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USING ARTIFICIAL NEURAL NETWORK TECHNIQUE TO ESTIMATION THE CONCENTRATION OF COPPER FOR CONTAMINATED SOILS

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ABSTRACT

The aim of this paper is to design artificial neural network (ANN) as an alternative accurate tool to estimate concentration of Copper (Cu) in contaminated soils. First, sixteen (4x4) soil samples were harvested from a phytoremediated contaminated site located in AbuDsheer in Baghdad city in Iraq. Second, a series of measurements were performed on the soil samples.

The inputs are the soil amendment, the soil pH, and the soil electrical conductivity and the output is the concentration of Cu in the soil of depth x and time t.

Third, design an ANN and its performance was evaluated using a test data set and then applied to estimate the concentration of Copper (Cu). The performance of the ANN technique was compared with the traditional laboratory inspecting using the training and test data sets. The results of this study show that the ANN technique trained on experimental measurements can be successfully applied to the rapid estimation of Cu.

Keywords: Artificial neural networks (ANN), Soil contamination, pH, EC.

I. INTRODUCTION

Analysis of aqueous solution for determination of metal components is an important subject not only for chemists but for many other professionals including chemical engineers, metallurgists, biologists, geologists etc. The higher concentrations of metallic compounds are harmful to plant, animal and aquatic life cycles. Heavy metals may cause severe health problems and may affect the functioning of vital organs; kidney, nervous system, blood composition, liver, reproductive systems etc (Yetilmezsoy, K., and Demirel).

Soils contaminated with Cu have serious consequences for terrestrial ecosystems, agricultural production and human health (Adriano, 2001).

Quantifying Cu mobility in a given soil is a critical aspect of predicting its toxicity. Since performing experimental measurements to investigate the relationship between soil parameters and Cu mobility in soil is time-consuming, difficult and expensive, the development of models simulating soil processes has increased rapidly in recent years (Minasny and McBratney, 2002).

Generally two common methods are used to develop prediction models, egression methods and artificial neural networks (ANN). Several multiple linear regression (MLR) models have been developed over the past 20 years to predict the sorption of trace metals in soils Schug et al., 2000. With MLR methods, the relationships between soil inputs (properties) and soil output characteristics have to be stated a priori in the regression models. An alternative to MLR is the application of ANN models where such relationships do not need to be formulated beforehand (Anagu et al., 2009; Sarmadian and Taghizadeh Mehrjardi, 2008; Hambli, 2009; Behrens et al., 2005; Buszewski and Kowalkowski, 2006; Gandhimathi and Meenambal, 2012). It has been reported that ANNs provide superior predictive performance compared to conventional mathematical methods including MLR models (Sarmadian and Taghizadeh Mehrjardi, 2008).

In regression models in many soil engineering situations, the input-output relationships are highly complex and are not well understood. The lack of physical understanding and of a powerful general tool for mathematical modeling leads to either simplifying the problem or incorporating several assumptions into mathematical models.

Consequently, many mathematical models fail to simulate the complex behavior of most soil engineering problems. ANNs have been widely used in the field of soil science for prediction of soil hydraulic properties (Minasny et al., 2004) generation of digital soil maps (Behrens et al., 2005) and modeling of the behavior of trace metals (Buszewski and Kowalkowski, 2006; Anagu et al., 2009; Gandhimathi and Meenambal, 2012).

In the cases, ANN are trained to find model input-output relations using an iterative calibration process (training phase). Moreover, ANNs have the advantage of not imposing restrictions on inputs and outputs and can be easily applied to carry out inverse calculation (Hambli et al., 2006).

In the present study, we design ANN model as an alternative accurate tool for the estimate of Cu concentration in soils. The inputs are soil amendment, soil pH, and soil EC, whereas the output is Cu concentration in the soil with

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depth x and time t. The performance of the ANN technique was compared with a traditional laboratory inspecting using the same training and test data sets. The comparative study revealed that ANN provided a better performance in predicting soil properties. Results showed
that the neural network technique led to a very rapid and accurate prediction of the soil outputs.

II. ARTIFICIAL NEURAL NETWORK

Last two decades has seen advent of Artificial Neural Network which has been successfully applied to various fields of engineering, medical sciences, economics, meteorology, psychology, neurology, mathematics and many others. Neural networks exhibit many advantageous properties for solving complex problems of developing nonlinear multivariable correlation and with speed, accuracy and have the ability to generalize from given training data to unseen data (Khonde and Pandharipande, 2011),

An Artificial Neural Network (ANN) is a black box modeling tool having its working principle based on the way the biological nervous system processes information. It is composed of a network of largely interconnected neurons working together to solve a specific problem. It consists of input and output layers with at least one hidden layer in between them. The numbers of nodes in input and output layers are decided by the number of input and output parameters whereas the number of hidden layers and number of nodes in each hidden layer is decided by the complexity of the multivariable relationship to be developed. Every input signal or its value is altered by a connectionist constant called as weight. The node receives the summation of all the altered input signals and transforms into an output by using a function, either sigmoid or hyperbolic. The layer to layer processing of input signal is carried out which leads to an array of output signals that are compared with their respective known values so as to generate error signal. Many training rule is applied for reducing the error further by altering the connectionist weights or constants. The iterative process is terminated by applying the criterion of either reaching a value of desired error or the number of iterations (Khonde and Pandharipande, 2011; Tawfiq, and Oraibi, 2013).

There are number of applications of ANN, that include, standardization of digital colorimeter (Khonde and Pandharipande, 2011), estimation of composition of a ternary liquid mixture (Pandharipande et al., 2012), mass transfer predictions in a fast fluidized bed of fine solids, modeling for estimation of hydrodynamics of packed column (Pandharipande, and Singh, 2012), fault diagnosis in complex chemical plants, adsorption study (Yetilmezsoy, and Demirel, 2008; Khonde, and Pandharipande, 2012), modeling combined VLE of four quaternary mixtures (Pandharipande, and Shah, 2012), and similar other (Pandharipande, et al, 2012; Mandavgane et al, 2006; Godini et al, 2011) are also reported.

