USING ARTIFICIAL NEURAL NETWORK TECHNIQUE FOR THE ESTIMATION OF CD CONCENTRATION IN CONTAMINATED SOILS

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ABSTRACT

The aim of this paper is to design artificial neural network as an alternative accurate tool to estimate concentration of Cadmium in contaminated soils for any depth and time. First, fifty soil samples were harvested from a phytoremediated contaminated site located in Qanat Aljaeesh in Baghdad city in Iraq. Second, a series of measurements were performed on the soil samples.

The inputs are the soil depth, the time, and the soil parameters but the output is the concentration of Cu in the soil for 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 Cadmium. The performance of the ANN technique was compared with the traditional laboratory inspecting using the training and test data sets. The results of this work show that the ANN technique trained on experimental measurements can be successfully applied to the rapid estimation of Cadmium concentration.

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

INTRODUCTION

The determination of concentration of heavy metal in soil is an important for many professionals including chemical engineers, metallurgists, biologists, geologists etc. Heavy metals may cause severe health problems (Yetilmezsoy, K., and Demirel).

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

Quantifying Cd 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 Cd 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 work, we design ANN to estimate the concentration of Cd in soils for and depth and any time.

2. DEFINITION OF THE ARTIFICIAL NEURAL NETWORKS

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.

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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 Cd for any depth and times.

3. MATERIALS AND METHODS

The Capital of Iraq Baghdad City (33°14'-33°25'N, 44°31'-44°17'E), is located in the Mesopotamia alluvial plain. It is characterized by arid to semi-arid climate with dry hot summers and cold winters; the mean annual rainfall is about 151.8 mm (Al-Adili, 1998). For the purpose of collection of soil samples, the study area was divided in three main types of land use viz. residential, commercial, and industrial; and two main source areas, within each land use type viz. roadside and open areas (see Figure 1).

Control soil sample was collected from a rural soil area. Soil samples were collected during winter seasons during 2015.

Fifty soil samples (0 - 20 cm) were carefully collected from each source area in different land use types with a stainless steel spatula. They were air-dried in the laboratory, homogenized and sieved through a 2-mm polyethylene sieve to remove large debris, stones and pebbles, after they were disaggregated with a porcelain pestle and mortar. Then these samples were stored in clean self- sealing plastic bags for further analysis. Metal determinations were done by Atomic Absorption Spectrometry (AAS 6300, Shimadzu, Japan).

4. CADMIUM

Some metals, such as Cd, accumulate in the human body over a long period of time so that negative effects may appear only after a long period of chronic exposure, Cd is highly mobile and toxic, which means that the few maxima found are critical values (Bloemen et al, 1995). The Cd content varies from 0.14 to 1.05 mg/kg. The observed values in the industrial roadside and open areas soils exceed the calculated worldwide mean of non-polluted soil (0.53 mg/kg) reported after analytical surveys (Kabata-Pendias, and Pendias, 2001). Concentrations above 0.5 mg/kg could reflect the influence of the human activity. Human activity can contribute to increased Cd levels as a result of urban- industrial activity and/or agricultural practices (Adriano, 2001).

The Cd content in all soil samples was also observed to be 8.8 times higher than the values in rural soil, which contains lower amount of Cd (0.05 mg/kg). It was reported that inputs of Cd into soils maybe of different origins such as agricultural amendments, sludge and atmospheric deposition. Cadmium has a wide range of uses in the industry, including paints, pigments, electroplating and plastic stabilizer (Volensky, 1990) and many anthropogenic activities can increases soil Cd to the levels well above background levels, such as the application of solid waste from industries and home and sewage sludge, wastewater irrigation and phosphate fertilizer application had resulted in the release of significant quantities of Cd to the environment (Kisku et al, 200).

Figure 1: A real photo showing the sites of study areas in Baghdad city-Qanat Aljaeesh

5. DESIGN OF NEURAL NETWORK

One hidden layer ANN is suggest to estimate the concentration of Cd efficiency, fifty experimental sets were used to develop the ANN model. A sigmoid transfer function (tansig.) was used for hidden layer. The data gathered from batch experiments were divided into input matrix and desired matrix. The Levenberg-Marquardt algorithm is fastest training algorithm for network of moderate size, therefore, used in the design to train the suggested network. The architecture of suggested network is shown in the Figure 2. It is made up of four input node, one hidden layer with 15 hidden nodes and one output node represent the concentration of Cd.

