InversionOf Magnetic Anomalies Due To 2-D Cylindrical Structures –By An Artificial Neural Network

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ABSTRACT

Application of Artificial Neural Network Committee Machine (ANNCM) for the inversion of magnetic anomalies caused by a long-2D horizontal circular cylinder is presented. Although, the subsurface targets are of arbitrary shape, they are assumed to be regular geometrical shape for convenience of mathematical analysis. ANNCM inversion extract the parameters of the causative subsurface targets include depth to the centre of the cylinder (Z), the inclination of magnetic vector(Ө)and the constant term (A)comprising the radius(R)and the intensity of the magnetic field(I). The method of inversion is demonstrated over a theoretical model with and without random noise in order to study the effect of noise on the technique and then extended to real field data. It is noted that the method under discussion ensures fairly accurate results even in the presence of noise. ANNCM analysis of vertical magnetic anomaly near Karimnagar, Telangana, India, has shown satisfactory results in comparison with other inversion techniques that are in vogue.The statistics of the predicted parameters relative to the measured data, show lower sum error (<9.58%) and higher correlation coefficient (R>91%) indicating that good matching and correlation is achieved between the measured and predicted parameters.

KEYWORDS

Magnetic anomaly, Artificial Neural Network, Committee machine, Levenberg – Marquardt algorithm, Hilbert transform, modified Hilbert transform, trial and error method.

1. INTRODUCTION

In quantitative interpretation, the gravity and magnetic anomalies over a mineralized zone or geological structure can be approximated to simple geometrical shapes. Quantitativeinterpretation of the magnetic and gravity anomalies due to anticlines and synclines is accomplished by approximating them to two-dimensional, long horizontal circular cylinder. Linear concentrations of the mineral magnetite in a mineralized zone may be approximated some times to a horizontal cylinder. There are several methods of analyzing magnetic anomalies due to cylindrical structure.Parker Gay(1965) presented a set of master curves for the interpretation of the magnetic anomalies due to cylindrical bodies [25]. Rao et al. (1973) have developed direct methods for carrying out such interpretations [28]. Murthyand Mishra (1980) have proposed spectral approaches[23].

Mohan et al. (1990) used the Mellin transform in interpreting magnetic anomalies due to some two dimensional bodies [21].Sundararajan et al. (1985, 1989) interpreted the magnetic anomalies of various components due to thin infinite dyke and spherical source by using Hilbert transform([34], [35]). Srinivas(1998) used the modified Hilbert transform to interpret magnetic anomalies caused by 2-D horizontal circular cylindrical structures [32].During 1999-2013, different methods Wavelet transform([22], [16]), Displacement of the maximum and minimum by

upward continuation [9], Euler deconvolution [12], Fraser filter [5], Hartley transform [18] and Direct analytic signal [6] were used for inversion of magnetic data.

TDX is a normalized version of the horizontal derivative filter and can recognize the edges of the shallow and deep bodies simultaneously. This filter is commonly used in the edge detection of potential field data.Alamdar et al. (2015) used combination of this balanced edge detection filter and Euler deconvolution to real magnetic data from Soork iron ore mine in Iran to estimate source location [1].Tavakoli et al. (2016) used singular value decomposition method for the interpretation of magnetic anomalies by 3D inversion [38]. Very fast simulated annealing global optimization technique is used for interpretation of gravity and magnetic anomaly over thin sheet-type structure byArkoprovo Biswas (2016) [3]. Recently, YunusLeventEkinci et al. (2017) used differential evolution algorithm for amplitude inversion of the 2D analytic signal of magnetic anomalies [39].In the recent years, soft computing tools like Artificial neural network (ANN), Fuzzy logic, Genetic algorithm gained great importance in geophysical data inversion([17], [33], [30], [14], [10], [26], [2]).

A committee machine consists of a group of intelligent systems named experts (ANN) and a combiner which combines the outputs of each expert[8].Its advantages aremore accuracy in prediction,speed learningand better generalization.If the combination of experts in committee machine were replaced by a single neural network, one would have a network with a correspondingly large number of adjustable weight parameters. The training time for such a large network is likely to be longer than for the case of a set of experts trained in parallel. Moreover, the risk of over fitting the data increases when the number of adjustable weight parameters is large compared to size of the set of the training data.

In this paper, the analysis of vertical magnetic anomalies due to a 2-D horizontal circular cylinder is carried out using ANN-based committee machine.The method is illustrated with the study of theoretical model and validity of procedure is tested with the addition of random noise to the source data. Further, the technique is exemplified with magneticanomaly over a narrow band of quartz magnetic nearKarimnagar, Telangana, India [32]. Both the theoretical as well as field data yield reasonably good resultsand are compared with other methods that are in vogue.

2. ARTIFICIAL NEURAL NETWORKS

An artificial neural network is a computing system which consists of massively parallel interconnection of large number of neurons. It is capable of capturing and representing complex input/output relationships and is an abstract simulation of a human brain. It learns incrementally from environment (data). On this basis it provides reliable predictions for new situations containing even noisy and partial information. ANN has two main components, namely the processing elements and the connections between them. The processing elements are called neurons and connection between two neurons is called a link. Every link has a weight parameter associated with it. A neuron (j) computes a single output$(a_j)$from multiple inputs $(x_1, x_2, \dots, x_{S_0})$ by forming linear combination according to its input weights $(w_{j1}, w_{j2}, \dots\dots, w_{jS_0}, b_j)$and then possibly putting the output through some activation function ($f(.)$) and is shown in Figure (1)([20], [29], [8]), where S_0 is the number of inputs. Activation functions such as sigmoid are commonly used since they are nonlinear and continuously differentiable([11], [31]).The neurons take input data and perform simple operations on the data. The result of these operations is passed to other neurons. ANNs are capable of learning, which takes place by altering weight values.

