1D INVERSION OF GEOELECTRICAL SOUNDING USING ARTIFICIAL NEURAL NETWORK(ANN)

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ABSTRACT *This paper is concerning to application of Artificial Neural Network (ANN) for Inversion of the Vertical Electrical Sounding (VES). For investigate the resistivity structure and layers thickness of the subsurface earth, here we used the three layer neural networks (feed forward) for modeling and prediction measuring VES data. The utilized algorithm is Levenberg-Marquard, which applies for training the network.*

INTRODUCTION

Through the recent decades, different methods are presented for 1D Inversion of resistivity data (coefod, 1979-zohdi, 1989), which contains:

1-Linear Filters theory

2-Worldwide using of Digital Computers

3-General Linear Inversion theory

However traditional methods for 1D Inversion of resistivity data, because of nonlinear nature of data, include many of problems. In few recent year application of artificial neural network techniques is accepted as a suitable method for Geophysical data processing like Prediction, Inversion, Catagorizing and data compressing and etc.

Artificial Neural Network

This isn’t our goal to speak about detail of ANN here, however for familiarizing and using this paper, the summarized explanation about function of this method is coming in below (figure 1). Several methods among neural network techniques are available. In fact the major classification of these methods is difference between supervisory and non-supervisory training (Nigrin1993). Most common of those are Back-Propagation, Correlative Resonance theory (Carpenter1987) and Hopfield network (Hopfield1984).Three-layer non-linear feed forward neural network in schematic form is illustrated in figure 2. Generally an ANN contains Input layer, layer in which neurons enter data to network, one or more hidden layers and an output layer which generate the network’s respond. In an ANN that designed properly, neurons of each layer connect to the next layer via special weights. Training starts with sending input values to network and calculating the difference between desired and calculated output; this difference, which considered as error, propagate in network backwardly and weights is regulated. After some iteration, training will be stop while difference between desired and calculated output is become equal to defined error in designing of network.

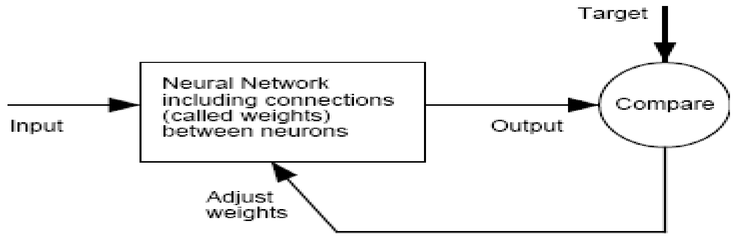

Figure-1. Flowchart of Neural Network function

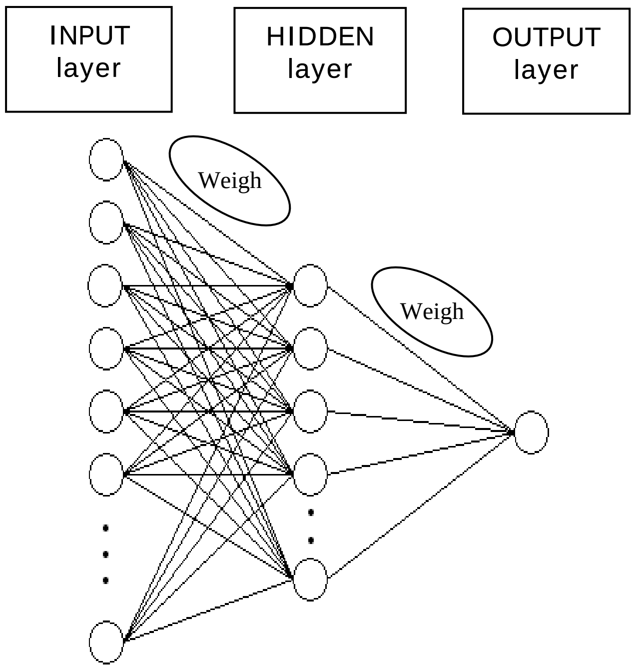

Figure-2. Schematic design of a three layer non-linear feed forward neural network.

In this paper an iterative non-linear feed forward network with Levenberg-Marquard algorithm is used. Back-Propagation algorithm, uses learning rate (μ) for training the network; if μ is very high, the network may doesn't meet to desired minimum and if μ is very small, the network take so much time to meet to desired minimum. The mentioned algorithm adds the momentum for decreasing probability of the error accumulation and also reducing the number of training.

Momentum and Learning Rate

Values of momentum and learning rate are important parameters in ANN analysis that controls changes rate to connection weights. Therefore finding a proper learning rate for the network is challengeable. Learning rate and momentum is connected to each other clearly, but their mathematical relations are not still explicit. The results suggest a correlative learning rate with value of 1/1000 and momentum of 8/10 and also correlative learning rate of 1/100 and 1/10 with momentum of 2/10(Chart 1).

