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Joint Inversion of Seismic and Geoelectric Sounding using Genetic Algorithm for Geothermal Prospect Identification

Kriti Yadav and Anirbid Sircar

Pandit Deendayal Petroleum University, India

E-mail address, Kriti.yphd15@spt.pdpu.ac.in Anirbid.sircar@spt.pdpu.ac.in

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ABSTRACT

Combination of various geophysical data within a single inversion framework improves model resolution of subsurface mapping. Genetic algorithm is a global optimization method that mimics Darwinian evolution and is well suited for nonlinear geophysical inversion problems. In this paper we have implemented a new approach of genetic algorithm for integration of seismic and geoelectric data for geothermal subsurface mapping. Ray inversion for Near Surface Estimation method is used for inversion of seismic refraction data. In genetic algorithm a best of fittest models from a population is selected and then applied to operators such as crossover and mutation to combine the most successful characteristics of each model. Genetic algorithm is applied to seismic and geoelectric data of Unai region to identify geothermal potential of the region. Results of inversion in this region suggests genetic algorithm is effective in solving problems with reasonably large number of free parameters along with the computation of objective function calculations.

1. INTRODUCTION

Joint inversion of different potential data sets is a very popular technique to understand the subsurface environment. In this technique the data sensitivities of different geophysical potentials are used to improve resolution of subsurface features by reducing the influence of noise and limiting the model range. Depending on the types of geophysical parameters, joint inversion is divided into two classes: (1) Inversion of data sets that are sensitive to same geophysical parameters such as seismic waves and receiver functions (Julia et al., 2000), and (2) Inversion of data sets that are inherently sensitive to different geophysical parameters like seismic velocity, electrical resistivity, etc. (Gallardo and Meju, 2003; Gallardo and Meju, 2007).

Joint inversion of magnetotelluric (MT) data and seismic data are sensitive to electrical resistivity and seismic wave respectively. Both the geophysical potentials are affected by subsurface pressure and temperature conditions. The value of seismic velocity in the subsurface depends on the bulk composition and mineralogy, while the electrical conductivity depends on the variation in subsurface zone conductivity (Jones et al., 2001). Velocity and resistivity are expected to change at major lithological boundaries, so in order to interprate the subsurface we should observe some common features by joint inversion of these two methods. Popular global and local methods of MT and seismic joint inversion modelling include Gauss- Newton (GN), Conjugate Gradient (CG), Simulated Annealing (SA) and Genetic Algorithm (GA). Genetic Algorithm is a very famous technique nowadays, it emerged in the 1960s with the idea of evolutionary programing. Holland (1975) and Goldenberg (1989) described the genetic algorithm, followed by Sen and Stoffa (1995) with its two different applications. Genetic Algorithm is used for the global optimization of multimodal, irregular functions. These algorithms start with a set of initial solutions and progressively modify the solution set by mimicking the evolutionary behaviour of the model until an acceptable result is achieved.

The objective and motivation of this work is to integrate seismic and MT data to understand the subsurface behaviour for geothermal prospect identification in Unai, Gujarat, India. In this paper we have used Genetic Algorithm method for joint inversion of MT and seismic data. Initially the MT and seismic data were inverted separately. The inversion results of seismic data are used as seed points for resistivity inversion. The integration results of data are used for identification of potential geothermal zones in the area.

2. STUDY AREA

Unai area is situated 96m above from sea level in the Vansda Taluka region of Navsari district (Sahajpal et al., 2015). The Unai hot spring is located in Narmada-Son Lineament. A mid-continental rift system called Narmada-Son Lineament (NSL) (Figure 1), divides the Indian shield into two halves (Mehr, 1995). One half is a thick pile of Deccan lava flows which predominate in the western part of NSL. The basaltic lava flows of the Deccan Trap constitute the major rock formation of the southern part of Gujarat. These trapping rocks are comprised of horizontal lava flows and cover a large portion of the area. They are compound flows and each flow unit consists of different sub-flows. Due to variation in hardness of the different flows, and of parts of the flows, the traps show flat-topped hills. The traps attain their maximum elevation near the border of Gujarat and Maharashtra, i.e. Dangs area. Here they show escarpments of about 1200 m height.

Seismic and MT data are inverted for understanding of the subsurface model. The relation between seismic and MT is established according to the requirement of coincident layer interfaces. In each layer the values of seismic velocity and resistivity are uniform but are mutually independent. Hence the fitted parameters for the interpretation are layer thickness, logarithmic resistivity and seismic wave velocity. The seismic and MT data are acquired along three profile lines, two parallel and one perpendicular. PASI seismograph and 24 Hz frequency geophones were used to acquire the data. In the case of the MT survey, a Phoenix Geophysics Ltd. instrument was used to acquire the data. In the MT survey, two ranges of data were acquired – one high frequency ranging from 10- 0.001 kHz and the other low frequency data of 0.0001 Hz. These frequency ranges give effective understanding of MT up to a depth of 13-15 km.