Multi-layer perceptron (MLP) is a feed forward artificial neural network with one or more layers between input and output layers.Figure (2) shows a two-layer feedforward network.The net input to a neuron j in layer $k+1$ is given by [7]:

$$n_j^{k+1} = \sum_{i=1}^{S_k} w_{ji}^{k+1} a_i^k + b_j^{k+1} \qquad \text{..... (1)}$$

The output of neuron j will be

$$a_j^{k+1} = f_j^{k+1}(n_j^{k+1}) \quad \text{where} \quad k = 0,1, \qquad \text{......(2)}$$

where w_{ji}^{k+1} represents the weight associated with the i'th input to neuron j in layer $k+1$, b_j^{k+1} is a bias to neuron j and S_{k+1} is the number of neurons in the layer $k+1$. It has $(S_1 \times (S_0 +1) + S_2 \times (S_1 +1))$ weights. One may observe that if $\underline{x} = [\ a_1^0 \ \ a_2^0 \ ... \ ... \ a_{S_0}^0\ ]^T$ is presented to the network and $AN(\underline{x})$ is the output of MLP, then

$$AN(\underline{x}) = [a_1^2 \ a_2^2 \ ... \ a_{S_2}^2]^T \qquad \text{...... (3)}$$

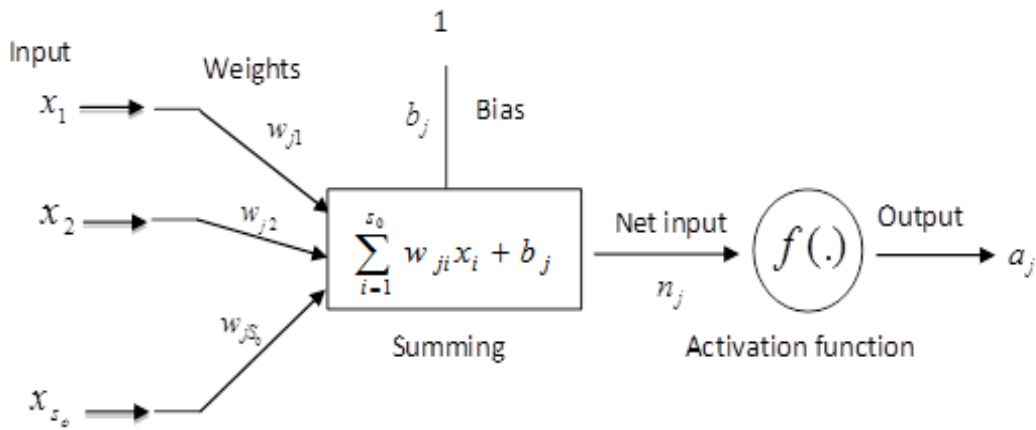where a_j^2's are given by Eq. (2).
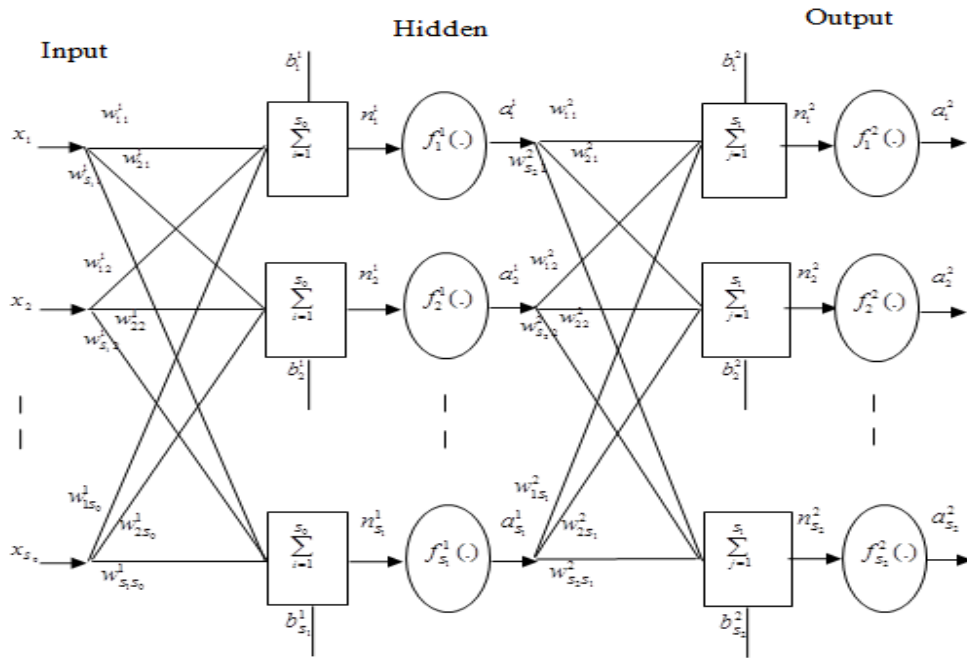

Figure 1 A model of an artificial neuron

Figure 2 A two-Layer feed forward network (Multilayer perceptron)

MLP learns the problem behavior through a process called training and it would be taught with measured/simulated samples from a training set say $T = \{(\underline{x}_1, \underline{t}_1), (\underline{x}_2, \underline{t}_2), ..., (\underline{x}_P, \underline{t}_P)\}$. The performance (*Perf*) of MLP is calculated using the following error function:

$$E(\vec{w}) = \frac{1}{2}\sum_{p=1}^{P}\left(t_p - AN(\underline{x}_p)\right)^T \left(t_p - AN(\underline{x}_p)\right) = \frac{1}{2}\sum_{p=1}^{P} e_p^T e_p \qquad \text{..... (4)}$$

where $AN(\underline{x}_p)$ is the output of network, $\vec{w}$ is the weight vector containing all the weights of the network, t_p - target, e_p - error and P -total number of training samples. The goal of the training is to find the weights that will impact the output from MLP to match the targets as closely as possible. If the outputs of MLP come as close as possible to match the targets for all the samples, then performance function $E(\vec{w})$ of network is minimized. Levenberg-Marquardt back-propagation algorithm ([15], [19], [7]) is one of the numerical optimization techniques that minimizes $E(\vec{w})$. It is fast with stable convergence. Levenberg-Marquardt algorithm(LMA)[4] is given by:

$$\vec{w}(n+1) = \vec{w}(n) - \left(J(\vec{w})^T(n)J(\vec{w})(n) + \mu I\right)^{-1} J(\vec{w})^T(n)e(\vec{w})(n) \qquad \text{.....(5)}$$

where $e(\vec{w}) = [e_1(\vec{w}) \ e_2(\vec{w}) \ ... \ ... \ e_P(\vec{w})]^T$ is the error vector comprising the errors for all the training samples, $J(\vec{w})(n)$ is a Jacobian matrix, n is an iteration number and μ is a damping parameter.
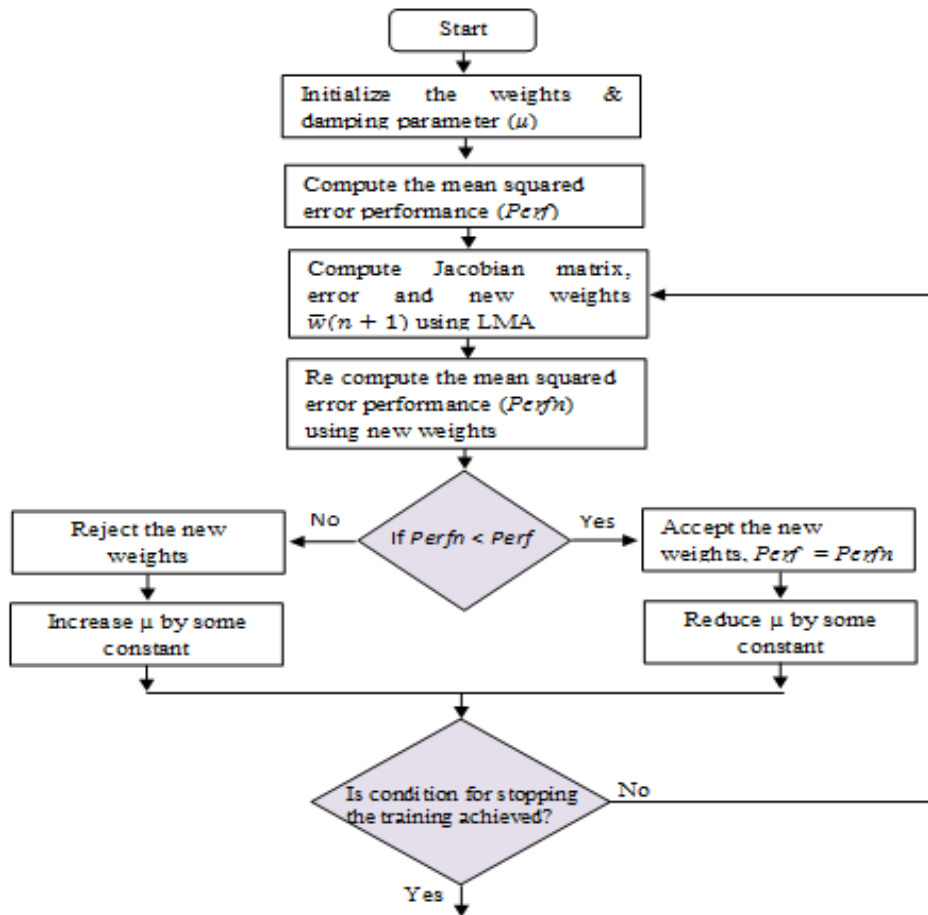
Figure 3 Flow-chart of Implementation of the LM algorithm

When μ is large, the method takes a small step in the gradient direction. As the method nears a solution, μ is chosen to be small and the method converges quickly via the Gauss Newton method. The flowchart of implementation of the LM algorithm during training a network is shown in Figure (3). A method for calculation of $\vec{w}(n+1)$ using Eq. (5) requires both forward and backward calculations. First, feed forward calculations which are made to determine the error at the output layer. The elements of the Jacobian matrix are then obtained by propagating this error back through the network which can be computed by a simple modification to the standard backpropagation algorithm[7]. The backpropagation process has to be repeated for every output separately in order to obtain consecutive rows of the Jacobian matrix.

2.1. Artificial Neural Network Committee Machine (ANNCM)

Committee machines with static structure, the outputs of several predictors (expert) are combined by a mechanism that does not involve the input signal with *ensemble* and *boosting* methods. Figure (4) shows a number of differently trained neural networks (i.e., experts), which share a common input and whose individual outputs are combined using rules such as averaging, voting etc., to produce an overall output. Such a technique is referred to as an*ensemble averaging* method. This method is most popular [24]. Ensemble averaging creates a group of networks (experts); each with low bias and high variance, then combines them to a new network with low bias and low variance. Further the idea behind such network is to fuse knowledge acquired by

experts in order to arrive at an overall decision that is superior to that of any of the individual experts ([13], [24], [8]).
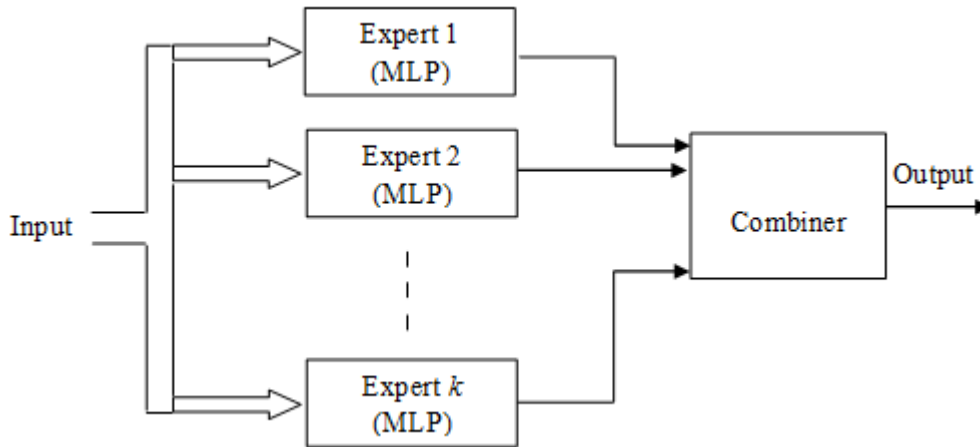