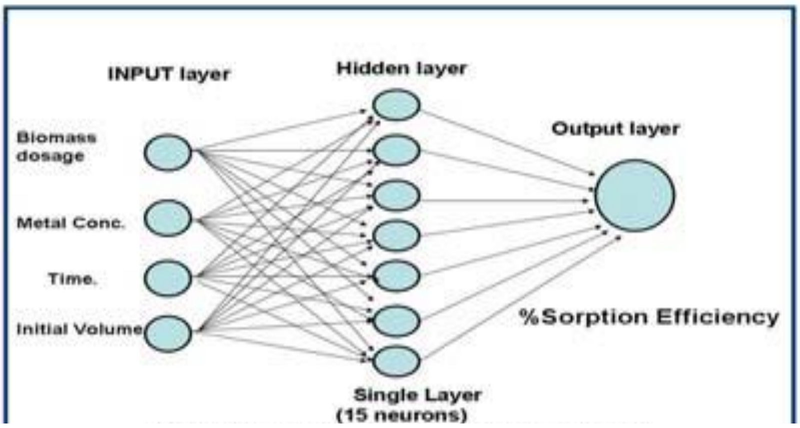

Figure 2: The architecture of suggested network

6. RESULTS AND DISCUSSION

According to experimental process described in Section 3, the concentration of cadmium can be obtained for any depth and time by suggested ANN. Comparing the result obtained by suggested ANN with that obtained by Atomic Absorption Spectrometry (AAS), illustrated by Figure 3, where the concentration calculated for different times.

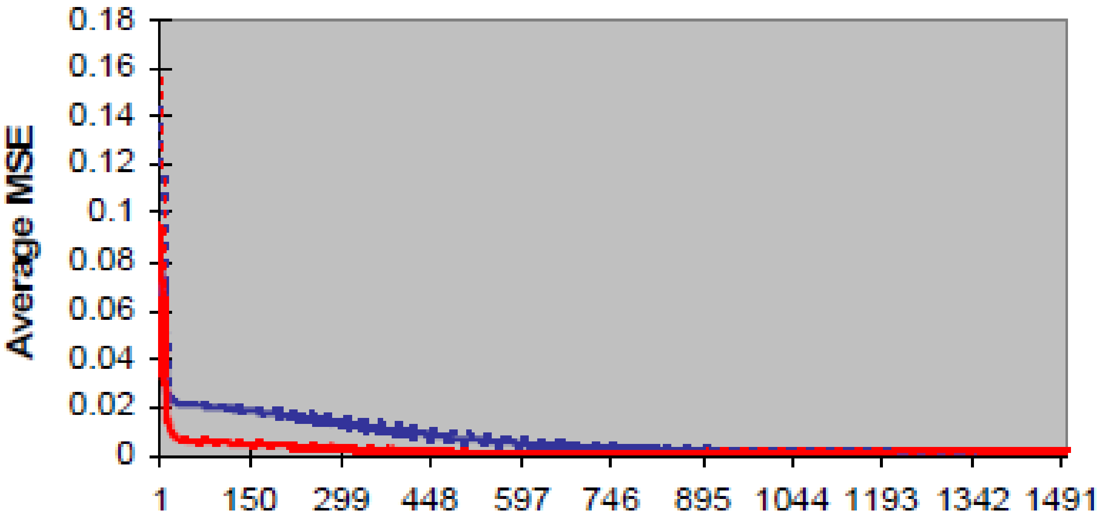

Figure3: A Comparing of the concentration calculated by suggested ANN &by AAS, illustrated

7. CONCLUSION

The present work demonstrates the successful calculation of concentration of Cd in soil for different depth and times. The ANN technique was designed to optimize this process. The Levenberg–Marquardt algorithm of back propagation training algorithms with a minimum mean squared error (MSE) for training and testing as 0.001725798 and 0.001732187 respectively is used.

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