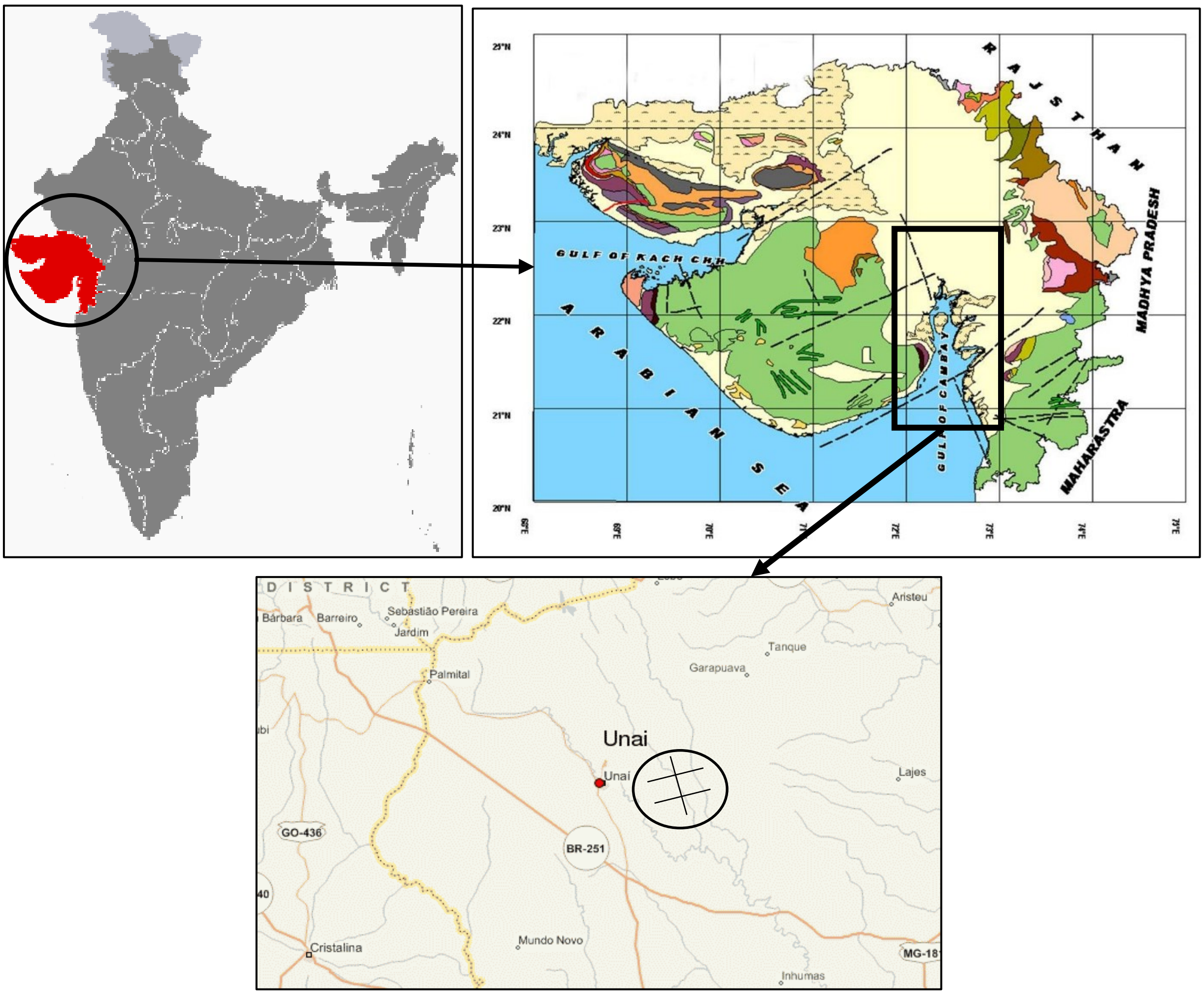

Figure 1: Geological map of Gujarat indicating Unai and profile lines along which seismic and MT data are acquired

3. METHODOLOGY

After testing various methods, an iterative deconvolution (Ligorria and Ammon, 1999) for processing and modelling of our data was done. Genetic algorithm method was used in this case as it is a multi-objective inversion method (Deb et al., 2002). The advantage of genetic algorithm over other stochastic inversion methods is that it can escape local minima and gives superior results for unknown number of local minima problems (Goldenberg, 1989). Genetic algorithm method is much more effective for inversion compared to linearized inversion methods. In genetic algorithm, the problem constraints can be simply resolved by embedding them into chromosome coding. It can solve the multimodal, non-continuous and even non-differential types of problems. Genetic algorithm is generally performed in six stages starting form generation of population, coding, fitness function, selection, crossover and mutation. In the first step of genetic algorithm, a population is generated. The initial populations are a set of initial values of the optimisation variables. Population generation will depend on two major criteria, namely size of population and seed number randomization. The seed number randomization depends on the computational efficiency required. After the population is developed the coding is done. Random variables are coded into string structures. These are coded in binary representation having 0's and 1's. The length of the string is defined according to the required solution accuracy. Coding of data is followed by the determination of fitness function value. Every string of the population is defined by its fitness function. Fitness function is generally derived from the objective function which is further used in successive genetic operations. The fitness function can be obtained as follows:

$$F(m) = \frac{2u_0 \infty u_s(m)}{(u_0 \infty u_0)+(u_s(m) \infty u_s(m))} \quad (1)$$

where,
u_0 & $u_s(m)$ = observed and synthetic data for model 'm' ∞ = correlation
F(m) = fitness