Figure 4 Artificial Neural Network Committee Machine

3. MAGNETIC EFFECT DUE TO A 2-D HORIZONTAL CIRCULAR CYLINDER

The vertical magnetic effect $V(x)$ due to a 2-D horizontal circular cylinder extending infinitely along the Y-axis with its normal section parallel to the X-Z plane (Figure(5)) at a point $'x'$ is givenby [37]:

$$V(x) = A \left[\frac{(z^2 - x^2)\sin\theta - 2xz\cos\theta}{(x^2 + z^2)^2} \right] \dots (6)$$

where,

      z- is the depth to the centre of the cylinder,

      θ - is the inclination of magnetic vector,

      A-is the constant term comprising the radius (R) and the intensity of the magnetic field (I) and is given as $A = 2\pi R^2 I$.
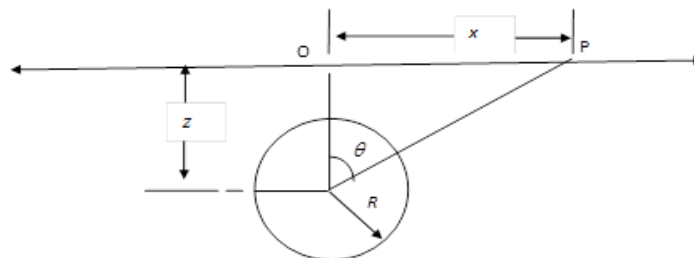

Figure 5 Geometry of the 2D Horizontal Circular Cylinder

The inversion of magnetic effect due to a 2-D horizontal circular cylinder is achieved by ANNCM which consists of phase-I and phase-IIand is discussed in the following subsections. In phase-I coarse values of parameters are obtained whereas in phase-II fine values of parameters are obtained. We call, phase-I and phase-II as coarse and fine application.Flow chart of phase-I and phase-II is shown in Figure(6).

3.1. Phase-I

In phase-I, a trial and error method is implemented for the analysis of magnetic anomaly $(V(x) = X)$ generated with the model parameters (z_o, θ_o, A_o). The trial and error method assumes (i.e. trial) an initial set of parameter range, (z_i, θ_i, A_i) (where i = 1,2,3, …..) and computes the magnetic model responses (Y_i) and compares them with (X) and then the mean square error (E) between Y_i and X are estimated. For a particular value of "i", the parameters (z, θ, A) that result $E < \delta$ may be considered as the appropriate set of parameters of magnetic anomaly X, where δ is a small positive real number. Selection of an initial set of parameters range is based on Hilbert transform analysis in which case it may narrow down the choice although the initial set of parameters may also given randomly.

Let $\tilde{z}, \tilde{\theta}, \tilde{A}$ be appropriate values of parameters obtained by trial and error method. These parameterswill be carried to phase-II in order to increase their accuracy.

3.2 Phase-II

Phase-II can be implemented in stepwise as hereunder.

Step -1: Create models to train an ANN in the following way.

Let $Z = \left\{ \tilde{z}_1, \tilde{z}_2, ..., \tilde{z}_{m_1} \right\}$, $I = \left\{ \tilde{\theta}_1, \tilde{\theta}_2, ..., \tilde{\theta}_{m_2} \right\}$ and $C = \left\{ \tilde{A}_1, \tilde{A}_2, ..., \tilde{A}_{m_3} \right\}$ be three sets of parameters that are selected in a small neighborhood of $\tilde{z}$, $\tilde{\theta}$ and $\tilde{A}$ respectively. Then the number of models of type $\left(\tilde{z}_i, \tilde{\theta}_j, \tilde{A}_k \right)$ is $m_1 \times m_2 \times m_3$, where $\tilde{z}_i \in Z$, $\tilde{\theta}_j \in I$ and $\tilde{A}_k \in C$.

For simplicity, rename each $\left(\tilde{z}_i, \tilde{\theta}_j, \tilde{A}_k \right)$ as $\left(z_p, \theta_p, A_p \right)$ for $p = 1, 2, ..., P$, where $P = m_1 \times m_2 \times m_3$. Let $V^p(x_j)$ be vertical magnetic effect due to a 2-D horizontal circular cylinder generated by Eq. (6) at a point x_j with the model parameters (z_p, θ_p, A_p) where $1 \le p \le P$, $1 \le j \le S_0$. Let $V^p = (V^p(x_1), ..., V^p(x_j), ..., V^p(x_{S_0}))$, $t_p = (z_p, \theta_p, A_p)$ and

$$T = \{(V^1, t_1), (V^2, t_2), ..., (V^P, t_P)\} \qquad ... (7)$$

Realization of an inversion estimation of parameters of the anomaly (X) is achieved by training an ANNCMwith the models (V^p, t_p), where $(V^p, t_p) \in T$, $(p = 1, 2, ..., P)$.

