Inversion of Magnetic Anomaly using Machine Learning Regression Techniques along with PSO

Introduction
The magnetic method is widely used in geophysical exploration to map the subsurface structures, identifying the shallow/concealed mineral deposits and basement depth mapping of a sedimentary basin. The most commonly used interpretation methods for the estimation of source parameters (depth, location, and geometry) are Euler Deconvolution (Thompson 1982), enhanced local wavenumber (Thurston and Smith 1997), and Werner Deconvolution (Ku and Sharp 1983). A simple shape body (sphere, cylinder, sheet, and thin dyke) is assumed in these techniques, and a set of linear equations are solved to obtain the source parameters. The main disadvantage of these techniques is that they show erroneous solutions due to a lack of idea about the causative source bodies, noise, and improper choice of window sizes. Global optimization techniques have been used to overcome these problems for the past few decades to estimate the anomalous bodies' source-depth parameters. These methods include genetic algorithm, the differential evolution algorithm method (Balkaya et al., 2017), very fast simulated annealing algorithm (Biswas et al. 2015), ant colony and particle swarm optimization (PSO) methods (Srivastava et al., 2014). Nowadays, machine learning (ML) techniques are also widely used for the interpretation of geophysical data. These ML algorithms are automatically learned and create rules from data without giving a single rule. Some of these ML algorithms are Artificial Neural Network (ANN), Random Forest Regression (RF), and K-Nearest Neighbors Regression machine learning algorithms, and these methods have been applied for interpretation of magnetic data of two field regions, namely Bankura Anomaly, India and Pima copper deposit, Arizona USA.

Particle Swarm Optimization (PSO) Method
Particle swarm optimization (PSO) is a nature-inspired evolutionary algorithm to solve the computationally hard optimization problem (Kennedy and Eberhart, 1995). In this algorithm, a swarm of ‘n’ particles are selected randomly from the given search space, and a position defines each particle in the search space (\(x_i^k\)) and velocity (\(v_i^k\)) vectors. During the iteration process, each particle’s velocity is updated based on its own previous best position (\(p_i^{best}\)) and the best position of the swarm (\(g_{best}\)). Here, the update in the position vector can be defined as follows:

\[
v_i^k = c_1 v_i^k + c_1 \text{rand} (p_i^{best} - x_i^k) + c_2 \text{rand} (g_{best} - x_i^k) \quad \text{........................................... (1)}
\]

\[
x_i^{k+1} = x_i^k + v_i^{k+1} \quad \text{........................................... (2)}
\]

Where \(p_i^{best}\) and \(g_{best}\) are global best at \(k_n\) iteration and personal best of particle i at \(k_n\) iteration, respectively. \(c_1\) is inertia weight, and \(\text{rand} ()\) represents a random number defined in the interval of [0,1]; \(c_1\) and \(c_2\) are randomly initialized values that are used to define the weight of the contribution of cognitive parameters and social parameters. In the present study, the PSO algorithm is implemented to invert the magnetic anomalies over simple geometrical bodies by minimizing the Objective function Q

\[
Q = \frac{2 \sum (T_i^o - T_i^e)}{\sum (T_i^o + T_i^e)} \quad \text{........................................... (3)}
\]

Where N denotes the number of data points, \(T_i^o\) and \(T_i^e\) represent the observed and calculated magnetic anomalies at the point \(x_i\).

Machine Learning Technique
Here, Artificial Neural Network (ANN), Random Forest Regression (RF), and K-Nearest Neighbors (KNN) Regression machine learning algorithms have also been applied to interpret magnetic data. These algorithms are implemented by constraining q values obtained from PSO, and a brief description of these methods is provided below.

Artificial Neural Network (ANN): ANN works similarly as the human brain analyzes and processes information. Neural Networks are made up of layers of neurons, which are the core processing unit of networks. These neurons are interconnected to each other and create a network to store information.
Algorithm takes the data, and train the weights through back-propagation. We minimize the loss function during the training process and then predict the outputs for new sets of similar data. In the present study, a 7-layer Artificial Neural network has been developed for inversion of magnetic anomaly with Adam optimizer and mean square error loss function. Algorithm trained on 500000 synthetic examples for 50 epochs and batch size 32.

