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Enhanced behaviour of the Adaptive Neuro-Fuzzy Inference System (ANFIS) algorithm in comparison to Artificial Neural Networks (ANN) in the use of geoelectrical resistivity data

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ABSTRACT

Soft computing techniques are widely used for many non- linear problems in the real world. Many Earth's nonlinear characteristics exhibit uncertainty problems that have to be interpreted with advanced soft computing tools. Ambiguity always presents in realistic processes. The efficiency of knowledge–based systems depends upon the algorithms, which are cumbersome as their implementations require extensive computational time. Here, we present a work about interpreting the subsurface parameters of the Earth from electrical resistivity data using the Artificial Neural Networks (ANN) and Adaptive Neuro-Fuzzy inference (ANFIS) techniques. We focus on the advantage of the hybrid neuro-fuzzy systems, compared with the Artificial Neural Networks (ANN), in efficiency in interpreting electrical resistivity data. Hybrid systems that fuse fuzzy systems and neural networks (NN) have been propounded for utilizing numerical data. It expected that ANFIS can be used in many nonlinear problems. The network model is successful in training with large number of self-generated synthetic data sets. The interpretation using the ANFIS technique gave promising results with better accuracy, compared with the ANN inversion. Problems with parameter estimation can be solved more efficiently with this ANFIS geoelectrical resistivity inversion algorithm.

***KEYWORDS:** Neuro-Fuzzy Inference System, Artificial Neural Networks, subsurface parameters, electrical resistivity* inversion

1. INTRODUCTION

The Neuro-fuzzy approach is becoming one of the major areas of interest because it gets the benefits of neural networks as well as of fuzzy logic systems and it removes the individual disadvantages by combining them on the common features. Different architectures of neuro-fuzzy system have been investigated by number of researchers. These architectures have been applied in many applications including the interpretation of geoelectrical resistivity data. Neural Networks and fuzzy logic have some common features such as distributed representation of knowledge, model-free estimation, the ability to handle data with uncertainty and imprecision etc. Fuzzy logic has tolerance for imprecision of data, while neural networks have tolerance for noisy data. The most widely researched of all hybrid systems at the present time, are a combination of neural networks and fuzzy logic. Fuzzy logic provides a structure within which the learning ability of neural networks is employed [25]. In this field of geophysics, it has been more useful on interpreting the non-linear behavior of earth's electrical resistivity data. Many numbers of applications has been done using this tool efficiently in control, prediction and inference studies [7, 14, 30, 31 and 41]. The fuzzy modeling was first explored by Takagi and Sugeno [31] and later ANFIS network was developed by Jang in 1993. An adaptive network is a multilayer feed forward network in which each node performs a particular function on giving the input to the network. Electrical resistivity data collected from the VES (Vertical Electrical Sounding) data is used for training the data set. The data collected from the field will be the apparent resistivity data and while on interpreting will give the sub surface parameters of three layer resistivities and thickness of the respective layers. Trained data set will be the reference data for interpreting the sub surface layer parameters of the earth. This dataset will be used to train ANFIS by adjusting the membership function parameters that best model this data. Layer parameters viz., apparent resistivity and Thickness of earth's subsurface can be estimated using this tool with less error percentage.

II. GEOPHYSICAL METHOD

The Geophysical method consisting of vertical electrical sounding (VES) survey has been carried out in order to know the variation of resistivity of the aquifer parameters. Schlumberger electrode array (Fig. 1) is used to study the subsurface layer parameters such as resistivity, thickness and depth. The field procedure involves, the potential electrodes (M and N) remain fixed and the current electrodes (A and B) are expanded symmetrically about the centre of the spread. With very large values of current electrodes, however, it is necessary to increase the potential electrodes. 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.