*Step-2:*In this step, first design an artificial neural network committee machine with suitable number of experts (MLPs)and in turn each will be trained in batch mode with themodels (V^p, t_p) ,$(p = 1, 2, ..., P)$ using LM algorithm.
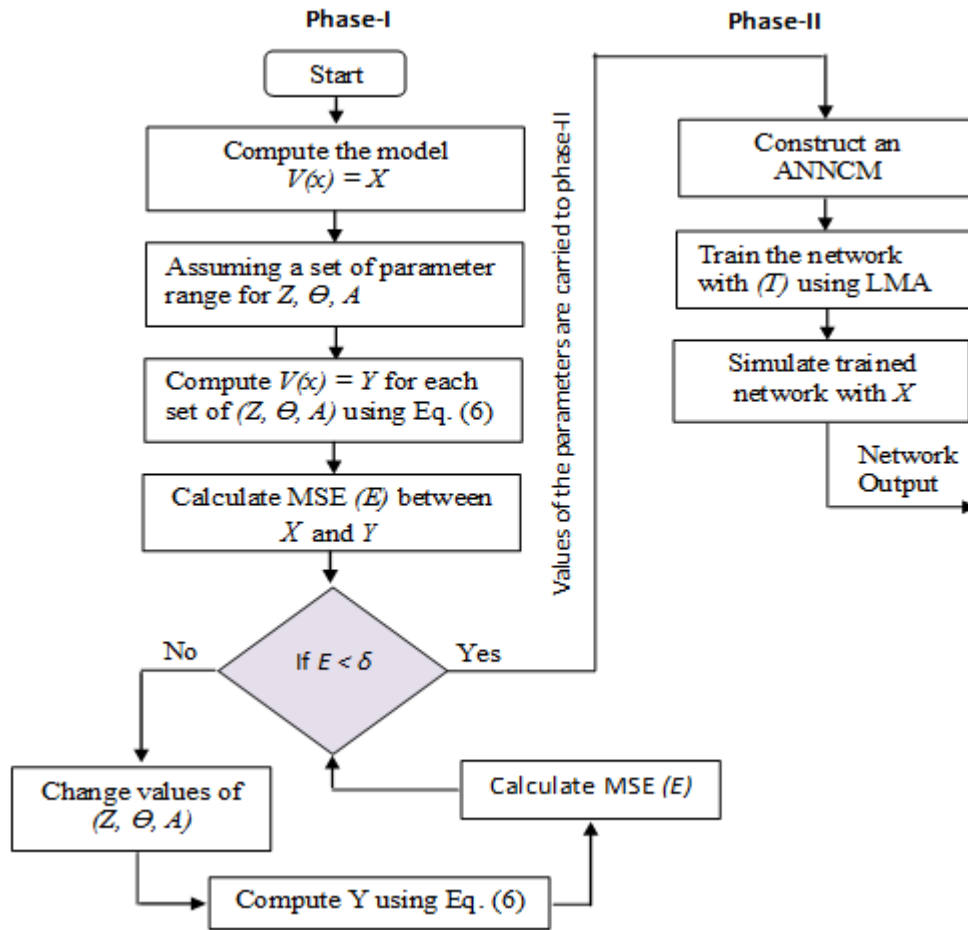
Figure 6 Flow-chart of implementation of the Phase-I and Phase-II

3.3. Hilbert and modified Hilbert Transform

Selection of a range of initial set of parameters is based on the procedure of Hilbert and/or modified Hilbert transforms as briefed below.

The Hilbert transform $H(x)$ and the modified Hilbert transform $MH(x)$ of the vertical magnetic anomaly $V(x)$ due to an inclined sheet are computed by [32]:

$$H(x) = -A\left[\frac{(z^2 - x^2)\cos\theta + 2xz\sin\theta}{(x^2 + z^2)^2}\right] \qquad ….. (8)$$

$$MH(x) = -A\left[\frac{(z^2 - x^2)\cos\theta - 2xz\sin\theta}{(x^2 + z^2)^2}\right] \qquad ….. (9)$$

Sundararajan and Srinivas[36] reported in literature that the Hilbert transform and its modified version intersect exactly over the origin (centre of the subsurface target). From the equations of

vertical magnetic anomaly $V(x)$ and the modified Hilbert transform $MH(x)$, the depth to the top of the sheet (z), the inclination (θ) and the constant term (A) are given as:

$$z = -\frac{x_1 + x_2}{2} \qquad\qquad\qquad \dots\dots (10)$$

$$\theta = \tan^{-1}\left[\frac{2zxMH(x)-(z^2-x^2)V(x)}{(z^2-x^2)MH(x)-2zxV(x)}\right] \qquad\qquad \dots\dots (11)$$

$$A = z^2\sqrt{V(0)^2 + MH(0)^2} \qquad\qquad\qquad \dots\dots (12),$$

where x_1 and x_2 are the abscissa of the points of intersection of $V(x)$ and $MH(x)$.

4. THEORETICAL MODELS

The vertical magnetic anomaly $V(x)$ due to a 2D horizontal circular cylinder of theoretical model-I is generated using Eq. (6) with input parameters $(z = 12, \theta = 40$ and $A = 800)$ consisting of 51 samples with 2 units as sampling. Parameters ranges used in trial and error method during phase- I are given in Table (1). The selection of parameter ranges are based on the results obtained by modified Hilbert transformand they are given in Table (1). The appropriate values of parameters obtained in phase-I are: $\tilde{z} = 10.5$, $\tilde{\theta} = 40°$ and $\tilde{A} = 650$. The range of parameters and number of steps that were used in phase-II to generate ANN models (V^P, t_p) are given in Table (2). The ANNCM with fiveMLPs(Figure(4)) of same topology (i.e., number of layers, number of neurons in each layer are same) with different initial weightsis used to invert the model-I by assigning 51 samples $V^P = \left[V^P(x_1) \quad \dots \quad \dots \quad \dots \quad V^P(x_{51})\right]^T$ to the input layer. Ten neurons with hyperbolic tangent transfer functions are used for hidden layer. Threeneurons with linear transfer functionsare used for output layer to extract the required parameters (z, θ, A). Each MLP has 553 weights $(10 \times (51+1) + 3 \times (10+1))$. While training the networks the set $T = \{(V^1, t_1), (V^2, t_2), \dots, (V^P, t_P)\}$ is randomly divided into three subsets namely training, validation and testing sets,each are containing 70%, 15% and 15% models respectively. A training set is one that is used for computing the gradient and updating the network weights and biases in the ANN to produce desired outcome. On the other hand, validation test is used to find out the best ANN configuration and training parameters. The error on validation set is monitored during training process. The validation error normally decreases during the initial phase of training. However, when the network begins to over fit the data, the error on the validation set typically begins to rise. The network weights and biases are saved at the minimum of the validation set error. But, a test set is used only to evaluate the fully trained ANN. The test set error is not used during training, but it is used to compare different models. It is also useful to plot the test set error during the training process. If the error on the test set reaches a minimum at a significantly different number of iterations than the validation set error, this might indicate a poor division of the data set [40].The performance of each MLP is calculated using Eq. (4) and weights are adjusted according to Eq. (5). Outputs of ANNCM are computed by *ensemble averaging* method and given in Table (3). The vertical magnetic anomaly $V(x)$ and the ANNCM inversion response are shown in Figure (7). The Hilbert transform $H(x)$ and the modified Hilbert transform $MH(x)$ of the vertical magnetic anomaly $V(x)$ using Eq. (8)-(9) are computed and shown in

