the recorded data by mini disk infiltrometer. The method requires measuring cumulative infiltration vs. time and fitting the results with the function:

$$I = C_1 t + C_2 \sqrt{t} \quad \text{.....(4)}$$

Where I is the cumulative infiltration (*cm*), t is the time (*sec*), and $C_1$ (cm/sec) and $C_2$ (cm/sec$^{-0.5}$) are parameters. $C_1$ is related to hydraulic conductivity and $C_2$ is related to soil sorptivity. The hydraulic conductivity (Ki) of the soil is then computed from

$$Ki = \frac{C_1}{A} \quad \text{.....(5)}$$

Where $C_1$ is the slope of the curve of the cumulative infiltration vs. the square root of time (Fig. 2) and (A) is a value relating the van Genuchten parameters for a given soil type to the suction rate and radius of the infiltrometer disk. (A) is computed from:

$$A = \frac{11.65\left(n^{0.1} - 1\right)\exp\left[2.92\left(n - 1.9\right)\alpha h_0\right]}{\left(\alpha r_0\right)^{0.91}} \qquad n \geq 1.9 \quad \text{.....(6)}$$

$$A = \frac{11.65\left(n^{0.1} - 1\right)\exp\left[7.5\left(n - 1.9\right)\alpha h_0\right]}{\left(\alpha r_0\right)^{0.91}} \qquad n < 1.9 \quad \text{.....(7)}$$

Where $n$ and $\alpha$ are the van Genuchten parameters for the soil, $r_0$ is the disk radius and $h_o$ is the suction at the disk surface. The van Genuchten parameters for the 12 texture classes were obtained from Carsel and Parrish [38].

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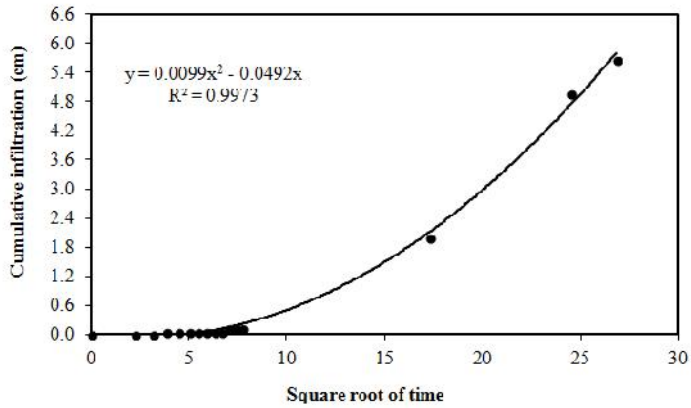


**Fig. (2). Cumulative iinfiltration versus square root of time for a soil.**

## 2.4 Measurement of soil hydraulic conductivity

The unsaturated hydraulic conductivity was measured using a mini disk infiltrometer (Decagon Devices Inc.). It consists of two chambers (water reservoir and bubble chamber), which are connected via a Mariotte tube to provide a constant water pressure head of 0.5 to 7 cm (equivalent to 0.05 to 0.7 kPa) as depicted in Fig. (1). The bottom of the mini disk infiltrometer contains a porous sintered steel disk. The water filled tube is placed upon the soil surface (Fig. 3) resulting in water infiltrating into the soil, with the volume of water and speed of infiltration depending on the sorptivity and hydraulic conductivity of the soil. A pressure head of 6 cm (equivalent to 0.6 kPa) was chosen in this study as the recommended head for sandy soil [14]. All measurements within one sample test were taken on the same day. The mini disk infiltrometer measurements were taken three times for every soil sample. During the measurement, the volume of the water in the reservoir chamber was documented in regular intervals**.**

**Fig. (3). Mini disk infiltrometer used for laboratory infiltration measurements.**

## 2.5 Artificial neural networks

Today artificial neural networks (ANN) have become an alternative method for predicting soil properties [39-40]. The ANN tool is a computational approach that simulates biological neuron function. The performance of ANN is sensitive to their physical architecture, such as the number of input nodes, hidden layer nodes and output nodes. The appropriate ANNs architecture is, therefore, highly problem dependent [41]. The ANN is trained to reproduce the input–output relation used to find the optimal weights. Training process consists of calculating the output variables from the input variables; comparing the measured output with ANNs calculated outputs; and then adjusting the

weights and bias for each node to minimize the difference between the measured and calculated values.