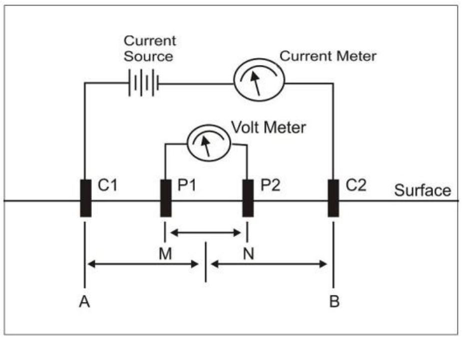

Fig. 1 Schlumberger electrode configuration

III. ARTIFICIAL NEURAL NETWORKS

Artificial Neural Network Interpretation

The artificial neural network plays a prominent role in the field of non-linear. Artificial Neural Networks have a particular number of hidden layers to process the information from the input layers to output layers. More complex structures especially earth's non-linear behavior can be studied using Artificial Neural Network (ANN). It is nothing but reproducing the natural occurring neural network, the human brain. From the fundamentals of the natural neural network, ANN computation has been performed by a dense mesh of computing nodes and connections [11]. Thus Artificial Neural Network (ANN) can play a major role to dig out the mystery of earth science by means of the previously learned examples used in the Network. Network capabilities can be very well proved to be good for noise immune system and fault tolerant cases [27]. The ANN inversion has been used for many years to interpret electrical resistivity data [1, 4, 5, 8, 10, 13, 15, 26, 34, 35]. ANNs are also being increasingly applied for Engineering Geophysics [2]. Aquifer parameters such as thickness and resistivity can be studied by direct current resistivity methods mainly used in the field of geophysical exploration [14, 16, 30, 39]. Vertical Electrical Sounding (VES) data can be interpreted using curve matching technique is well useful for estimating the subsurface geology [7, 9, 19]. But due to advancement in computational science the interpretation can be done by soft computing tools. One of such is Artificial Neural Network. Raw field data contains many noises and deviations. Before giving to the network the data should be smoothened and the interpretation can be done further.

Artificial Neural Network has been applied to various fields including the geophysical applications. Many researchers found ANN to be a useful tool for analyzing the parameters of the earth's subsurface [3, 8, 19, 23, 36]. In the present study we have adopted Feed forward Backpropagation algorithm for the interpretation of the subsurface layer model. MATLAB 7.7 has been used to execute the program and the output graphs are shown here.

III. ANN architecture

Feed forward back propagation (FFBP) algorithm is the technique used here for studying the field data by means of training function which updates weights with the specified learning function. Thus the network is trained with synthetic electrical resistivity data in the present study. Training large number of data will provide us good results of the problem and make the hidden units to train the data more effectively.

The backpropagation algorithm updates neuronal activations in the network for the input layer as

$\delta(x_i^k) = x_i^k$, i=1,……., n (1)

$\delta(x_0^k) = x_0^k = 1$ (2)

Where x_i^k is the ith component of the input vector presented in the network, and $\delta(x_0^k)$ is the input layer bias neuron signal that is independent of iteration index.

And for the hidden layer the network activation will be

$$z_h^k = \sum_{i=0}^{n} w_{ih}^k \,\delta(x_i^k) = \sum_{i=0}^{n} w_{ih}^k \, x_i^k \text{ , h = 1,……,q} \quad (3)$$

$$\delta(z_h^k) = 1/(1+e^{-z_h^k}) \text{ , h=1,……,q} \quad (4)$$

$$\delta(z_0^k) = 1,$$

Where w_{oh}^k are the biases of the hidden neurons, and $\delta(z_0^k)$ is the hidden layer bias neuron signal which is independent of the iteration index.

The output layer neuronal activations for the backpropagation will be

$$y_j^k = \sum_{h=0}^{q} w_{hj}^k \,\delta(z_h^k)\text{, j=1……, p} \quad (5)$$

$$\delta(y_j^k) = 1/(1+e^{-y_j^k})\text{, j=1,…..,p} \quad (6)$$

Where w_{oj}^k are the biases of the output neurons.

The learning rate η in the Backpropagation algorithm has to be kept small in order to maintain a smooth trajectory in weight space, because large learning rate can lead to oscillations during learning.

$$\Delta w_{hj}^k = \eta \sum_{t=1}^{k} \alpha^{k-t}\, \delta_j^t s_h^t = -\eta \sum_{t=1}^{k} \alpha^{k-t} \frac{\partial \varepsilon_t}{\partial w_{hj}^t} \quad (7)$$

The above equation generalizes the weight change at the k th iteration in terms of the weight gradient at each of the previous iterations [22].

The actual output for a given input training pattern is determined by computing the outputs of units for each hidden layer in the forward pass of the input data [40]. The function approximation interpretation of a single layer feedforward neural network enables us to view different hidden layers of the network performing different functions. FFBP algorithm is used here to invert the Vertical Electrical Sounding Data. Backpropagation learning technique will be the most efficient technique for obtaining good results [17].