Figure (8). The well trained network can invert any data that falls within the training range in almost no time.
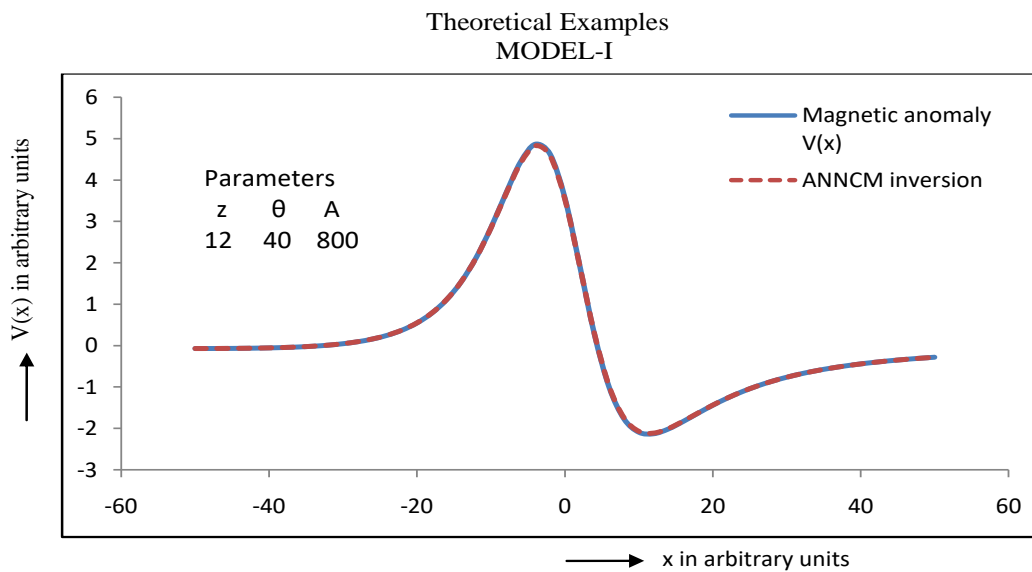

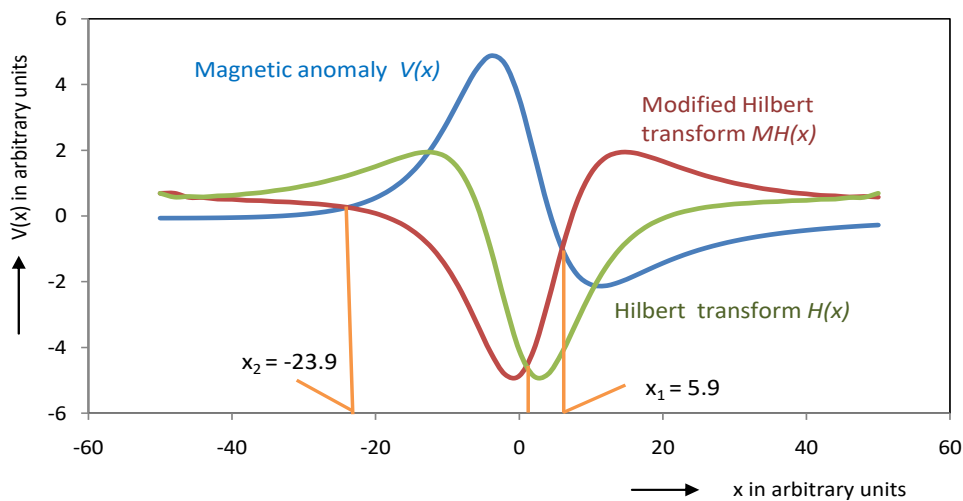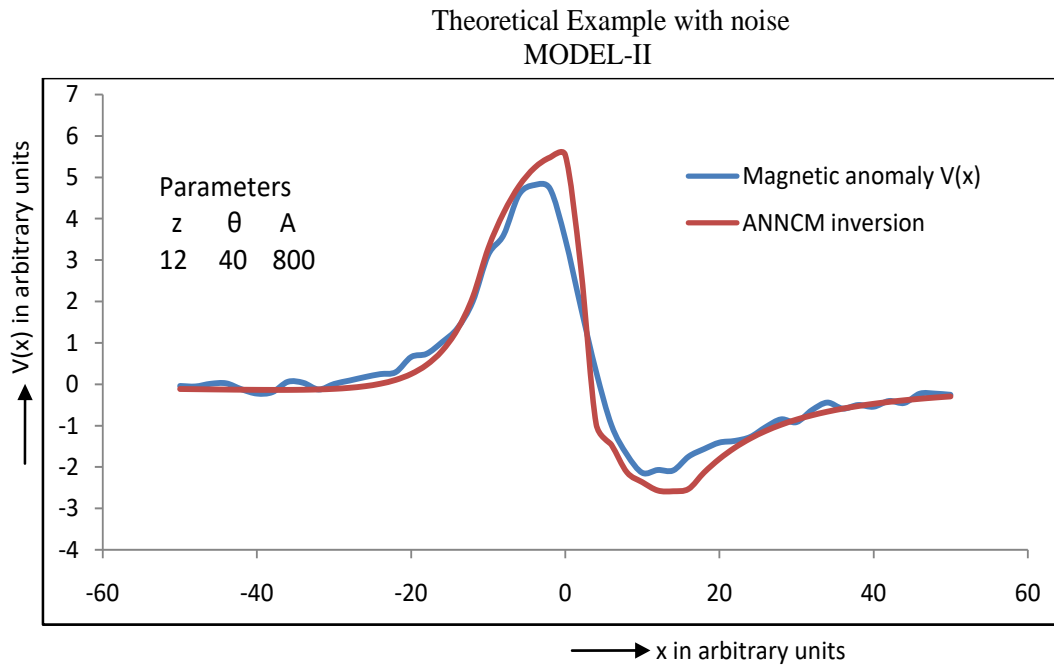**Figure 7 Vertical magnetic anomaly *V(x)* and ANNCM inversion response of model-I**

