10.1 ESTIMATING THE ELECTRICAL ANISOTROPY COEFFICIENT, STRIKE DIRECTION, AND DIP ANGLE USING SQUARE ELECTRODE ARRAY DATA WITH GENERALIZED REGRESSION NEURAL NETWORKS

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ABSTRACT

The Direct Current Resistivity (DCR) method is established as one of the oldest and most extensively used techniques in applied geophysics. DCR measurements are influenced by electrical anisotropy (EA). Electrical anisotropy characterizes the directional dependence of electrical resistivity measurements. This study focuses on the integration of a square electrode array with electrical anisotropy, offering an effective tool for estimating the strike, dip, and electrical resistivities of subsurface layers along both the x and y directions of the medium using a generalized regression neural network.

KEY WORDS: square array, electrical anisotropy, generalized regression neural network

INTRODUCTION

The Direct Current Resistivity (DCR) method is one of the oldest and most extensively employed techniques in applied geophysics (Telford et al., 1990). DCR measurements are influenced by several factors, including formation porosity, cementation factor, water saturation, fracturing, resistivity of formation water, temperature, and electrical anisotropy (EA). Electrical anisotropy, denoting the directional dependence of electrical resistivity measurements, has been a subject of investigation since Maillet's pioneering work in 1947. Numerous studies on electrical anisotropy have been conducted to date. In this study, we focus on the application of a square electrode array with electrical anisotropy. Square arrays have proven valuable for investigating the strike and dip of subsurface layers (Habberjam, 1972; 1975), a particularly relevant technique given the prevalence of karstic geological features in Türkiye, as demonstrated by Şener et al. (2021) in their work on the Menekşe karst plateau.

Herein, we present an innovative approach that uses this effective square electrode array in conjunction with the Generalized Regression Neural Network (GRNN) to estimate the strike and dip of subsurface layers, as well as the electrical resistivities along both the x and y directions of the medium.

METHOD and APPLICATION

Figure 1 illustrates a geological model incorporating a square electrode array. Within this model, ρx represents the resistivity measured along the x direction, while ρy corresponds to the resistivity measured perpendicular to the x-direction. The apparent resistivity value (ρa) can be calculated using Equation (1):

$$\rho_a = \frac{\rho_n}{2-\sqrt{2}}\left\{\begin{array}{l}\left(\dfrac{2}{\left(1+(N^2-1)\,cos^2(\theta)\right)^{\frac{1}{2}}}\right)-\left(\dfrac{1}{\left(2+(N^2-1)(1+sin(2\theta))\right)^{\frac{1}{2}}}\right)\\ -\left(\dfrac{1}{\left(2+(N^2-1)(1-sin(2\theta))\right)^{\frac{1}{2}}}\right)\end{array}\right\}$$

where $N = \left((1+(f^2-1)\,sin(\alpha)^2)\right)^{\frac{1}{2}}$ is the effective anisotropy coefficient. $f = \sqrt{\frac{\rho_{hy}}{\rho_{hx}}}$ is the electrical anisotropy coefficient of electrical. $\rho_n = \sqrt{\rho_{hy}\rho_{hx}}$ is the mean resistivity. θ is the strike and α the dip angle (Habberjam, 1972). Figure 1 also provides examples of the horizontal electrical anisotropy model, depicting variations in electrical anisotropy, strike directions, and dip angles.

