Estimation of Heavy Metals Contamination in the Soil of Zaafaraniya City Using the Neural Network

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Abstract. The aim of this paper is to estimate the heavy metals contamination in soils which can be used to determine the rate of environmental contamination by using new technique depend on design feedback neural network as an alternative accurate technique. The network simulates to estimate the concentration of Cadmium (Cd), Nickel (Ni), Lead (Pb), Zinc (Zn) and Copper (Cu). Then to show the accuracy and efficiency of suggested design we applied the technique in Al-Zafaraniyah in Baghdad city. The results of this paper show that the suggested networks can be successfully applied to the rapid and accuracy estimation of concentration of heavy metals.

Keywords. Artificial Neural Network, Feedback Neural Network, Heavy metals.

1. Introduction
Mathematical modeling is important to describe the different problems in the real world and the solution of this modeling represents the solution for the problems in life, Quarteroni A. (2009) [1]. This paper studies and modifies a model equation to represent a suitable form which describes the environment contamination. Especially, soil contamination by heavy metals. We suggest the artificial neural network (ANN) as a technique to solve the model.

There are many studies for solving the soil contamination using ANN. For instance, Buszewski and Kowalkowski, 2006 [2] present the results of chemo metric treatment of data from experiment of column leaching to find dependencies between physicochemical parameters of soil and heavy metals concentration by using ANN model. Yetilmezsoy and Demirel, 2008 [3] used ANN model to predict the removal efficiency of Pb from aqueous solution. Kardam et al., 2010 [4] presented ANN model to describe the removal efficiency of Cadmium from aqueous solution using Shelled Moringa Oleifera Seed (SMOS) powder. Yin Li et al., 2011 [5] employed BP-NN model and Geographic Information System (GIS) for heavy metals described the spatial dynamics of distribution in Huizhou city. El-Badaoui et al., 2013 [6] predict the concentration of HMs in Moroccan river sediments relying on a number of physico-chemical parameters using ANNs. Pandhuripande et al., 2013 [7] estimated the concentration of Ni and Cr in aqueous solution with its physical properties using ANN. Krishna and Sree, 2014 [8] suggested the ANN for remove efficiency of Cr from aqueous solution used a Borasus flabellifer coir powder as adsorbent. Zongshu Wu et al., 2015 [9] explained the optimization way for
soil sampling to spatial distribution of heavy metals concentrations using ANN with genetic algorithm. Madhloom 2015[10] suggested using ANN to describe the removal efficiency of Cu from wastewater by fungal biomass. This paper suggested an effective, low cost and easily accessible design of Artificial Neural Network to estimate soil contamination problems and compared the results with the traditional laboratory devices such X-ray fluorescence analysis (XRF) to illustrate the accuracy and the efficiency of the suggested technique. Note that all algorithms in this work implemented using MATLAB version 7.12.

2. Mathematical Model
The paper aims at developing equation of mathematical model given in [11, 12] that estimate the rate of concentration of HMs in soil. This aim can be achieved through the realization of the following objectives:

- Collection of data illustrating the concentration of some of HMs at different percentage of the soil with respect to depth.
- Developed the mathematical model equations for the concentration of HMs in the soil.
- Simulation of the model equation using software program Mat lab 2014 professional.
- Compare the result with the experimental data.

Models that include retention and release reactions of solutes with the soil matrix are needed. Retention and release reactions in soils include precipitation / dissolution, ion exchange, and adsorption / desorption reactions (Amacher et al. 1986) [13]. Retention and release are influenced by number of soil properties including texture, bulk density, power of hydrogen (PH), Electric Conductivity (EC), organic matter, and type and amount of clay minerals. Then the model equation which describes this problem has the form [14, 15]:

$$\rho \frac{\partial C}{\partial t} = D_L \frac{\partial^2 C}{\partial x^2} - V_x \frac{\partial C}{\partial x}, \quad 0 < x < \infty, \quad t > 0$$  \hspace{1cm} (1)

Which is a second order linear PDE, with initial - boundary conditions:

$$C(0, t) = C_0 \quad \text{and} \quad \frac{\partial C}{\partial x}(\infty, t) = 0.$$  

$$C(x, 0) = Cx$$

Where; $C_0$: Initial concentration.  
$C_x$: Concentration for depth x ($\frac{mg}{L}$).  
$V_x$: The average pore – water velocity, ($\frac{cm}{hr}$).  
$x$: Soil depth (distance) (cm).  
t : Time (day$^{-1}$).  
$\rho$: Retardation factor ($\frac{gL}{cm^3}$)

The amount of each element retained by each soil ($\frac{mg}{kg}$) was calculated from the initial concentration in solution ($\frac{mg}{L}$) and the final concentration C in solution ($\frac{mg}{L}$). ‘As in equation (1)’, which can be represented as a mathematical model for spread of contamination through soils which can be used to determine the rate of contamination. The solution of model equation gives the concentration of the HMs in soil.

3. Solution & Design of the Model Equation
To solve that model we suggest artificial neural network (ANN) of type Feedback Neural Network (FBNN) used to estimate the concentration of HMs in Zafaraniyah soil.
We suggest a multilayer FBNN which consist three layers: input layer consist five input nodes, one hidden layer consist eleven hidden nodes with tansig. Transfer function and one node for output layer with purelin. Transfer function. The output of the suggest FBNN which represent the solution of trial can be written as:

\[ C = N ( x, t, c_0, s, p ) \]  

(2)

Where; \( x, t, c_0 \) are defined ‘as in equation (2)’, and \( s \) is the soil parameters defined; ‘as in equation (1)’, represent the weights.

