

## Use of Soil EC Data for Zoning the Production Field by Artificial Neural Network for Applying the Precision Tillage

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**Abstract:** A high-energy input is required to disrupt the hardpan layer so variable-depth tillage could result significant savings in energy and fuel consumption in soil compaction management. Soil electrical conductivity (EC) describes the ability of a soil to transmit an electrical current and is expressed in milliSiemens per meter (mS/m). A number of researchers have used the soil electrical conductivity data in soil and tillage studies with various applications such as, determining soil physical and chemical properties, detection of different soil layers, sensing of soil moisture content, and estimation of the expected crop yield. The objective of this study was the prediction of soil clay and sand percent (soil texture) based on soil EC and moisture content data by artificial neural networks (ANNs). Field experiments were conducted at four different soil types: loamy clay, loamy sand, sandy loam, and sand. A commercially available soil electrical conductivity meter, Veris Technologies 3100, and handy soil EC meter (ELE International/ Soiltest Inc) were used to obtain EC data in the experimental field. Soil cone index data were obtained by a tractor mounted soil penetrometer and hand pushed soil penetrometer (ELE International/ Soiltest Inc). Back propagation neural networks with Levenberg-Marquardt training algorithm were adopted for predicting soil clay and sand percent (soil texture) based on soil EC and moisture content data and also for predicting of the soil cone index (CI) based on soil EC data. Results showed that use of soil EC and soil moisture content data were very successful in prediction of soil clay and sand percent. Moreover there was a strong correlation between soil EC data and soil compaction data (CI). Regarding to strong correlations between soil EC, soil CI, and draft force of tillage operation, the mentioned results indicated that the draft force varies with soil texture and for applicable usage in precision farming management; use of soil EC data for identifying the zones with high or low draft force could be very profitable.

**Key words:** Soil electrical conductivity; precision tillage; artificial neural network.

### INTRODUCTION

Since a high-energy input is required to disrupt the hardpan layer to promote improved root development, variable-depth tillage could result in significant savings in the energy required for the tillage operation. Variable-depth or site-specific tillage technology can be defined as any tillage system, which optimizes the physical properties of soil only where the tillage is needed by applying tillage at the required depth. Raper (1999) estimated that the energy cost of subsoiling could be

decreased by as much as 34% with variable-depth tillage as compared to the uniform-depth tillage technique currently employed by farmers. Cotton yield increased 10% from variable-depth tillage with an energy saving of 57% and a fuel savings of 60% (Raper, 1999). Fulton et al. (1996) reported that fuel consumption could be reduced by 50% using variable-depth tillage. Abbaspour-Gilandeh et al. (2006) reported that energy saving of 50% and fuel saving of 30% were achieved by site-

specific variable-depth tillage as compared to conventional uniform-depth tillage in a loamy sand soil type. Therefore, there is a need for a technology to determine the tillage depth based on soil mechanical strength at different depths of soil.

Soil cone penetrometers have been used as an indicator of the soil resistance by several researchers due to their simplicity and accuracy. Since soil cone penetrometers require a stop-and-go operation that can be time-consuming and costly, some researchers studied on different methods that could be used on-the-go. Continuous measurement systems such as soil electrical conductivity appear to be promising alternative technologies (Sudduth et al., 1998).

Soil electrical conductivity describes the ability of a soil to transmit an electrical current and is expressed in milliSiemens per meter (mS/m). Soil electrical conductivity depends on a numbers of factors such as moisture content, texture and organic matter, bulk density, temperature, cation exchange capacity and depth (Gorucu, 2003). A number of researchers have used the soil electrical conductivity data in soil and tillage studies with various applications such as determining soil physical and chemical properties, detection of different soil layers, sensing of soil moisture content, predicting the draft requirements of tillage implements, and estimation of the expected crop yield.

The topsoil depth above the claypan horizon determined by Sudduth et al. (1998) by using two different sensor systems on claypan soils: a non-contact electromagnetic induction sensor and a direct contact, coulter-based sensor. They reported that both methods could be used for investigating the soil variations in precision agriculture practices. The non-contact electromagnetic induction sensor gave better results in deeper topsoil depths (up to 1.5 m) while the coulter-based system was more appropriate in shallower topsoil depths (up to 0.9 m).

Kitchen et al. (1999) investigated the relationship between soil electrical conductivity and crop yield on claypan soils. They conducted field experiments in four claypan field soils and they measured the soil electrical conductivity, soil nutrient concentrations, and the yield. They found a significant relationship between grain yield and electrical conductivity. They also reported that the soil electrical conductivity data was a good estimate of the topsoil thickness. The method can also be used to diagnose the negative effects of soil compaction on crop productivity.