Commercially available QNET 2000 was employed in this study [42]. This software is a Windows-based package, which supports standard back-propagation algorithm for training purposes. QNET 2000 operates via a graphical user interface (GUI) that enables the user to load the training and test sets, design the network architecture and feed values for the training parameters. The ANN used in this study was a standard back-propagation neural network. The neurons in the ANN layers are connected by weights. The weights connecting input neuron $i$ to hidden neuron $j$ are denoted by $w_{ji}^{h}$ , while the weights connecting hidden neuron $j$ to output neuron are denoted by $w_{j}^{o}$ . The input of each neuron is the weighted sum of the network inputs, and the output of the neuron is a sigmoid function value based on its inputs. More specially, for the $j$ th hidden neuron [43].

$$\begin{cases} net_j^h = \sum_{i=1}^{P} w_{ji}^h x_{t-1} + b_j \quad , \\ y_j = f\left(net_j^h\right) \end{cases} \qquad \text{.....(8)}$$

While for the output neuron

$$\begin{cases} net^o = \sum_{j=1}^{m} w_j^o y_j + c \quad , \\ \tilde{x}_t = f\left(net^o\right) \end{cases} \qquad \text{.....(9)}$$

Where $b_j$ and $c$ are thresholds (bias), this network has $P$ neurons in the input layer and $m$ neurons in the hidden layer, $f$ is typically taken to be an transfer function and in this study, it was changed to be sigmoid function as shown in equation (9) or hyperbolic tangent (tanh) as shown in equation (10).

$$f(x) = \frac{1}{1+e^{-x}} \qquad \text{..... (10)}$$

$$f(x) = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}} \qquad \text{..... (11)}$$

It must be noted that because the variables (input or target) presented were of different orders of magnitude, all of the original inputs or target variables were normalized between 0.15 and 0.85 before entering into the network structure using the following equation:

$$T = \frac{(t - t_{\min})}{(t_{\max} - t_{\min})} \times (0.85 - 0.15) + 0.15 \qquad \text{.....(12)}$$

Where t is the original values of input and output parameters, T is the normalized value; $t_{max}$ and $t_{min}$ are the maximum and minimum values of the input and the output parameters in training data set, respectively. The training data set was used to compute the network parameters. The testing data was used to ensure robustness of the network parameters. Table 2 illustrates minimum and maximum values of input and output variables in training date set for ANN model.

In the study, trial and error approach [44] was used to determine the optimum neurons in the hidden layers of the network. Transfer function was also varied; however, they were sigmoid and hyperbolic tangent (tanh) in the hidden layers. The training data set was consisted of 9 laboratory-measured electric conductivity of soil, soil sodium adsorption ratio, initial soil water contents, sand, silt and clay contents, soil bulk density and soil organic matter. These variables were considered as input variables. The output (target) variable in this study consisted of 9 laboratory measured unsaturated hydraulic conductivity of soil at applied tensions of 6 cm. Preliminary trails indicated that two hidden layers network performed better results to learn and predict the correlation between input and output parameters. To determine the optimal number of neurons in the hidden layers, training was used for

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8-n1-n2-1 architectures. The number of neurons in the hidden layer (n1) was studied from 1 – 12. The number of neurons in the hidden layer (n2) was studied from 2 – 20. Results show that among the various structures, the best training performance to predict unsaturated hydraulic conductivity of soil was belong to the 8-8-14-1 structure. The best ANN model was elected based on the highest correlation coefficient and the lowest training error. Fig. (4) illustrates the best ANN structure in the study. Meanwhile, root mean square error during training process is shown in Fig. (5). Additionally, network definitions to predict unsaturated hydraulic conductivity of agricultural soils is depicted in Table 3 and Table 4 illustrates network statistics after training process.

