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A new Approach for Residual Gravity Anomalies Interpretations: Artificial Bee colony Optimization Algorithm

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ABSTRACT

In this paper, we applied a meta-heuristic algorithm in solving inverse problems in geophysics. Artificial bee colony optimization algorithm works based on probability, test and trial and it stems from honey bees in the nature. Such behavior in bees is closely similar to the inverse problems in geophysics for finding the actual/real parameters. Therefore, this idea is applied to solve an inverse problem. Firstly, the efficiency of this method is evaluated using synthetic model with and without random noise and after a theoretical verification, the procedure is applied to the field data from Qom salt dome, Iran. A very good agreement was observed/ revealed between the results obtained by the artificial bee colony algorithm and drilling information.

Key words: Bee Colony Algorithm, Gravity Data Inversion, Synthetic and Real Data, Salt Dome, Qom Area

INTRODUCTION

Gravity method has been used in investigations of wide range of investigations such as tectonic studies, geotechnical and archaeological studies; regional geological mapping; engineering studies; coal, petroleum and mineral explorations; groundwater finding, environmental studies; volcanology and geothermal studies (Blakely 1996; Paterson and Reeves, 1985; Hinze 1990). Gravity data inverse modeling refers to a numerical procedure that constructs a model of subsurface geology from measured data on the earth surface (Qiu et al., 2009). Modeling is one of the most critical and sensitive stages of interpretation of Gravity Anomalies (Shadmehri et al., 2014). In the inverse modeling of gravity data, two different types of operators are applied irrespective of whether the relationship between model parameters and data is linear or not Figure 1. In the first case, if the distribution of density is going to be specified, the geometry is assumed constant and a linear operator used (Mottl and Mottlova, 1972; Oldenburg 1974; Last and Kubik, 1983; Shadmehri et al., 2014). In the second case, if the geometric parameters of the source are going to be determined, the density contrast must be assumed constant and a non-linear operator used (Barbosa et al., 1997; Farquharson and Oldenburg, 1998; Montesinos et al., 2005). Most practical geophysical inversion problems are non-linear (Yang 1997; Wang 2002), so non-linear inversion methods may be the best choices to solve these problems (Sanyi et al., 2009; Greenhalgh et al., 2006). Since in most of the inverse modeling problems, the number of the model parameters is more than the observations, the application of the numerical method is more effective (Rama Rao et al., 1999). In addition, as the problem has great dimensions, meta-heuristic algorithms are appropriate to solve these problems (Sanyi et al., 2009; She Yang 2011). Metaheuristic algorithms have many advantages over conventional algorithms due to their global search capability (Yang 2008, 2009 and 2010). Meta-heuristic algorithms are becoming increasingly popular and powerful and they have the potential to provide better solution strategies (She Yang 2011).

Accordingly, in order to carry out/perform the inversion of gravity data through Simulated Annealing (SheYang, 2011), Genetic Algorithm (GA) (Montesinos et al., 2005; Tiampo et al., 2004), Particle Swarm Optimization (PSO) (Sanyi et al., 2009; Roy, 2009; Toushmalani 2013), Ant Colony Optimization (ACO) (Sanyi et al., 2009; She Yang 2011; Sanyi et al., 2008; Shadmehri et al., 2014), Simulated Annealing (SA) (Sanyi et al., 2009; She Yang, 2011), Firefly Algorithm (Yang 2008, She Yang 2011) etc. are being used till now. The present paper has used artificial bee colony optimization (BCO) as a new and effective procedure for the inversion of gravity data. Theoretical data with and without random noise are investigated to depict the efficiency of this procedure, Artificial bee colony optimization algorithm is discussed in section II. In section III, the produced theoretical data and ground survey data set from Qom salt dome, Iran is analyzed.

Artificial Bee Colony Optimization Algorithm

There was a great interest among the researchers to generate search algorithms that find near-optimal solutions in reasonable running time (Sousa et al., 2003; Salem et al., 2009). The swarm-based algorithms (For example, ant colony optimization (ACO) algorithm; particle swarm optimization (PSO) algorithm; artificial bee colony optimization (BCO) Algorithm; Imperialist Competitive

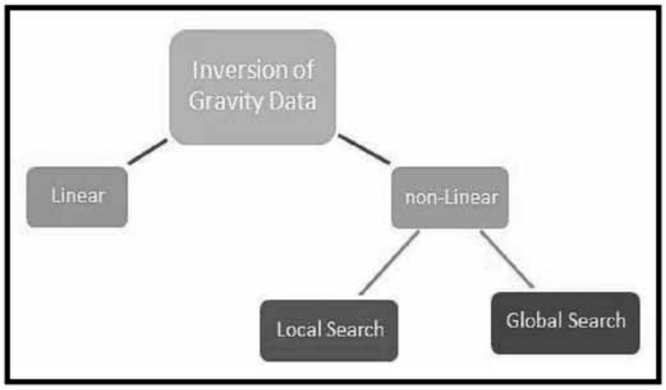

Figure 1. Operators of gravity data inversion (Sanyi et al., 2009)

Table1. Relationship between the behavior of bees and the optimization problem (Wei Gao et al., 2014).

