
BARGAIN OPTIMIZATION (BO) ALGORITHM FOR NON-LINEAR PARAMETER ESTIMATION

A. Stanley Raj

Assistant Professor, Department of Physics, Loyola College, Nungambakkam, Chennai 600034, India

D. Hudson Oliver

Assistant Professor, Department of Physics, Scott Christian College, Nagercoil, India

Y. Srinivas

*Professor and Head, Centre for GEO Technology, Manonmaniam Sundaranar
University, Tirunelveli, Tamil Nadu, India*

J. Viswanath

*Associate Professor, Department of Mathematics, Vel Tech Rangarajan Dr. Sagunthala
R&D Institute of Science and Technology, Avadi, Chennai 600062, India*

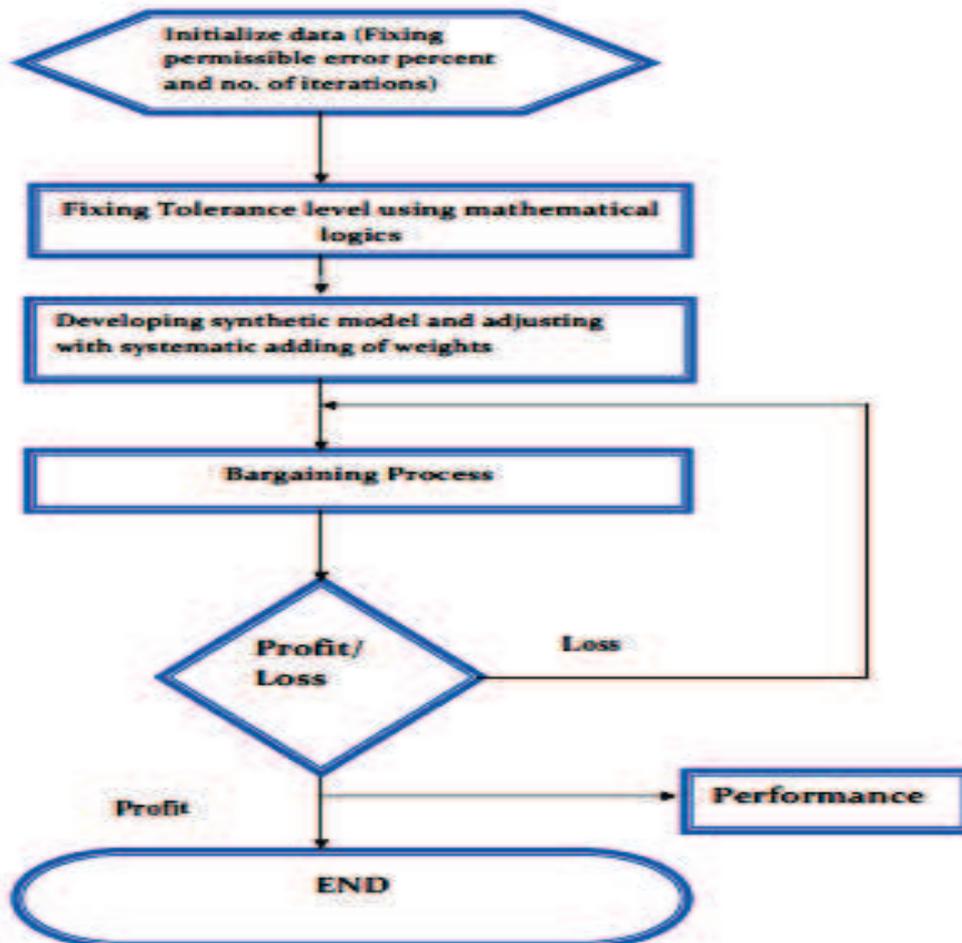
Abstract: In this work, we propose a novel, nature inspired Bargain optimisation algorithm to interpret non linear data. Though many optimisation algorithms were available, most of the non-linear estimation algorithm depends on iterative logics rather than referring standard model. In the earlier days, mathematical models were used in most of the conventional interpretation techniques. After the evolution of soft computing algorithm, it dominates over the conventional techniques. In this research work, the implementation of novel and innovative Bargain algorithm is put forward to solve complex and multimodal geophysical interpretation problems. This algorithm is based on the analogy of purchasing articles in a shop with profit or loss. The properties of the bargain concept is implemented i.e., a buyer purchases the articles from the shop with reduced price after bargaining. Thus bargaining reduces the price of the article which can be taken as a concept of developing the model with minimum error. Standard model is developed for the input data, and the system bargains to get the maximum fitting which will be helpful for improved levels of result with profit or loss. The validity of the technique is applied to real world geoelectrical dataset obtained from various geological regions. The data is tested and the results were good which proves to be the best optimisation algorithm for interpreting non-linear data.

