Forecasting Groundwater Contamination Using Artificial Neural Networks

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Abstract

Water is one of the basic and fundamental requirements for the survival of human beings. Nearly 80% of all the diseases arise as a result of using unsafe and contaminated water. Groundwater contamination has long been a deep concern to environmentalists due to its harmful effects on human health.

The presence of different effluents in groundwater should be known as accurately as possible so that necessary arrangements can be made to provide treatment to this contaminated water. Artificial Neural Networking (ANN) model was used for future prediction of the quantities of different effluents. The model was applied to real data from groundwater in Faisalabad, the largest industrial city of Pakistan. The city has more than 8000 big and small industrial units. Satiana road sullage carrier in Faisalabad city, receiving effluents of a large number of textile mills, laundries and other factories was selected for the future prediction of quantities of heavy metals (Fe, Cu and Pb) in groundwater due to seepage from carrier. The data for both the lined and unlined channel was obtained from Pakistan Council of Research in Water Resources. The results obtained from the model were compared with actual values as well as the World Health Organization Standards.

Keywords: Artificial Neural Networks, Effluents, Groundwater and World Health Organization**.**

Introduction

Water is one of the basic requirements for the survival of human beings on the surface of the earth. In this present world, with the increase in the population, the requirement for safe and good quality water free from all the pollutants is essential. With the development of countries, more and more industries are being made.

Industries usually produce a significant amount of waste products, which include many types of chemicals and heavy metals, depending upon the type of industry. Generally these chemicals and heavy metals are thrown into the ponds, streams drains and open fields through which they reach the groundwater. As a result of this, the groundwater gets polluted.

Faisalabad, is one of the largest industrial cities of Pakistan. The city is famous for its different industries, which include paper, leather, textile, sugar, vegetable oil, soaps and detergents and other industries. It is estimated that nearly 1.5 million cubic meters of untreated solid wastes and heavy metals are being disposed off into the natural streams (Rehman, K.1993). These heavy metals and other pollutants are quite harmful to both the environment and the groundwater because this water is the main source of drinking water. Satiana road sullage carrier located in the southern side of Faisalabad was selected was selected for this purpose. It collects the domestic wastewater of Peoples colony no. 1 and industrial and domestic effluents of Maqbool road and Ghulam Rasool Nagar. Along with municipal waste, nearly 67 textile industries, 4 oil mills, 2 ice factories and 3 laundries are among the main contributors to the carrier (Niaz Ahmad. 1996). About 3-km of the carrier from the city side onward to the main drain is lined while the remaining portion of approximately 5-km is unlined. In this study, Artificial Neural Networking (ANN) model has been used to forecast the quantities of different effluents.

Neural Networking Models:

Artificial Neural Networks are now being increasingly used in the prediction and forecasting of variables involved in water resources. (Nash, J.E. and Sutcliffe (1970), French et, M.N. (1992), Zhu, M.L. and Fujita, M. (1994), Dawson C. W. & Wilby R. L. (2001), Yi-Ming Kuo (2003)). Broadly speaking hydrologic models can be divide into three categories. They are: Lumped Conceptual Models, Physical Distributed Models and Black Box Models.

Lumped conceptual models require a large number of parameters and their calibration is also quite complex, whereas in case of Physical distributed models, excessive field data is required. Both of these models are used where detailed understanding of the hydrological phenomenon is necessary. Although Black box models do not enhance the hydrological and hydraulic phenomena much, but they are of utmost importance in operational hydrology. Neural Networking Models can be considered as Black box models. They have generally less data requirements and are easy to construct, as a result they are increasingly becoming popular in the field of Water Resources. There are several Neural Network software, EasyNN has been used in this study.

Training:

The training process involves the estimation of the Artificial Neural Networks (ANN) weights and is considered to be quite similar to the calibration of a mathematical model. The ANNs are trained with training set of input and known out put data. The initialization of the weights can be done in two ways: (i) either with a set of random values, or (ii) based upon some previous experience. These weights keep on changing till the goal is achieved. The goal is to determine a set of weights that will minimize the error function.

