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Research Article

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Modeling of Manyas (Turkey) Depression Area with Forced Neural Network Method

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Abstract Modeling of potentially originating anomaly maps is important in geophysical studies. It is desired to model the geological structure under the ground by calculating parameters such as the upper depth, lower depth and width of the structure that causes the anomaly under the ground from the sections taken from the potential source anomaly maps. It is used to distinguish the density difference from the cross section taken from the anomaly maps and to find the depth of the object according to gravity according to the anomaly and its geometric structure, which we call the Forced Neural Network (FNN) while assuming the x and density of the object. In this algorithm, we use neurons to model the system. We apply back propagation algorithm to find the density difference. Then, a two-level quantization process is applied and this process continues until the mean square error of the system is small enough. In this proposed system, we can find the structure depth accurately. The depression area of the Manyas region, located in the northwest part of Turkey, was chosen as the study area.

Keywords Forced Neural Network, Gravitational anomaly, modelling, Manyas region

Introduction

In the solution of geophysical problems, it is an important issue to determine the parameters of the structures that cause the anomalies in the underground and to model them. The most important issue in geophysical modeling is to determine the dimensions of the geological structure. It is necessary to determine the depth of the upper surface, the depth of the lower surface, and the dimensions of the structure of the geological structures that create geophysical anomalies. We consider this as modeling the geological structure. Early publications such as [1] were concerned with calculating gradients of the gravitational field. [2] used the line integral approach to calculate the gravitational pull of two-dimensional masses. [3] studied the inversion approach on the gravity profile using Backus-Gilbert inversion techniques. [4] determined the underground density distribution using the iteration inversion technique. [5] used singular value separation (SDV) to solve problems in Gravity and Seismic prospecting methods and gave examples of their solution. [6] made an inverse solution using the Fourier Trasform method to find the density distribution in Gravity. [7 and 8] used numerical integration techniques to calculate the areas to be modeled. [9 and 10] They modeled the structures using the Forced Neural Network method in modeling the geological structures from the gravity anomaly maps. [11] They modeled two-dimensional geological structures using the Genetic Algorithm method.

In this study, the gravity anomaly map made by the Mineral Research and Exploration (MTA) institution in the Manyas depression area in the North West Anatolian region of Turkey was used. The geological structure in the Manyas depression area was modeled using the FNN method. The purpose of FNN is to estimate the physical parameters of embedded objects.

Forced Neural Network

Back Propagation Algorithm

The error signal at the output of neuron j at iteration n is defined by

$$e_j(n) = d_j(n) - y_j(n), \text{ neuron j is an output node} \quad (1)$$

The instantaneous value of the error energy for neuron j can be defined as $\frac{1}{2}e_j^2(n)$. Correspondingly, the instantaneous value $\mathcal{E}(n)$ of the total error energy is obtained by summing $\frac{1}{2}e_j^2(n)$ over all neurons in the output layer; these are the only "visible" neurons for which error signals can be calculated directly [9]. We may thus write,

$$\mathrm{E}(n) = \frac{1}{2}\sum_{j\in C} e_j^2(n) \quad (2)$$

where the set C includes all the neurons in the output layer of the network [12]. Let N denote the total number of patterns (examples) contained in the training set. The average squared error energy is obtained by summing $\mathcal{E}(n)$ over all n and then normalizing with respect to set size N, as shown by,

$$\mathrm{E}_{\mathrm{av}} = \frac{1}{N}\sum_{n=1}^{N} \mathrm{E}(n) \quad (3)$$

The instantaneous error energy $\mathcal{E}(n)$, and therefore the average error energy $\mathcal{E}_{av}$, is a function of all the free parameters (i.e., synaptic weights and bias levels) of the network. For a given training set, $\mathcal{E}_{av}$ represents the cost function as a measure of learning performance. The objective of the learning process is to adjust the free parameters of the network to minimize $\mathcal{E}_{av}$. To do this minimization, we use an approximation similar in rationale to that used for the derivation of the LMS algorithm. We consider a simple method of training in which the weights are updated on a pattern-by-pattern basis until one epoch, that is, one complete presentation of the entire training set has been deal with

$$\Delta w_{ij}(n) = \eta\delta_j(n)y_i(n) \quad (4)$$

Where $\delta_j(n)$ is the local gradient [12]. Local gradient points are required changes in synaptic weights [9].