In the selection process, strings are selected on the basis of their fitness which forms a mating pool. The string with high fitness value are more likely to be selected than the strings with lower fitness value. There are three basic models of selection namely: (1) fitness proportionate selection; (2) rank selection and (3) fitness proportionate selection. The fitness of a string can be determined as:

$$P_s(m_i) = \frac{F(m_i)}{\sum_{j=1}^{n} F(m_j)} \quad (2)$$

where,
n = number of models
m_i = initial model

After the models are selected and paired, the genetic operator of crossover and recombination takes place. In the crossover process, the genetic information between the paired models are shared. In terms of geophysical inversion, crossover allows exchange of some information between paired models by generating a new pair of models. The last step of genetic algorithm is mutation. In mutation, random alteration of bits takes place which can be carried out during the crossover process. The rate of mutation is specified by the probability determined by the algorithm design. Low mutation probability will limit the number of random walks while high mutation probability will result in a great number of random walks. High probability mutation rate can delay convergence of the algorithm to the optimal model fit.

The genetic algorithm in this case was run with the number of models in each iteration of 1000 for 100 iterations, which resulted in 10,000 forward computations. Each model set in the genetic algorithm method is optimal in regard to a distinct relative factor between the inverted data. The Chi-square error for different objective functions is minimized by the distribution of misfit values and number of final models (Dal Moro and Pipam, 2007). The final result set is made up of models with similar model and misfit parameter. The compatibility of seismic and electrical models were verified from additional information. The shape of the Chi-square error curve indicates the minimization extent of the misfit for each data set.

4. RESULTS & DISCUSSION

In this case Ray Inversion of Near Surface estimation is done where the seismic refraction data are used to determine the combination of compressional wave velocity, shear wave velocity, impedance and Poisson's ratio. Pre-stacking of seismic data is done in order to understand the thickness and velocity of the subsurface formation. Change in angle due to the physical properties of the subsurface formation affects the reflection coefficient and arrival times of the seismic energy. Figure 2 shows the first break pre stacking of seismic data to determine velocity and thickness of the layer.