Behavior of Bees	**Optimization Problem**
position of nectar	feasible solution
yield of nectar	value of fitness function
honey speed	converge speed
greatest gain	optimal solution

Algorithm (ICA) are search algorithms capable of locating good solutions efficiently (Sousa et al., 2003; Salem et al., 2009). The artificial bee colony optimization (BCO), proposed by Karaboga from Turkey Erciyes University in 2005 for real parameter optimization, is a recently introduced swarm intelligence algorithm (Wei Gao et al., 2014). The BCO represents the new meta-heuristic algorithm capable of solving optimization problems (Lucic et al., 2006) and behaves partially alike, and partially differently from bee colonies in nature (Lucic et al., 2006). The BCO algorithm is applied to solve the optimization problems and finding the optimal degree of a function or a combination of multi-variable numerical functions (Pham et al., 2005, 2006 and 2007; Karaboga et al., 2007; Karaboga et al., 2008; Marinakis et al., 2011). In the BCO algorithm, the food foraging process of a bee colony is started by onlooker bees that are sent to forage randomly for food sources in promising lands. A bee colony is able to forage food sources for a long distance and in different feasible directions. As the food foraging behavior process starts, some colony bees are selected continuously as onlookers. If food from a direction reaches a standard level, the onlooker bees store it in hive and proclaim a relative direction through waggle dance. The waggle dance is a significant relational instrument for colony, which includes all information outside hive. In Table 1, a one to one relationship exists between the behavior of bees and the optimization problem.

BCO begins with presenting an initial random population of search space, i.e. the initial population phase:

$$s_{mi} = s_i^{min} + rand * \left(s_i^{max} - s_i^{min}\right) \tag{1}$$

Which in equation (1) s_{mi} is a solution to the optimization problem and each s_i is an n-dimensional vector. Then fitness function of each solution is calculated (Marinakis et al., 2011). The next step of the algorithm employs bees' phase in which a new solution (Y_{mi}) in the neighborhood of s is generated for each s_i.

$$Y_{mi} = s_{mi} + \rho_{mi}(s_{mi} - s_{ki}) \tag{2}$$

$$k = int(rand * SN) \tag{3}$$

In equation (2), ρ_{mi} is a uniform distribution of the real random numbers on the interval [1,–1]. s_{ki} suggests i^{th} from k^{th} solution of population in which k is randomly chosen among different pupulation categories {1, 2, 3... *SN*, *SN*: population size}. If the new solution is a better fitting, it is replaced with previous solution. In the phase of onlooker bees, each bee choosing a solution based on the probability calculated with equation (4), with a selective approach. Then onlooker bee chooses a new solution for chosen solution, the previous one is replaced by new solution, provided the latter is better than the former.

$$\vec{P}_m = \frac{fit_m(\vec{s}_m)}{\sum_{m=1}^{SN} fit_m(\vec{s}_m)} \tag{4}$$

Which in the equation (4), $fit_m(\vec{s}_m)$ is fitting function$(\vec{s}_m)$. If the number of the cycles, which are not improved by the solution is higher than a pre-determined degree, the solution is discarded and a new solution is randomly generated (Karaboga 2005). These phases are repeated until some stopping criteria are satisfied (Pham et al., 2006; Pham et al., 2007; Lucic et al., 2006; Hadidi et al., 2010; Zhang and Wu, 2011).Pseudo code of the BCO algorithm in its simplest form is shown in Figure 2.

```
1. Initialise population with random solutions.
2. Evaluate fitness of the population.
3. While (stopping criterion not met)
   //Forming new population.
4. Select sites for neighbourhood search.
5. Recruit bees for selected sites (more bees for
       best e sites) and evaluate fitnesses.
6. Select the fittest bee from each patch.
7. Assign remaining bees to search randomly
   and evaluate their fitnesses.
8. End While.
```

Figure 2. Pseudo code of the basic BCO algorithm (Pham et al., 2006; Salem et al., 2009).