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**Table 2. Statistical values of input and output variables in training data set for ANN model.**

| | Input variables | | | | | | | | Output variable |
|---|---|---|---|---|---|---|---|---|---|
| | **Sand** | **Silt** | **Clay** | **EC** | **SAR** | **Organic matter** | **Initial soil water content** | **Soil bulk density** | **Unsaturated hydraulic conductivity** |
| | **(%)** | **(%)** | **(%)** | **(dS/m)** | **(---)** | **(%)** | **(%,db)** | **(g/cm$^3$)** | **(cm/sec)** |
| Minimum | 52 | 2 | 1 | 1.06 | 2.00 | 0.26 | 3.60 | 1.30 | 0.00017 |
| Maximum | 95 | 28 | 39. | 91.10 | 57.60 | 2.62 | 7.54 | 1.54 | 0.02037 |
| Average | 76.22 | 11.11 | 12.67 | 13.93 | 11.42 | 1.68 | 5.65 | 1.46 | 0.00624 |
| Standard deviation | 15.18 | 9.57 | 13.71 | 29.09 | 17.46 | 0.82 | 1.16 | 0.07 | 0.00813 |
| Coefficient of variation (%) | 5.02 | 1.16 | 0.92 | 0.48 | 0.65 | 2.05 | 4.86 | 19.49 | 0.76780 |

SAR= Soil sodium adsorption ratio EC =Soil electric conductivity

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## 2.6 Evaluation of ANN model predictability

In order to perform a supervised training, a way in which the ANN output error between the actual and the predicted output could be evaluated is therefore required. A popular measure is the mean absolute error (MAE), root means square error (RMSE) and mean relative error (MRE) as follows:

$$MAE = \frac{1}{N} \times \sum_{i=1}^{i=N} \left| K_{viobs} - K_{vipre} \right| \quad \text{.....(13)}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{i=N} \left( K_{viobs} - K_{vipre} \right)^2}{N}} \quad \text{.....(14)}$$

$$MRE = \frac{100}{N} \times \sum_{i=1}^{i=N} \left( \frac{K_{vipre} - K_{viobs}}{K_{iobs}} \right) \quad \text{.....(15)}$$

Where $K_{viobs}$ and $K_{vipre}$ are experimental and predicted unsaturated hydraulic conductivity of soil, N is number of observations. In addition, the coefficient of determination ($R^2$) was selected to measure the linear correlation between the calculated and the predicted values. However, $R^2$ reflects the degree of fit for the mathematical model [45]. The closer the $R^2$ value is to 1, the better the model fits to the actual data [46].