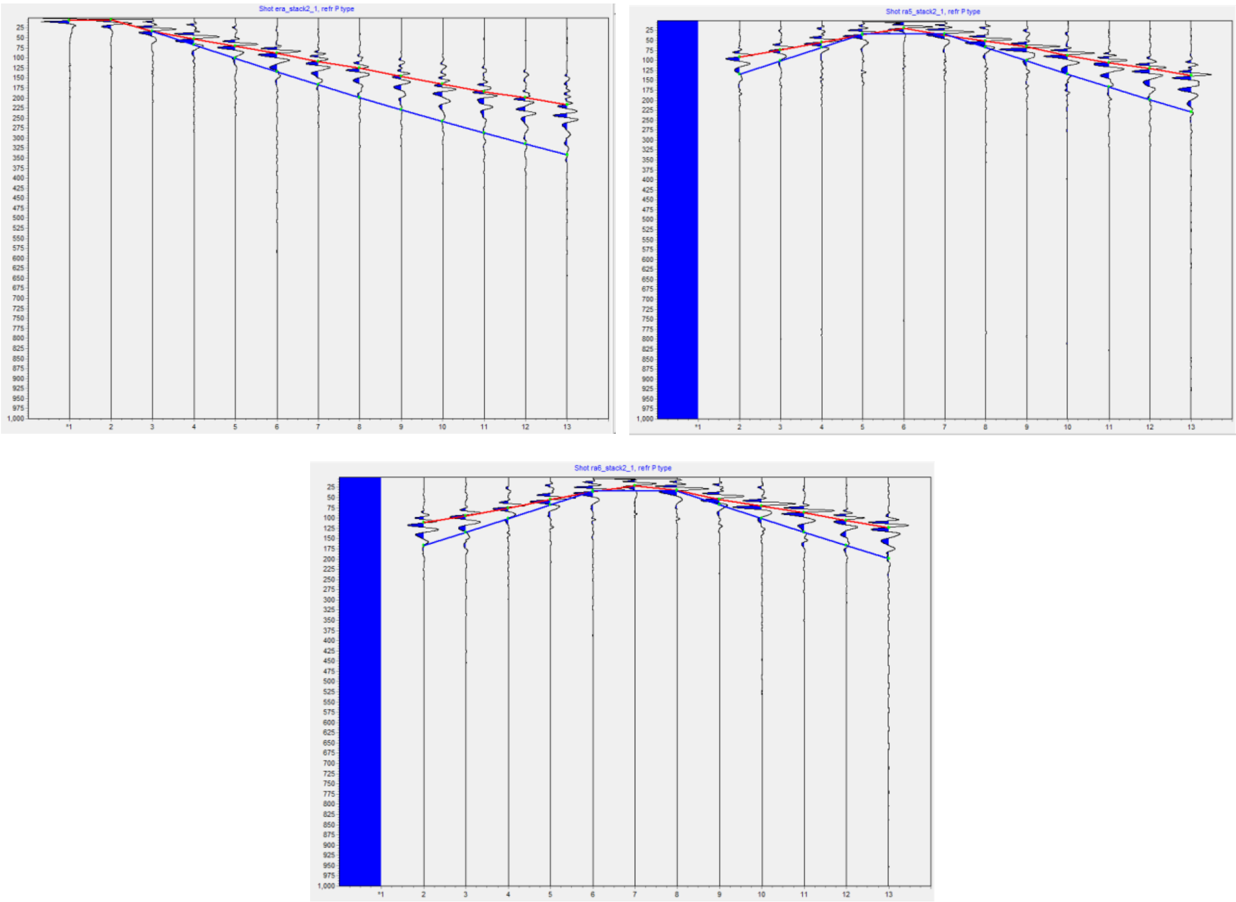

Figure 2: Pre-stacking of seismic refraction data for profile 1, 2 and 3

After pre-stacking of seismic data, velocity of each layer has been calculated and the inverse of the slope helped in determining the thickness of the layer. The results of seismic data analysis suggests the presence of three layers. Table 1 represents the velocity and thickness of each layer for each an individual profile.

The subsurface topography results were obtained by calculating the velocity of P-waves in each and every layer and then calculating the zone thickness. It can be observed from Figure 3 that a three layer system is observed for all the three profiles. The thickness and velocity of layers was calculated by using two-way time vs. offset plot as shown in Figure 3. The velocity of layer 1 ranges from 900 m/sec to 118.6 m/sec with a thickness ranging from 5.789 m to 6.777m. The velocity of layer 2 ranges from 1732 m/sec to 2100 m/sec with a thickness range between 7.995 m to 10.996 m. The velocity of layer 3 varies from 923 m/sec to 2200 m/sec and the thickness goes to infinity due to lack of data.

Table 1: Velocity and thickness of layer 1 and layer 2 along profile 1, 2, & 3

Profiles	Velocity in Layer-1	Velocity in Layer-2	Velocity in Layer-3	Thickness of Layer 1	Thickness of Layer 2	Thickness of Layer 3
Profile 1	118.6 m/s	Single layer model	923m/s	5.789 m	7.995 m	Infinity
Profile 2	900 m/s	1732 m/s	1834m/s	6.777 m	10.996 m	Infinity
Profile 3	900 m/s	2100 m/s	2200m/s	Infinity	Infinity	Infinity