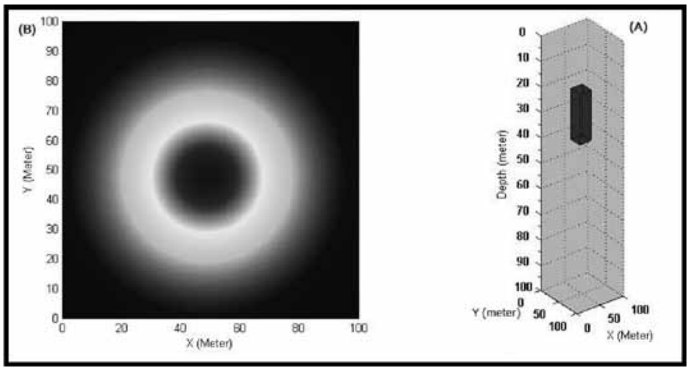

Figure3. a) The three-dimension subsurface synthetic model; b) The gravity anomaly map of the causative body.

Modeling of Gravity Data

The model used here is one of the most popular ones described by Last and Kubik (1983) in order to model the gravity anomalies. The gravity effect at the observation point i is given by:

$$g_i^{calculated} = \sum_{j=}^{M} a_{ij} v_j + p_i \qquad i = 1,2, \dots N \tag{5}$$

Where g is the gravity anomaly, M is the number of blocks, a_{ij} is the kernel matrix, p_j is the noise of the i^{th} data, v_j is the density contrast of the j^{th} block. Here, density contrast is solved by BCO algorithm. A MATLAB Code for the BCO algorithm was implemented and was tested on theoretical and real gravity data.

The Synthetic Modeling

In this section, one simple model is applied to test the abilities of the BCO algorithm for inversion of gravity data. Depths to the bottom and top of causative body were selected as 40 and 20 m respectively while the widths of body in the x and y coordinates were selected as 20m. The density contrast is set to 1000 kg/m^3 for the causative body. The 3D causative body model and its gravity anomaly are shown in Figure 3.The map of inverse modeling without random noise is shown in Figures 4. Then, 20% random noise was added to the synthetic model. The picture of inverse modeling with random noise is shown in Figures 5. Root mean square (RMS) values and the iteration number for synthetic model are shown in Figure 6.

The Real Modeling

In this section, the real data inversion is considered. The case study for performing gravity method was a salt dome in Qom province located in the central Iran (Figure 7) (Motasharreie et al., 2010; Aghashahi and Zomorrodian, 1981; Alvandi and Babaei, 2017). This research is aimed to investigate the depth of salt dome of Qom (Motasharreie et al., 2010). The gravity measurement was done by Institute of Geophysics University of Tehran. Based on a priori information, a density contrast of 0.6 g/cm^3 is chosen for the inversion (Salimi and Teymoorian, 2014). Residual gravity anomalies measured over salt dome of Qom is shown in Figure 8. The result from the inversion of bee colony optimization algorithm is presented in Figure 9. RMS values and the iteration number for real model are shown in Figure 10. The depth obtained in this case is found to be in very good agreement with wavelet transform, least squares approach, Oldenburg-Parker inversion and Euler Deconvolution methods (Table 2).

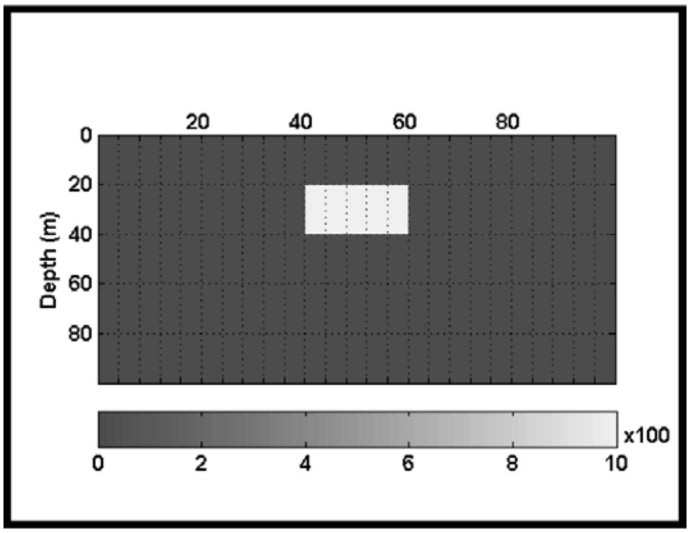

Figure 4. The result of the inverse modeling for the theoretical model.

