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RESEARCH ARTICLE

A NOVEL AND PROFICIENT ALGORITHM FOR THE INVERSION OF GEOELECTRICAL RESISTIVITY DATA USING ADAPTIVE NEURO FUZZY INFERENCE SYSTEM (ANFIS)

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ABSTRACT

Electrical Resistivity Method is one of the Geophysical techniques used to investigate the nature of the subsurface formations of earth. Generally, this kind of non-linear parameter estimation problem needs high computation to obtain the probable model. Moreover the error performance and computational time are more important while interpreting the model parameters of the subsurface viz., true resistivity and depth. But recent development in computational techniques paves way for producing approximate solutions to the non linear problem that are very much resembling the true nature of the earth. One of the most emerging soft computing techniques is Adaptive Neuro Fuzzy Inference System (ANFIS) in which the concepts of Artificial Neural Networks and Fuzzy logic have been integrated. This integrated concept helps the algorithm to generate more synthetic data to obtain best fit model on the basis of minimizing the root mean square error percent. In this paper, Vertical Electrical Sounding (VES) data has been interpreted by newly proposed efficient algorithm supported by ANFIS to identify the subsurface strata of the earth. The inverted results have been correlated with available lithologs and found to be correlating very well. Thus this paper projects a different approach in interpreting the geoelectrical resistivity data using ANFIS. In this novel and generalized algorithm, the interpretation of the vertical electrical sounding has done successfully with more accurate layer model and is represented as Graphical User Interface (GUI).

INTRODUCTION

Inversion of electrical resistivity data can be done by various means viz., straightforward inversion scheme, Occam's or Zohdy's method etc., This paper projects a novel approach used for the inversion of electrical resistivity data with the efficient Adaptive Neuro Fuzzy Inference System (ANFIS). Many numbers of tools has been applied by earlier researchers (Flathe, 1955; Kosinky and Kelly, 1981; Singh *et al*., 2012; Srinivas *et al.,* 2010; Srinivas *et al.,* 2012a, Srinivas *et al.,* 2012b; Sri Niwas and Singhal, 1981; Sugeno, 1985 and Zadeh, 1965). But ANFIS- soft computing tool provides a different approach in interpreting geoelectrical resistivity data. ANFIS network was developed by Jang (1993) and found that this technique has the capability of adaptive nature. Electrical resistivity data was obtained from the VES (Vertical Electrical Sounding) method and the resulting interpretation thus supports the adaptive nature of the system. ANFIS algorithm has been applied here for interpretation.

Geophysical method

Direct current resistivity methods of geophysical exploration are in extensive use globally for aquifer mapping and estimation of aquifer parameters viz., resistivity and thickness (Kosinky and Kelly, 1981; Mazac *et al.,* 1985, Sri Niwas and Singhal, 1981; Yadav and Abolfazli, 1998). The physical basis of the resistivity method is based on the relative distribution of impressed current in the earth controlled by subsurface resistivity distribution. The electrical resistivity method still proves the most powerful technique and analysing the data is less tedious and is economical (Ako and Olorunfemi, 1989; Batte *et al.,* 2008, Ekine and Osobonye, 1996; Zohdy *et al.,* 1974). Due to the excessive computational requirement and the interpretation of Vertical Electrical Sounding (VES) data has been interpreted using different computational methods. (Flathe, 1955; Ghosh, 1971; Mooney *et al.,* 1966; Van Dam, 1964).

The Geophysical method consisting of vertical electrical sounding (VES) survey is used to know the variation of resistivity of the aquifer parameters (Rijo *et al.,* 1977). Schlumberger electrode array is used to study the electrical resistivity distribution of the subsurface in order to understand the groundwater conditions such as resistivity, thickness and depth. The Schlumberger electrode configuration is shown in Fig. 1. Usually the depth of penetration is proportional to the separation between the electrodes and varying the electrode separation provides information about the stratification of the ground. The apparent resistivity value depends on the electrical conductivities of different rocks and minerals available in the subsurface. Thus electrical prospecting can be carried out to understand the subsurface earth. The data collected from the field has been interpreted using ANFIS

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algorithm. The ANFIS algorithm provides the necessary database needed for interpretation. Moreover, the best model of the trained database fits with the apparent resistivity curve. The corresponding layer model will be produced as an output with lowest root mean square error in particular number of epochs.