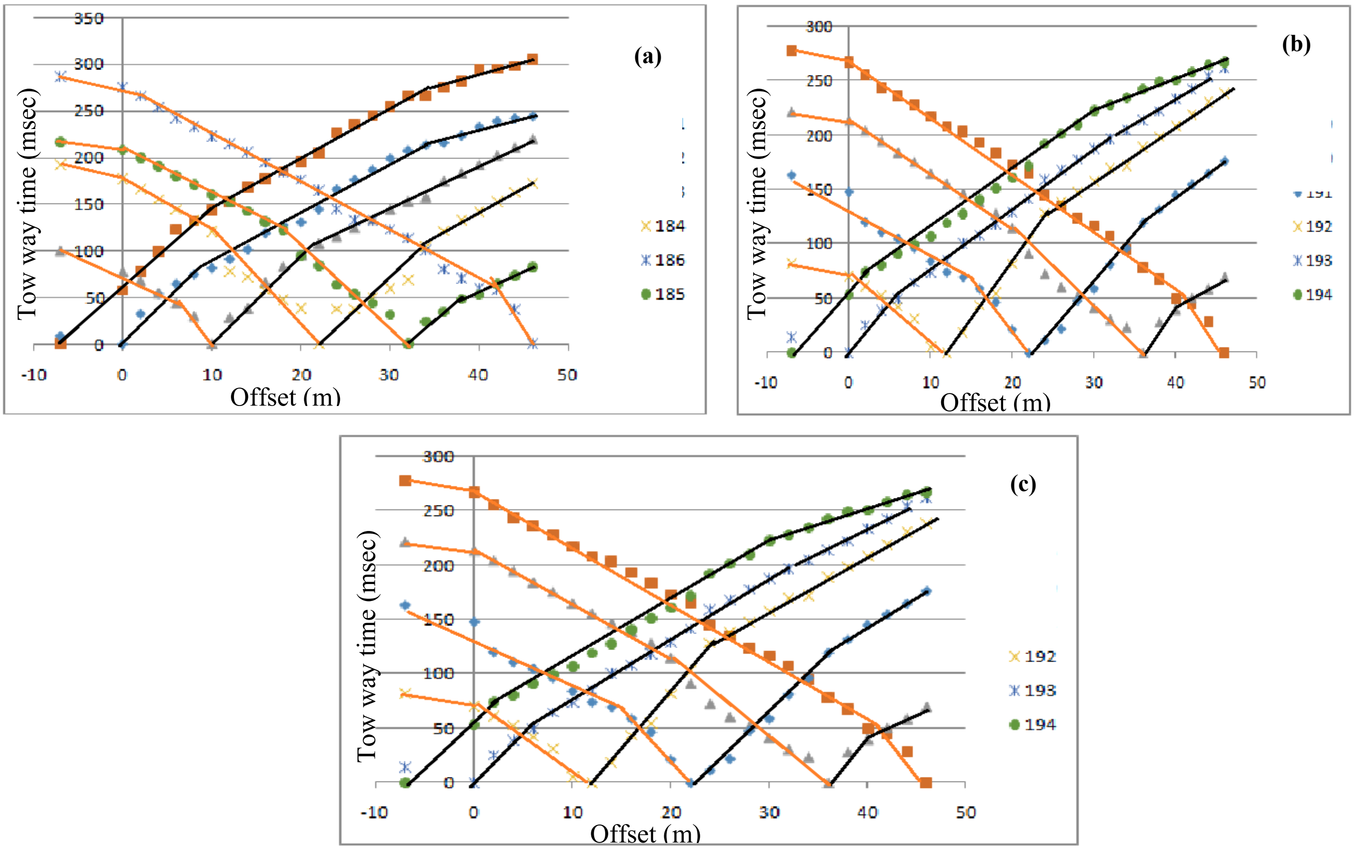

Figure 3: (a), (b) and (c) Two way time Vs offset plot for three profiles used to predict the subsurface structure

Figure 4 represents the subsurface layer obtained from two-way time vs. offset data and depth of each layer along profiles 1, 2 & 3. It should be noted that the third layer could extend to infinity. The depth of investigation is proportional to the spread of geophones. To this point, the seismic data acquired results suggest a three layered system. Now, the densities of these layers were found using the Gardner's equation. The average densities of each layer can be tabulated as in Table 2.

Table 2: Average Density of Layers Interpreted by Seismic

PROFILES	**AVERAGE DENSITY g/cc**		
	Zone 1	**Zone 2**	**Zone 3**
Profile 1	1.013	1.176	1.312
Profile 2	1.009	1.166	1.3115
Profile 3	1.002	1.2	1.28