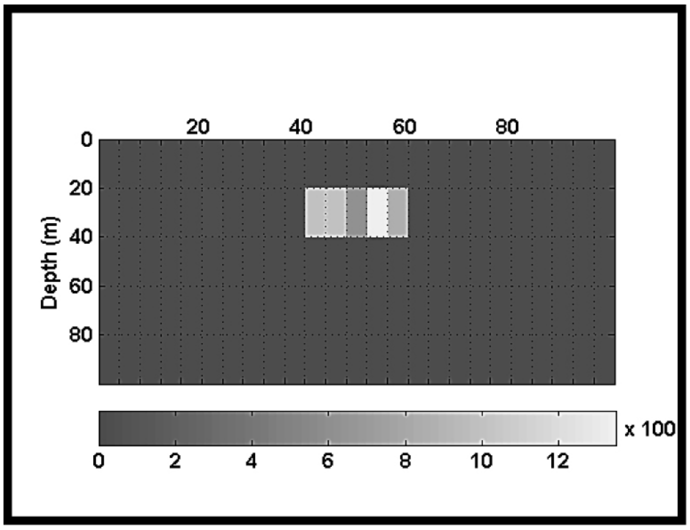

Figure 5. The result of the inverse modeling for the theoretical model (with 20% random noise).

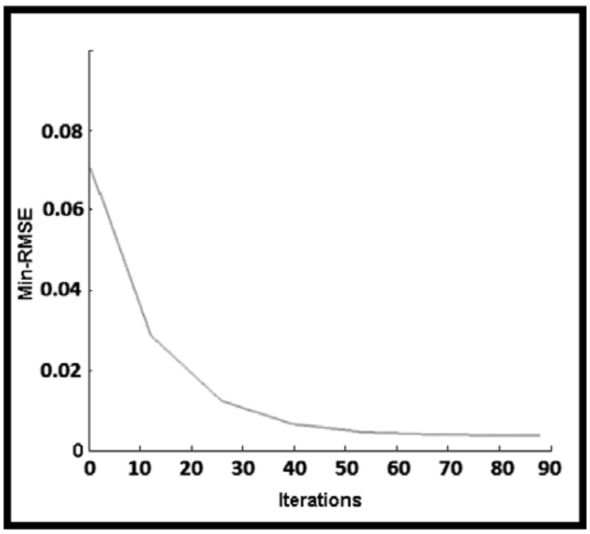

Figure 6. RMS values against the iteration number for synthetic model (Iteration Number =100; Convergence Value=45).

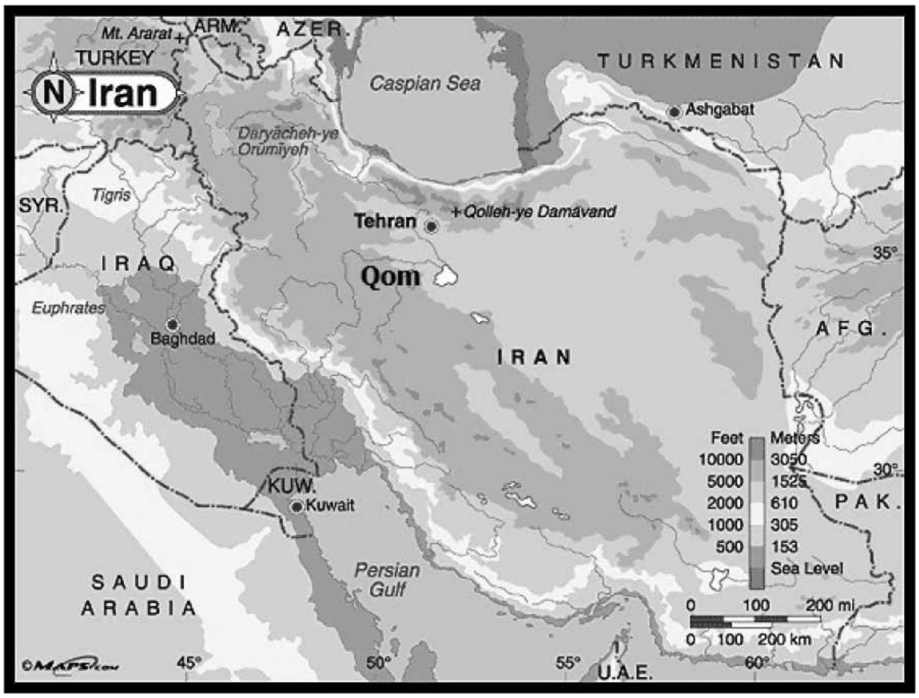

Figure7. Geographic location of Qom area in the map of Iran.