Keywords: Bargain, Best Fit, Optimization algorithm, Profit, Loss.

Introduction: Optimization is the best mode to approximate the result in better way. It is the process of minimizing the error between the observed and expected results within the optimal constraints. Input can be of any number of variables that the function can fit into the condition to achieve most favorable result. Most of the optimization methods are nature inspired algorithms; for example Genetic Algorithm (GA) (Sivanandam & Deepa, 2007), Cuckoo Optimization Algorithm (COA) (Rajabioun 2011) and Particle Swarm Optimization (PSO) Kennedy & Eberhart, 1995) are all nature inspired algorithms. Bio mimicking methods are very helpful in attaining certain frame work of the algorithm. Moreover the framework of the algorithm helps the researchers to launch their own innovative ideas in different branches. It is very useful in the context of 1) simplicity 2) flexibility 3) derivation of free mechanism and 4) local optimal avoidance. Meta heuristics algorithms are simple as it is inspired from the physical characteristics of nature. Because of this easily adaptable concept, it has been applied by many researchers in solving most of the non-linear problems. Flexibility in solving problem cannot be easily fixed with certain functions. The problem in deriving a solution through optimization algorithm may sometimes become vulnerable when it is concise within the global minima. Generalized algorithm is difficult to frame for a particular problem. Local minima can be easily approached stochastically or obtaining random solutions. But it is not reasonable in fitting data with random model. Certain structures can be created to run over the algorithm to maintain consistency in performance for any kind of data.

Bargain Optimization Algorithm (BO) is one such algorithm which is inspired by the bargaining of a customer purchasing an article from shops.

Concept of Bargaining: If a seller selling an article with a particular price, consumer purchases it with profit or loss. For attaining profit consumer bargains the article with reduced price. This concept has been applied here mathematically converges the problem to accomplish the optimum result.



Steps Involved in Process of Bargaining:

Step 1:

Initialization:

- a) Feeding input data
- b) Set up minimum error percent
- c) Set up time limit

In this process of initialization any nonlinear data can be feed as an input. Here in this article geoelectrical resistivity data obtained from different field data has been applied to evaluate the algorithm. As geology varies from region to region, electrical resistivity data obtained from the field is completely non-linear. It depends on many parameters, viz., porosity, humidity of the soil, atmospheric variations, etc. If the subsurface geology is very complex the resistivity variations can rapidly vary over short distances. Table 1 gives the resistivity values of common rocks, soil materials and chemicals (Keller and Frischknecht 1966, Daniels and Alberty 1966).

Material	Resistivity (Ω-m)
Igneous and Metamorphic Rocks	
Granite	$5 \times 10^3 - 10^6$
Basalt	$10^3 - 10^6$
Slate	$6 \times 10^2 - 4 \times 10^6$
Marble	$10^2 - 2.5 \times 10^8$
Quartzite	$10^2 - 2 \times 10^8$
Sedimentary Rocks	
Sandstone	$8 - 4 \times 10^3$
Shale	$20 - 2 \times 10^3$
Limestone	$50 - 4 \times 10^2$
Soils and Waters	
Clay	1-100
Alluvium	10-800
Groundwater(fresh)	10-100
Sea Water	0.2
Chemicals	
Iron	9.074×10^{-8}
0.01M Potassium Chloride	0.708
0.01M Sodium Chloride	0.843
0.01M Acetic acid	6.13
Xylene	6.998×10^{16}

Thus setting up the minimum error percent and time required for 'bargaining' is very important. Bargaining concept is very similar to training in neural networks but exclusively novel in the concept of utilizing weights and profit/loss conception.