ANFIS – Architecture and Theoretical Background

ANFIS is a combined fuzzy logic neural network systems. This kind of inference system has the adaptive nature to rely on the situation it trained. Thus it has a lot of advantages from learning to validating the output. Takagi-Sugeno fuzzy model is shown in Fig. 2.

As shown in Fig.2, the ANFIS system consists of 5 layers. Each layer is symbolized by the box that is adaptive. Meanwhile, symbolized by the circle is fixed. Each output of each layer is symbolized by a sequence of nodes. Each output of each layer is symbolized by $O_{1,i}$ with i is a sequence of nodes and 1 is the sequence showing the lining. Here is an explanation for each layer, namely:

Layer 1

Layer 1 serves to raise the degree of membership with input variables of each node. Generally, in this layer membership function changes its form corresponding to the value of the parameters of fuzzy sets.

$$O_{1,i} = \mu_A(x), \quad i = 1,2. \tag{1}$$

and

$$O_{1,i} = \mu_B(y), \quad i = 1,2. \tag{2}$$

with x and y are the input for the i-th node

$\mu_A(x) \quad = 1/[1+(det(x-c_i)/a_i)^2b_i]$,

by $\{a_i , b_i$and $c_i\}$ are the parameters of membership function or called as a parameter premise.

Layer 2

In this layer, every node is fixed and the output is the product of all incoming signals. Each node represents the firing strength of a rule.

$$O_{2,i} = w_i = \mu_A(x) \text{ x } \mu_B(y), \quad i = 1, 2. \tag{3}$$

Layer 3

Normalize the firing strength has been done in this layer.

$$O_{3,i} = \overline{w_i} = \frac{w_i}{w_1 + w_2}, \quad i = 1,2. \tag{4}$$

Layer 4

Layer 4 is an adaptive node, where normalized firing strength of layer 3 is the parameter set of this node. Parameters in this layer are referred to as consequent parameters. Calculating the output based on the parameters of the rule consequent $\{p_i , q_i$ *and* $r_i\}$

$$O_{4,i} = \overline{w_i} f_i = \overline{w_i}\,(p_i x + q_i y + r_i). \tag{5}$$

Layer 5

Finally, the layer 5 computes the overall output by summing up all the incoming signals. Thus the constructed adaptive network is functionally equivalent to a sugeno fuzzy model. Counting the ANFIS output signal by summing all incoming signals will produce

$$\textstyle\sum_i \overline{w_i}\, f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}. \tag{6}$$

ANFIS algorithm description and application

In the present algorithm, ANFIS training has been classified into two major parts Fig. 3(a) and (b).

Primary training

The input data obtained from the user has been processed in the primary training (Fig. 3a). In the application for geoelectrical resistivity inversion, the Vertical Electrical Sounding data (AB/2 and apparent resistivity) is fed to the primary training, smoothing the raw data obtained from the field is done by applying random weights to each input with certain controlling parameters. The number of synthetic data set which is proportional to the number of epochs is produces after the training. Initially, the multilayer models will be obtained for each synthetic data after training using the slope variation method.

Slope variation method

Slope variation refers to the basic method for obtaining the trend of the curve changing with the subsurface layers obtained from the field curve. Whenever the curve changes its trend, it is considered as a line segment. Each line segment is treated as a separate layer and the corresponding subsurface layer parameters are obtained. Mathematically, each line segment is a linear curve and is represented by the straight line equation y = mx+c, where m represents the slope of the linear segment. Whenever the tangent of the slope varies, corresponding subsurface layer parameters can be obtained. Initially the multilayer model will be obtained since each and every point obtained from the field may not be linear. Fig. 4 shows the representation of slope variation model.

Slope is normally described by the ratio of the "rise" divided by the "run" between two points on a line. The line may be practical – a set obtained by the AB/2 and apparent resistivity data values. Whenever the curve changes its behavior then slope changes.

The change for the y-axis can be depicted as $y_2 - y_1$ i.e., Δy. Similarly for the x- axis it is $x_2 - x_1$ i.e., Δx. Thus slope m of the line can be expressed as

$$m = \frac{y_2 - y_1}{x_2 - x_1}.$$

The concept of slope applies directly to grades or gradients in geography, geophysics and civil engineering. Through trigonometry, the grade m of a curve is related to its angle of incline θ by

$$m = \tan\theta.$$

Thus at the end of the primary training, we have more number of synthetic datasets with corresponding multilayer models.