4. Sampling

Baghdad City it was the capital of Iraq (33°14'-33°25'N, 44°31'-44°17'E), the climate with cold winters and dry hot in summers; the mean rainfall is about 151.8 mm. For the purpose of collection of soil samples, the study zone is Zafaraniyah was included in to 5 main types of land use viz. residential, agricultural, commercial, industrial and main roads [16]; and two main source zones, within each land use type viz. open zones and roadside. The sample zones are illustrated by geographic information system (GIS) give in ‘figure 1’.

Soil samples were collected during winter season of 2016 with depth (0 – 40 cm) were carefully collected from different Zafaraniyah land using types with a stainless steel spatula and dried it in the laboratory and sieved through a 2mm polyethylene sieve to remove large debris, pebbles and stones, 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 X–ray fluorescence analysis (XRF). The laboratory results for many states in Baghdad (Zafaraniyah) are given in (table 1).

![Figure 1. Illustrate the study areas in Baghdad city- Zafaraniyah by GIS](image)

| Samples   | Depth       | Cu  | Zn  | Pb   | Ni  | 1  |
|-----------|-------------|-----|-----|------|-----|----|
| State 1   | 0 – 20 cm   | 9.5 | 25  | 34.5 | 52  | 0.25|
|           | 20 – 40 cm  | 6   | 10  | 6.1  | 55  | 0.15|
| State 2   | 0 – 20 cm   | 11  | 18.8| 9.7  | 66  | 0.7 |
|           | 20 – 40 cm  | 12  | 25  | 8.8  | 80  | 0.2 |
‘Figure 2’ illustrates the training, testing and validation results when we used modified LM algorithm. Figure 3 illustrates the training, testing and validation results with regularization. ‘Figure 4’ illustrates the architecture of the FBNN.

We simulate suggested FBNN for Cd, Ni, Pb, Zn and Cu with the measured data. The comparison between the predicted concentrations and the measured data resulted in the performance function. (Table 2) gives the target values for training, testing and validation samples and regularization parameter γ of HMs. (Table 3) gives the accuracy of the train for time and epoch. ‘Figure 5’, ‘figure 6’, ‘figure 7’, ‘figure 8’ and ‘figure 9’ illustrates the performance of suggested design for concentration of Cd, Ni, Pb, Zn and Cu.

| State   | 0 – 20 cm | 20 – 40 cm | 0 – 20 cm | 20 – 40 cm |
|---------|-----------|------------|-----------|------------|
| 0.65    | 7.65      | 2.5        | 2.5       | 0.1        |
| 4.0     | 18        | 1.00       | 7.00      | 20.6       |
| 9.5     | 0.65      | 20.6       | 17.283    | 45.833     |
| 0.1     | 5.8833    | 42.5       | 0.15      |

Average: 6.333

‘Figure 2’. Training, testing and validation first FBNN by modify LM.
Figure 3. Training, testing and validation first FBNN with regularization.

Figure 4. Architecture of the FBNN.

Table 2. Target values for concentration of HM.

| Type     | Target values | MSE            | $\gamma$            |
|----------|---------------|----------------|---------------------|
| Training | 68            | 2.31128e -11   | 9.9999999 e-1      |
| Validation | 16          | 2.52614e -12   | 9.9999999 e-1      |
| Testing  | 16            | 6.69947e -12   | 9.9999999 e-1      |

Table 3. The accuracy of the train for time and epoch.

| Train Function | Performance of train | Epoch | Time       | $\mu$   |
|----------------|----------------------|-------|------------|---------|
| Modify Trainlm | 2.31e-11             | 252   | 00:00:06   | 1.00e-08 |
Figure 5. Performance of suggested FBNN for concentration of Cd

Figure 6. Performance of suggested FBNN for concentration of Ni.

Figure 7. Performance of suggested FBNN for concentration of Pb

Figure 8. Performance of suggested FBNN for concentration of Zn
Figure 9. Performance of suggested FBNN for concentration of Cu

We applied the suggested design in Al- Zafaraniyah zone in Baghdad. Then comparing these results with that obtained by XRF which are illustrated in ‘figure 10’.

![Figure 9](image_url)

1500 day

Figure 10. A Comparing of the concentration calculated by FBNN (blue curve) and by XRF (read curve).

5. Heavy metals and their effect on health

In nature there are 35 elements classified as metals, which of only 23 are HMs. This label appeared in the 1960s and was used to denote elements and compounds containing high atomic mass or high density metals and have adverse effects on healthy and the environment. It was initially named heavy metals, most of which had a higher density or an atomic mass than the carbon element, while the other metals were added to the list because they were similar in their properties to these minerals. Some HMs are found in nature, such as iron and copper, some of which are found at a lower rate such as gold, silver, chromium and lead. Heavy metals have been found to be of varying degrees of toxicity. The damage caused by them varies. Some of them affect the senses, including what affects the nerves, and internal members. Heavy metal compounds are used in a large number of applications for their excellent physical and chemical properties. They are good conductors of heat and electric current and their compounds are colored and have high stability. They are not affected by rapid weather conditions. They are highly susceptible to roads, clouds and formation. However, the most important result is the toxins that affect plants, humans and animals. Compounding the complexity of the problem is that it builds accumulative concentrations within the body, whether in the liver, muscle or fat, which increases the likelihood of human exposure to damage without knowing the direct cause [6].

6. Conclusion

The Scientific results showing the following:

- For comparing upon the depth of soil, we see the effect of depth on the concentration of HMs that are when the depth increase the concentrations of HMs are decrease, i.e., the concentration of HMs in depth 0 – 20 cm are larger than the concentration in depth 20 – 40 cm for the same soil.
The developed model can be considered to be a good representation of that estimate the concentrations of HMs in the soil for any depth.
The prediction errors of this technique are less than 10% compared with those of XRF. This technique is fast, convenient, sensitive, and can eliminate the interference among various species.

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