Step 2: Finding tolerance level: In this step algorithm find the difference between each data and the mean difference is fixed as the tolerance level. For a sample data size of n, mean absolute deviation can be calculated as the tolerance level,

$$T_l = \frac{1}{n} \sum_{i=1}^n x_i - \bar{x}_i$$

\bar{x}_i is the mean of distribution. This will be helpful in bringing the optimal solution for the problem, because the convergence rate and weight based learning is within this tolerance level. This step is very important to prepare the data for bargaining process

Step 3: Process of Bargaining: This process starts with all the prerequisites of the algorithm and the systematic weight based learning starts here at this step. Systematic weight learning method is the one which adds weights to the data to form a synthetic data for learning purpose. Thus in each iteration process of bargaining follows a 'weight reduction technique' i.e., If the weights added up is very close or within the tolerance level then the data with added weights will not appear in the next iteration. This saves the time in learning process. Continuous bargaining results in effective time bound learning methodology with profit/loss. Moreover, the technique of bargaining may result failure in some attempts of bargaining and it has been recorded as bargain chart which clearly mentions the bargain failure at specific iteration.

Step 4: Relative variation (Statistical analysis)

Finding the mean for sample data

$$\mu = \frac{\sum x}{n}$$

Where 'x' is the data and 'n' represents the number of data points

Standard deviation for the data

$$\sigma = \sqrt{\frac{\sum(x-\mu)^2}{n-1}}$$

Coefficient of variation (CV) can be calculated as

$$CV = \frac{\sigma}{\mu}$$

This step checks the relative variation between the synthetic data and the field data taken for study. The uncertainties involved in the data process can be analyzed using this relative variation.

Step 5: Profit/ Loss: The algorithm checks with the permissible error percent and conditions the loop to break or to proceed. Profit can be obtained if the data fits in the tolerance value but the accuracy and precision is based on the error percent. Thus the algorithm may continue its iteration though small amount of profit is obtained. The algorithm continuously iterating until it attains the maximum profit (the desirable one)

Step 6: Performance Evaluation: L2 - norm is the performance evaluation based on least square estimates. It is basically minimizing the sum of square of the differences (E) between the target (Y_i) and estimated values (f(x_i)):

$$E = \sum_{i=1}^n (Y_i - f(x_i))^2$$

Intelligent approach in data analysis: The intelligent technique for data analysis and interpretation are becoming more powerful tools for making breakthroughs in the science and engineering fields by transforming the data into information and information into knowledge in recent days. These intelligent techniques can be used in oil and gas industry for uncertainty analysis, risk assessment, data fusion and mining, data analysis, interpretation and knowledge discovery from diverse fields of geophysical/geological data, well log, and production data (Masoud Nikravesh 2004). Yasala Srinivas (2013) applied ANFIS model to find the lithology of study area. The last decade has witnessed significant advances in inverting geosciences data with associated characteristics. This has been made possible through improvements in data integration and quantification of uncertainties.

Validation of Datasets: Data 1 (Katol Taluk, Nagpur District, India- S.N. Rai et al., 2011) Geoelectrical Sounding data obtained from the published work of S.N. Rai et al., 2011 taken from the field of Deccan traps terrain in Katol Taluk, Nagpur District, Maharashtra, India. Groundwater study was carried out in the unevenly distributed aquifer of the study area and the sounding interpretation reveals the water bearing zones found in the fractured zones. Using bargain algorithm the interpretation made with minimum number of iterative loops and minimum error percent.

