Modeling of Turkey-Manyas region using Forced Neural Networks

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Abstract In this study, we perform Forced Neural Network (FNN) method to find the parameters of a model according to gravity anomaly profile. Geological modeling is a promoting method to find the shape and location of underground structures. In this method first, one neuron is used and back propagation algorithm is applied to find the density difference. Then, density differences are quantized and mean square error of the model is computed. This process is stopped when the mean square error of the model is small enough. FNN method is applied to synthetic data, and then Marmara-Manyas basin map in Turkey. As a result, anomalies of the cross section and the model obtained by FNN are very close to each other.

Keywords Forced Neural Network (FNN), geophysical modeling, Gravity anomaly profile, Marmara-Manyas region.

Introduction

There are lots of studies about modeling and determining the parameters of underground structures. They have crucial studies about computing the gravity anomalies of different type of structures [1]. Introduces a method to determine the depth and density difference from the gravity anomalies in some limitations [2]. In geophysics gravity anomalies of the sedimentary basin is interpreted [3]. Backus-Gilbert investigates inverse solution method on gravity profiles [4]. Utilize the iterative inverse solution method to estimate the distribution of density difference of underground [5]. Fourier Transform use to find the invers solution [6]. Determine some rules about the effects of horizontal and vertical cylindrical structures [7]. Applied asymmetrical trapezoidal modeling [8]. They are study on a program to find the density differences of 2D and 3D models according to anomaly maps [9]. Nomogram using gravity anomaly model for Sivas-Gurun region [10]. Calculate the inverse solution of gravity and magnetic anomalies of 2D polygonal structures using Marquart method [11]. They are use Monte Carlo method in inverse solution problems [12]. Calculate the parameters of underground structures using FNN method [13-14]. Apply genetic algorithm for modeling in the Sivas-Gürün gravity anomaly [15].Markov random fields using Fault Lines in Iskenderun Bay has to be examined [16]. Buried archaeological structures in the state modeled using Wavelet Cellular Neural Network method with image processing method [17]. In this study, we apply FNN method to obtain the model of the basin in Manyas, Balıkesir in Marmara region.

Method
Back Propagation Algorithm

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

$$e_j(n) = d_j(n) - y_j(n)$$

(1)

neuron j is an output node 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 $E(n)$ 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. We may thus write,

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

where the set *C* includes all the neurons in the output layer of the network [18]. Let *N* denote the total number of patterns (examples) contained in the training set. The average squared error energy is obtained by summing $E(n)$ over all *n* and then normalizing with respect to set size *N*, as shown by,

$$E_{av} = \frac{1}{N}\sum_{n=1}^{N} E(n) \tag{3}$$

The instantaneous error energy $E(n)$, and therefore the average error energy E_{av}, is a function of all the free parameters (i.e., synaptic weights and bias levels) of the net-work. For a given training set, 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 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,
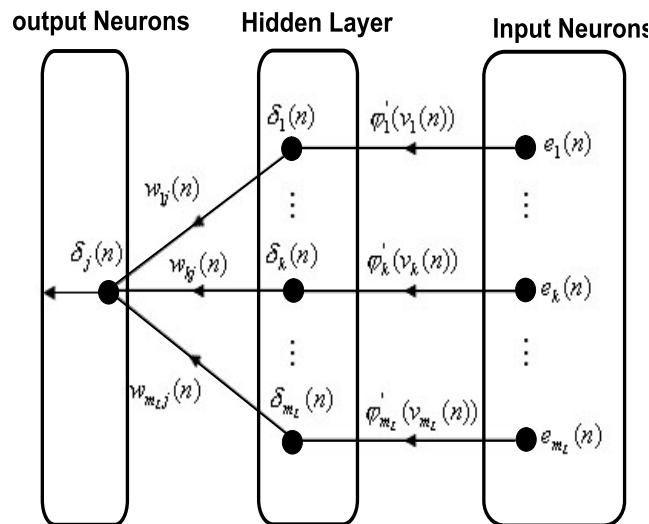

Figure 1: The signal-flow graph representation of Eq.(3), assuming that the output layer consists of m_L neurons.