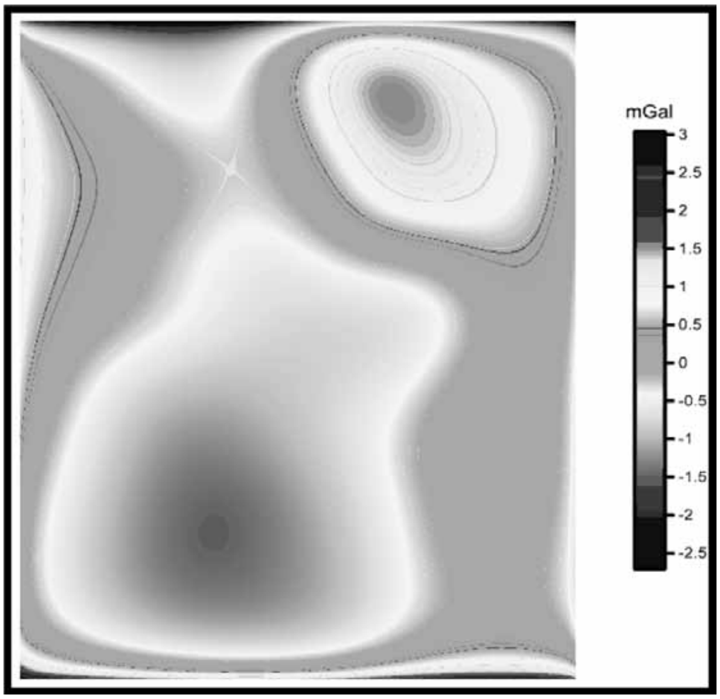

Figure 8. The gravity anomaly map of the study area.

Table 2. Depth Estimation from Gravity Data of Qom Salt Dome.

Method	Depth (km)	Reference
Wavelet	1.06	Motasharreie et al., 2010
Least Squares	1.05	Motasharreie et al., 2010
Oldenburg - Parker	1.2	Salimi and Teymoorian, 2014
Euler Deconvolution	1.1	

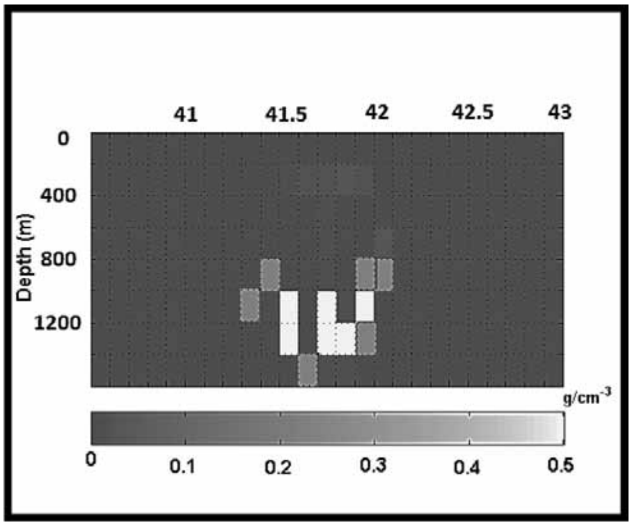

Figure 9. The result of the inverse modeling for the salt dome.

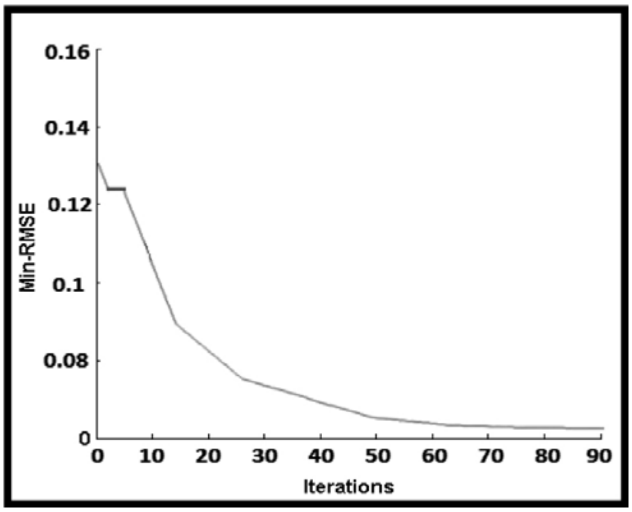

Figure 10. RMS values against the iteration number for real model (Iteration Number=100; Convergence Value=50).

CONCLUSION

By using the proposed inverse modeling method of gravity anomaly, i.e. honey bee colony optimization algorithm, it is possible to optimize models with simple geometries. However, it is to be noted that having a basic knowledge of model helps significantly in solving the problem of non-uniqueness of the answer in inverse modeling. This approach was tested on one theoretical and real data, and very good results were achieved in determining the depth.

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Compliance with Ethical Standards

The authors declare that they have no conflict of interest and adhere to copy right norms.

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