Figure 8 Vertical magnetic anomaly *V(x)*, the Hilbert transform *H(x)* and modified Hilbert transform *MH(x)* of model-I

4.1. Effect of Random Noise

Ten percent of Gaussian random noise is added to the vertical magnetic anomaly $V(x)$ of model-I [Figure (7)] and is shown in Figure (9). As in the case of noise free analysis, of magnetic anomalies, the values of parameters obtained during phase-I are $\tilde{z} = 10.5$, $\tilde{\theta} = 40°$ and $\tilde{A} = 600$. Modified Hilbert transform results and parameters ranges that are used in trial and error method during phase- I are given in Table (1). The range of parameters, number of steps and the number of ANN models that are generated in phase-II are given in Table (2). The ANNCM inversion response is shown in Figure (9). The Hilbert transform $H(x)$ and the modified Hilbert

transform $MH(x)$ of the noisy vertical magnetic anomaly $V(x)$ are computed and shown in Figure (10). The result of the ANNCM inversion parameters is given in Table (3).

Theoretical Example with noise
MODEL-II

Figure 9 Noisy vertical magnetic anomaly _V(x)_ and ANNCM inversion response of model-II
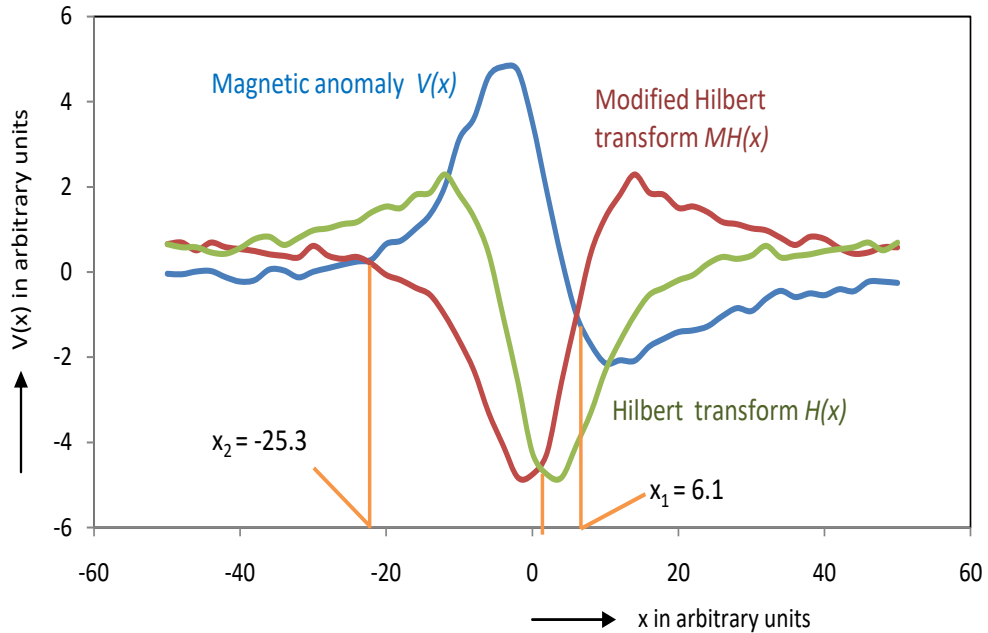
Figure 10 Vertical magnetic anomaly _V(x)_, the Hilbert transform _H(x)_ and modified Hilbert transform _MH(x)_ of model-II.

Table 1   Initial set of parameters to Phase-I

Examples		z	θ	A
Model-I	Range	1 – 20	20º – 60º	350 – 650
	By modified HT	8.96	36.24º	485.26
Model-II (with noise)	Range	1 – 20	20º – 60º	300 – 600
	By modified HT	8.47	36.42º	424.51

Table 2 Target range of parameters, number of steps and ANN models (Phase-II)

Examples	z	θ	A	Number of ANN models
Model-I	8– 12 (5)	35º – 45º (6)	550– 750 (9)	270
Model-II (with noise)	8– 12 (5)	35º – 45º (6)	500– 700 (10)	300

Table 3 Theoretical examples (* in arbitrary units)

	Parameters	z^*	θ	A^*
Theoretical Model-I	Assumed values	12.00	40º00′	800.00
	ANNCM processed parameters	12.05	40º02′	799.60
	Error in percentage	0.41	0.08	0.05
Theoretical Model-II (with noise)	Assumed Values	12.00	40º00′	800.00
	ANNCM processed parameters	10.85	41º17′	872.93
	Error in percentage	9.58	3.20	9.11

5. FIELD EXAMPLE

The applicability of the proposed technique is demonstrated on an observed vertical magnetic data near Karimnagar district, Telangana, India (Srinivas 1998) and is shown in Figure (11). The total length of the profile (182.60 meters) was digitized into 60 equal parts at an interval of 3.0433m. The quality of the data is determined by the signal to noise ratio (*SNR*) and is given as:

$$SNR = \frac{m}{s},$$

where m is the mean and s is the standard deviation of the data. If the ratio is less than 3, the data is assumed to be very poor quality. If the ratio is greater than 3, then the level of noise is negligible and the data shall be considered clean. Signal to noise ratio of the field datais calculated and is given by:

$$SNR = \frac{5017.1}{646.8136} = 7.7567$$

The parameters ranges that were used in trial and error method during phase-I obtained by modified Hilbert transform $(z = 21.90m, \tilde{\theta} = 68.68°, \tilde{A} = 45592411)$ and are given as:

- the depth z (19m–50m)
- the inclination θ (1°–150°)
- the constant A (450,00,000–550,00,000)

The appropriate values of parameters obtained in phase-I are $\tilde{z} = 24.38m, \tilde{\theta} = 73°$, $\tilde{A} = 46592000$. Three hundred training models were created by assigning different values to (z, θ, A) in a close range of $(\tilde{z}, \tilde{\theta}, \tilde{A})$ which were used in phase-II are as follows:

- the depth z (19m – 29m), with five points in this range
- the inclination θ (70° – 80°), with six points in this range
- the constant A (465,62,000 – 466,22,000), with ten points in this range;

ANNCMinversion response compared with the field data are shown in Figure (11). The Hilbert transform $H(x)$ and the modified Hilbert transform $MH(x)$ of the vertical magnetic anomaly $V(x)$ are computed and shown in Figure (12). The estimated parameters are given in Table (4). Results shown are better and agree well with other inversion methods (Table 4).