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

where $\delta_j(n)$ is the local gradient [18]. Local gradient points are required changes in synaptic weights. We obtain Back-Propagation (BP) formula for the local gradient   as: neuron *J* is hidden, Figure 1 shows the signal-flow graph representation of Eq.(5), assuming that the output layer consists of   neurons.

$$\delta_j(n) = \varphi_j'(v_j(n))\sum_{k} \delta_k(n) w_{kj}(n) \tag{5}$$

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* (Figure 2). The second set of terms, the $w_{kj}(n)$, consists of the synaptic weights associated with these connections.

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

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

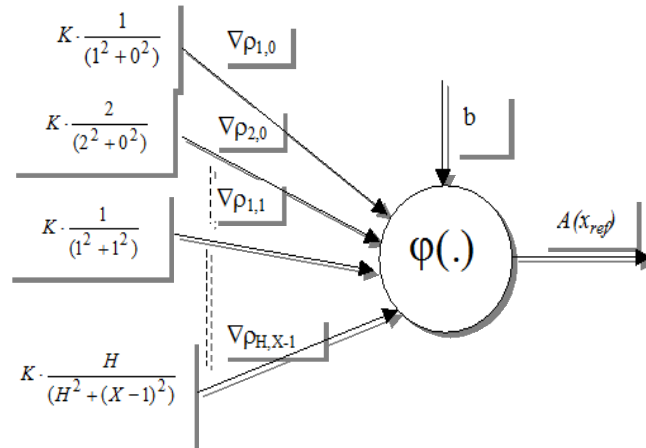$$= -\frac{\partial \mathcal{E}(n)}{\partial y_j(n)} \varphi_j'(v_j(n)) \tag{7}$$

Figure 2: FNN method.

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 [18]. 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[18].

Synthetic Data Application of FNN Method
FNN method is applied to synthetic prismatic structures. In these examples, density contrasts are chosen as $\Delta\rho$=1 gr/cm^3. In FNN, as input data, the obtained anomaly is concerned; the parameters of the buried structure are estimated using forward modeling technique, FNN. We used a synthetic study prismatic structure. This model upper depth is 200 m, and lower depth is 650 m. the width is 900 m, vertical length 450 m as shown in Figure 3. The anomalies of this model are considered as input data of FNN. In synthetic examples, every learning cycle is comprised of 345 epochs and two-level quantization ($\Delta\rho$ or zero) is applied for each 10 learning cycle, which is found experimentally. The estimated geological structure obtained after the FNN application, results in similar anomaly profile (light blue line and dark blue symbol) as the observed anomaly (dark line and red symbol) shown in Figure 3.
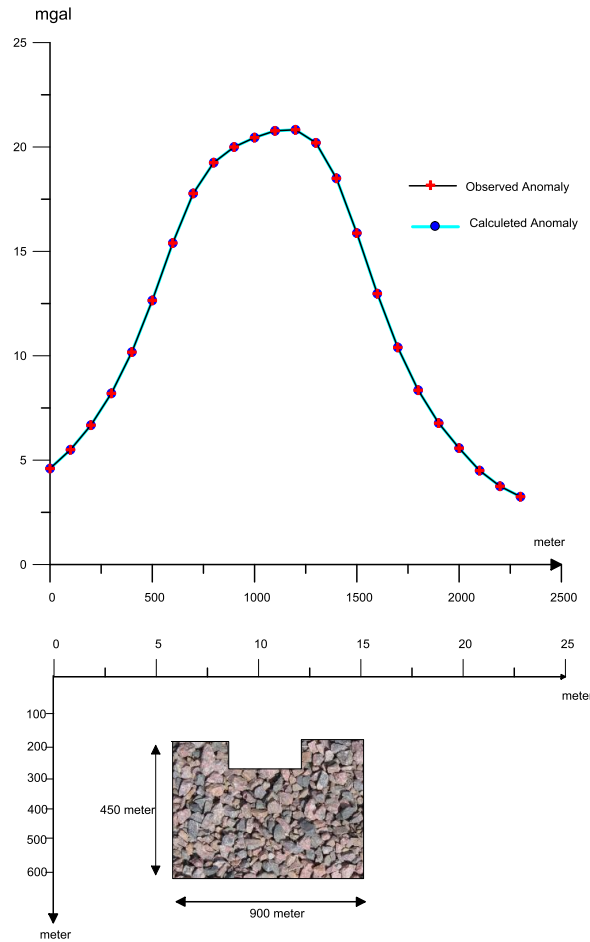
Figure 3: The output of the FNN method with gravity anomalies of the synthetic model.