We obtain Back-Propagation (BP) formula for the local gradient $\delta_j(n)$ as:

$$\delta_j(n) = \varphi_j'(v_j(n))\sum_k \delta_k(n)w_{kj}(n) \text{ , neuron } j \text{ is hidden} \quad (5)$$

The factor $\varphi_j'(v_j(n))$ involved in the computation of the local gradient $\delta_j(n)$ in Eq.(5) depends solely on the activation function associated with hidden neuron j. The remaining factor involved in this computation, namely the summation over k, depends on two sets of terms. The first set of terms, the $\delta_k(n)$, requires knowledge of the error signals $e_k(n)$, for all neurons that lie in the layer to the immediate right of hidden neuron j, and that are directly connected to neuron j. The second set of terms, the $w_{kj}(n)$, consists of the synaptic weights associated with these connections [9 and 10].

We may redefine the local gradient $\delta_j(n)$ for hidden neuron j as

$$\delta_j(n) = -\frac{\partial\mathcal{E}(n)}{\partial y_j(n)}\frac{\partial y_j(n)}{\partial v_j(n)} \quad (6)$$

$$= -\frac{\partial\mathcal{E}(n)}{\partial y_j(n)}\varphi_j'(v_j(n)) \text{, neuron j is hidden} \quad (7)$$

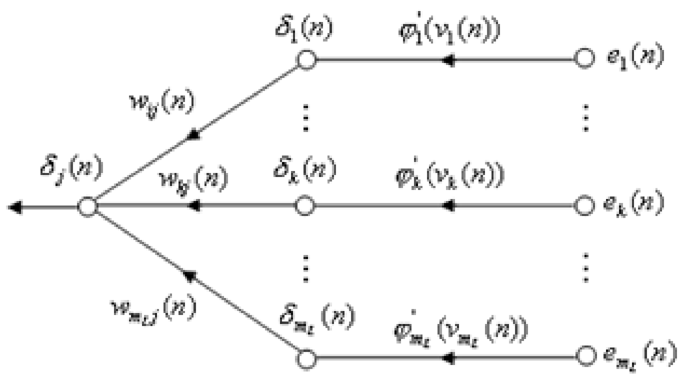

Figure 1: Signal flow graph of a part of the adjoint system pertaining to Back-Propagation of error signals [9].

The induced local field $v_j(n)$ produced at the input of the activation function associated with neuron j is therefore

$$v_j(n) = \sum_{i=0}^{m} w_{ij}(n) y_i(n) \tag{8}$$

where m is the total number of inputs (excluding the bias) applied to neuron j [12]. The synaptic weight w_{j0} (corresponding to the fixed input $y_0 = +1$) equals the bias b_j applied to neuron j. Hence the function signal $y_j(n)$ appearing at the output of neuron j at iteration n is

$$y_j(n) = \varphi_j(v_j(n)) \tag{9}$$

Next differentiating Eq.(9) with respect to $v_j(n)$, we get

$$\frac{\partial y_j(n)}{\partial v_j(n)} = \varphi_j^{'}(v_j(n)) \tag{10}$$

where the use of prime (the right-hand side) signifies differentiation with respect to the argument [12, 9 and 10].

Forced Neural Network for Gravity Anomaly

It is very important to find out the geophysical section respect to the gravity from the gravity anomaly. Here we assumed that the structure is cylindrical and the gravity anomaly function is shown below.

$$A(x_{ref}) = \sum_{i=1}^{H} \sum_{j=0}^{X-1} \nabla\rho_{i,j} \cdot K \cdot \frac{i}{(i^2 + (j - x_{ref})^2)} \tag{11}$$

We use $K \cdot \frac{i}{(i^2 + (j - x_{ref})^2)}$ as an input of the neuron and there should be (*H* x X) inputs and these inputs are constant for every *A*(x_{ref}), and the neuron can be modeled as below [9 and 10].