Best training performance can be achieved after the iterations has been successfully completed the goal using the number of epochs for the synthetic data. The training stops whenever the goal has been achieved in a particular number of epochs. The test using trained data indicates that the ANN system can converge to the target rapidly and accurately. 1D resistivity inversion procedure using the ANN system was carried out because the procedure works well for the observed data. The synthetic and ANN trained data along with layer model is plotted and the layer model for the field data also predicted with the performance and regression plots. After testing the data the network has to interpret the layer model of the subsurface. For the interpreting the layer model the network will call the memory associated with the layer parameters. If the model parameters, on comparison, matching with the memory of the synthetic trained data already stored in the network it produces the corresponding model parameters with respective error percentage. The well trained network will increase the performance level of the output parameters. The inversion thus represents the layer parameters of subsurface geology viz., thickness and resistivity. Successful interpretation was produced only after the training and determines the model parameters with the trained data. The results of interpretation of the near-subsurface features by means of this ANN technique is satisfactory and are more efficient and the error has been checked with the synthetic trained data.

For 1D inversion of geoelectrical data, batch back propagation algorithm was chosen earlier and the resultant works of all back propagation paradigms were compared by Gad El-Qady et al. [8]. The entire back propagation algorithms are different from each other in calculating the weights and their updation [38]. Further research on iterative feed forward network proves that the Levenberg-Marquardt algorithm is the best optimization algorithm for interpreting geoelectrical data [24, 28].

IV. ANFIS Architecture

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

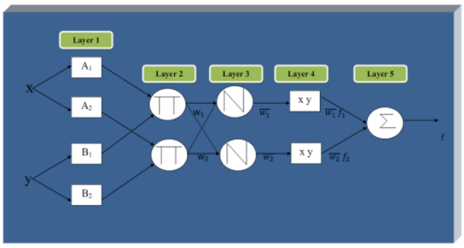

Fig. 2 Takagi Sugeno fuzzy model

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

Layer 1.

Serves to raise the degree of membership

$O_{1,i} = \mu_A(x)$ i=1,2 (8)

and

$O_{1,i} = \mu_B(y)$ i=1,2 (9)

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

$\mu_A(x)$ = 1/[1+(det(x-c_i)/a_i)^2b_i] (10)

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

Layer 2

Serves to evoke *firing-strength* by multiplying each input signal.

$O_{2,i} = w_i = \mu_A(x) \times \mu_B(y)$ i=1,2 (11)

Layer 3

Normalize the *firing strength*

$O_{3,i} = \overline{w_i} = \frac{w_i}{w_1+w_2}$ i=1,2 (12)

Layer 4

Calculating the output based on the parameters of the rule *consequent* {p_i , q_i and r_i}

$O_{4,i} = \overline{w_i} f_i = \overline{w_i}\,(p_i x + q_i y + r_i)$ (13)

Layer 5

Counting the ANFIS output signal by summing all incoming signals will produce

$$\sum_i \overline{w_i} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \quad (14)$$

5. 1 Sugeno type ANFIS model for parameter Optimization

Geological subsurface can be studied easily from the VES data [21]. Raw field data contain many noises and deviations. Before giving to the network the data should be smoothened and the interpretation can be done further.

Using a given input and output data set, ANFIS network membership function parameters will be adjusted by back propagation algorithm (here used) or the least square method. This allows the network to learn from the data set and predict the result with respect to the trained data set. The operations were explained by Takagi-Sugeno-Kang (TSK) Fuzzy system [32, 33] and the mathematical details of ANFIS was explained by Jang [12].

Initially, the data have been subjected to clustering analysis where subtractive clustering technique has been used before applying ANFIS algorithm. The resultant membership functions have been mapped to raise certain degree of membership grade between the input and output, and serves to raise the firing strengths for each membership function. Each function has a significant feature on rule framing and consequent parameters.