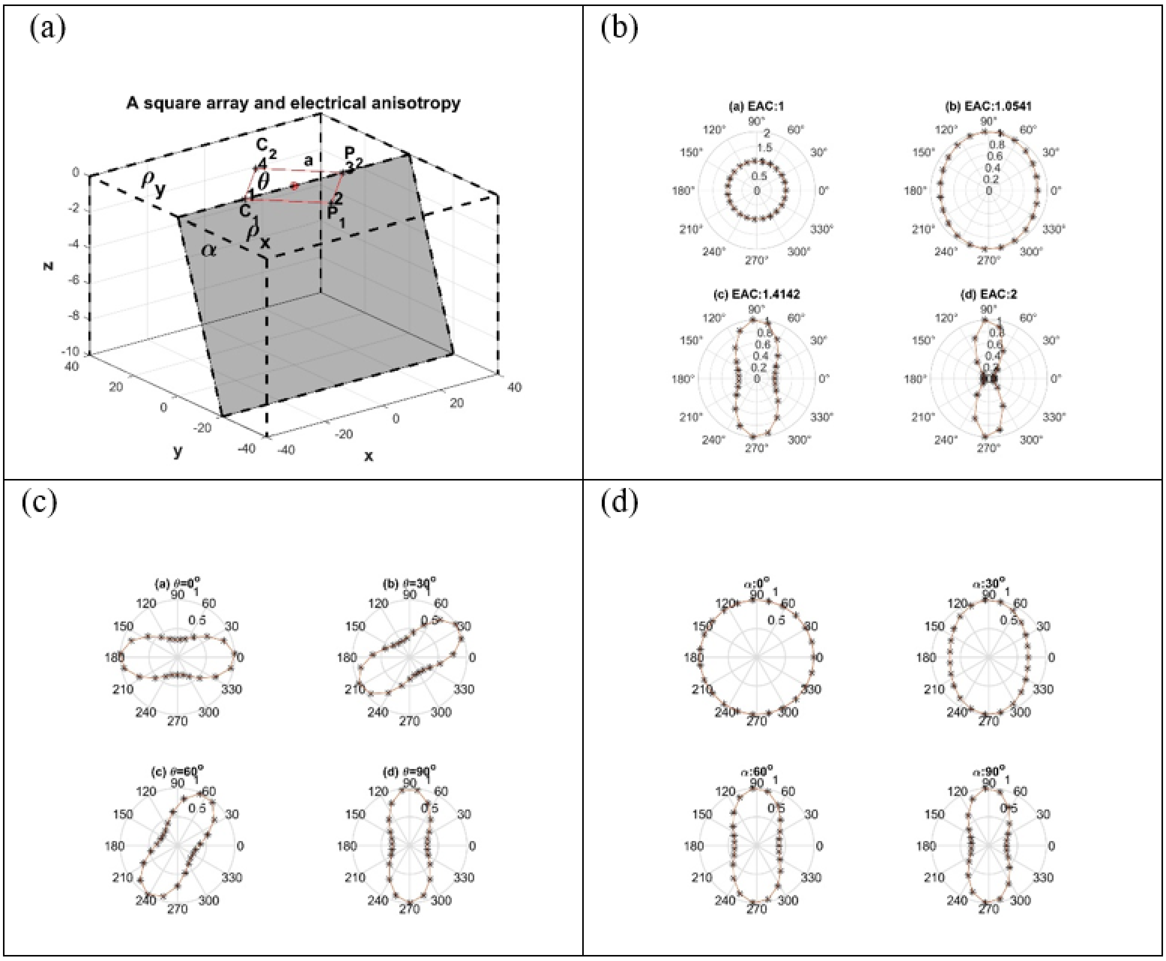

Figure1 (a) A square array and electrical anisotropic model. C_1 ve C_2 are current electrodes. P_1 ve P_2 are potential electrodes. The distance among electrodes is a. (b) Various electrical anisotropies of the earth model response. (c) Various strike directions of the earth model response. (d) Various dip angles of the earth model response.

Artificial neural networks (ANNs) are a class of nonlinear models designed to mimic biological nervous systems. ANNs have been widely applied to solve many difficult problems, including in different fields such as pattern recognition, signal processing, language learning, function approximation, prediction, and modeling. Typically, a biological nervous system (consisting of several layers, each composed of multiple neural units (neurons)) can process information in a parallel manner. Models with these features are known as ANN models (Haykin, 1999).

GRNN was proposed by Specht in 1991. Its general structure consists of four layers divided into input pattern collection, and output sections. GRNN has many advantages over other nonlinear neural network techniques. A benefit of GRNN is that it does not require an iterative training phase. In other words, the network learns directly (single pass learning) from the input data. Another advantage is that predicted model individuals can encounter minimums and maximums of the input data. Moreover, although local regime methods converge to undesirable solutions corresponding to local minima, the GRNN method does not. The calculation time of GRNN includes fast calculation time, database-based prediction ability, and low error rate.

