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## Comparison Result of Inversion of Gravity Data of a Fault by Cuckoo Optimization and Levenberg-Marquardt Methods.

Reza Toushmalani\*, Zeinab Parsa and Amir Esmaili

Department of Computer, Faculty of engineering, Kangavar Branch, Islamic Azad University, Kangavar, Iran.

### ABSTRACT

The purpose of this study was to compare the performance of two methods for gravity inversion of a fault. First method [The **Cuckoo Optimization**(COA)] is new evolutionary optimization algorithm which is inspired by lifestyle of a bird family called cuckoo. Second method [The Levenberg-Marquardt algorithm (LM)] is an approximation to the Newton method used also for training ANNs. In this paper first we discussed the gravity field of a fault ,then describes the algorithms of COA and LM And presents application of Levenberg-Marquardt algorithm, and a **Cuckoo Optimization** in solving inverse problem of a fault. Most importantly the parameters for the algorithms are given for the individual tests. Inverse solution reveals that fault model parameters are agree quite well with the known results. A more agreement has been found between the predicted model anomaly and the observed gravity anomaly in COA Method rather than LM method.

**Keywords:** Particle swarm optimization, Levenberg-marquardt method, inversion, gravity data, fault

*\*Corresponding author*

## INTRODUCTION

Optimization has been an active area of research for several decades. As many real-world optimization problems become more complex, better optimization algorithms were needed. In all optimization problems the goal is to find the minimum or maximum of the objective function. Thus, unconstrained optimization problems can be formulated as minimization or maximization of D dimensional function:

$$\text{Min (or max) } f(x), x = (x_1, x_2, x_3, \dots, x_D) \quad (1)$$

Where, D is the number of parameters to be optimized. Many population based algorithms were proposed for solving unconstrained optimization problems. Genetic algorithms (GA), particle swarm optimization (PSO), are most popular optimization algorithms which employ a population of individuals to solve the problem on hand. The success or failure of a population based algorithms depends on its ability to establish proper trade-off between exploration and exploitation. A poor balance between exploration and exploitation may result in a weak optimization method which may suffer from premature convergence, trapping in a local optima and stagnation. [K Khan, A Sahai, 2012].

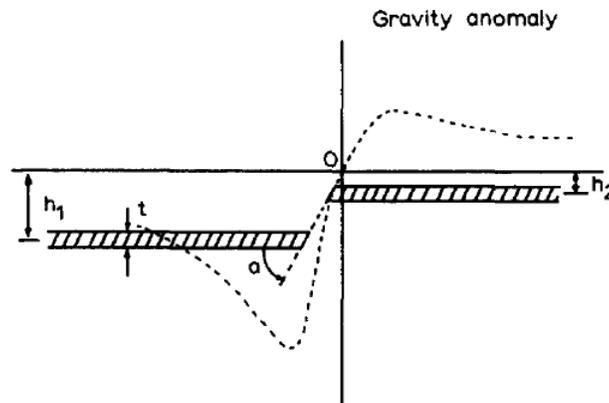
Another algorithm which is inspired by cuckoo lifestyle is “Cuckoo Optimization Algorithm (COA)” developed by Rajabioun. Through using a benchmarking study, he demonstrated the efficiency of this algorithm which can be considered as the most appropriate algorithm for discrete issues, proving its accelerated confluence and global optima accomplishment. [Rajabioun R,2011].

The gravity method was the first geophysical technique to be used in oil and gas exploration. Despite being eclipsed by seismology, it has continued to be an important and sometimes crucial constraint in a number of exploration areas. In oil exploration the gravity method is particularly applicable in salt provinces, over thrust and foothills belts, underexplored basins, and targets of interest that underlie high-velocity zones. The gravity method is used frequently in mining applications to map subsurface geology and to directly calculate ore reserves for some massive sulfide ore-bodies. There is also a modest increase in the use of gravity techniques in specialized investigations for shallow targets. Also it has application in agriculture and archeology .Data reduction, filtering, and visualization, together with low-cost, powerful personal computers and color graphics, have transformed the interpretation of gravity data. Also in gravity methods, Euler and Werner deconvolution depth and edge - estimation techniques can help define the lateral location and depth of isolated faults and boundaries from gravity data. Complex geology with overlapping anomalies arising from different depths can, however, limit the effectiveness of deconvolution fault-detection results.(M. N. Nabighian et al.(2005);Toushmalani Reza,(2010a);Toushmalani Reza,(2010b) Toushmalani Reza,(2010c); Toushmalani Reza,(2010d);;Toushmalani Reza,(2011) Toushmalani(2013a) Toushmalani(2013b) Toushmalani, R., & Esmaeili(2013)).