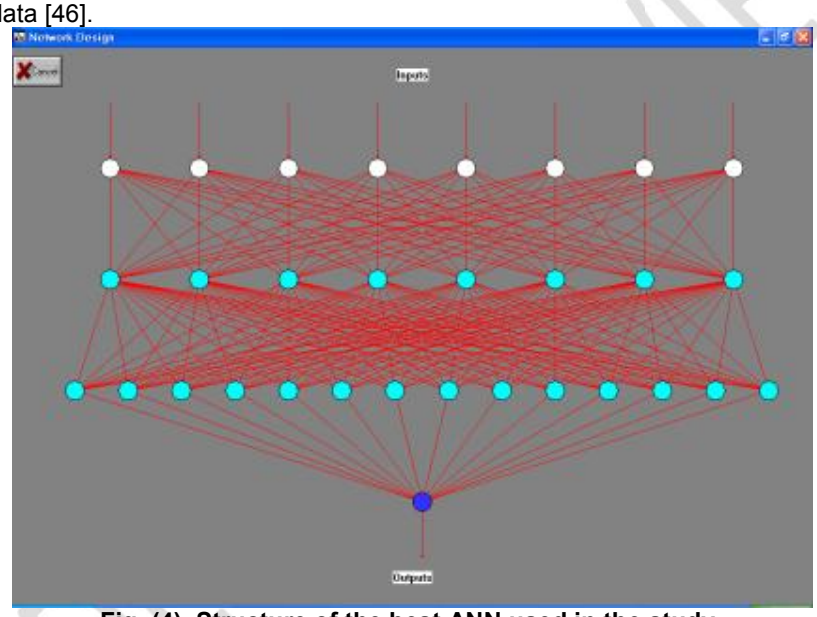


**Fig. (4). Structure of the best ANN used in the study.**

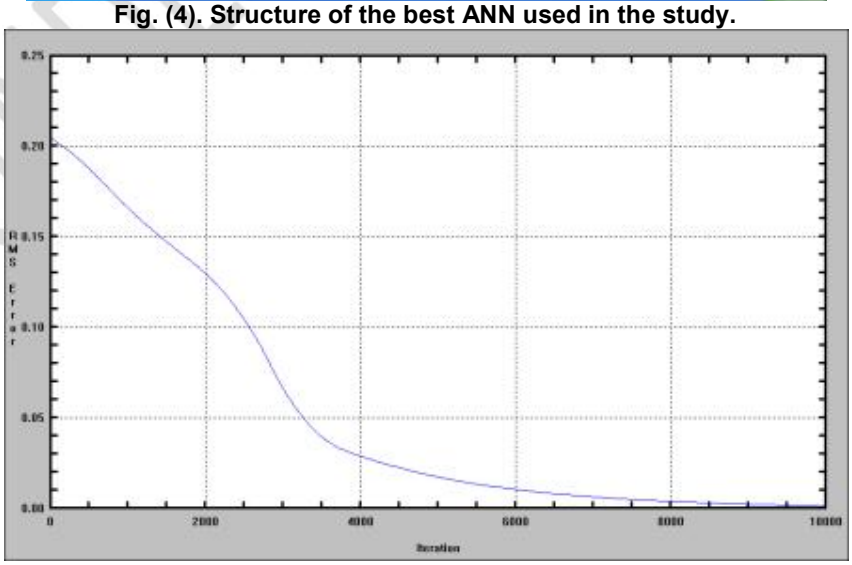


**Fig. (5). Error curve during training proces.**

**Table 3. Network definitions to predict unsaturated hydraulic conductivity of agricultural soils.**

| Network definitions | Value |
|---|---|
| Number of Layers | 4 |
| Input Layer Nodes | 8 |
| Hidden Layer 1 Nodes | 8 |
| Transfer Function | Sigmoid |
| Hidden Layer 2 Nodes | 14 |
| Transfer Function | Sigmoid |
| Iterations | 10000 |
| Training Error | 0.001277 |
| Learn Rate | 0.095193 |
| Momentum Factor | 0.8 |
| Training Patterns | 9 |

**Table 4 .Network statistics from Qnet software after training process to predict unsaturated hydraulic conductivity of agricultural soils.**

| Standard deviation (cm/s) | Bias (cm/s) | Maximum error (cm/s) | Correlation coefficient |
|---|---|---|---|
| 0.0000369 | -0.000000395 | 0.0000728 | 0.99999 |

## 2.7 Application of C# program

C# (C-Sharp) programming language available under.NET programming environment has been used for developing an application to predict unsaturated hydraulic conductivity of agricultural soils. This software has been developed keeping in view of its user friendliness and easily operable. Moreover, C# was chosen because it is a generic portable language and will run on other operating systems [47]. In addition, C# is also a clean, well-designed and implemented object-oriented language. Additionally, Sharma and Lal [48] reported that by using C# language, a fast development of MS-Windows based applications could be implemented for easy analysis of agricultural data. The current C# application was developed based on the weights obtained from the developed ANN model during training stage. These weights were formulated into equations and can be computed with the help of programming by C# to easy use of neural network model for unsaturated hydraulic conductivity of agricultural soils. The developed application was validated with experimental data to ascertain its suitability for unsaturated hydraulic conductivity of agricultural soils predictions. Fig. (6) depicts the starting screen of the developed application.