Sudduth et al. (2000) evaluated an automated soil cone penetrometer system that measures both the soil cone index and the electrical conductivity simultaneously. Soil electrical conductivity was sensed immediately above the penetrometer tip. Because of the geometry of the cone, the cone index values were found to be significantly different from those obtained with standard cone penetrometer. They investigated the use of the data from the electrical conductivity sensing penetrometer for soil characterization. The electrical conductivity sensing penetrometer data had same trend similar to those taken by mobile electrical conductivity measurement system.

Nehmdahl and Greve (2001) investigated the possibility of soil electrical conductivity measurements to describe soil management zones (soil texture and soil organic matter content). They found a remarkable correlation between soil electrical conductivity data and actual variations in soil types. They reported that soil electrical conductivity maps offer fast and detailed analysis and were powerful tools for defining management levels at field scale in Denmark.

Ehrhardt et al. (2001) used electrical conductivity measurements for predicting tillage draft of field cultivator. They utilized an electrical conductivity cart which had been equipped with a load cell for their study. The draft from the reference implement was used to predict the draft force for the field cultivator. A strong correlation ( $r=0.89$  to  $0.95$ ) between the measured and predicted draft forces of field cultivator achieved.

Abbaspour-Gilandeh et al. (2006) reported that soil EC data were highly correlated to soil texture (%clay content) with a correlation coefficient of 0.916 and also there was a strong linear correlation between soil electrical conductivity and draft force across the field.

The purpose of this study was to predict clay and sand content of soil (soil texture) based on soil electrical conductivity data and soil moisture using artificial neural networks (ANNs). In many cases, when the sufficient information between input parameters is not available, artificial neural networks utilizes as a powerful tool in soil system modeling.

## **MATERIALS and METHOD**

### **Equipment**

A commercially available soil electrical conductivity meter, Veris Technologies 3100, and handy soil EC

meter (ELE International/ Soiltest Inc) were used to measure the electrical conductivity (EC) of the test fields. Soil cone index data were obtained by a tractor mounted soil penetrometer and hand pushed soil penetrometer (ELE International/ Soiltest Inc). In both systems, soil cone index values were calculated from the measured force required pushing a 130-mm<sup>2</sup> base area, 30-degree cone into the soil (ASAE Standards, 2001).

### Field test

Field experiments were carried out at four different soil types: loamy clay, loamy sand, sandy loam, and sand.

EC measurements were obtained with the Veris unit and handy soil EC meter to study the variations in soil texture and soil physical properties across the field and their correlation with EC.

A complete set of cone penetrometer measurements were obtained with tractor mounted soil penetrometer and hand pushed soil penetrometer systems across the entire experimental fields.

### ANNs model

The network used in this research to predict soil clay and sand percent (soil texture) based on soil EC and moisture content data was a multilayer network back propagation type. Lavenberg-Marquardt algorithm was used for network training. Multilayer networks as was shown in previous researches, provide high ability in predicting enough neurons in the hidden layers. But it should be noted that more neurons in hidden layers may cause overtraining for network, and also it is possible that the network may lose its ability of extension. In general, one can not define the number of hidden layers and also the current number of neurons in the hidden layer; so the number of neurons in the middle layer is obtained by trial and error method. In this research the number of hidden layers and neurons in the middle layer (or layers) are chosen proportional to the number of neurons of the middle layer by comparing networks operation. Also, the functions of tangent hyperbolic conversion, sigmoid and linear motion function among layers were used.

The best method of training for data and also the performance of developed networks were compared

between the actual and predicted data, based on the scale of Mean Square Error (MSE), Sum of Square Error (SSE) and Coefficient of Determination ( $R^2$ ). In order to compare the accuracy of prediction of models, variation of accuracy was used as a parameter for designed networks (Gautam et al. 2003, MATLAB, 1994). The ratio between the difference of actual and predicted data, divided to the actual data is defined as Prediction Accuracy (PA).

### Data used in designed ANNs

As the aim of developing the ANNs model in this work is to predict soil clay and sand percent (soil texture). The effective input vectors must be chosen from the parameters. In this research input parameters to ANN would be: soil EC and soil moisture content. Data needed were collected from different locations of the experimental fields considering the five different soil types.

Number of 900 soil samples were investigated in this study. As mentioned previously, sand, clay and silt percentage, EC value, the value of cone index and soil water contents were measured for each soil sample.

It was necessary to divide the data into two separate files in order to test and to train designed networks. Hence, all data used in each type of soil in the field were uploaded to a separate worksheet in excel software. After transferring data to worksheet, a random number in the range of zero to one was assigned to each row. Then, rows of data were sorted in ascending order according to the column of random numbers. The arrangement of data was changed and they were listed randomly. For training and testing the network, 75% and 25% of data were used, respectively.