Chart-1

Learning Rate	Momentum	Epoch	Time(s)	Learning Speed
a)				
0.001	0.00	32172	814.96	39.47
0.001	0.20	6200	156.67	39.57
0.001	0.40	9042	229.35	39.42
0.001	0.60	9042	233.12	38.78
0.001	0.80	3070	77.86	39.43
0.001	1.00	3070	77.35	39.69
b)				
0.01	0.00	3382	85.09	39.75
0.01	0.20	3382	85.34	39.63
0.01	0.40	6712	169.25	39.66
0.01	0.60	6712	171.13	39.22
0.01	0.80	7973	204.44	38.99
c)				
1.00	0.00	10739	274.85	39.07
1.00	0.20	7702	193.49	39.81
1.00	0.40	17774	447	39.76
1.00	0.60	35181	892.76	39.41
1.00	0.80	10739	272.45	39.41

Training and Testing ANN using artificial data

It should be say that in all of our analysis that comes in next sessions we use Matlab 6.5 Software. For confidence in ANN technique, firstly some methods applied for generating the artificial data. So our main goal initially is ANN training with artificial resistivity curves and then testing the trained network with new resistivity data. Problem of generating the artificial data was carried out with using Guptasarma Filter (1981) appropriately. Our input vector into network is consisted of N value of apparent resistivity, which in fact equals to number of reading data points in each sounding and can be represented as below:

$$x = [\rho_{a1}, \rho_{a2}, \rho_{a3}, ..., \rho_{aN}]^T$$

While the output vector is defined by model parameter as follows:

$$y = [\rho_1, \rho_2, \rho_3, ..., \rho_m, h_1, h_2, ..., h_{m-1}]^T$$

Which contains M= (2m-1) model parameter and ρ_i and h_i are True resistivity and ith layer thickness respectively. Figure 3 shows the artificial sounding curve for 5-layer models, which has been selected randomly and sampled in 10 different electrode spacing. These curves have a correlation with HKH curve type.

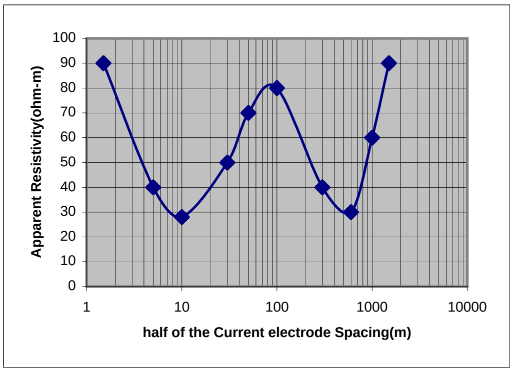

Figure-3. Forward Model, which used for generating the artificial data

Interpretation of Resistivity data

In this study our input data to the network has a $10 \times n$ matrix, which 10 represents number of electrode spacing and n represents number of the sounding and the output is a $9 \times n$ matrix, which 9 and n represent the earth model parameters and number of the sounding respectively. The mentioned network consists of three layers that include one input layer, one hidden layer and one output layer.

After training the network, with attention to this fact that value of error should be in desired range, simulation is carry out on the new data and network responds is analogous with True results; an example was presented in figure below.

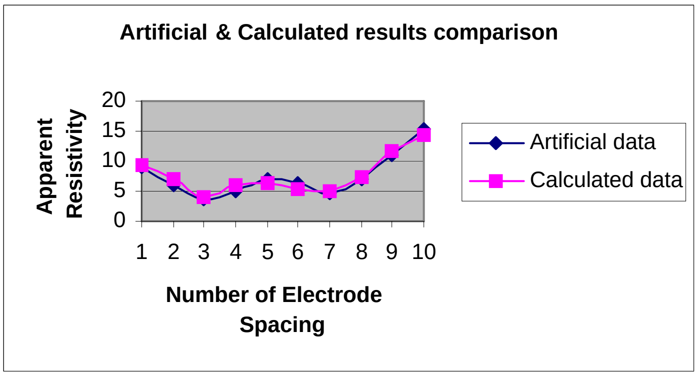

Figure-4

CONCLUSIONS

The individual advantage of using Neural Networks in 1D Inversion of resistivity sounding data is Uniqueness of results; if we enter a complete profile dataset which contain several sounding data to the network then we can achieve a cross-section model from the subsurface earth without need to interpretation the sounding one by one, consequently it help us to decreasing the error in final model. According to similarity of the network result with the true models and high responding velocity of the network, it is clear for us that applying the Artificial Neural Network in Interpretation of the apparent resistivity data has very high capability and also has relatively high confidence.

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