RESULTS

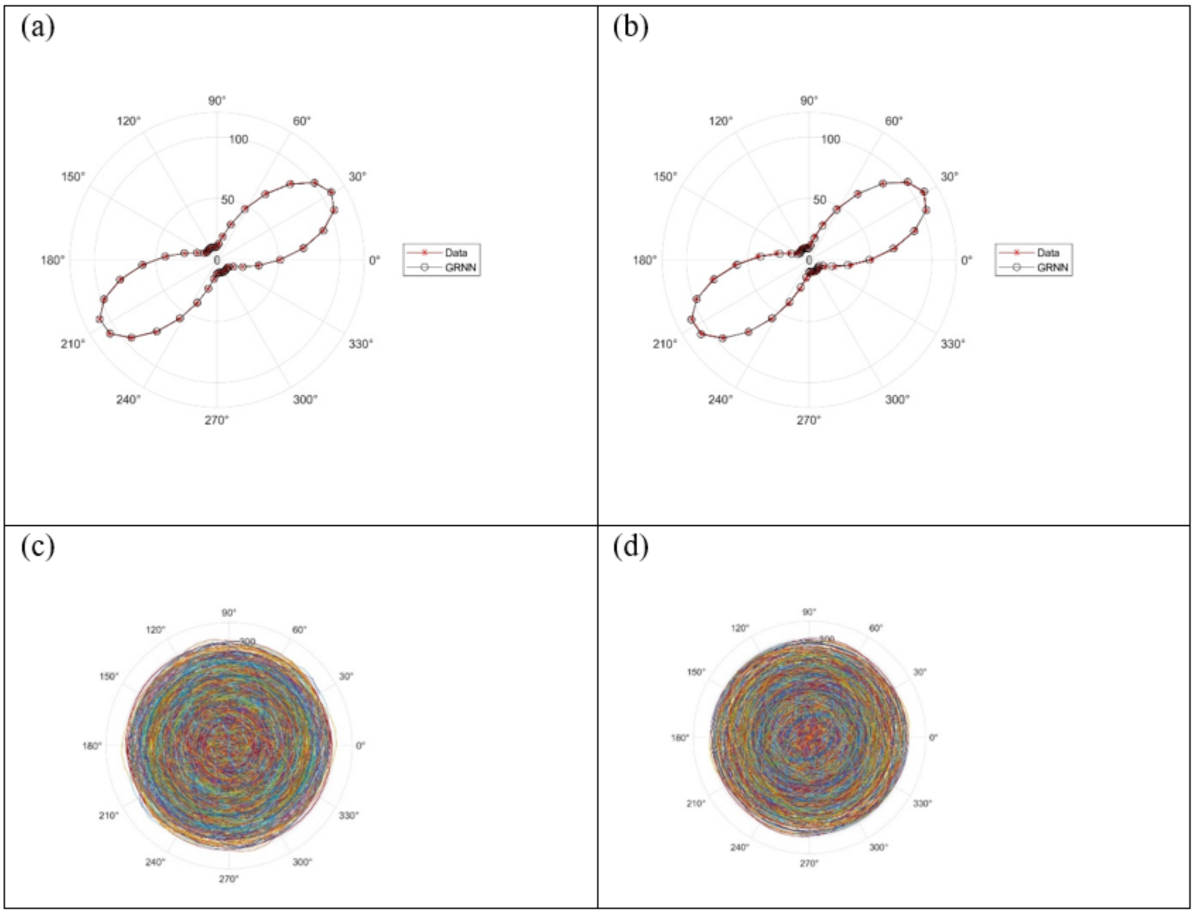

Figure2 (a) Polar plot of a model with two parameters estimated by GRNN using synthetic data. (b) Polar plot of a model with four parameters estimated by GRNN using synthetic data. (c) Training set of parameters space for model (a) with two unknowns. (d) Training set of parameters space for model (b) with four unknowns.

Figure 2 shows the estimated model parameters using the GRNN method with synthetic data. The estimated model parameters are given in Table 1.

Table1 Estimated model parameters using the GRNN.

Parameters	ρ_x (ohm.m)	ρ_y (ohm.m)	θ (degrees)	α (degrees)
Model	100	15	120	45
Noise-Free 2 Parameters			119.21	44.94
Noise-Free 4 Parameters	100.94	14.58	120.17	45.70
Training Set Range	(0-200]	(0-200]	[0-180]	[0-90]

CONCLUSION

This study demonstrates the successful application of the GRNN method to estimate the strike direction, dip angle, and anisotropy coefficient of an anisotropic earth model. We rigorously tested this approach using synthetic data, both with and without noise, highlighting its adaptability to karst environments and various geophysical problems. Effective parameter estimation relies on defining the solution space for the model parameters, with the training set range playing a crucial role in computational efficiency. Selecting an appropriate parameter range is essential, because an excessively large range can lead to increased computational demands.

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