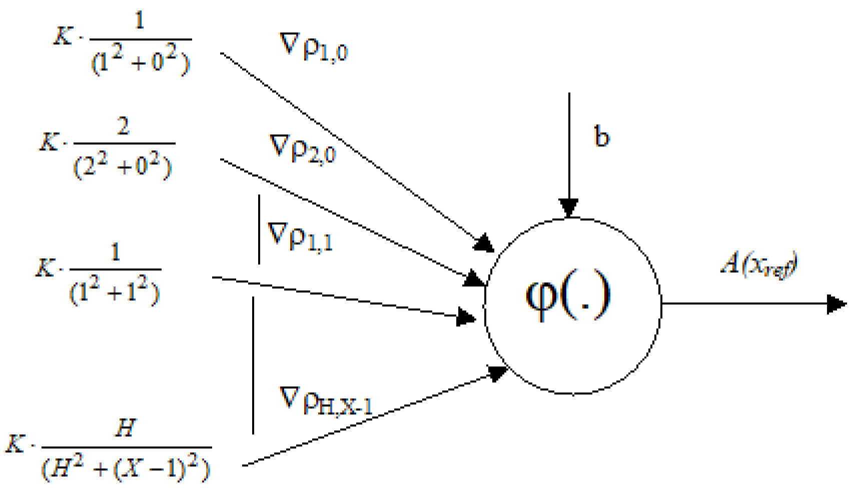

Figure 2: Forced Neural Network (FNN) design for gravity anomaly [9]

Here the weights of the neuron are assigned as $\nabla\rho_{I,j}$ for each pixel and linear function is assumed as an activation function. After using the back propagation $\nabla\rho_{I,j}$ are updated and the output of the neuron gives the gravity anomaly. Hence the density differences are found. But the results of this system are not sufficient because it finds scattered objects, therefore x is restricted and the outputs are fixed to the known one $\nabla\rho$ or zero and thresh hold value b is set to zero.

Forced neural network means that after sufficient epoch is applied fixed values are assigned to the output of the neuron according to the density difference$\nabla\rho$, and this process is continued until the mean square error of the quantized output gets sufficiently minimum value [9 and 10].

Geology of Manyas Lake Area

Geomorphology: Manyas lake is in the north of Manyas town and 10 mt altitude of sea level. It is 12 km width and 18 km length, about 200 squared km area. It is very shallow and the water tastes very soft. The base and around is composed of neogen lime-stones, neogen and pre-neogen hills form an interesting topology [13].

Geology: Manyas Lake is generally surrounded by neogen limestones and alluvions layers. In recent years, there occurred metamorphic shiest and marvels related to Paleozoic period. Jura and upper cretasine lime-stones are also observed [13].

Techtonic: Manyas Region takes place at Gönen–Bursa depressions (Figure 3). This structure is surrounded by West Anatolian in the south and by Mudanya mountains on the north neogen region. Many faults is formed around the lake and they are related to north Anatolian fault system. Marmara is formed at the Pliocene period but Manyas is younger and assumed to be formed at Quaternary [13].

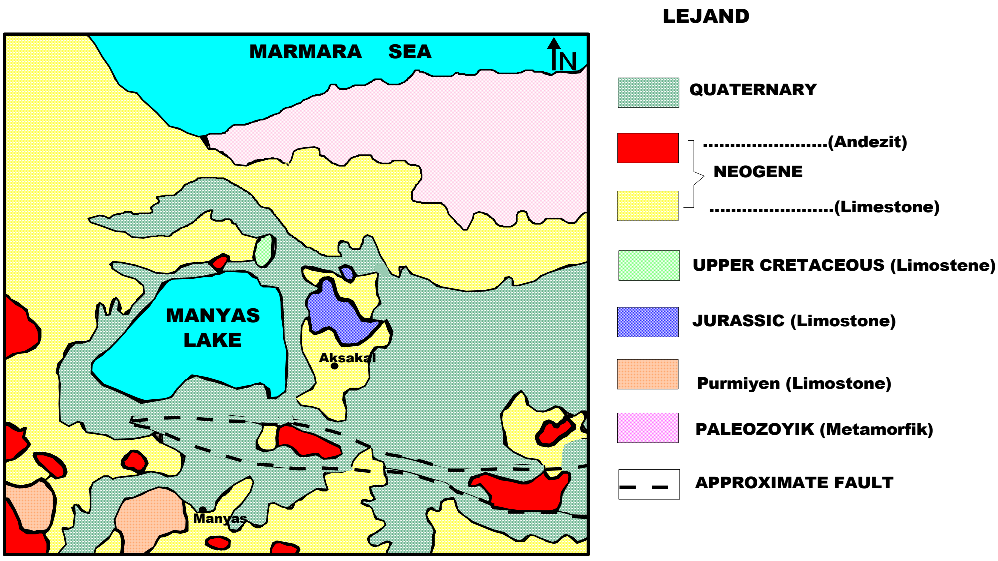

Figure 3: Geology map of manyas regional (MTA).

Gravity anomaly map of Manyas depression area

Negative anomaly closure observed on the Bouguer anomaly map (Figure 4) of the Manyas depression area determines the location of the mentioned depression on the southern shore of the lake. The contour formed with the lowest gravity value also reflects the deepest part of the depression.