Major class training

In the major class training (Fig. 3(b)), the synthetic data obtained from the primary training session is fed as an input to the ANFIS network. After this training, multilayer model is obtained for the corresponding synthetic data. Moreover, other parameter limitations follow the same rule as that of parameters used in the previous session.

In testing phase, the trained datasets were tested with the original field data and the output model will be linearly regressed with each multilayer and provide a compressed layer model as an output. The output model parameters viz., true resistivity and depth were plotted in the framed GUI and the user can save both the models individually. The specially designed algorithm provides many models in each iterations and the user can able to fix certain model.

Graphical user interface (GUI) representations on VES application

Step by step procedure

The workflow of the GUI panel works on the path of algorithm description shown in flowchart of Fig. 5.

- In Fig. 5(a), (b) and (c) are the user options in the GUI where the user can fix permissible error, number of epochs and number of layers. Number of layers is an optional. When it is not fixed the ANFIS algorithm produces its own model at each number of iterations.
- In Fig. 5(d), the push button is used to import the data by means of Microsoft excel format. AB/2 and apparent resistivity data can be imported here.
- The user can edit the imported data using the "Edit data" push button.
- Fig. 5(e) shows the main push button for ANFIS inversion.
- After ANFIS inversion, the outputs are shown in Fig. 5(f), (g), (i) and (k).
- Fig. 5(j) shows the geoelectric section for the corresponding layer model.
- Running message will be shown in the GUI panel of Fig. 5(h).
- After iterating the algorithm, the user can save the respective plots and can exit easily while pushing the corresponding push buttons of Fig 5(l).

RESULTS AND DISCUSSIONS

The resistivity data of different geological regions has been interpreted for validating the algorithm and comparative analysis. The performance measure shows that the ANFIS algorithm works well for electrical resistivity data. If the raw field data contains more noises or field errors, the converging rate will be slow but it can be achieved by increasing more number of iterations.