The outline of this paper is as follows. In first section we discussed the gravity field of a fault, Section II describes the algorithms of COA and LM. Section III presents application of Levenberg-Marquardt back propagation algorithm, and a Cuckoo Optimization Algorithm in solving inverse problem of a fault. Most importantly the parameters for the algorithms are given for the individual tests. Section IV presents conclusions and final comments.

**APPLICATION TO THE GRAVITY FIELD OF A FAULT**

A fault structure can be approximated by two Semi-infinite horizontal sheets, one displaced vertically from the other. The general situation of a fault is presented in Figure 1, together with the shape of the Expected anomaly which is described by the formula 2 [Telford, et al 1976]:



**Figure 1: Fault model illustrating various parameters used in work, and shape of expected gravity anomaly.**

$$(2) \quad g=2k\delta t[\pi+\tan^{-1}\{(x/h_1+\cot (a))\}- \tan^{-1}\{(x/h_2+\cot (a))\}]$$

K=6.672e-3

$\delta$  =density contrast

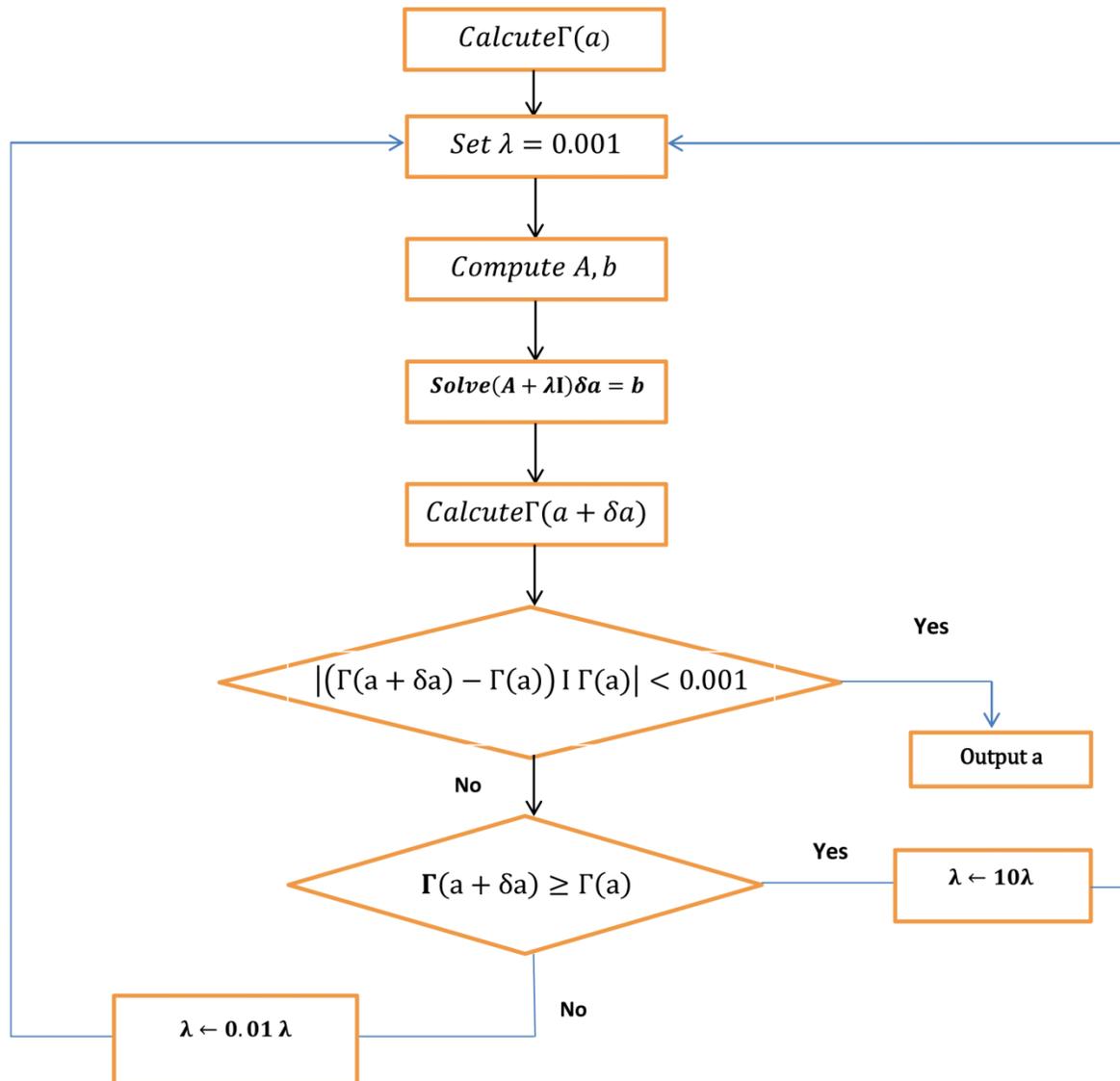
t=thickness of sheet

$h_{1,2}$ =depth of each side to the middle of the sheet

a =fault angle.[ Thanassoulas, C.; Tselentis, G.A.; Dimitriadis, K. 1987.Telford, et al 1976,Toushmalani, R. 2010.Toushmalani 2013].

**Levenberg-Marquardt**

The Levenberg-Marquardt algorithm (LM) [[Juutinen, S. & Saariluoma, P., 2007.] is an approximation to the Newton method (cf. Figure 2) used also for training ANNs.



**Figure 2: Flow chart of Levenberg-Marquardt**

The Newton method approximates the error of the network with a second order expression, which contrasts to the Backpropagation algorithm that does it with a first order expression. LM updates the ANN weights as follows:

$$\Delta w = [\mu I + \sum_{p=1}^p J^p(w)^T J^p(w)]^{-1} \nabla E(w) \quad (3)$$

Where  $J^p(w)$  is the Jacobian matrix of the error vector  $e^p(w)$  evaluated in  $w$ , and  $I$  is the identity matrix. The vector error  $e^p(w)$  is the error of the network for pattern  $p$ , that is,  $e^p(w) = t^p - o^p(w)$ .

The parameter  $\mu$  is increased or decreased at each step. If the error is reduced, then  $\mu$  is divided by a factor  $\beta$ , and it is multiplied by  $\beta$  in other case. Levenberg-Marquardt performs the steps detailed in Fig. 3. It calculates the network output, the error vectors, and the Jacobian matrix for each pattern. Then, it computes  $\Delta w$  using (3) and recalculates the error with  $w + \Delta w$  as network weights. If the error has decreased,  $\mu$  is divided by  $\beta$ , the new weights are maintained, and the process starts again; otherwise,  $\mu$  is multiplied by  $\beta$ ,  $\Delta w$  is calculated with a new value, and it iterates again. [K Khan, A Sahai, 2012]

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Initialize Weights;
While not stop-Criterion do
    Calculates  $C^P(W)$  for each pattern
     $e_1 = \sum_{p=1}^p e^p(W)^T e^p(W)$ 
    Calculates  $J^p(w)$  for each pattern
    Repeat
        Calculates  $\Delta w$ 
         $e_2 = \sum_{p=1}^p e^p(w + \Delta w)^T e^p(w + \Delta w)$ 
        If  $e_1 \leq e_2$  then
             $\mu = \mu * \beta$ 
        End If
    Until  $e_1 < e_2$ 
     $\mu = \mu / \beta$ 
     $W = w + \Delta w$ 
End While
    