After importing AB/2 and apparent resistivity data, it is subjected to subtractive clustering algorithm (*"genfis2" command used in MATLAB software*). The cluster centers formed have been assigned a particular membership function (here *"gaussmf"- Gaussian membership function"* command is used in MATLAB R2008b software). Each membership function corresponds to each rule. After framing the rules, the ANFIS network has been initialized with hybrid learning algorithm with least square estimation and gradient descent method. The synthetic dataset has been obtained after the training, and this dataset has been subjected to slope variation method where the true resistivity and depth information are obtained. At this stage the primary training stops, and the output parameters i.e., synthetic datasets with corresponding true resistivity and depth are ready for training with ANFIS major class training as input and output parameters respectively. The output multilayer model has been compressed by linear regression so as to obtain a crisp compressed layer model.

Fuzzy inference system would be considered modeling the parameters by means of analyzing the input characteristics and model them to a particular membership functions. The membership functions regarding to the input will make the rules to model the output characteristics. For converting the input characteristics to the output characteristics it possesses certain membership functions to make a decision associated with the output. On comparing the input parameters with the membership functions to obtain the membership values is termed as fuzzification. Then combine the membership values with the firing strength the network can be able to obtain a crisp output. Converting the qualified consequent (either fuzzy or crisp) of each rule depending on the firing strength to produce a crisp output is called defuzzification [12]. The basic learning rule for ANFIS network can be done on the basis of gradient descent and the chain rule, which was earlier proposed by Werbos [38]. In order to develop a learning procedure that implements gradient descent E over the parameter space first we should know the error rate $\frac{\partial E}{\partial O}$ for the training data of each node output O. Suppose if the adaptive network has L layers. We can denote the ith position of the nodal function (or node output) as O_i. Assuming the given training data set has P entries we can define the error measure (or energy function) as

$$E_p = \sum_{m=1}^{L} (T_{m,p} - O_{m,p}^{L})^2 \qquad (15)$$

Thus the error rate can be calculated as

$$\frac{\partial E_p}{\partial O_{i,p}^{L}} = -2(T_{i,p} - O_{i,p}^{L}) \qquad (16)$$

The overall measure E with respect to the parameter of the given adaptive network α, then the equation will be

$$\frac{\partial E}{\partial \alpha} = \sum_{p=1}^{P} \frac{\partial E_p}{\partial \alpha} \qquad (17)$$

According to the update formula for the generic parameter α is

$$\Delta\,\alpha = -\eta \frac{\partial E}{\partial \alpha} \qquad (18)$$

In which η is a learning rate which can be further expressed with k of the step size (length of each gradient transition in the parameter space) will be

$$\frac{k}{\sqrt{\sum_{\alpha}\left(\frac{\partial E}{\partial \alpha}\right)^2}} \qquad (19)$$

The overall output of all the input can be calculated with the firing strength as follows

$$\sum_i \overline{w_i}\, f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \qquad (20)$$

The neuro-adaptive learning techniques provide a method for the fuzzy modeling procedure to learn procedures about the apparent resistivity data set trained, in order to compute the membership parameters that best suits with the associated fuzzy inference system to track the given input-output data used for interpreting the sub surface parameters.

V. ANN AND ANFIS GENERALIZED ALGORITHM DESCRIPTION AND APPLICATION

In the present algorithm, the training has been classified into two major parts viz., primary and major class training.

ANN Primary class training:

In the primary training, the input data is processed here. In the present application of geoelectrical resistivity inversion, Vertical Electrical Sounding (VES) data (AB/2 and apparent resistivity) is fed to the primary training. Here, the raw data is smoothened by applying random weights to each input and trains the input data. After the training, it produces a number of synthetic data which are proportional to the number of epochs. Then a multilayer model is obtained based on the variation of slope of VES curve for each synthetic data after training as output.

Slope variation refers to the basic method for obtaining the trend of the VES curve changing with respect to the subsurface layers obtained from the field curve. Whenever the VES curve changes its trend, then the slope varies and this represents the change in the subsurface layer [29]. Initially, a multilayer model is obtained, as each and every data point obtained from the field may not be linear.

The 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.

The change can be depicted as $(y_2 - y_1) = \Delta y$. Similarly, for the x axis, it is $(x_2 - x_1) = \Delta x$.

Thus slope m of the line is

$$m = \frac{y_2 - y_1}{x_2 - x_1} \qquad (21)$$

ANN Major class training:

In the major class training, the synthetic data obtained from the primary training session is fed as an input to the FFBP networks with Levenberg Marquardt training algorithm, where the output of the FFBP algorithm is the multilayer model for the corresponding synthetic data. Moreover, other parameter limitations follow the same rule as that of parameters used in the previous session.