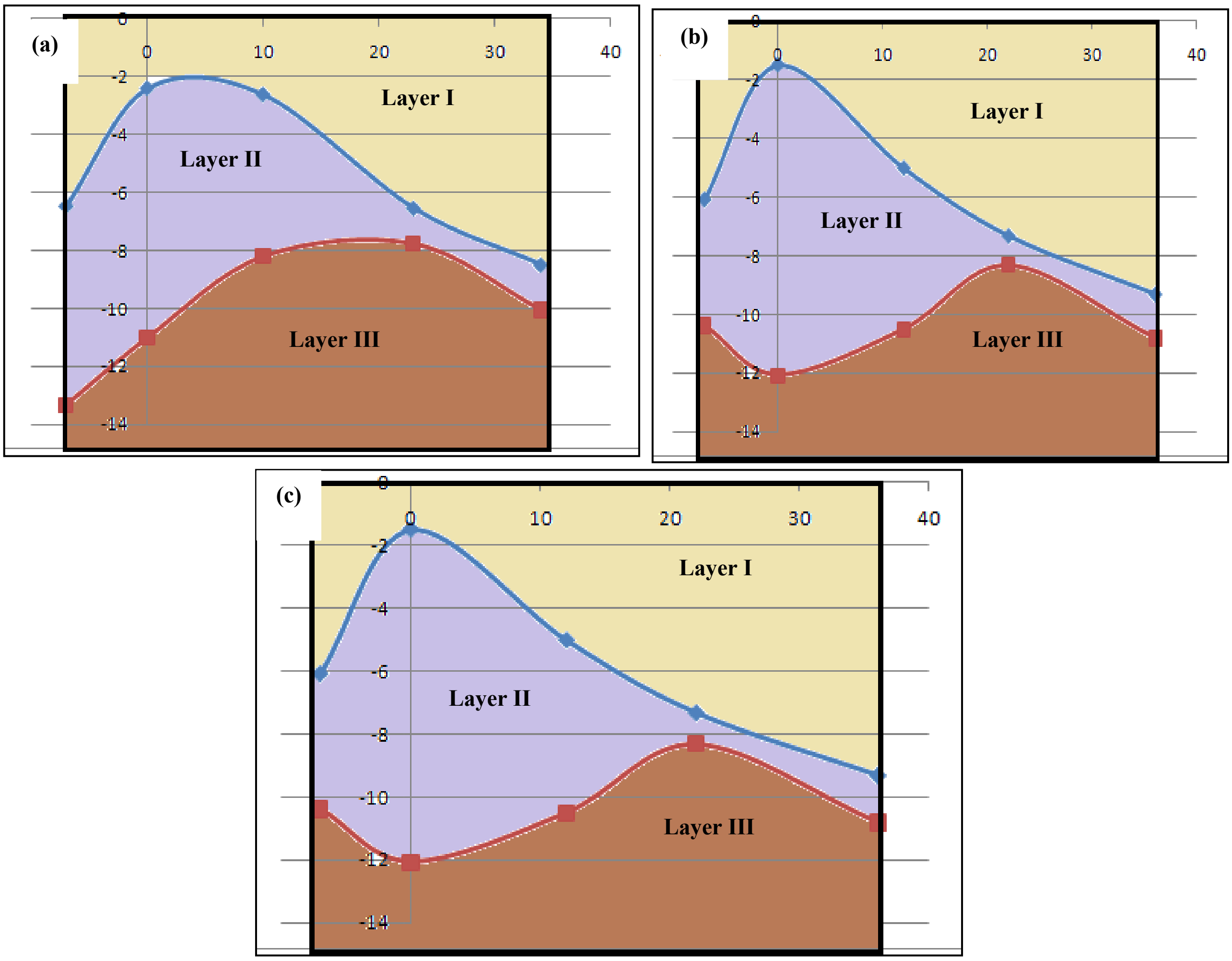

Figure 4: Depth estimation of Sub-surface layers along (a) profile 1, (b) profile 2 and (c) profile 3

These densities are then used while integrating the subsurface model and also using understanding of the lithology present at different depth. The density of layer 1 varies in ranges from 1.002 g/cc to 1.013 g/cc, for layer 2 it ranges from 1.176 g/cc to 1.2 g/cc and for layer 3 it ranges from 1.28 g/cc to 1.312 g/cc. Another important observation that could be made is that the anticlinal structures are shifting in each profile, i.e. a skewed trend of these structures could be obtained. This observation is schematically portrayed in Figure 5. If we assume that the structures observed at shallower depths will be replicated at greater depths as well, we can safely say that a directional well needs to be drilled in order to hit all the structural highs, which could act as a trap to a water aquifer.

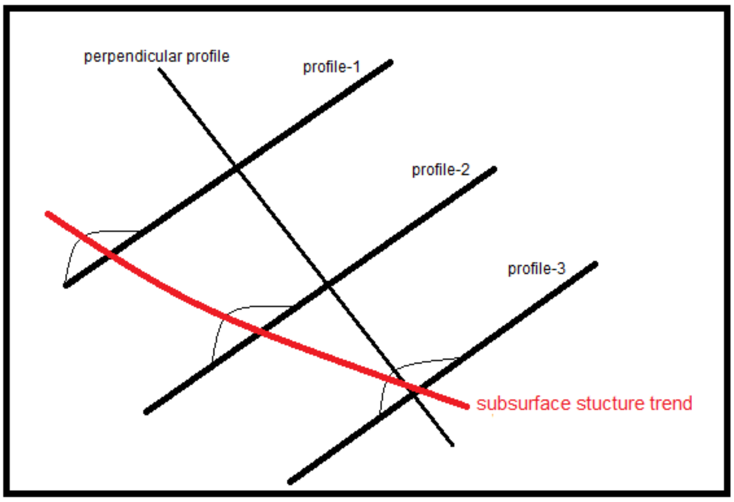

Figure 5: Subsurface structure trend along three profiles.

After the understanding of subsurface velocity and thickness from seismic refraction survey the obtained model were integrated with geoelectrical data of the area. Based on the analysis of the distribution of skew of impedance tensor it can be said that for the frequency 10000 Hz – 1 Hz , the survey area is characterized by the geological structure equivalent to 1D or 2D geoelectrical model (skew values for the whole area are about 0.05). This parameter increases from 0 to 0.25 for frequencies from 1 Hz to 0.01 Hz. Skew parameter is bigger than 0.3 for frequencies greater than 0.01 Hz.