Training And Validation:

The input data for the model was taken as the observed concentrations of the metals at different points within the channel in the year 1995. Also the measured concentrations of the metals in the groundwater were set as the targets in the model calibration. The aim was to forecast the concentrations of the effluents in groundwater in the following year. With the annual increase also in mind, the simulated values were compared with the actual values and the percentage error was calculated. The results obtained were also compared with the World Health Organization (WHO) Standards**.**

Network Architecture:

Unlined Channel*:*

Test Run 1:

In the grid, three input columns and three output column were made. The total number of training example rows was 5. The grid did not contain any validating rows and had only one querying row. The learning rate and momentum were set to be 0.7 and 0.9 respectively and were optimized. Growing layer no. 1 generated the new network with the growth rate changing after every 10 cycles or 5 seconds.

In the network three input nodes and three output nodes were selected. Hidden layer no. 1 was provided with four nodes whereas hidden layers 2 and 3 were not provided with any nodes. The test then started learning and gave the following results.

Hidden layer	1 no.	Hidden Nodes	4 nos.
Learning Cycles	50	Learning Rate	0.7
Learning Momentum	0.9	Minimum error	0.019125
Average error	0.049850	Maximum error	0.0756
Target error	0.05		

Test Run 2:

In the grid, three input columns and three output column were made. The total number of training example rows was 5. The grid did not contain any validating rows and had only one querying row. The learning rate and momentum were set to be 0.7 and 0.9 respectively and were optimized. Growing layer no. 2 generated the new network with the growth rate changing after every 20 cycles or 2 seconds.

In the network three input nodes and three output nodes were selected. Hidden layer no. 1 was provided with three nodes whereas hidden layers 2 and 3 were not provided with any nodes. The test then started learning and gave the following results.

Hidden layer	1 no.	Hidden Nodes	3 nos.
Learning Cycles	54	Learning Rate	0.7
Learning Momentum	0.9	Minimum error	0.024751
Average error	0.049065	Maximum error	0.66894
Target error	0.05		

Lined Channel:

Test Run 1:

In the grid, three input columns and three output column were made. The total number of training example rows was 5. The grid did not contain any validating rows and had only one querying row. The learning rate and momentum were set to be 0.7 and 0.9 respectively and were optimized. Growing layer no. 1 generated the new network with the growth rate changing after every 15 cycles or 2 seconds.

In the network three input nodes and three output nodes were selected. Hidden layer no. 1 was provided with four nodes whereas hidden layers 2 and 3 were not provided with any nodes. The test then started learning and gave the following results.

Hidden layer	1 no.	Hidden Nodes	4 nos.
Learning Cycles	56	Learning Rate	0.7
Learning Momentum	0.9	Minimum error	0.011091
Average error	0.049605	Maximum error	0.093
Target error	0.05		

Test Run 2:

In the grid, three input columns and three output column were made. The total number of training example rows was 5. The grid did not contain any validating rows and had only one querying row. The learning rate and momentum were set to be 0.6 and 0.8 respectively and were optimized. Growing layer no. 3 generated the new network with the growth rate changing after every 25 cycles or 5 seconds.

In the network three input nodes and three output nodes were selected. Hidden layer no. 1 was provided with five nodes whereas hidden layers 2 and 3 were not provided with any nodes. The test then started learning and gave the following results.

Hidden layer	1 no.	Hidden Nodes	5 nos.
Learning Cycles	65	Learning Rate	0.6
Learning Momentum	0.8	Minimum error	0.00301
Average error	0.049738	Maximum error	0.189
Target error	0.05		

It was found that for Unlined portion, Test Run 2 gave the better results and for Lined portion of the channel, Test Run 1 gave better results. Further it was also found out that the seepage of the effluents in case of Unlined channels was much more than that for the lined channel.