In the testing phase, the trained datasets were tested with the original field data and the output model is linearly regressed with each multilayer, and these provide a compressed layer model as an output. .

The output model parameters viz., true resistivity and depth are plotted in the framed GUI and the user can save both the models individually. The newly designed algorithm provides a separate model for each iteration and the user can choose a certain model.

ANFIS Primary class training:

After importing AB/2 and apparent resistivity data, it is subjected to subtractive clustering algorithm (*"genfis2" command used in MATLAB software*). The cluster centers formed have been assigned a particular membership function (here *"gaussmf"- Gaussian membership function"* command is used in MATLAB R2008b software). Each membership function corresponds to each rule. After framing the rules, the ANFIS network has been initialized with hybrid learning algorithm with least square estimation and gradient descent method. The synthetic dataset has been obtained after the training, and this dataset has been subjected to slope variation method where the true resistivity and depth information are obtained. At this stage the primary training stops, and the output parameters i.e., synthetic datasets with corresponding true resistivity and depth are ready for training with ANFIS major class training as input and output parameters respectively. The output multilayer model has been compressed by linear regression so as to obtain a crisp compressed layer model

ANFIS Major class training:

In major class training ,

- The AB/2 and apparent resistivity synthetic data have been mapped as input and the corresponding layer model (true resistivity and thickness) as output.
- After initializing ANFIS training, Fuzzy subtractive clustering technique is applied to form the cluster centers on the basis of density measures of each data point.
- After framing the cluster centers, the FIS training successively runs to map the cluster centers to the appropriate rules of membership functions. In this application gaussian input membership function and the linear output membership functions are used.
- These membership functions correspond to certain rules and the entire membership function parameters are subjected to training using ANFIS architecture.
- The multilayer model is obtained based on the slope variation method.
- The output multilayer model with true resistivity and depth information has been obtained.
- The multilayer model has been thus regressed linearly to obtain the compressed layer model.

Performance criteria

To achieve desired optimal neural network model, Root Mean Square Error (RMSE) correlation coefficient (R) and correlation of determination (R^2) are used in the current study.

The Root Mean Square Error (RMSE) is used to measure the difference between values predicted by a model and the values actually observed from the environment that is being modelled. The error is calculated as the difference between the target output and the network output. The goal is to minimize the average of the sum of these errors. Here, the difference is between the ANN tested synthetic data output and the observed field data RMSE = $\sqrt{\sum_{i=1}^{n} \frac{(t(k)-a(k))^2}{n}}$ (22)

where t(k) is the target output which is the observed field data, 'n' is the number of data points and a(k) is the network output which is the synthetic data obtained after ANN training. ANN weights parameter was adjusted each time while iterating is controlled by the minimum RMSE error percent. Whenever the network is unstable or the error is higher than the permissible limit then the loop of the major class training continues until the error is fixed in the range of permissible error percent.

Correlation – often measured as a correlation coefficient (r) – indicates the strength and direction of a linear relationship between two variables (for example model output and observed values). A number of different coefficients are used for different situations. Here, ANN trained output is correlated to targeted observed field data output.

$$r = \frac{\sum_{i=1}^{n}(x_i - \bar{x})\cdot(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \cdot \sum_{i=1}^{n}(y_i - \bar{y})^2}} \qquad (23)$$

where x and y variables are the target field data and the ANN trained output respectively. $\bar{x}$ indicates $\frac{\sum x}{n}$, similarly $\bar{y}$.

The correlation is +1 in the case of a perfect increasing linear relationship, and -1 in case of a decreasing linear relationship, and the values in between indicate the degree of linear relationship between example model and observations. A correlation coefficient of 0 means the there is no linear relationship between the variables. The square of the correlation coefficient (r^2), known as the coefficient of determination, describes how much of the variance between the two variables is described by the linear fit [37].

VI. GRAPHICAL USER INTERFACE (GUI) REPRESENTATIONS OF VES INVERSION

GUI is designed for inverting the geoelectrical reisistivity data. GUI is framed on the MATLAB 2008 platform and one can easily attain the necessary user interface using this tool. GUI framed is very user-friendly and one can get more number of models for each iteration. The model which is having less error percentage between the field data and the synthetic data can be produced as the output from the GUI. If this model is not suitable, one can go for iteration, till the effective model is obtained. The algorithm can be stopped whenever necessary. The output panel buttons can be used to get the specific output.