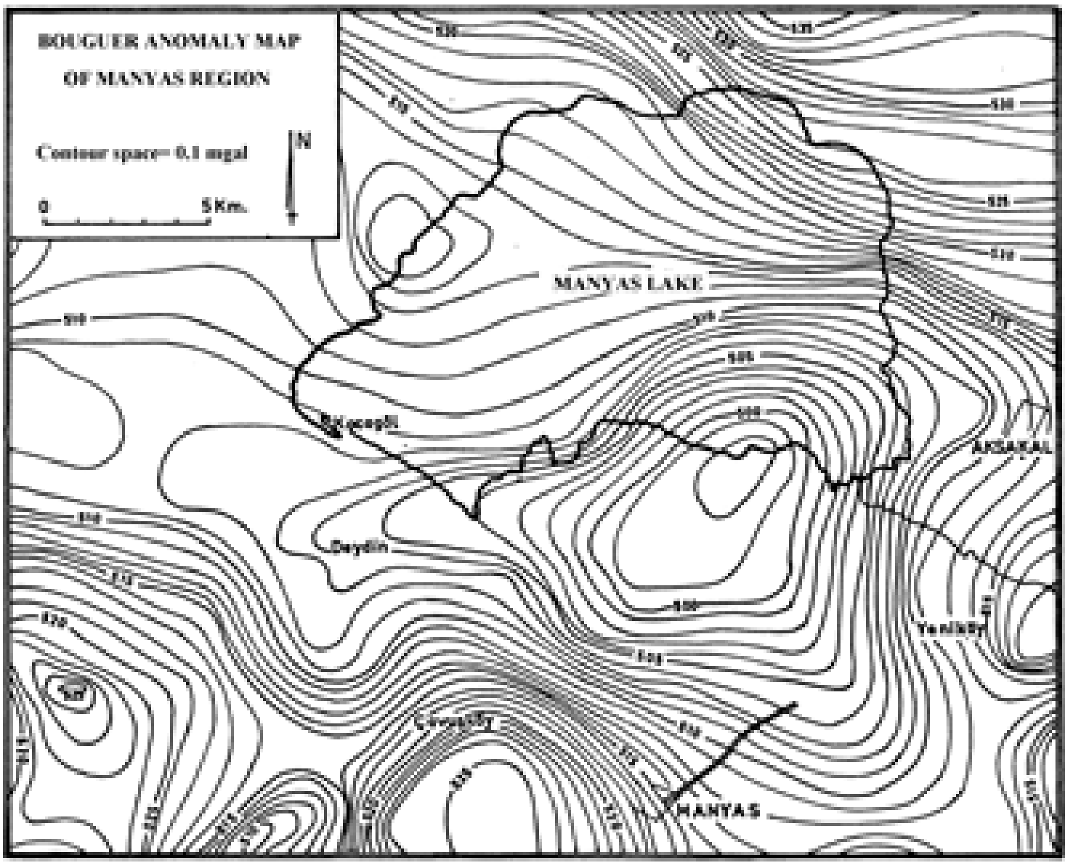

Figure 4: Bouguer anomaly map of Manyas region (MTA)

The closure of the gravity anomaly contours in the south of the lake indicates that the depression may have a bowl-shaped sediment-filled structure. A residual anomaly map was obtained from the Bouguer anomaly map (Figure 5). On the residual anomaly map, only the negative anomaly value limited to the zero contour is drawn. It was determined in the south of the lake of the Manyas depression area. The increase in gravity towards north and south shows large values. The area where the anomaly is located has a topography close to the lake level. When the anomaly increases in the north and south are examined, it is clearly seen that they are in the form of typical fault anomalies.

When the residual anomaly map is examined, it is seen that the anomaly closure depression in the south of the lake has a bowl-shaped structure. AB section was taken from the residual anomaly map. Obtained anomaly section is given in figure 6a. By applying the FNN method to the anomaly map given in Figure 6a, the geological structure given in Figure 6b was obtained.