Real Data Application of FNN Method

The application region is known as the Manyas plain inside the border of Balıkesir city. This area includes settlements of Şevketiye, Darıca, and Manyas as shown in Figure 4, and some parts are surrounded by Manyas Lake. The Bouguer anomaly map of the site is given in Figure 5.

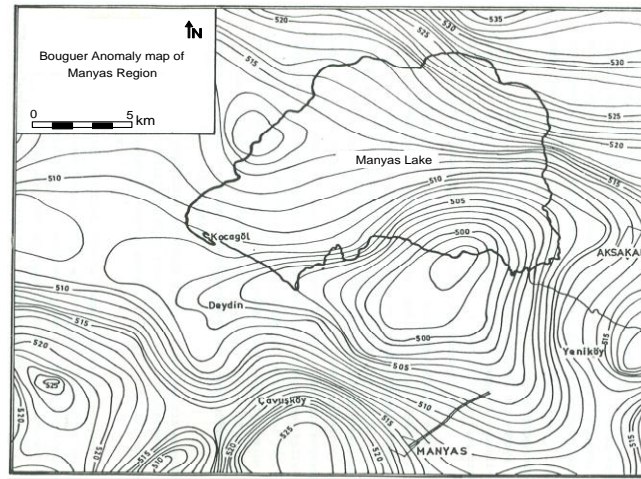
Figure 4: Map of studying site.

Figure 5: Bouguer anomaly map of Manyas basin. (obtained from Mineral Research and Exploration Institute of Turkey).

This region is represented by old and new formations. Alluviums carried by Simav-Karadere and Mustafa Kemal Paşa streamlets fill South Frikyagarben. The Alluvium thickness near the south of Karacabey plain is less than 6 meters (Figure 6). At the center part of the plain thickness approaches about 25-30m. Alluviums that covers neogene is clayish, sandy, and gritty [19].
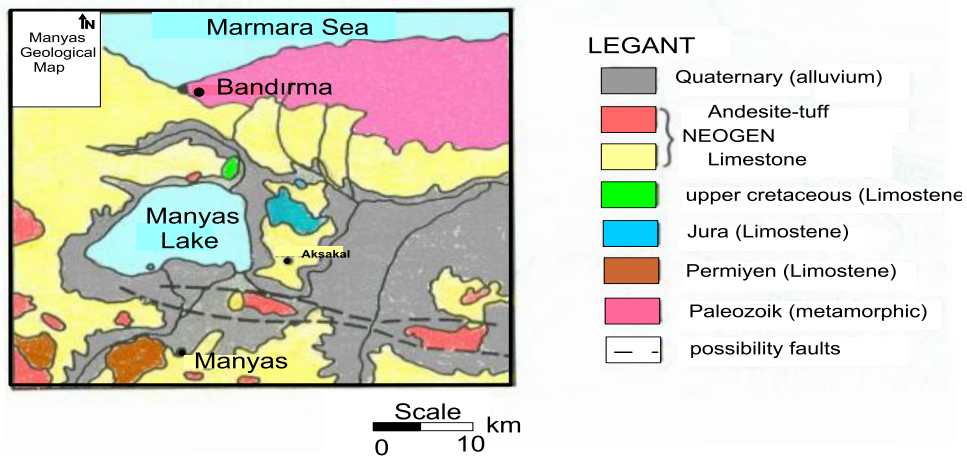

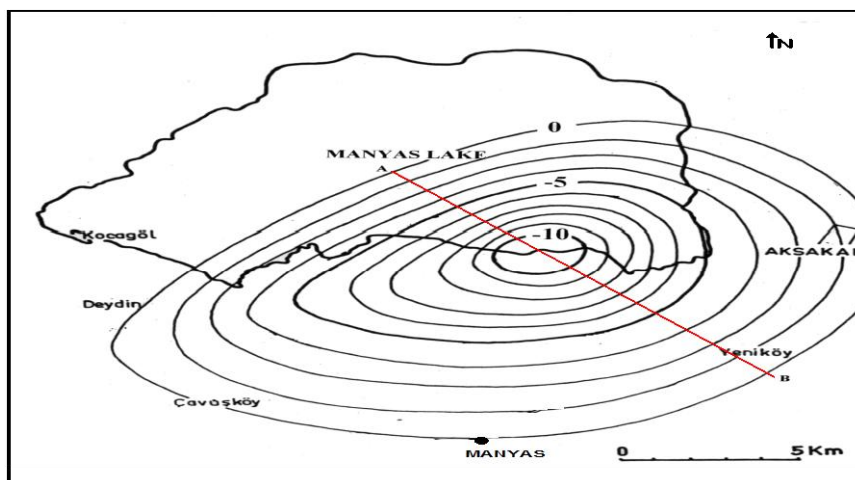*Figure 6: Geological map of Manyas basin (based on [20]).*