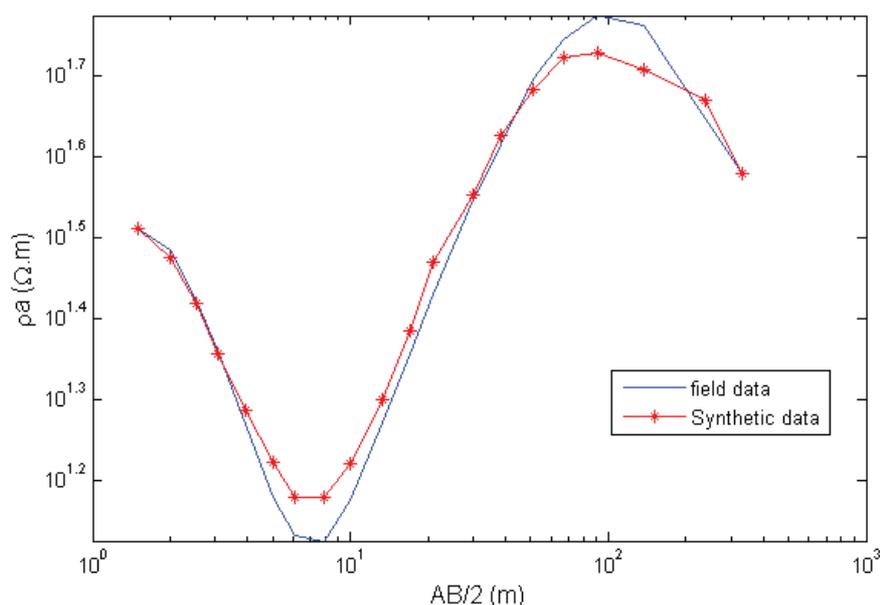


Fig. 2 Shows the Generated Synthetic Data Along With the Field Data

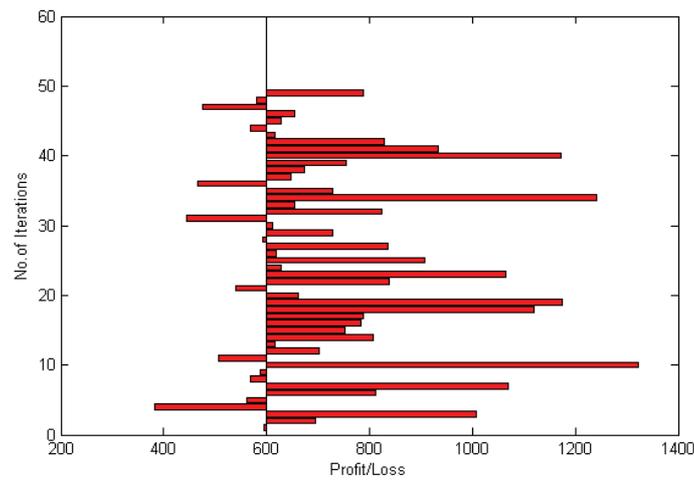


Fig. 3: Shows the Profit/Loss Categorization Graph Which Reveals the Number Of Profit/Loss Model for Particular Number of Iterative Loops

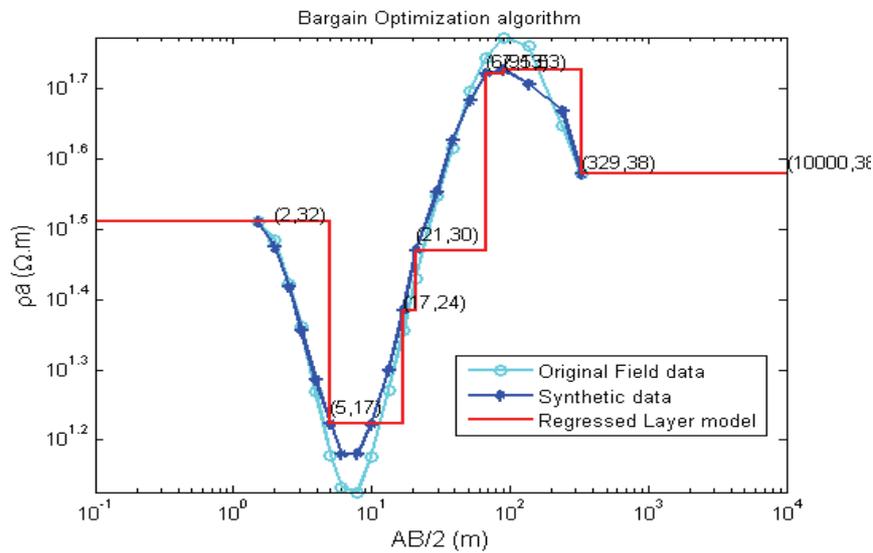


Fig. 4: Shows the Bargain Optimization Algorithm (BO) Interpreted Results With True Resistivity and Thickness of Subsurface