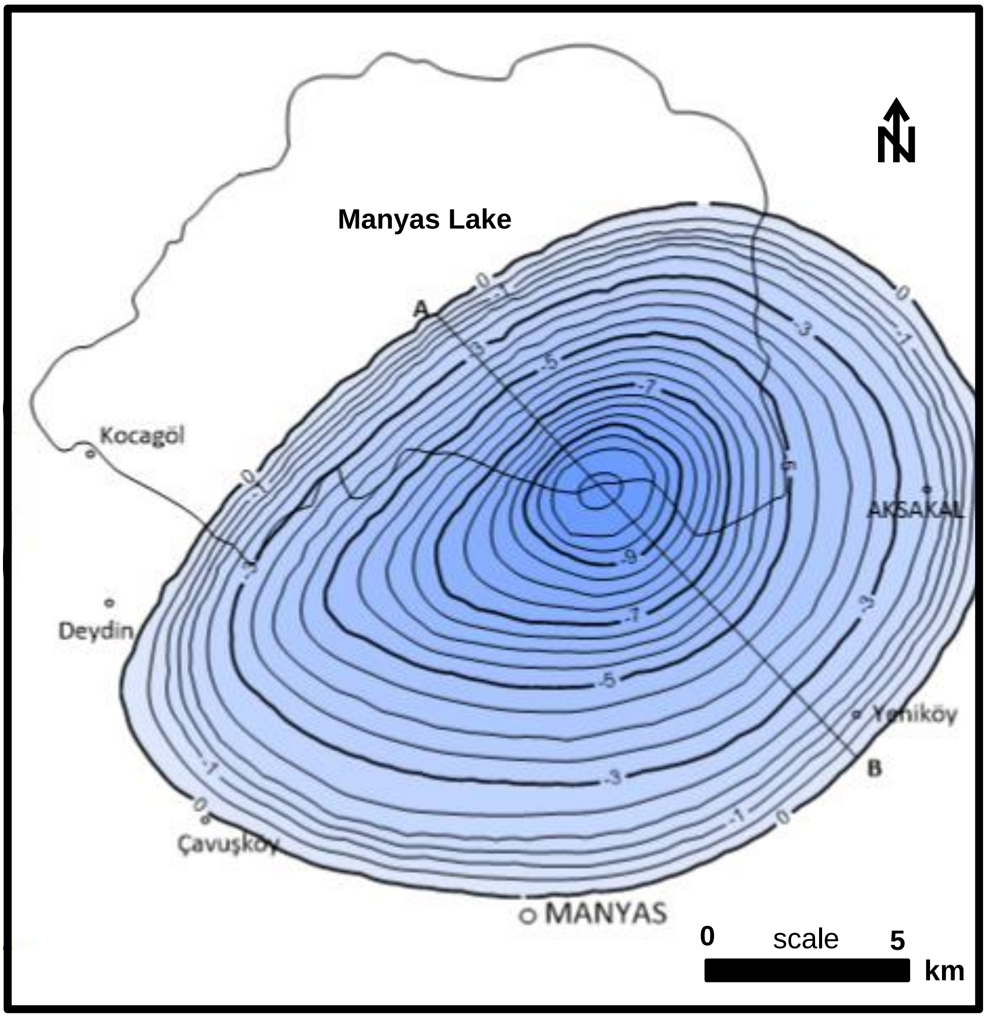

Figure 5: Regional anomaly map of Manyas region

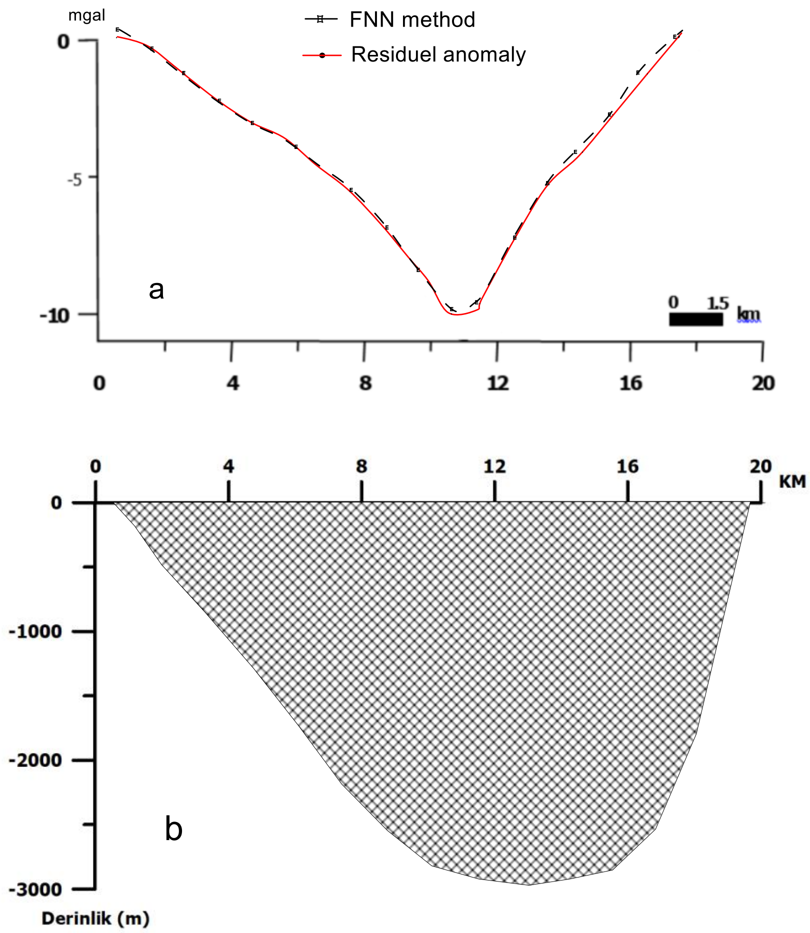

Figure 6: Manyas depression area a) AB section obtained from the residual anomaly map b) Geological structure obtained by applying the FNN method

Conclusion

In the evaluation of gravity anomaly data in geophysical studies, it is important to calculate the gravity anomalies created by geological structures with models. If a homogeneous density is not available and the shape of the structure that creates the anomaly cannot be determined geometrically, it may be more difficult to reach the model structure from gravity anomalies. For this reason, when analyzing gravity anomalies with mathematical models during the calculations, the geological models are assumed to be of constant density until today. In gravimetric studies, two new methods have been introduced that can appropriately express the mathematical relationship between the anomaly model, which will enable the calculation of gravity anomalies formed by three-dimensional geological structures of any shape. A new algorithm, Forced Neural Networks (FNN) presented in this paper clearly shows that the gravity field at any point due to a solid body having uniform volume density can be computed as the field due to a fictitious distribution of surface mass-density on the same body.

The determining of the depth of a buried body from the gravity anomaly has been transformed into the problem of solving a forced neural network. The advantage of the proposed algorithm over the classical inversion techniques is that any initial estimate for the depth parameter works well.

One of the possible faults in the south of the lake shown on the geological map is confirmed and it is assumed that the second possible fault will cross the north of the lake. The depression was formed between these two faults, at 3000 m. It can be said that it is found in accordance with the calculated model structure with depth.