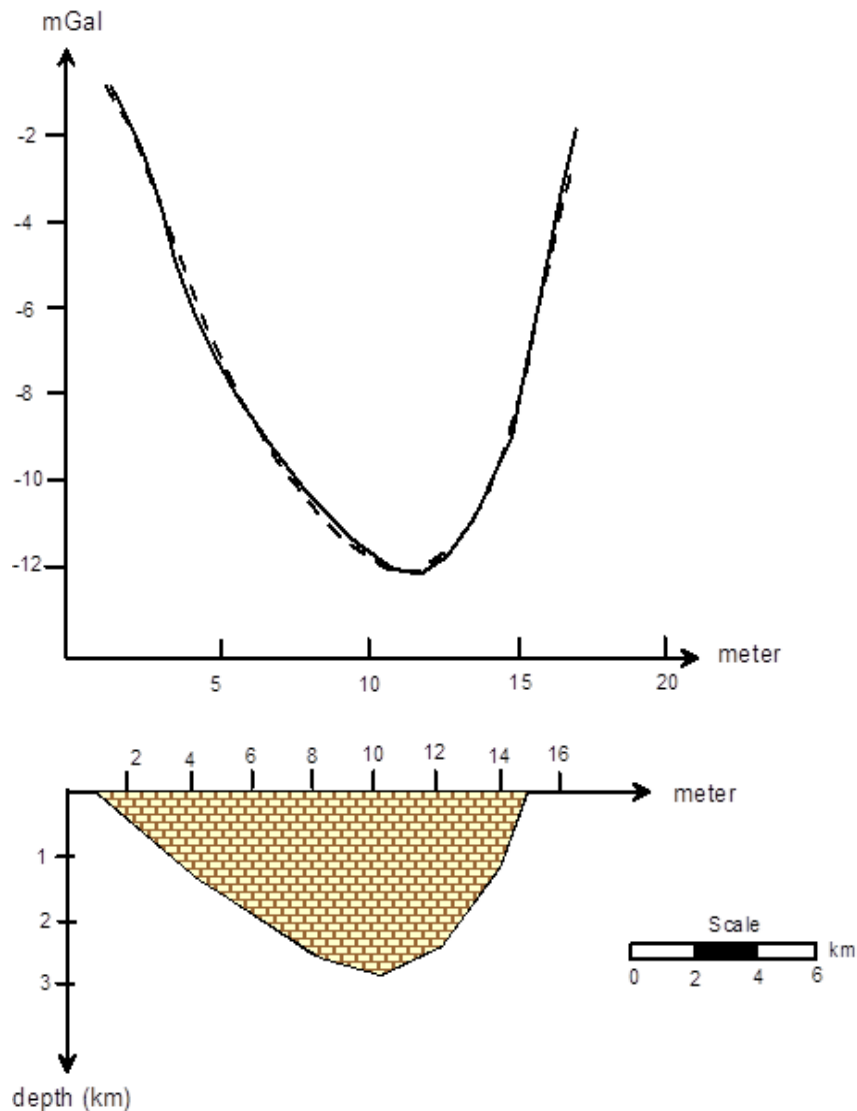*Figure 7: Residual anomaly map of Manyas basin.*

Figure 8: The model of Manyas basin according to FNN method straight line measured anomaly, the dotted line calculated anomalies).

Conclusion

In this study residual anomaly map of Manyas basin is used for modeling. FNN method is applied to the AB crossection in Figure 7. According to the results of the method, the depth of the Manyas basin is found about 3km in Figure 8. Dashed lines are the calculated value of the anomaly. Straight lines are measured anomalies. FNN is provided as a result of a very good fit.

Acknowledgements

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