**Random Forest (RF):** It is a supervised learning algorithm that uses ensemble learning for classification or regression. It is a bagging technique of ensemble learning where deep decision trees are run parallel as base learner. It involves random sampling of small subsets of data from the dataset. Output prediction of Random forest algorithm is the mean prediction of individual trees in case of regression where small subsets of data are used as input.

**K-Nearest Neighbors (KNN):** KNN is a non-parametric machine learning algorithm first developed by Fix and Hodges (1951). They have used KNN for both classification and regression. The algorithm is based on the assumption that similar things exist in close proximity. In regression, the output property value is the average of the values of k nearest neighbors. The neighbors are taken from a set of objects for which the object property value (for regression) is known based on the Euclidean distance.

**Synthetic examples**
The general expression for magnetic anomalies due to simple geometrical bodies (sphere, horizontal cylindrical, and thin sheet) is given by the following equation (Gay 1963; Abdelrahman and Essa, 2015)

\[ T(x, z) = Kz^n \frac{A \sin^2 \theta + B (x-x_0)z + C (x-x_0)^2}{(x-x_0)^2} \]  

\[ \text{for sphere (n = 3)} \]

\[ A = \begin{cases} 
3 \sin^2 \theta - 1 \\
\cos \theta 
\end{cases} \quad B = \begin{cases} 
-3 \sin \theta \\
2z \sin \theta 
\end{cases} \quad C = \begin{cases} 
3 \cos^2 \theta - 1 \\
-\cos \theta \\
0 
\end{cases} \]

\[ \text{for horizontal cylinder (n = 0)} \]

\[ \text{for thin dyke (n = 0)} \]

Where, \( K \) denotes the amplitude coefficient; \( \theta \) represents the effective polarization angle; \( z \) is the depth to the centre/top of the source body. \( x_0 \) is the position of the centre of the body. Here \( q \) denotes the shape factor, and its value depends on the geometry of the body. Generally, the value of \( q \) is 2.5 for the sphere, 2.0 for horizontal cylinder 2, and 1 for thin dyke (Abdelrahman and Essa, 2015).

![Figure 1](image1.png)

**Figure 1** Inversion result of noise-free synthetic anomalies

![Figure 2](image2.png)

**Figure 2** Inversion result of noisy (10% Gaussian noise) synthetic anomalies

To evaluate the efficiency of the PSO and machine learning technique, these algorithms were tested for both noise-free (Figure 1) and noisy (10% Gaussian noise) magnetic anomaly data (Figure 2) due to three simple geometrical bodies, namely sphere, horizontal cylinder and thin-dyke. The parameters
considered for generating all the three synthetic models and results of PSO, ANN, KNN, and Random forest algorithms are presented in Table 1. Machine learning algorithms are implemented by constraining q value obtained from PSO. The parameters corresponding to position appears to be stable even after adding 10% Gaussian noise compared to other model parameters, which show an increase in error in the estimated values with the addition of noise.

<table>
<thead>
<tr>
<th>Body Type</th>
<th>Parameters</th>
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<th>Result</th>
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<td>x0(m)</td>
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<td>q</td>
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</table>

Table 1 Model parameters computed from PSO, ANN, KNN, and Random forest algorithms for three simple geometry bodies Sphere, Horizontal cylinder, and thin dyke

Figure 3 Results of PSO, ANN, KNN, and Random forest algorithms for two different field examples right) Bankura Anomaly, India, left) Pima copper deposit, Arizona USA,

Field examples
To test the validity of PSO and machine learning technique, these algorithms were also implemented for two field examples, namely Bankura Anomaly, India, and Pima copper deposit, Arizona USA (Figure 3). Here first, we obtain the values shape factor q, and afterward, other model parameters were obtained by constraining the q value. The model parameters obtained from these algorithms are presented in Table 2. The modeling result suggests a q value of 2.5 (sphere) for Bankura anomaly and a q value of 1.0 (thin dyke) for the Pima copper deposit. It is also observed that a single body can model magnetic anomaly over Bankura and Pima copper deposits.
### Conclusion

The value of the model parameters found by PSO and these machine learning techniques for the above two field examples are similar to those of previous studies using different methods. So PSO has very good efficiency for inversion of magnetic anomaly also. Machine learning algorithms also have very good efficiency when combined with PSO, which provides them with the source body's geometry. This study allowed us to say that the Bankura anomaly is the magnetic anomaly associated with the spherical mass, and the Pima copper deposit anomaly arises due to dipping thin dyke at a depth of about 70 meters.

### References


