ENVIRONMENTAL IMPACT ASSESSMENTS OF HEAVY METAL ON SOIL USING ANN MODELING TECHNIQUES

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Abstract- Artificial Neural Network Model used to predict the Heavy metal in various localities Topsoil samples (0-20cm) were taken at various locations with reference to latitude and longitude. The concentration of heavy metal Fe were analyzed in the Atomic Absorption spectrometer. An artificial neural network technique is used to develop a model to predict the constituents of the heavy metal in the soils such as Mercury, Cadmium, Iron. The developed neural networks consists of 2 input neurons for latitude and longitude, 6 hidden layers consisting of 10 to 20 neurons in each layer for training the data and 1 neuron to predict the constituents of the heavy metal in the soils.

Keywords- Heavy Metal, Artificial Neural Network, Soil pollution, Assessment of Heavy metal.

I. INTRODUCTION

Artificial Neural Network techniques to develop a model to predict the constituents of the heavy metal in the soils such as mercury, cadmium, iron. The developed neural networks consists of 2 input neurons for latitude and longitude, 6 hidden layers

II. ARTIFICIAL NEURAL NETWORK

Artificial Neural networks are designed to simulate information processing similar to that of the functioning of a human brain or neural system. Neural network consists of basic elementary element called neuron which processes the input signals and feed it to a differentiable transfer function to generate output in a similar way the neurons of a human brain functions. The advantage of neural network is the potentiality to accommodate lager input data and to filter the noisy and incomplete data. This neural network uses network training function that updates weights and bias values according to gradient decent to reduce error. The network is a multi- layer network consists of input layer (longitude and latitude), output layer (generates output response) and at least one hidden layer (uses training function to processes input to yield output) Backward propagation network is supervised with the concordance of learning algorithm where the set of inputs and response obtained from the experiment are provided at the training stage. The input is fed forward from input layer, propagated through one of the hidden layers. This in return paves the way for obtaining the output through training function. Actually, training assumes a pivotal and crucial function in predicting the accuracy of responses. The accuracy of the network is measured by the mean sum of squared error (MSE) between the measured and predicted values. During the training the output obtained from the network is compared to the experimental value and the error thus gets minimized by adjusting the weights used in the network. The newly adjusted weight and bias value is again propagated backwards for further training. The training is an iterative process and will stop once an acceptable error is reached.

III. BACK PROPAGATION ALGORITHM

The back propagation is gradient decent algorithm and the term back propagation refers to the way in which the gradient is computed for nonlinear multilayer networks. The algorithm allows experimental acquisition of the input/output mapping knowledge within the multilayer networks. A neural network model was developed using the machining parameters as input to predict the constituents of the heavy metal in the soils such as lead, chromium, arsenic, Fe, Hg and cadmium as output. The first step of the algorithm is to normalize the given input/output data to values between 0.1 - 0.9 by the following equation.

$$0.8 \frac{(Z_i - Z_{min})}{Z_{max} - Z_{min}} + 0.1$$

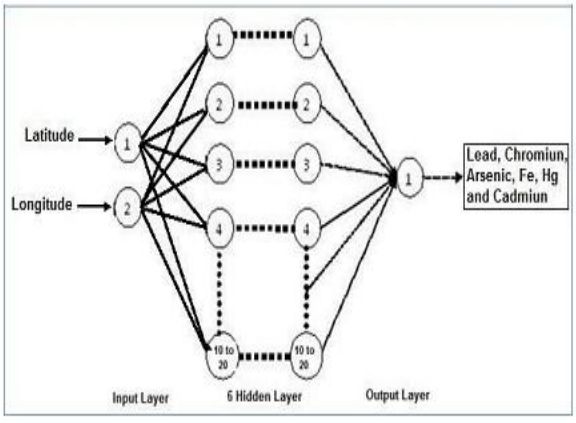


Fig 1: 1 Feed forward three layered back propagation network architecture

The feed forward three-layered back propagation network architecture is depicted in the fig. 1. The input layer consists of two nodes that represent latitude and longitude which used to predict the response. At the same time, the output layer consists of exclusively a single node which represents the constituents of the heavy metals in the soils such as lead, chromium, arsenic, Fe, Hg, cadmium. The number of hidden layers and neurons of the hidden layers have been determined by training several networks.

The inputs fed to the neuron are modified with the appropriate weights on inter-layer connections of a hidden layer neuron besides having added to bias producing input to the transfer function.

$$I_{yi} = f(W_{ij} X_i + \phi)$$

Where I_{yi} = input of the i^{th} neuron on the hidden layer
W_{ij} = numerical weight value of the connection between the two neurons, A differential transfer 'X' and learning activation function may potentially transform the input to transfer function to a scaled output y_i.

Where X_i = Normalized input/output value

Zi = Actual input/output value

$Zmax$ = Maximum input/output value

$Zmin$ = Minimum input/ output value

(1)

This shall be expressed through the subsequent strategy.

$$y_i = \frac{1}{1+e^{-s(I_{yi})}} \qquad (3)$$

Where 's' = slope of the sigmoid function

Output received from one layer of neurons is treated as input to the next layer of neurons. Similarly, output obtained from the last hidden layer is modified through the appropriate weight. Further, the sum of modified output signal is allowed to get modified through a differential transfer activation function. At this juncture the output is collected at the outer layer.
In training, every time a set of inputs x_i of a training sample is presented and the output y_o (predicted value) obtained from the network model is compared with the desired value y_d (actual value). The comparison is carried out by calculating the mean sum of squared error (MSE) between y_d and y_o.