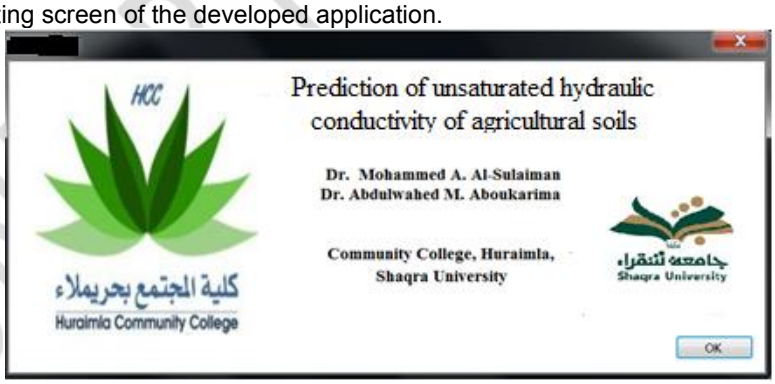


**Fig. (6). The starting screen of the developed application.**

## 3. RESULTS AND DISCUSSION

From Table 2, it is clear that the lowest and the highest unsaturated hydraulic conductivity of soil were 0.00017 and 0.02037 cm/sec, respectively with coefficient of variation of 0.7678 % which indicates that no big variations between measured unsaturated hydraulic conductivity of soil. However, Gulser and Candemir [49] reported that hydraulic conductivity gave significant positive correlations with silt, sand contents and bulk density values of soils. Besides, hydraulic conductivity gave negative correlations with clay content and soil moisture constant. Schaap et al. [40] reported that if clay content increases so hydraulic conductivity of soil decreases. Additionally, Hudson [50] stated that increased soil organic matter generally produced a soil with increased water holding

capacity and conductivity, largely as a result of its influence on soil aggregation and associated pore space distribution. Furthermore, Olourunfemi and Fasinmirin [51] indicated that hydraulic conductivity of soil increases with increase in soil organic matter content. Neshat and Farhad [19] showed that increases in volume soil moisture content and apparent density results increase in unsaturated hydraulic conductivity of soil. In this study, ANN technique was employed to predict of unsaturated hydraulic conductivity of soil based on physical and chemical properties of soil. The results showed that ANN model with two hidden layers gave best result compared to other structures; however, Moosavi and Sepaskhah [34] also employed ANN with two hidden layers for estimating unsaturated hydraulic conductivity from soil properties. After training process, the developed ANN model was tested by 3 patterns of data which were not use in training process. The error criteria during testing process of ANN model for prediction of unsaturated hydraulic conductivity of agricultural soils were shown in Table 5. In general, however, the RMSE, MRE and MAE (0.000333251 cm/sec, 4.184% and 0.000284699 cm/sec) measure showed a small error between the measured the predicted values for unsaturated hydraulic conductivity of agricultural soils (Table 5), suggesting that the employed ANN model was very accurate in predicting the values of the unsaturated hydraulic conductivity of agricultural soils. The results suggest that the model can be used as a reliable tool that can be employed for expected unsaturated hydraulic conductivity of agricultural soils at any values of independent variables, falling within the range of values in the study.

**Table 5. Error criteria during testing process of ANN model for prediction of unsaturated hydraulic conductivity of agricultural soils.**

| Error criteria | Unit | Value |
|---|---|---|
| RMSE | (cm/sec) | 0.000333251 |
| MAE | (cm/sec) | 0.000284699 |
| MRE | (%) | 4.184 |
| $R^2$ | (---) | 0.9979 |

Fig. (7) shows the relationship between the measured and the predicted unsaturated hydraulic conductivity of soil during testing phase using the developed ANN model. The figure clearly shows that the points, during the testing process, are uniformly scattered around the regression lines with high linear correlations represented by values of coefficients of determination ($R^2$) that were 0.9979.