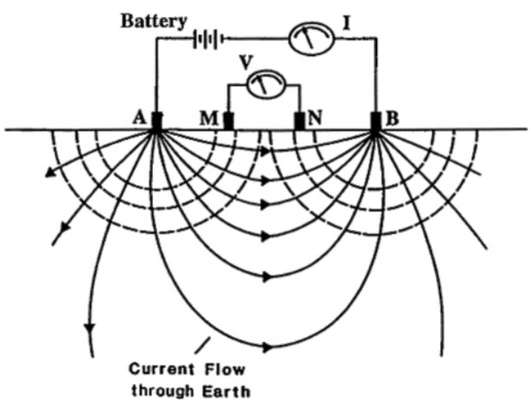

Fig.1 Schlumberger electrode configuration

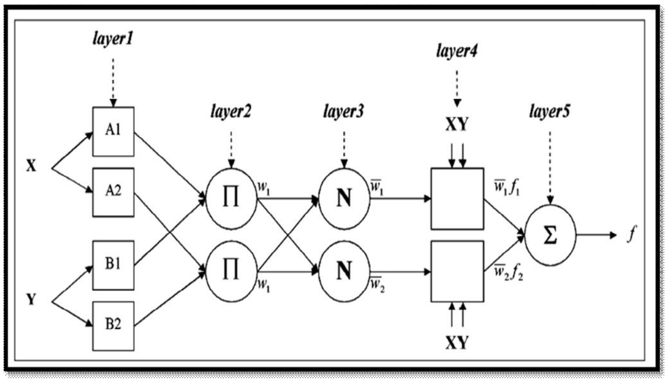

Fig. 2 Adaptive Neuro Fuzzy Inference System (ANFIS) architecture

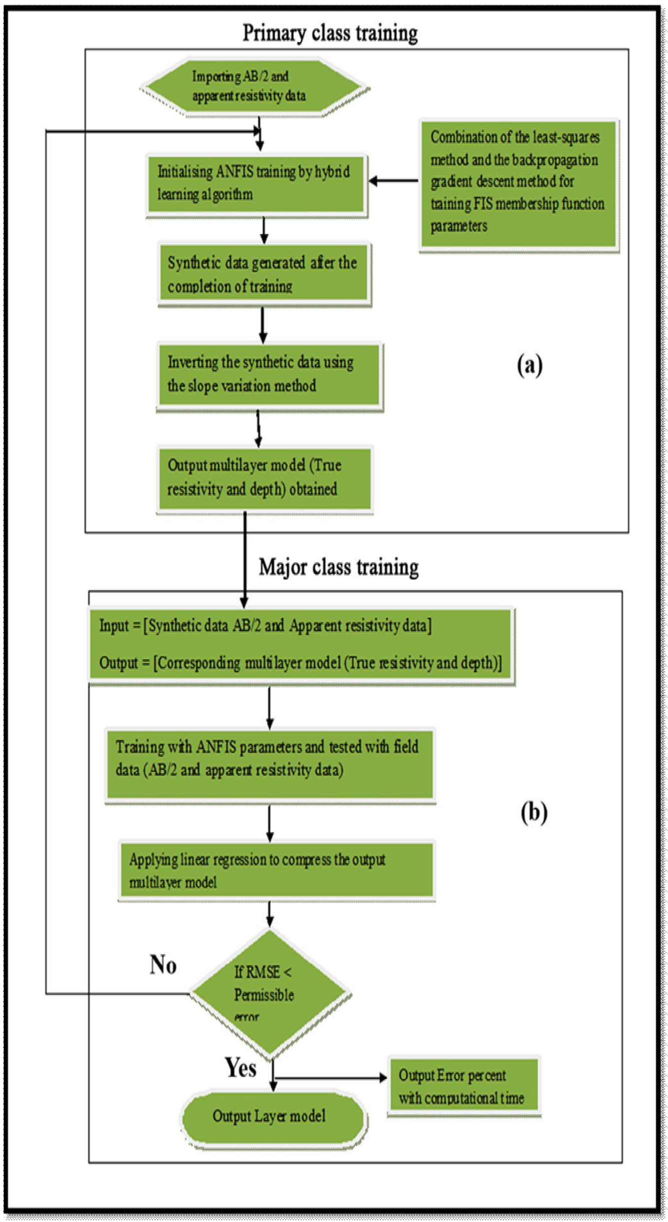

Fig. 3 Flow chart showing the self generated synthetic data of ANFIS algorithm used for geoelectrical resistivity inversion

Data 1 was chosen from the Oban massif, located in the Cross River State, Nigeria (Edet and Okereke, 1997). The GUI panel of Fig. 5 shows the interpreted model with successful ANFIS interpretation. The Fig. 6 shows the output panel for data 1. The output results are correlating very well with the litholog information.

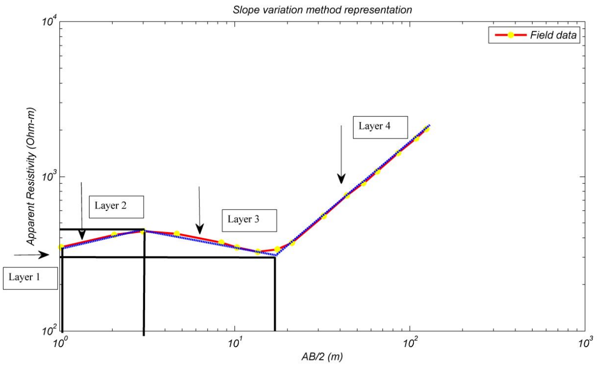

Fig.4 Field curve showing the measurement of slope variation method

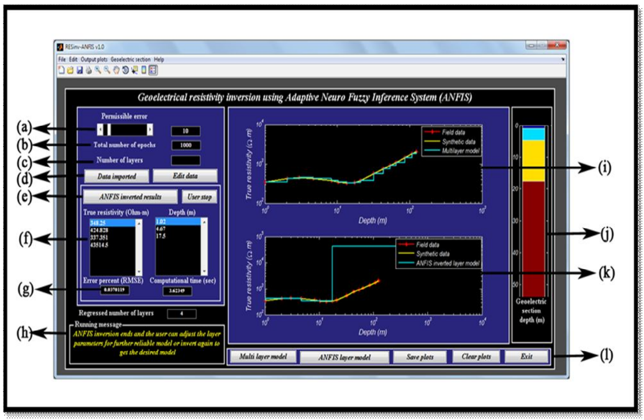

Fig.5 GUI panel showing the ANFIS used for geoelectrical inversion of data 1.