VII. VALIDATION OF THE ANN & ANFIS ALGORITHM WITH FIELD DATA

The designed algorithm has been validated with different field datasets obtained from different geological formations. Two datasets have been chosen and the results are compared with the earlier results/lithologs and the correlated results are given in Table 1.

Data 1 (*Location: Oban massif, Cross River State, Nigeria [6]*

Data 1 is chosen from Oban massif regions located in the Cross River State (Nigeria). It lies roughly between latitudes 5′00′′ and 5′50′′ N and longitudes 8′00′′ and 8′52′′ E. The massif is underlain by highly deformed Precambrian crystalline basement rocks, mainly granites, gneisses and schists.

Fig. 3 shows the interpreted model with successful ANN and ANFIS interpretation. The performance represents the least square error achieved for the particular number of epochs. The error is measured in terms of RMSE. Regression plot represents the linear relationship between target field data and the ANN trained output. The square of the correlation coefficient (r^2), known as the coefficient of determination, describes how much of the discrepancy is between the target and the output which is described by the linear fit.

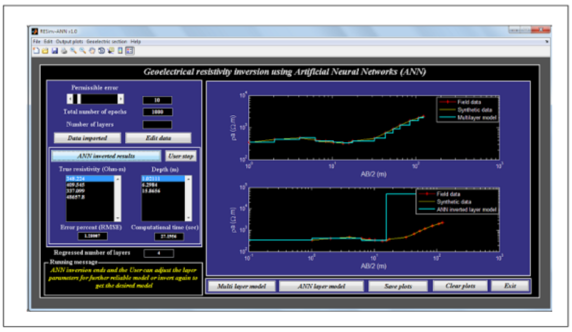

Fig. 3 Data 1 interpretation model

Data 2 (*Location: Roorkee, Uttaranchal, [18]*):

Data 2 was chosen from Roorkee, Uttaranchal, India [18]. The ANN inverted results, litholog comparison and performance results shown in Fig.4. However, minor layers shown in the litholog are not resolved in the ANN geoelectrical inversion for this data. It has been extracted in the ANFIS inversion results.

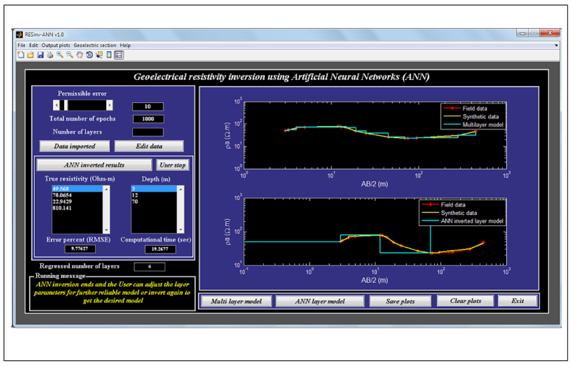

Fig. 4 Data 2 interpretation model

Data 3 (*Kanyakumari*):

Kanyakumari district is located in the southern tip of India. It lies between the latitude 77˚18′ 45″ E to 77˚35′15″ E and 8˚4′ N to 8˚13′45″ N longitude. The study area is underlain by the crystalline rocks like gneiss and charnockite of Archaean age. Along the coast the sands of recent origin are noticed. The location map of the study area is shown in Fig. 5.