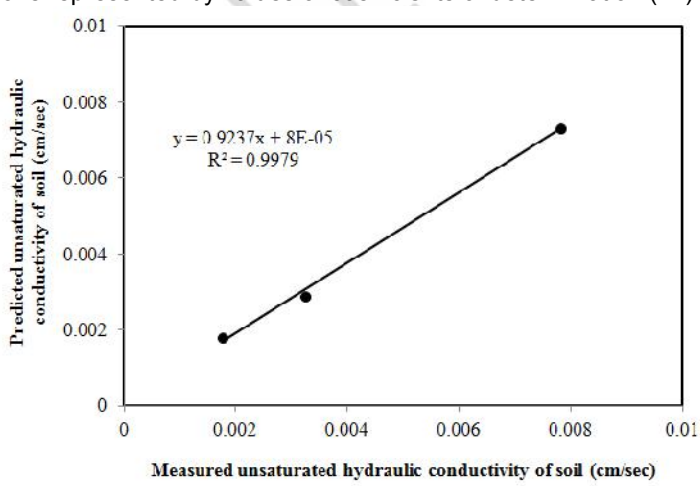


**Fig. (7). Relationship between the measured and the predicted unsaturated hydraulic conductivity of soil during testing phase using the developed ANN model.**

The Qnet algorithm provides a contribution calculation for how the change in each input, changes the output prediction. The contribution percentage of the eight input variables to the output (unsaturated hydraulic conductivity of agricultural soils) was calculated using the developed ANN model and results are illustrated in Table 6. It can be deduced from Table 6 that the major contribution to the unsaturated hydraulic conductivity of agricultural soils was attributed to the input variable of clay content with a contribution percentage of 22.2%. Hence, the accuracy with which the clay content was adjusted would greatly influence the resulting predicted the unsaturated hydraulic conductivity of agricultural soils within the boundaries of the training data set used in the study. This result is in agreement with the finding by Chiu and Shackelford [52] who reported that the major factor to predict

the unsaturated hydraulic conductivity of the sand-clay mixture was the amount of clay in the mixture. In addition, Al-Shayea [53] reported that the hydraulic conductivity sharply decreases with increasing clay content up to 40%.The other variables, i.e initial soil water content and soil bulk density however, were found to have high influence the predicted the unsaturated hydraulic conductivity of agricultural soils with a contribution percentage of 20.63 and 19.12%, respectively. Meanwhile, silt content, soil organic matter were also found to have moderate influence the predicted the unsaturated hydraulic conductivity of agricultural soils with a contribution percentage of 13.6 and 12.62%, respectively. Finally, soil electric conductivity, soil sodium adsorption ratio and sand content in a soil were found to have lower influence the predicted unsaturated hydraulic conductivity of agricultural soils with a contribution percentage of 6.88, 3.17 and 2.5%, respectively. However, McNeal and Coleman [54] reported that saturated hydraulic conductivity of soil decreased with decreasing total electrolyte concentration and increasing SAR values.

**Table 6. Contribution percentage of eight independent variables used in the 8-8-14-1 ANN model for prediction of unsaturated hydraulic conductivity of agricultural soils.**

| Input variables | Contribution (%) |
|---|---|
| Sand | 2.5 |
| Silt | 13.06 |
| Clay | 22.02 |
| EC | 6.88 |
| SAR | 3.17 |
| Organic matter | 12.62 |
| Initial soil water content | 20.63 |
| Soil bulk density | 19.12 |

To valid the C# application to predict unsaturated hydraulic conductivity of agricultural soils, an interface for input required data was developed as shown in Fig. (8). When the inputs were 82.9%, 13.08%, 4.02%, 4.6 dS/m, 2.08, 0.98%, 4.71%db and 1.36 g/cm$^3$ for sand, silt, clay, electric conductivity of soil, soil sodium adsorption ratio, soil organic matter, initial soil water content and soil bulk density, respectively, the unsaturated hydraulic conductivity of soil obtained by the C# application was 0.001815 cm/sec (Fig. 9), meanwhile, the measured unsaturated hydraulic conductivity of soil was 0.001756 cm/sec. Also when the inputs were 86.92%, 6.o4%, 7.04%, 2.9 dS/m, 2.15,0.62%, 6.26%db and 1.41 g/cm$^3$ for sand, silt, clay, electric conductivity of soil, soil sodium adsorption ratio, soil organic matter, initial soil water content and soil bulk density , respectively, the unsaturated hydraulic conductivity of soil obtained by the C# application was 0.002913cm/sec, meanwhile, the measured unsaturated hydraulic conductivity of soil was 0.003228cm/sec. Additionally, When the inputs were 90.95%, 6.04%, 3.02%, 0.69 dS/m, 3.73,1.14%, 4.87%db and 1.54 g/cm$^3$ for sand, silt, clay, electric conductivity of soil, soil sodium adsorption ratio, soil organic matter, initial soil water content and soil bulk density, respectively, the unsaturated hydraulic conductivity of soil obtained by the C# application was 0.007336 cm/sec, meanwhile, the measured unsaturated hydraulic conductivity of soil was 0.007816 cm/sec.