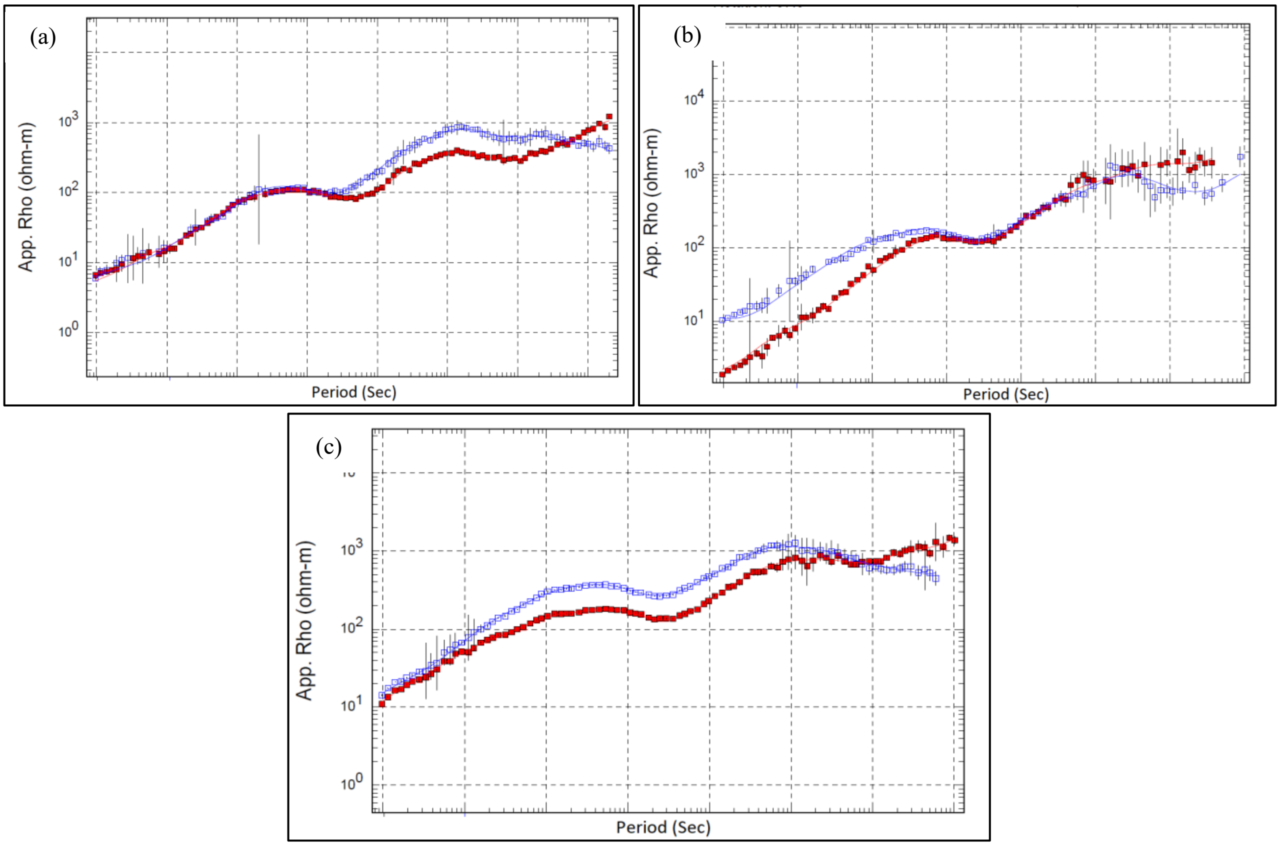

Figure 6: Skew and Tipper curves for profile (a) 1, (b) 2 and (c) 3

Figure 6 represents skew and tipper curves which are also known as apparent resistivity curves, for profiles 1, 2 and 3. These curves are prepared on the basis of data obtained from geoelectrical survey and the seed point obtained from seismic data for guesstimation of resistivity in the area. The apparent resistivity value for layer 1 varies from 50 Ωm- 72 Ωm with h1= 7.1m, for layer 2 it ranges from 61Ωm- 70 Ωm and h2 = 8.3 and for layer 3 the apparent resistivity value ranges from 72 Ωm - 81 Ωm with h3= infinity. The apparent resistivity curve in case of Unai is A-type where the resistivity of layers increases with depth. The low resistivity value indicates the presence of a high conductive body which gives signal for presence of a geothermal prospect.

After the inversion of the data, the Chi- Square error method is used to stabilize the model. For profile 1, the fitness function of the joint inversion stabilised after the 100th iteration when it reached an error criterion of 0.1, for profile 2, the fitness function of the joint inversion stabilised after the 150th iteration at 0.12 and for profile three, the fitness function of the joint inversion stabilised after the 200th iteration when it reached an error criterion at 0.1.