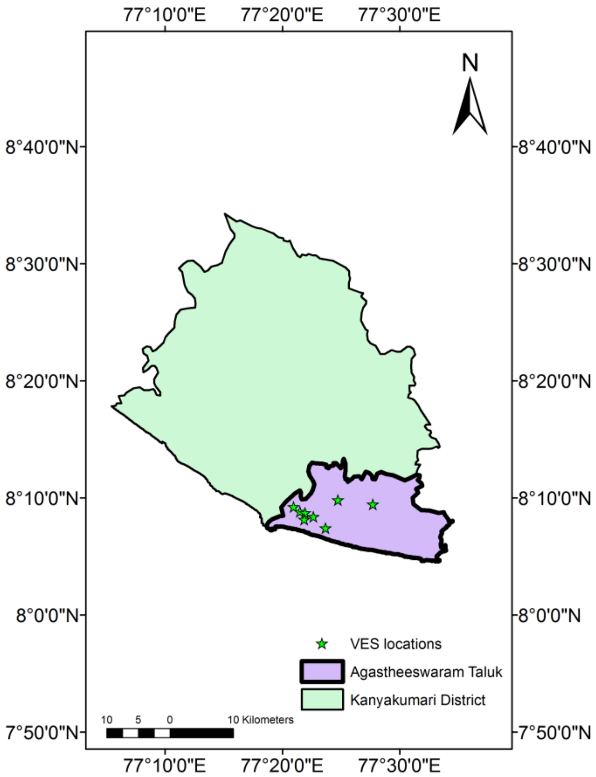

Fig. 5 study area-Kanyakumari district

The peninsular gneisses occupy the largest area in the district. The general trend of the strike of this area is in the N-NW to S-SE direction. Garnetiferous silliminate, graphite gneiss and garnet biotite gneiss are the two major group identified in Kanyakumari district (GSI, 2005). The charnockite group rocks are well exposed around Rajakkamangalam areas. Charnockite group mainly consists of charnockite, pyroxene granulite and their associated migmatites. Charnokites are also exposed within the gneiss as bands and lenses. Near Kanyakumari calcareous limeshell of sub recent origin is noticed. The general sand types seen along the coast are bay deposits or lateral deposits of sand, zircon, rutile, illemanite and garnet. The straight west coast line continuing without any break is itself suggestive of faulted one and the faulting would have taken place during the Pliocene period. The pediments and the structural hills are run off zones and hence have poor potential regions. The valleys have a good infiltration – recharge zone has a medium groundwater potential zones. The coastal plains are characterized by beaches and sand dunes comprising of medium to fine sandy windblown particles, which is also a good groundwater potential zone. For agricultural developments almost the entire shallow aquifer zone is tapped in the study area. The groundwater occurs in almost all the geological formations like crystalline rocks, sedimentary formations and quaternary alluvium and beach sands. The groundwater occurrence in hard rock region is limited to the weathered mantle of thickness 10 to 35 m below ground level. The weathered thickness in hard rock regions is discontinuous both in space and depth. Hence the groundwater potentiality is influenced by the intensity of weathering. In the sedimentary formations having alluvial deposits the water table is very shallow which is up to a maximum depth of 10 m. Using this hybrid algorithm all the VES data are interpreted and the three dimensional model for true resistivity and depth is shown in Fig. 6 and Fig. 7