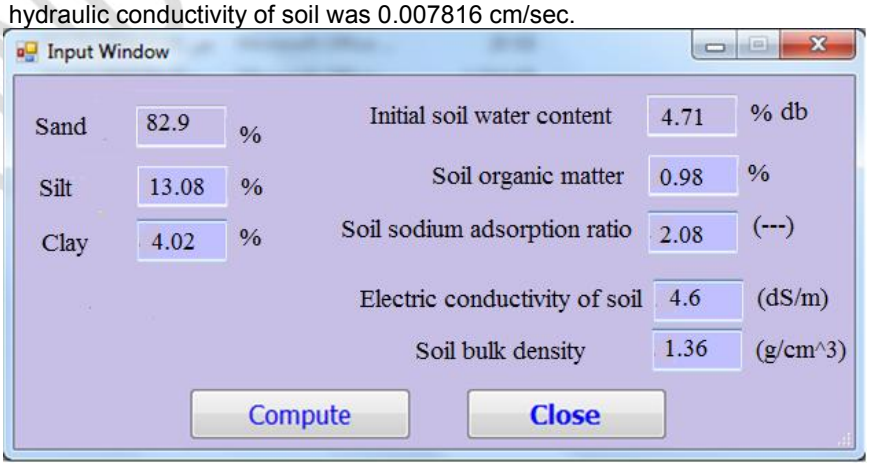


**Fig. (8).Screenshot of interface for input required data for unsaturated hydraulic conductivity of soil prediction.**

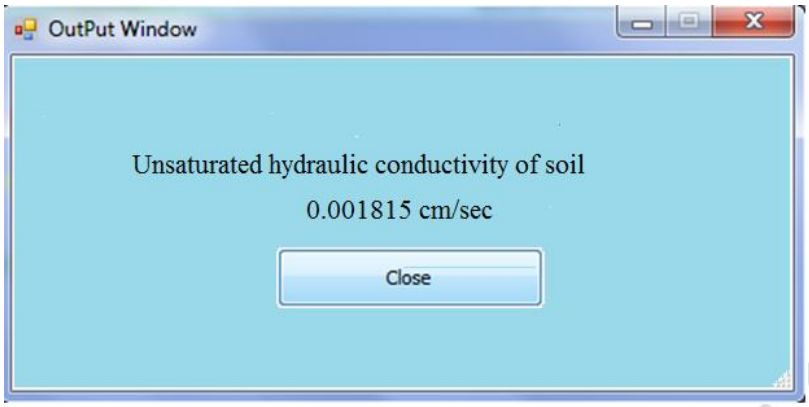


**Fig. (9).Screenshot of computer interface for predicting unsaturated hydraulic conductivity of soil at specific input data.**

## 4. CONCLUSION

As Saudi Arabia is semi-arid country, an applied model for unsaturated hydraulic conductivity of soil is needed for the moving of water in the unsaturated soil in order to prevent of water waste. The higher performance, higher prediction accuracy and ability to re-learn are important to create a powerful model. The results obtained from the study show that the ANN model learned the relationship between the eight input factors (sand, silt, clay, soil electric conductivity, soil sodium adsorption ratio, soil organic matter, initial soil water content and soil bulk density) and unsaturated hydraulic conductivity of soil. The root mean squared error (0.000333251 cm/sec), mean relative error (4.184%) and mean absolute error (0.000284699 cm/sec) for testing data set were showed a small error between the observed and the predicted values for unsaturated hydraulic conductivity of agricultural soils, suggesting that the employed ANN model was very accurate in predicting the values of the unsaturated hydraulic conductivity of agricultural soils.

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