Table 4 Field Example (Vertical magnetic anomaly, near Karimnagar, Telangana, India)

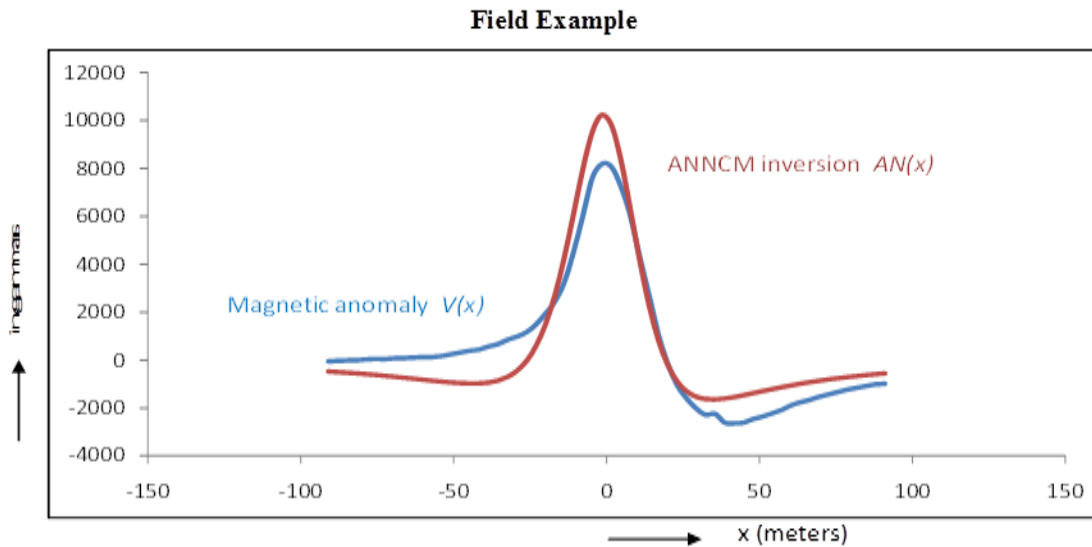| Methods	z (in meters))	θ	A
Gradient method [27]	23.23	56°00′	….
Modified Hilbert transformTechnique [32]	21.4	46°00′	….
Present Artificial Neural Network Committee Machine	22.66	78°18′	47493187.04

Figure 11 Vertical magnetic anomaly over a narrow band of quartz magnetite, near Karimnagar District, Telangana, India.
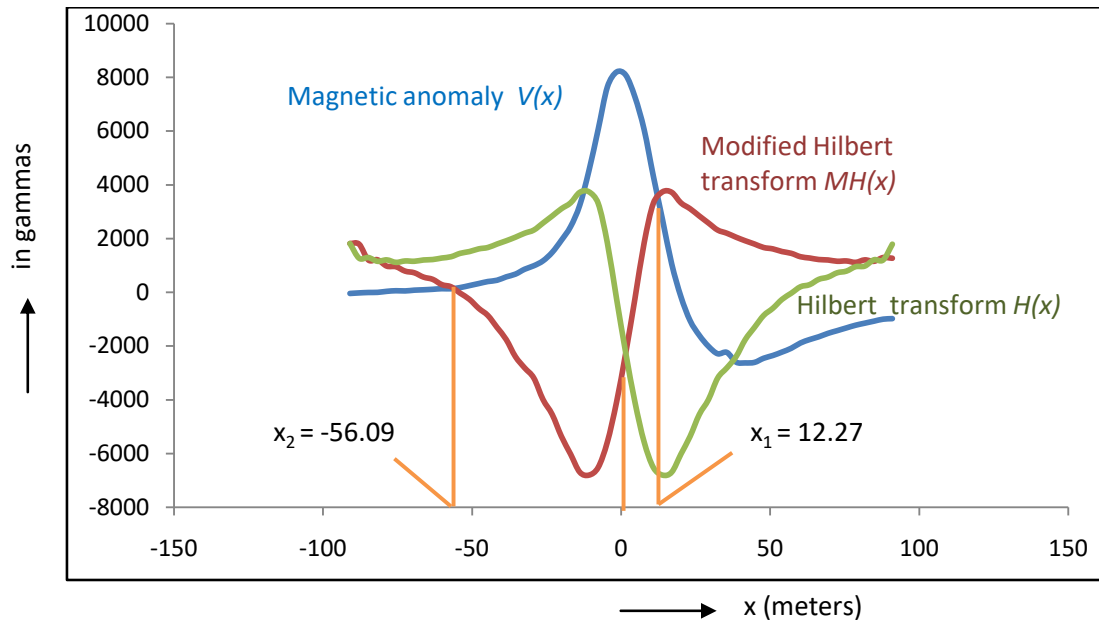

Figure 12 Vertical magnetic anomaly $V(x)$ the Hilbert transform $H(x)$ and modified Hilbert transform $MH(x)$ of field data.

6. RESULTS AND DISCUSSION

During training network, 870 training models were used for both theoretical and field data for which Levenberg-Marquart algorithm is very much suitable. From Table (3), it is observed that the results in general agree with the assumed values. However, the addition of random noise level

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to the magnetic anomaly and subsequent analysis show a marginal variation implying that the effect of such noise is almost negligible in the present method. The method with LM algorithm shows the best performance in extraction of parameters of a model. Hence, determination of the depth and inclination of various structures from magnetic data can be solved effectively.

7. CONCLUSIONS

The accuracy of ANNCM inversion results is fairly good. The ANN committee machine analysis of magnetic inversion is simple and elegant and the method is effective even in the presence of noise. In addition, it is independent of analytical nature of the data.

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