IV. NETWORK LEARNING RULE

A neurons are considered to be adaptive elements. Their weights are modifiable depending on the input signal they receive, the output value in addition to the associated teacher response. Let us consider the learning of the weight vector W_i, or its components W_{ij} connecting jth input with the i^{th} neuron. The weight vector undergoing training is represented by $W_i = [W_{i1}$

W_{i2}…....$W_{in}]^T$. The weight vector increases in proportion to the product of input 'X' and learning signal 'r'. The learning signal for the delta learning rule is defined by the following equation. The term f' $(w_i^t x)$ is the derivative of the activation function f $(w_i^t x)$. The explanation of the delta learning rule is depicted in fig 2. This learning rule can be readily derived from the condition of least square error between y_d and y_o.

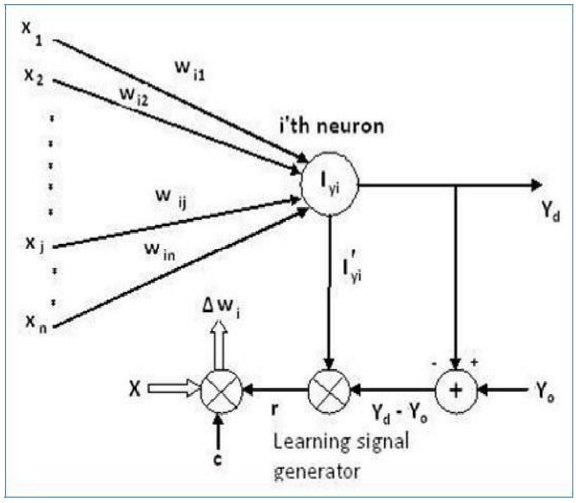


Fig. 2 Neural network learning rule

Calculating the gradient vector with respect to w_i of the squared error defined as

$$E \triangleq \frac{1}{2}(y_O - y)^2$$

Which is equivalent to

$$E = (y - f(w^t x))^2$$

The error gradient vector is obtained as

$$E = -(y_O - y) f'(w^t x) x \qquad (6)$$

The components of the gradient vector are

$$= -(y_O - y) f'(w^t x) x_j \quad \text{for } j = 1, 2 \ldots n \qquad (7)$$

Since, the minimization of the error requires the weight change to be in the negative gradient direction, change in weight becomes,

V. PREDICTIVE NETWORK MODEL

A feed forward back propagation network model was developed to predict the constituents of the heavy metal in the soils such as lead, chromium, arsenic, Fe, Hg, cadmium by using MATLAB 7.6 application tool. The procedure for the development of network using Neural Network tool is exhibited in Fig.3.

From the Survey, 123 are taken on random basis to develop the back propagation neural model to predict the responses, out of which 87 samples are used for training, 18 samples for testing and 18 samples for validation. The training data is presented to the network during training and the network is adjusted according to its error. The validation data is used to measure network generalization, and to halt training when generalization stops improving.

The testing data has no effect on training and so provide an independent measure of M network performance before and after training.

The input layers consist of two neurons (for two inputs) and output layer consists of only a single neuron (representing any one of the six outputs). Various network structures with varying the number of hidden layers and number of neurons in the hidden layers are observed and keenly examined to acquire the best performance.

VI. RESULTS AND DISCUSSION

The predictive neural network model thus developed gives spatial concentration [7] of heavy metal in the study area. The results of the six models developed to predict heavy metals are discussed in separate topics. The predicted value of the heavy metal is compared with the measured value and the error in prediction is determined to validate the model.

A. Predictive network model for Lead

The feed forward three layered back propagation network architecture as depicted in the Fig. 4, titled, neural network architecture to predict Lead is developed to predict presence / composition or availability of lead. The input layer consists of two nodes which represent latitude and longitude which used to predict the response and the output layer represents one node to receive response lead constituents.
The number of hidden layers and neurons in the hidden layer is determined by training several network, finally 6 hidden layers and 10 neurons in each hidden layer is chosen as optimum.

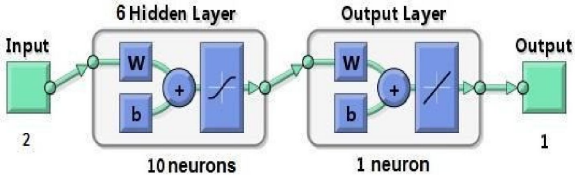


Fig. 4 Neural network architecture to predict Lead

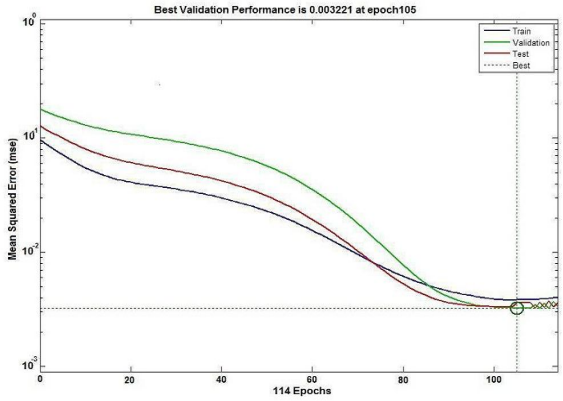


Fig. 5 Network training to predict Lead

The network was trained for several times by fixing 1000 epoch to obtain best validation performance. The best validation performance of mean squared error of 0.0032212 was obtained at 105 epochs as shown in the Fig 5, bearing the heading, Network training to predict lead. The lower value of the mean squared error indicates the neural network model developed will predict better result. The simulation results of the developed network from the network/data manager are then exported to the MATLAB workspace.. The error percentage between the predicted value and surveyed was found to be less than 4% error

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