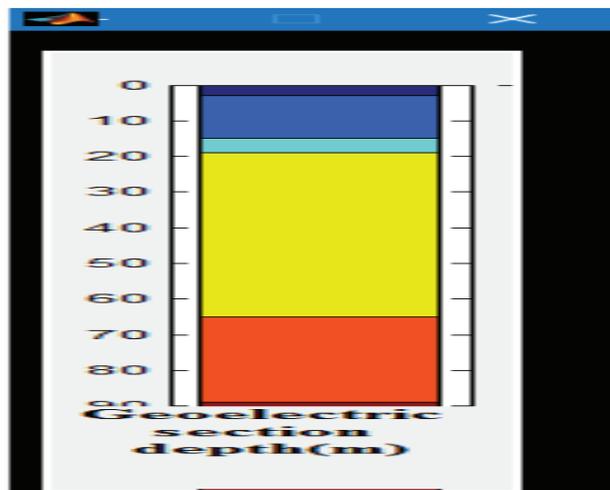


Fig. 5 Shows the Geoelectrical Model Obtained From The Interpreted Results Using BO

The interpreted results obtained using BO works well and the results correlated with the published results.

Data 2 (Orerokpe, Nigeria- Egbai, J. C., 2011): Data obtained from the clay deposits in Orerokpe, Okpe Local Government Area of Delta State using vertical electrical sounding (VES). The data is interpreted using Bargain algorithm and the results are validated. The results showed that the algorithm is more reliable and user friendly. Fig. 6 shows the field and generated synthetic data and the profit/ loss graph (Fig. 7) reveals the systematic training of the weights and its range of variation in searching optimised solution. Fig. 8 and 9 shows the interpreted layer model and geoelectric section.

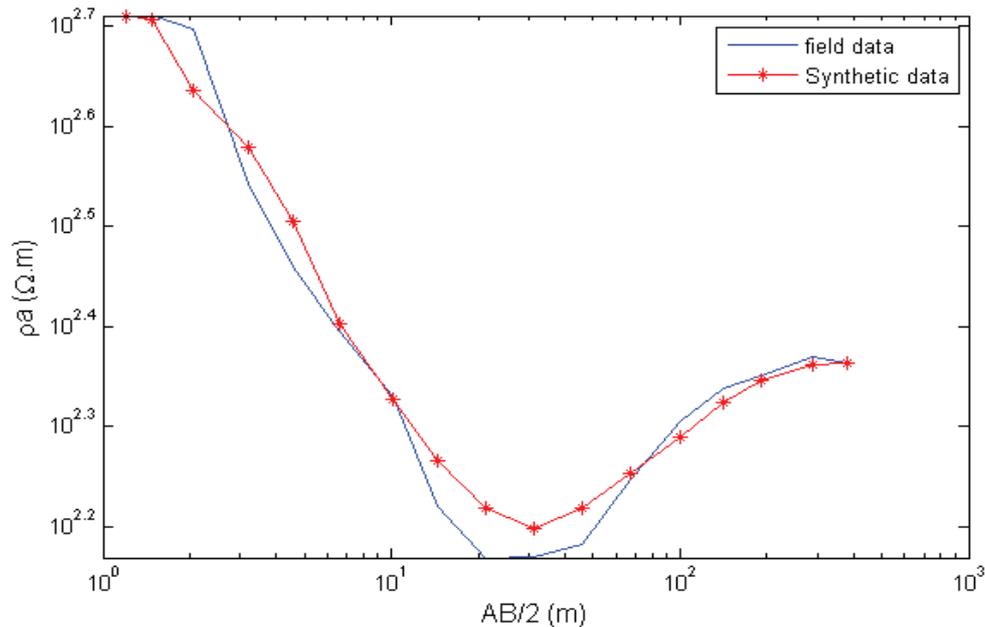


Fig. 6: Geoelectrical data obtained from Orerokpe, Okpe Local Government Area of Delta State, Nigeria (Egbai, J.C., 2011)