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References

[1]. Barton, D. C. (1929): Calculations in the interpretation of observations with the Eötvös torsion balance: AIME pp. 481-486.

[2]. Hubbert, M. K. (1948): A line integral method of computing the gravimetric effects of two-dimensional masses: Geophysics, 13, 215-225.

[3]. Green, W. R. (1975): Inversion of gravity profiles by use of a Backus-Gilbert approach. Geophysics, 45, 403-419.

[4]. Last, B. J., and Kubik K. (1983): Compact Gravity Inversion. Geophysics, 48, 713-721.

[5]. Lines, L. R. and Treitel S. (1984): Tutorial a Review of Least-Squares Inversion and its Application to Geophysical Problems. Geophysical Prospecting, 32, 159-186.

[6]. Mareschal, J. C. (1985): Inversion of potential field data in Fourier transform domain. Geophysics, 50, 685-691.

[7]. Talwani, M., and Ewing M. (1960): Rapid computation of gravitational attraction of 3D bodies of arbitrary shape: Geophysics, 25, 203□225

[8]. Talwani, M. (1965): Computation with the help of a digital computer of magnetic anomalies caused by bodies of arbitrary shape: Geophysics, 30, 797-817.

[9]. Osman, O., Albora, A. M. and Ucan, O. N. (2006): A new approach for resıdual gravity Anomaly profıle ınterpretatıons: Forced neural network (FNN): Annals of Geophysıcs, 49, 6. 1201-1208

[10]. Osman, O., Albora, A. M. and Ucan, O. N. (2007): Forward modeling with Forced Neural Networks for gravity anomaly Profile: *Mathematical Geology*, 39:593-605.

[11]. Osman O. and Albora A.M., (2015): Modeling of Gravity Anomalies due to 2D Geological Structures using Genetic Algorithm: IU-Journal of Electrical & Electronics Engineering, 15: 2, 1929-1935.

[12]. Haykin S. (1999): Neural Networks, Prentice Hall International Inc.

[13]. Ertekin, E. 1983. 3-D Geological Structures Anomalies Computerised by the digital diagrams. Istanbul University, Science Institute, Ph.D Thesis.