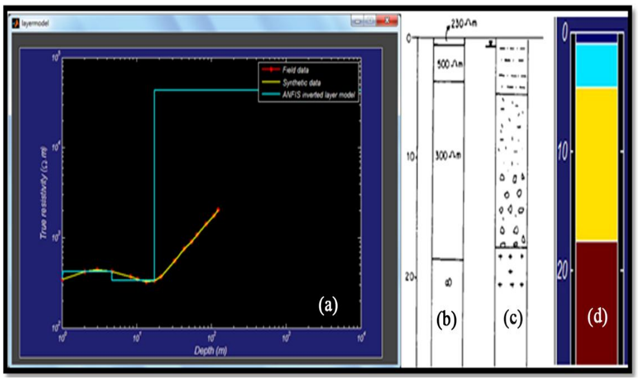

Fig. 6 Output GUI panel for the inversion of data 1. (a) shows the ANFIS inverted layer model, (b) & (c) shows the published geoelectric section and the litholog (after Edet and Okereke, 1997), (d) shows the ANFIS inverted geoelectric section.

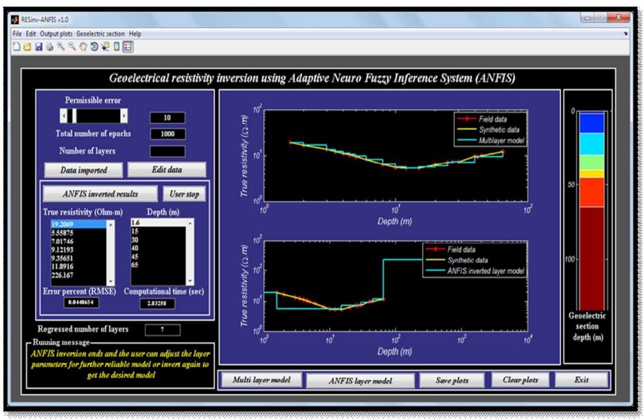

Fig.7 GUI panel showing the ANFIS inversion of data 2

Data 2 was chosen from Tuticorin district, India ($8^0$43’02’’N and $78^0$8’4.3’’E). ANFIS inverted result was shown in Fig. 7. Fig. 8 shows the output panel with corresponding litholog (Balachandran, 2009). The algorithm stops running after getting the reliable model by limiting the root mean square error as much as possible within the limits for reducing the computational time. Thus, these results the shows the efficacy of the proposed algorithm for the inversion of geoelectrical resistivity data.

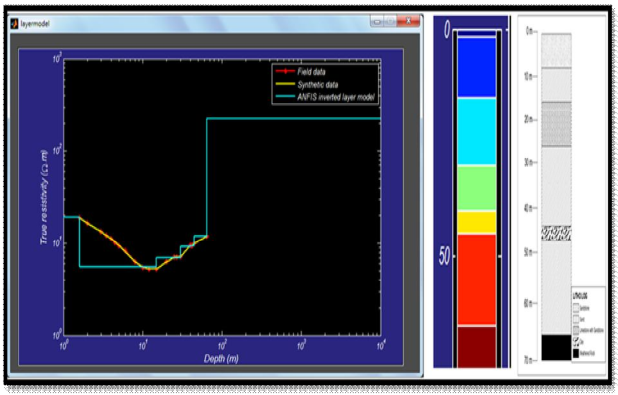

Fig. 8 Output panel showing the inversion model for data 2 with ANFIS inverted geoelectric section and the litholog (after Balachandran, 2009).

Advantages of using this algorithm

- User can choose any kind of model generated by the synthetic data base at each number of iteration. Different models can be obtained since the ANFIS algorithm assigns random weight at each number of iteration.
- Several models can be generated depends on the iterative procedure. There will be no limit for number of models since it depends on the user option.
- Values can be regressed or remodelling is possible.
- User can give any type of curves (A, K, H, Q) for interpretations. Even the raw field data also can be fed. Noises and field errors can be rectified during the process of ANFIS inversion.
- Very minor layers also can be traced easily. Though noise reduction is possible, the network doesn’t lose the original information presented in the data.
- User can adjust the error percent range so that different range of models can be generated.

CONCLUSIONS

The performance of ANFIS algorithm is satisfactory in applying for the 1D inversion on geoelectrical resistivity data. Thus, the newly framed algorithm used in the interpretation of geoelectrical data works well for all types vertical electrical sounding data (including A, H, K, Q types & for all multilayer cases). Thus the new computational approach paves way for inverting other non linear problems. The solutions obtained from this approach is more reliable and user friendly. Moreover not only for 1D inversion problem, ANFIS can be applied to 2D & 3D inversion problems with certain controlling parameters. Training database and acquiring knowledge are best accomplished by ANFIS algorithm.

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