```

Figure 3: Pseudocode of Levenberg-Marquardt algorithm.

## Methodology Approach of Cuckoo Optimization Algorithm (COA)

One of the most commonly used type of these optimization algorithms are meta heuristic algorithms which are inspired from nature. A most recent, yet powerful, kind of these evolutionary meta heuristic algorithms inspired by the cuckoos' lifestyle is the cuckoo optimization algorithm (COA), one of which is known as "cuckoo search", which was evolved by Yang and Deb [Yang X S & Deb S, 2009; Yang X S, 2011]. Proposed by these two researchers, the cuckoo search algorithm is mainly based on the behavior of obligate brood parasitic of certain cuckoo species accompanied with the Lévy flight behavior of some kind of birds and fruit flies. The cuckoo search algorithm has been compared to other metaheuristics algorithms in several studies.

Another algorithm which is inspired by cuckoo lifestyle is "Cuckoo Optimization Algorithm (COA)" developed by Rajabioun. Through using a benchmarking study, he demonstrated the efficiency of this algorithm which can be considered as the most appropriate algorithm for discrete issues, proving its accelerated confluence and global optima accomplishment. In the current study, this algorithm developed by Rajabioun [2011] is mostly applied, creating a random population of potential solutions (candidate elements) each indicating the nests in COA. Here, the parameters of the candidate elements are assessed in the fitness function, considering a violation term as a limitation. In the following, the steps through which one can achieve the optimum solution are outlined. First, considering an initial population of cuckoos which lay some eggs in some host bird's nest, the algorithm starts. Among these eggs those which are alike the host bird's own eggs have a great chance to grow up and attain maturity, others, however, are caught by the host birds and are destroyed. The suitability of the nests in the area can be figured out from the hatched eggs. The more hatched eggs in the area, the more profits are achieved in that area. Hence, the term based on which COA is going to optimize is the place where more eggs survive with each cuckoo having a "cuckoo's distance" to the goal point (best habitat).

Solving a problem with COA requires considering the valued of the issue as an array known as "habitat". When an issue is  $N_{var}$  dimensional problem, then a habitat is an array of  $1 \times N_{var}$  that indicates the position in which a cuckoo is currently lives. This can be summarized as follows:

$$\text{Habitat} = [x_1, x_2, \dots, x_{N_{var}}] \quad \dots(4)$$

The profit of a habitat can be calculated through profit function  $f_b$  at a habitat of  $(x_1, x_2, \dots, x_{N_{var}})$

$$\text{Profit} = f_b(\text{habitat}) = f_b(x_1, x_2, \dots, x_{N_{var}}) \quad \dots(5)$$

By creating a candidate habitat matrix of size  $N_{pop} \times N_{var}$  the optimization algorithm initiates. For each of these initial nests, random produced number of eggs is considered. This range is known

as “Egg Laying Radius (ELR), since the cuckoos lay their eggs within the maximum distance from their habitat. This ELR can be demonstrated as follows:

$$ELR = \alpha \times \frac{\text{Number of current cuckoos eggs}}{\text{total number of eggs}} \times (\text{var}_{hi} - \text{var}_{low}) \quad \dots(6)$$

Here,  $\alpha$  is an integer which manage the maximum value of ELR,  $\text{var}_{hi}$  and  $\text{var}_{low}$  are the variables’ upper and lower limit respectively. After the process of laying eggs, P% of all eggs (frequently 10%) with lesser profit values will be destroyed, having no chance to hatch. Others’ have the opportunity of hatch and grow up and the host birds feed them as their own chickens. Another matter at issue is that the groups of cuckoos are formed in various areas and to immigrate it is nearly impossible to figure out which cuckoo belongs to which group. To solve the mentioned issue, the author here employed an algorithm work with K-means clustering method. When immigrating, cuckoos do not fly to the destination habitat; however, they just fly a part of the way back to destination and have a deviation as well. Considering that each cuckoo fly  $\lambda\%$  of the overall distance of the considered habitat and has a deviation of  $\phi$  radians.  $\lambda$  and  $\phi$  are two parameters through which cuckoos can search many more places in various areas. These two parameters are defined for each cuckoo as follows:

$$\lambda \sim U(0,1), \quad (7)$$

$$\lambda \sim U(-\omega, \omega)$$

$\lambda \sim U(0,1)$  means that  $\lambda$  is a random number uniformly distributed between 0 and 1.  $\omega$  is a parameter, bounding the deviation from targeted habitat. For good confluence, an  $\omega$  of  $\pi/6$  (radian) is enough, the author suggests.

Based on what already noted, a brief summary of the cuckoo optimization algorithm (COA) is outlined in the following:

1. Starting cuckoo habitants with considering some random points on the profit function;
2. Apportioning a number of eggs to each cuckoo;
3. Illustrating ELR for each cuckoo;
4. Laying eggs inside corresponding ELR by each cuckoo;
5. Devastating the identified eggs by host birds
6. Other eggs which are not recognized hatch and attain maturity;
7. Assessing the habitant of each newly grown cuckoo;
8. Regarding cuckoo’s maximum number in environment, destroying those belong to worse habitat;
9. Clustering cuckoos and figuring out a best, targeted habitat for each;
10. Letting them immigrate to that targeted habitat;
11. If the condition is satisfied, stop otherwise go to 2.

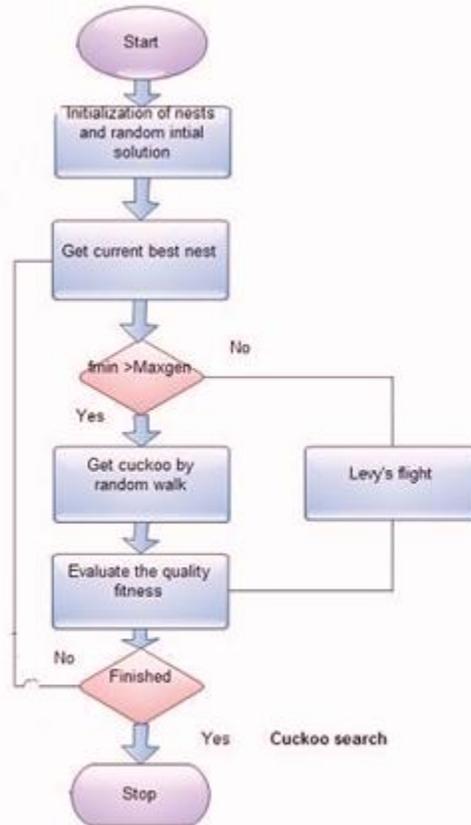


Figure 4. Scheduling flow chart

**Application of COA and LM optimization in inverse problem solving**

Using Equation (1), the theoretical anomaly which corresponds to a fault with  $t = 500\text{m}$ ,  $h_1 = 6000\text{m}$  (left),  $h_2 = 2000\text{m}$ ,  $a = 30^\circ$ , and  $b = 1$ , is presented as a continuous line in Figure 2. To test the program, the theoretical anomaly of Figure 2 is digitized every 5000m (Table 1), and a "bad" initial model with parameters  $h_1 = 3000\text{m}$ ,  $h_2 = 1600\text{m}$ ,  $t = 700\text{m}$ , and  $a = 30^\circ$  is entered. [Thanassoulas, C.; Tselentis, G.A.; Dimitriadis, K. 1987]. Table 1 shows Gravity anomaly for inversion .

**Table 1. Gravity anomaly for inversion**

x-coordinate (m)	Gravity anomaly(mgal)
-15000	- 2.24
-10000	- 3.47
-5000	- 5.60
0	0
5000	2.02
10000	1.61
15000	1.27
20000	1.04

During the iterations the density contrast is kept as a fixed parameter, assuming that its value has been estimated previously. The parameters which are optimized are:

- (a) the thickness of the sheet,
- (b) the left distance to the middle of the sheet,
- (c) the right distance to the middle of the sheet, and
- (d) the angle of the fault.

Table 2. Parameters of obtained solution with Levenberg-marquardt [ Thanassoulas, C.; Tselentis, G.A.; Dimitriadis, K. 1987].

Thickness of fault: 500m  
 Fault angle (a): 60 °  
 Depth to bottom of the fault (h1): 5780m  
 Depth to top of the fault (h2): 1753m  
 -. Parameters of obtained solution with COA :  
 Thickness of fault: 501.4m  
 Fault angle (a): 18 °  
 Depth to bottom of the fault (h1): 6003m  
 Depth to top of the fault (h2): 2001m

[Toushmalani 2013a, Toushmalani 2013a b]. Table 2 shows Parameters of obtained solution

**Table 2: Parameters of obtained solution**

Observed gravity	Calculated gravity with COA	Calculated gravity with IM
- 2.24	-2.23	2.23-
- 3.47	- 3.47	-3.48
- 5.60	- 5.60	-5.84
0	0	0
2.02	2.01	2.15
1.61	1.63	1.67
1.27	1.28	1.30
1.04	1.04	1.06

**CONCLUSION**

The parameters which are optimized with these methods are: (a) the thickness of the sheet,(b) the left distance to the middle of the sheet,(c) the right distance to the middle of the sheet, and(d) the angle of the fault. Inverse solution reveals that fault model parameters are agree quite well with the known results. A more agreement has been found between the predicted model anomaly and the observed gravity anomaly in COA Method rather than LM method.

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