5. CONCLUSION

Seismic and MT data were acquired along three profile lines, two horizontal and one perpendicular, in Unai study area. The survey was conducted to understand the subsurface formation and anomalies. In this case genetic algorithm method is used for joint inversion of seismic and geoelectrical data. Genetic algorithm is the most effective optimization solution for geophysical problems. In this paper genetic algorithm is used for nonlinear geophysical inversion of seismic and geoelectrical data. The best fit model is chosen from the population and applied to operators such as crossover and mutation for most promising features in the subsurface model. The results from seismic data suggest the presence of three subsurface layers. The velocity of the first layer ranges from 118.6 m/sec to 900 m/sec, velocity of the second layer ranges from 1732m/sec to 2100 m/sec and for layer 3 it ranges from 923 m/sec to 2200 m/sec. The thickness of the first layer varies from 5.78m to 6.77m while the thickness of the second layer varies from 7.99m to 10.99m and for layer 3 it goes to infinity. Densities of the subsurface layers are estimated by using Gardner's formula with the help of P- wave velocity. The average density estimated for layer 1 is 1.009g/cc, for layer 2 it is 1.176g/cc and for layer 3 it is 1.312g/cc. The apparent resistivity value of layer 1 ranges from 50 Ωm- 72 Ωm with h1= 7.1m and for layer 2 it ranges from 61Ωm- 70 Ωm and h2 = infinity. Layer 1 thickness obtained from seismic is very close to the thickness derived from geoelectric data. Layer 2 thickness was resolved from seismic however, the same could not be resolved using geoelectric interpretation. Both seismic and electrical data suggest presence of geothermal body in the shallow models for Unai. The fitness function of the joint inversion model stabilized for layer 1, 2 and 3 at 100th, 150th and 200th iteration when it reached error criterion of 0.1, 0.12 and 0.1 respectively.

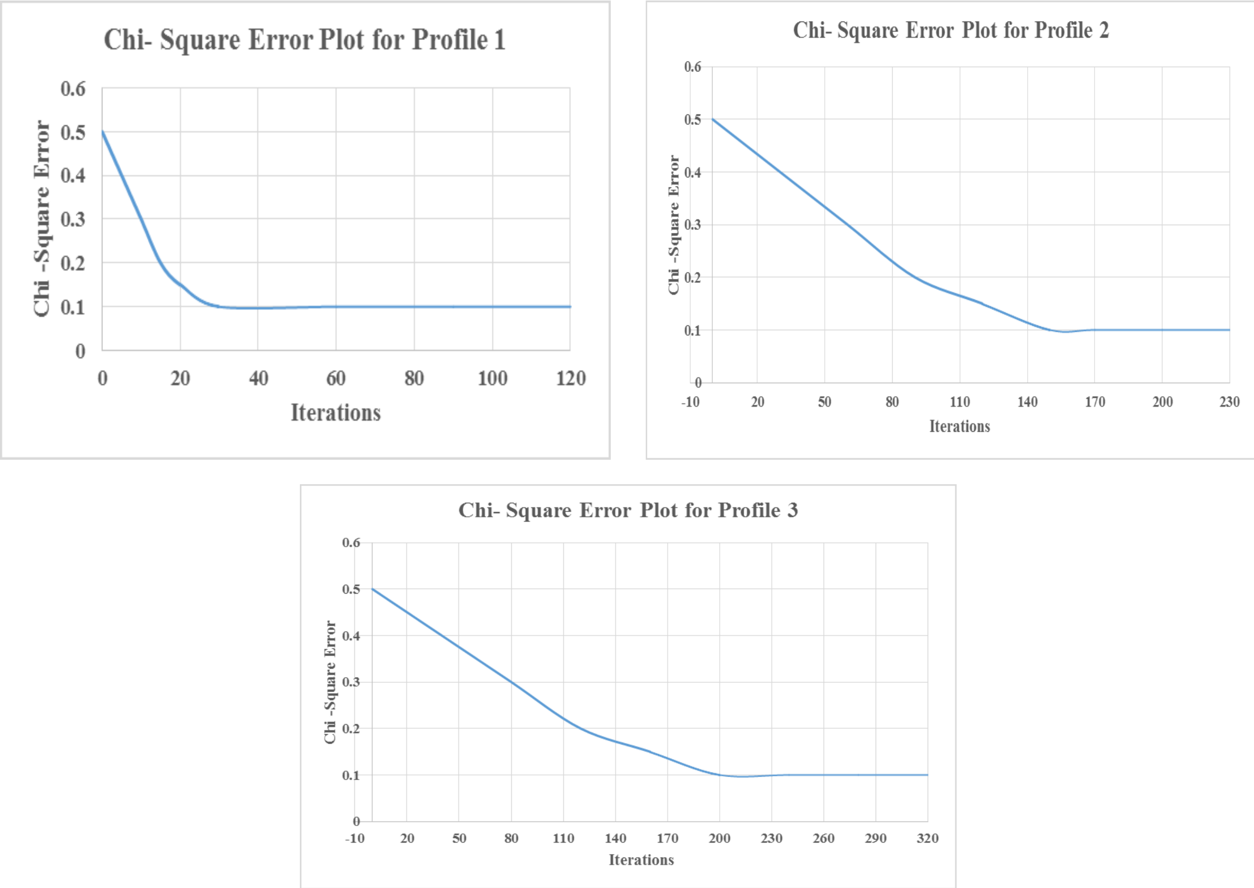

Figure 7: Chi- Square error plot for profile 1, 2 and 3

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