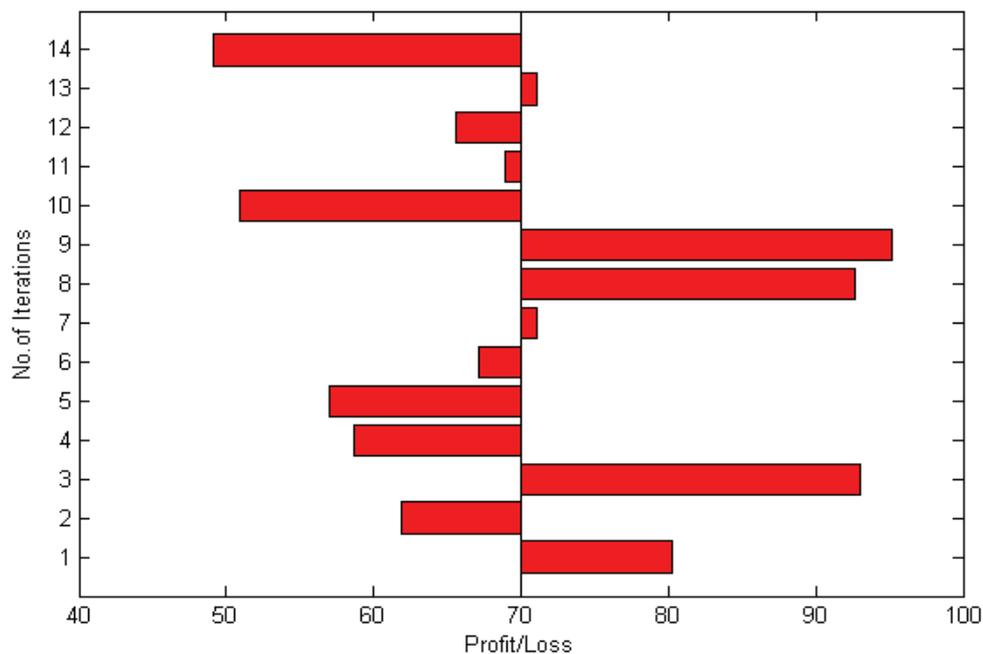


Fig. 7: Shows the Number of Profit/Loss Attempts While Training BO

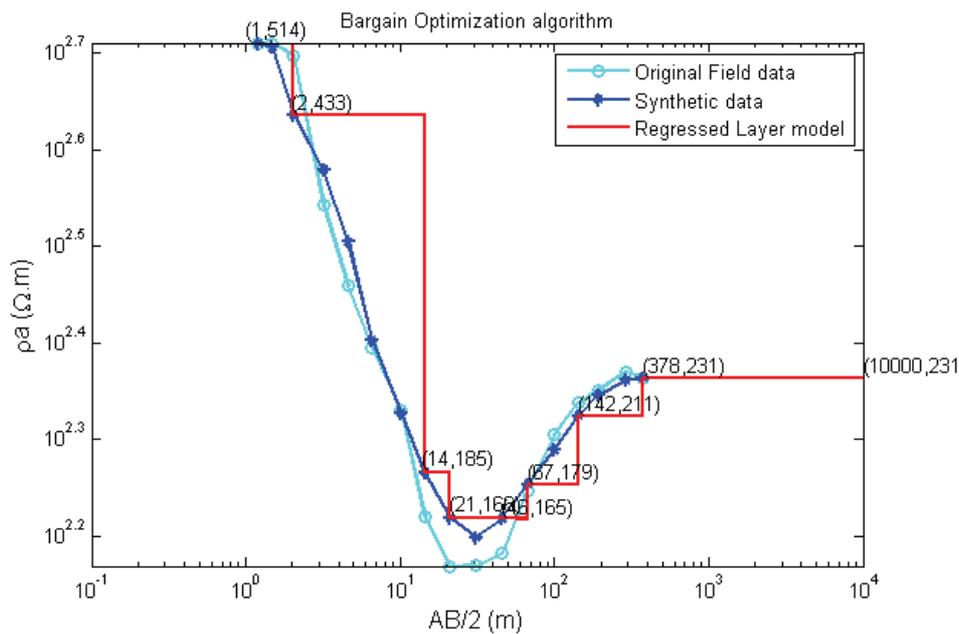


Fig. 8: Interpreted Layer Model Using BO

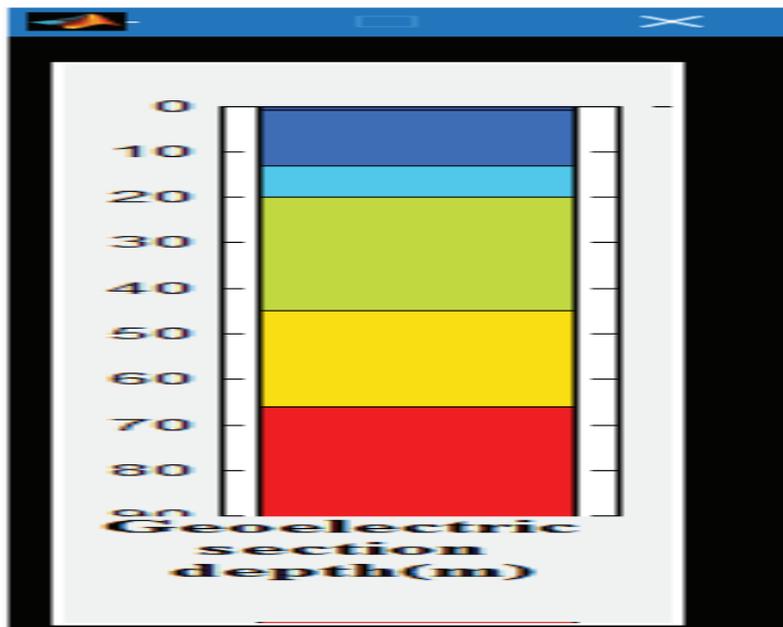


Fig. 9: Goelectric section of Nigerian data as interpreted by BO

Conclusions: This kind of geophysical optimising problem which includes the noise and missing data values works well with the soft computing approach. Mainly, if the study area chosen is vulnerable or cannot access the data clearly it would be better to adapt such intelligent techniques for inversion. The developments and advancements in the field of inversion which is dependable on the intelligent technique will possibly give the correct definition of the subsurface layer model. In these aspect of learning, the adaptive algorithm become accustomed itself for any kind of data. The results of the research work is summarised below

1. The program highlights on the generalised inversion than the conventional algorithm inversion. The major difference between the two approaches is that, in the earlier we need more number of field data that has been subjected for network training. The solution depends on the number of datasets involved in training. But in the latter part it is not necessary to have more number of data but the

network itself will generate more number of datasets and it indirectly supports the performance of the algorithm. So this would be the semi-supervised algorithm. Moreover it depends on the number of epochs which plays the major role in generating large number of synthetic datasets necessary for inversion.

2. This research work concentrates mostly on the performance of the algorithm by considering a) number of epochs, b) error percent, c) number of rules assigned to each iteration and d) computational time.
3. The algorithm framed on the generalised platform evaluates the complex field data. Performance analysis were made to check the algorithms reflection to the disturbed data.
4. The tested algorithm were subjected to inversion and it proclaims the best algorithm for inverting any non-linear data. Thus this algorithm would be the best weight reduction algorithm and efficient in picking the information necessary for inversion.
5. Different models can be generated while testing the BO algorithm. The more appropriate model with less error percentage can be chosen as the reliable model with more profit.
6. In general, large number of datasets collected from a particular area of study, is used to train the soft computing methods. However, the trained 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.
7. The conventional geophysical inversion techniques can be improved by using a certain kind of soft computing methods. By increasing the number of trained datasets, the BO will make the output to flow towards a distinctive solution. The BO can also be applied to 2D and 3D inversion problems with certain controlling parameters such as learning rate, momentum, the number of iterations and error percent. Acquiring knowledge through trained database is accomplished by BO algorithm. More reliable performance of BO technique will have the best scope in the future for estimating many optimization problems.

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