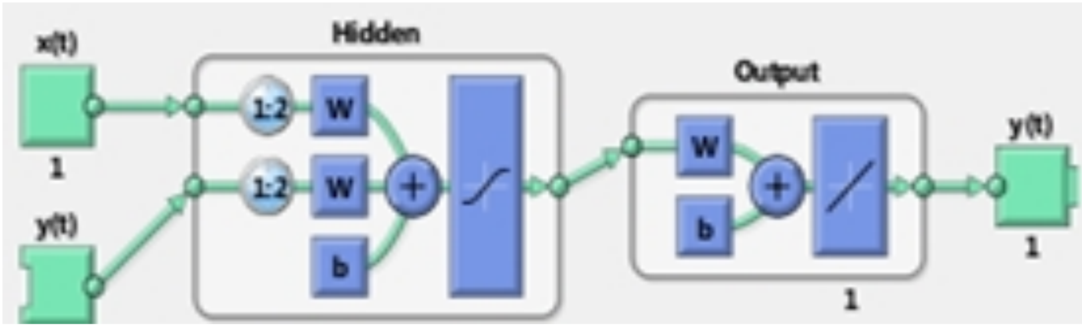
The objective of the present work is to suggest an effective, low cost and easily accessible design of ANN for estimation of the concentrations of Cu. Physical property of a solution is dependent upon the concentration of its constituents. In the present work pH are selected as physical properties of the solutions and are to be correlated with the concentrations of Cu in the solution.

The selected properties pH can be easily determined in a laboratory with low cost, high accuracy and easily accessible instruments.

III. DESIGN ANN TO ESTIMATION OF CONCENTRATION OF THE Cu

The accuracy of the ANN model is dependent upon number of factors that include selection of input parameters, the number of hidden layers and number of neurons in each hidden layer among others. The suggested ANN models consist 3 input nodes in the input layer: the depth x, time t and correlating input parameters pH and optical density, with one output node in output layer, which represent concentrations of Cu. The hidden layer contain 9 hidden nodes.

The architecture of ANN design is shown in Figures 1. The data generated is divided in two parts one part containing 40 data points as training set and the other with 20 data points as test set. With 50 epoch and with MSE of 0.0000072009.

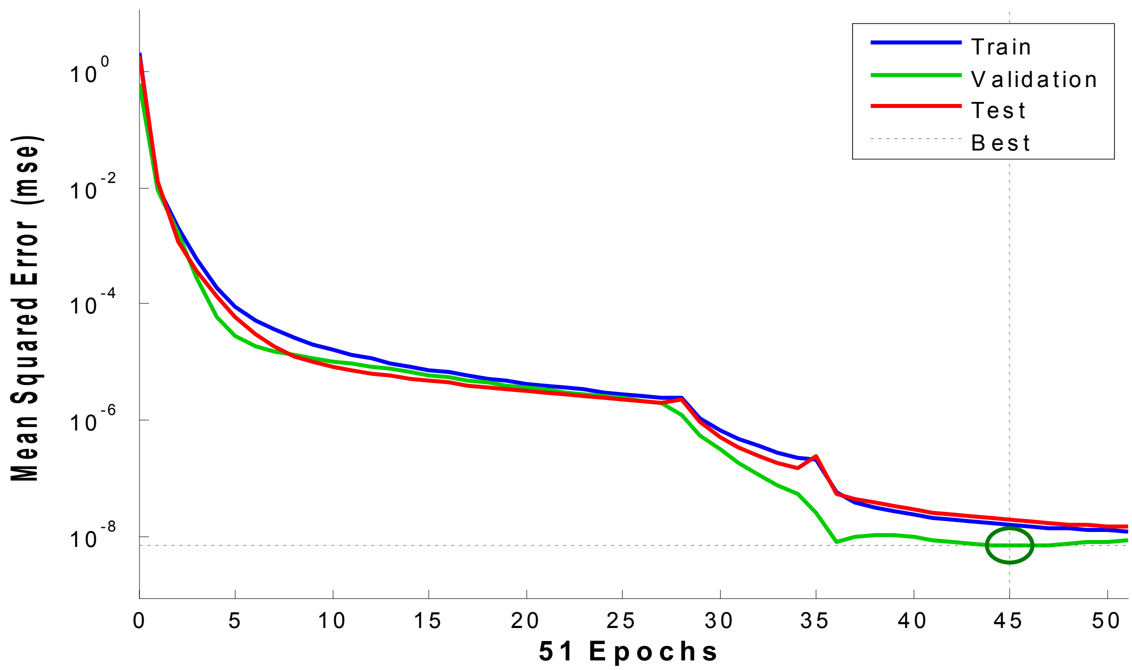


Figures 1: The architecture of suggested ANN

IV. RESULT & DISCUSSION

The suggested design is used for estimation of output parameter for given set of input parameters for both the training and test data sets. Comparison of actual and predicted values has also been carried out to arrive at the most suited model.

Figures 2 show the comparison for actual and predicted values of concentration of Cu for training, validation and test data sets as obtained by ANN model. As can be seen from these graphs there are deviation for prediction of Cu concentration for both training and test data set respectively using ANN design.



Figures 2: Comparison between actual and estimated values of concentration of Cu

V. CONCLUSIONS

In this paper we suggest ANN model as tool for estimation the concentration of Cu and the practical results show the suggested design is fast, convenient, sensitive, and can eliminate the interference among various species.

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