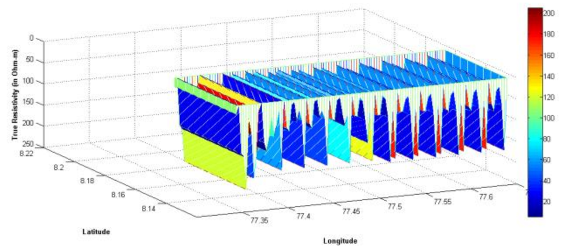

Fig.6 Three dimensional true resistivity inversion

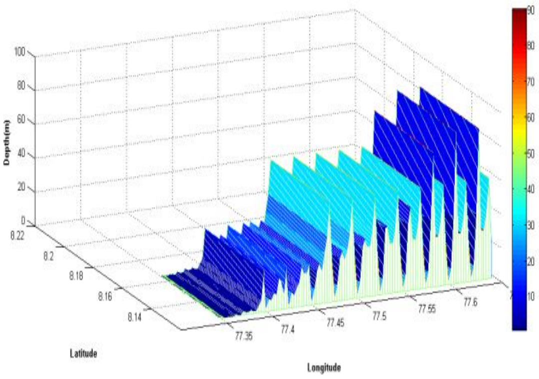

Fig.7 Three dimensional Depth inversion

9 Comparative analysis and discussions

Conventional geophysical inversion techniques can be improved by using a certain kind of soft computing tools that will enhance the research in a broader spectrum. The ANN algorithm uses random numbers to calculate the weights. Due to its random adjustment of weights while training, it makes the network lose its plasticity at one stage. This loss is in contrast to the initial motivation to develop neural networks that emulate brain like networks, and are adaptable (plastic) enough to learn new patterns. If changes are necessary, the algorithm calculates the new weight values and updates them. This means that the neural network implementation depends on a random number in calculating the weight adjustments, and this calculation of weight adjustments sometimes may lead to severe problems in converging the result. Though it depends on random numbers, the information on the network should be supplied by some other parameters. This has been done in ANFIS hybrid method where the results were balanced by the adaptive nature of the membership function parameters. So in applying this ANN algorithm to geoelectrical resistivity inversion, the output will converge to a particular extent. It will not converge below a particular error percent for each dataset. So, the permissible error percent can be changed in order to get the reliable model.

Table 1 Comparison of ANFIS geoelectrical interpreted layer model with Artificial Neural Networks (ANN) results.

Data	Inversion techniques	True resistivity (in Ohm- m)	Depth (in m)	Depth according to litholog (in m)
Data 1	ANN	348.24 409.545 337.099 48657.8	1.0211 6.2984 15.8656	0.68 4.64 17.4
	ANFIS	348.318 471.114 325.289 48657	1.0211 4.07723 17	
Data 2	ANN	49.568 78.0654 22.9429 810.141	3 12 70	3.05 12.1 71.3 93.26 148.746
	ANFIS	52.6984 76.6792 22.2362 24.9653 24.51 810.141	2.8 12 70 95 150	

Hybrid algorithm results thus favor more than the other algorithms used here (ANN & FL). The synthetic apparent resistivity data are obtained on the basis of field data for training. It is fed into the Sugeno type ANFIS architecture with the Gaussian shaped membership function. The initial parameters i.e., permissible error and number of iterations have to be given to the program. The ANFIS adjusts the membership function parameters, which specify their shapes and partition of membership functions and updates during training. The back propagation learning technique is employed in this hybrid approach associated with the input membership functions, and the least-squares estimation is used for the parameters of the output. The training section provides less training error which will be well suited for testing the data. The network is well-trained with the synthetic apparent resistivity data, and the trained network is used to invert the field data.

Neuro-Fuzzy logic enhances the generalization capability of a neural network system by providing more reliable output when extrapolation is needed beyond the limits of the training data. Neuro-fuzzy systems offer the precision and learning capability of neural networks, and yet are easy to understand like fuzzy systems. Explicit knowledge acquired from experts can be easily incorporated into such a system, and implicit knowledge can be learned from training samples to enhance the accuracy of the output or otherwise minimizing the error percentage. Comparative study based on error percentage reveals that ANFIS computing is more affordable than ANNs.

10 Conclusions

- The soft computing tools are very efficient in applying many non-linear problems. Here, these soft computing tools are very useful for studying the geological formations by inverting the geoelectrical data. The resistivity data of different geological regions have been interpreted using the ANN, FL and ANFIS algorithms. The accuracy of ANFIS inversion results is fairly good, and the tested data fall above 90% accuracy. If the raw field data contain more noises or field errors, the convergence rate will be slow but it can be achieved by increasing the number of iterations. The present algorithm used in the interpretation of geoelectrical data works well for all types of vertical electrical sounding data (including A, H, K, Q types and for all multilayer cases). The solutions obtained from this approach are more reliable, and the GUI developed using the MATLAB platform for this purpose is user friendly. Very minor layers also can be easily traced using the ANFIS algorithm than ANN and FL. Though noise reduction is possible, the network does not lose the original information available in the data. Data 2 contain minor layers that are successfully retrieved by ANFIS algorithm than the ANN algorithm.

- Different models can be generated while testing the ANFIS algorithm at each number of iterations within a limit of particular error percent. The most appropriate model with less error percentage can be chosen as the reliable model.

- In general, large number of datasets collected from a particular study area are used to train the soft computing methods, and the remaining data is used to test. However, the training datasets are generated by changing weights and membership functions based on the field data in the present concept. Thus, this approach can be applied to invert the VES data collected from any study area.

ANFIS has been the most common inference system in use recently, while the basic type of inference has been employed mainly during the 80's and 90's. Also, the applications of artificial intelligence methods have increased recently. ANFIS system models were proved to be a good tool for prediction mainly when neural network and fuzzy logic were combined with. Thus, the new computational approach paves the way for inverting the VES data more accurately.

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