### RESULTS and DISCUSSION

Initial investigations showed that networks built by Lavenberg-Marquardt algorithm after passing 300 epochs (the number of repetitions of network for reaching to the least amount of error and highest stability), there was no significant decrease in the MSE error building the network. To be more confident in reaching the least error and highest stability, process of networks were kept until 1000 times using this method. The least amount of MSE and SSE that

were determined in this work were respectively 0.001 and 0.01. Figure.1 shows the procedure of MSE decreasing for networks built by using Lavenberg-Marquardt algorithm.

For choosing the right number of middle layers along with the right number of neurons in the middle layers, comparisons of networks operation which had different number of neurons in the middle layer and also different number of middle layers were carried out. The type of function used between input and middle layers is sigmoid tangent and between the middle and output layers is linear. Results showed that the network with 32 neurons in the hidden layer has the least error and the highest accuracy of simulation related to the network. The prediction accuracy and coefficient of determination ( $R^2$ ) between predicted and actual data were 93.07% and 0.9976, respectively.

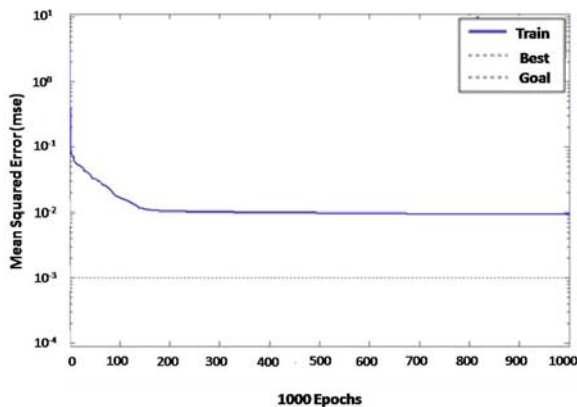
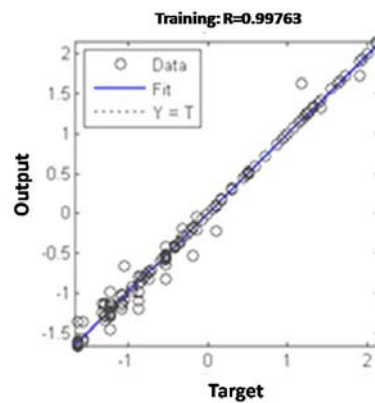


Figure 1. The decreasing trend of MSE for trained networks with Lavenberg-Marquardt algorithm

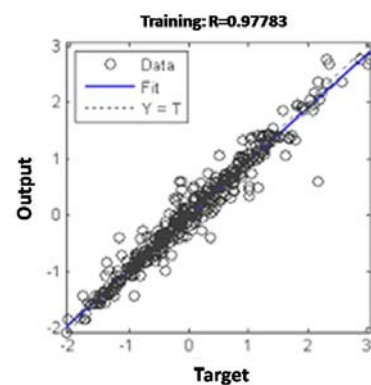
Figure 2 shows the spot diagrams obtained for the data used in the training stage with the best network performance data to evaluate the correlation between electrical conductivity and soil texture data and the correlation between soil electrical conductivity and cone index shows. The presented chart shows good correlation between actual data and predicted data by artificial neural networks. Networks with minimum training error of MSE and the high prediction accuracy were considered as the best prediction networks in predictions.

Results showed that use of soil electrical conductivity and soil moisture content data in order to predict soil texture (clay and sand) is very successful.

Furthermore, a strong correlation between electrical conductivity data and soil compaction data (cone index) exists. In another study, authors found very strong correlation between soil electrical conductivity values, soil cone index and tillage draft force (Abbaspour-Gilandeh et al., 2006). This suggests that generally the draft force varies significantly with soil texture, and this is dependent to the percentage of sand and clay soil. On the other hand for practical applications in precision agriculture management, use of soil electrical conductivity data in order to identify areas with high or low draft force could be very helpful. In other words, using soil electrical conductivity data could be useful for identifying the areas of agricultural land who are suffering from compaction and the need for high draft force.



(a)



(b)

Figure 2. Results of artificial neural networks training in order to investigate (a) the correlation between soil electrical conductivity and soil texture (b) the correlation between soil electrical conductivity and soil cone index data

## CONCLUSIONS

The followings were concluded from the study:

- In this study soil EC and moisture content data were used as parameters to develop prediction model of soil clay and sand percent (soil texture). Multi-layer network back propagation with Lavenberg-Marquardt algorithm utilized in this study for data simulation and training of the ANNs.

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