Results

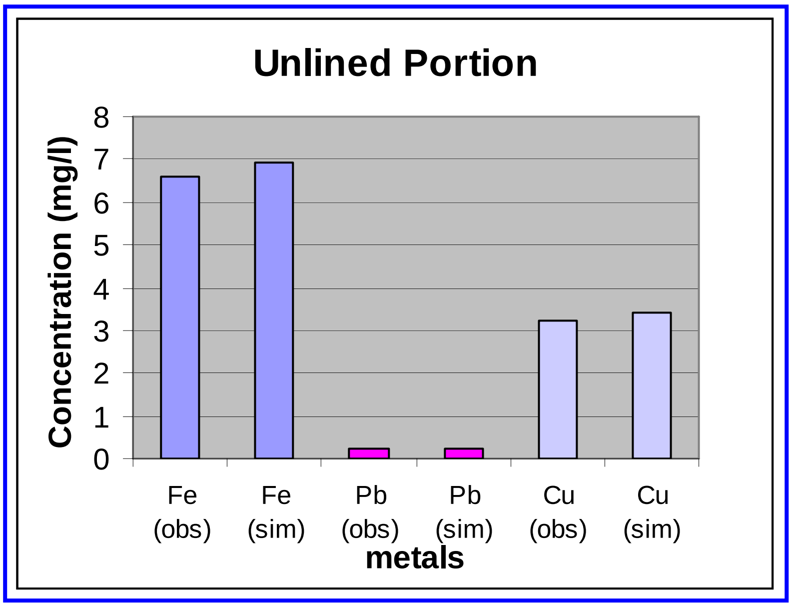

Fig (1)

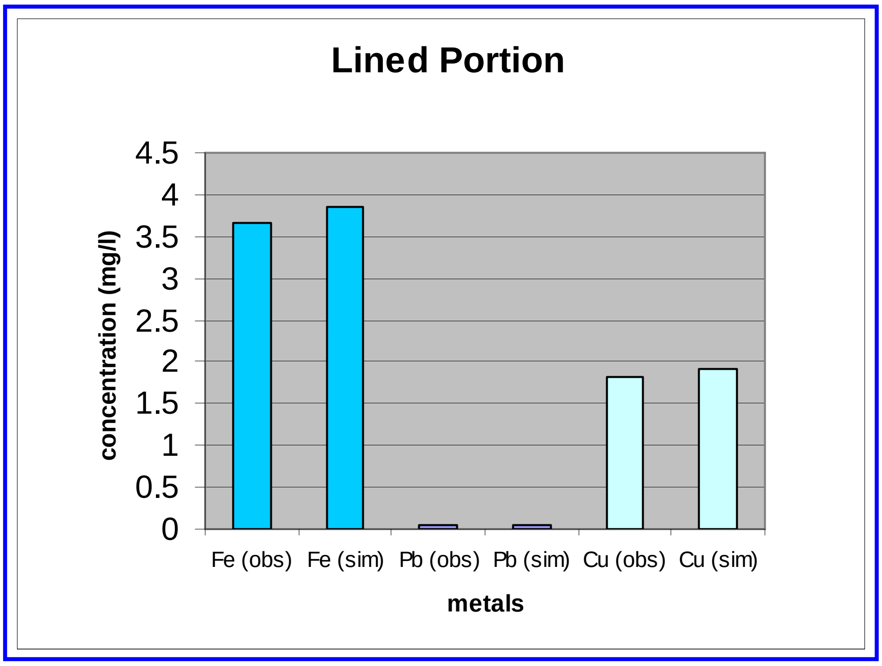

Fig (2)

WHO Standards:

Parameter	HDL (mg/l)	MPL (mg/l)
Fe	0.10	1.0
Cu	0.05	1.50
Pb	0.05	0.1

Source: WHO (1971)

It was found out that the groundwater is fully contaminated with effluents and is way above the standards of safe water by the World Health Organization (WHO).

Conclusions

In this study, a Neural Network Model for forecasting the concentration of different hazardous metals in groundwater has been developed. The model developed was found to be performing very well in both the training and **validation. The Neural** Networking Models, however, are still influenced by trial and error considerations. It is of utmost importance to mention here that the architecture of the network that has been developed is very important in order to obtain better results**.**

Future Recommendations

More studies are encouraged in the application of Neural Networks for the Forecasting of different effluents in groundwater. The models so developed will be quite helpful in determining the quality of water in different areas of Pakistan. Also it is highly recommended that the effluent be treated before discharging into drains.

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