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TWO-DIMENSIONAL DC RESISTIVITY MAPPING FOR SUBSURFACE INVESTIGATION USING SOFT COMPUTING APPROACHES

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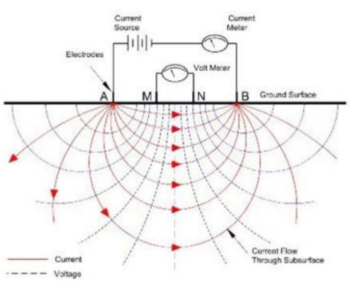
Graphical abstract



Abstract

In geophysical subsurface surveys, difficulty to interpret measurement of data obtain from the equipment are risen. Data provided by the equipment did not indicate subsurface condition specifically and deviates from the expected standard due to numerous features. Generally, the data that obtained from the laws of physics computation is known as forward problem. And the process of obtaining the data from sets of measurements and reconstruct the model is known as inverse problem. Researchers have proposed multiple estimation techniques to cater the inverse problem and provide estimation that close to actual model. In this work, we investigate the feasibility of using artificial neural network (ANN) in solving two- dimensional (2-D) direct current (DC) resistivity mapping for subsurface investigation, in which the algorithms are based on the radial basis function (RBF) model and the multi-layer perceptron (MLP) model. Conventional approach of least square (LS) method is used as a benchmark and comparative study with the proposed algorithms. In order to train the proposed algorithms, several synthetic data are generated using RES2DMOD software based on hybrid Wenner-Schlumberger configurations. Results are compared between the proposed algorithms and least square method in term of its effectiveness and error variations to the actual values. It is discovered that the proposed algorithms have offered better performance in term minimum error difference to the actual model, as compared to least square method. Simulation results demonstrate that proposed algorithms can solve the inverse problem and it can be illustrated by means of the 2-D graphical mapping.

Keywords: DC resistivity, 2-D mapping, inversion problem, radial basis function, multi-layer perceptron, neural network

1.0 INTRODUCTION

Geophysics is an interdisciplinary study that relates the physical science with nature of the earth. In order to understand the structure and physical properties of the earth, geophysics combines knowledge and laws of physics, mathematics and chemistry. This study demands crucial information on the characterization properties that applies in geotechnical investigation, petroleum reservoir study, mining and environmental application.

Geophysics is required to obtain conceptual model and visualization of the subsurface. Subsurface investigation requires multiple collections of data based on certain physical quantities such as electrical resistivity, thermal conductivity, dielectric permittivity, magnetic susceptibility, acoustic velocity, natural radioactivity, and density.

Geophysical surveys can be categorised into passive and active. Passive geophysical surveys involve the measurements of naturally occurring fields in the earth such as gravitational and magnetic fields, by means of measuring spatial variations in these fields to infer something about the subsurface geology. Active surveys are conducted by injecting a signal (e.g. an electrical current or an active radiometric source) into the earth and obtaining its responses to this signal. Electrical and electromagnetic techniques that employ active surveys represent the largest class of all geophysical methods.

DC electrical resistivity sounding method is the most popular technique to measure the subsurface resistivity. The conventional resistivity sounding is carried out on the earth's surface with a specified array of electrodes in order to obtain apparent resistivity data with respect to the variation of horizontal position and vertical depth. Typically, the apparent resistivity distribution is presented in a pseudosection using computer software, hence an inversion process is essential in order to determine the actual resistivity of the subsurface.

This paper will focus on two-dimensional apparent resistivity inversion process by using neural networks approaches in order to determine the actual resistivity of the subsurface. Real data measurements are normally required to train the proposed method, however, factors such as hardware and time limitation will cause implementation problem. Hence, synthetic data generation from software that are based on real measurement will be employed. Here, the inversion results are compared with the conventional inversion approaches to illustrate the effectiveness of the proposed technique. This paper is structured as follows: Section 2 presents the literature reviews of geophysical studies. The proposed technique, featuring a radial basis function neural network and multilayer perceptron for 2-D resistivity inversion is described in Section 3. Section 4 shows the results, followed by some analysis and discussion. Finally, a conclusion is drawn in Section 5.

2.0 REVIEW OF GEOPHYSICAL TECHNIQUES

2.1 Measurement Methods

Electrical methods are widely applied in geophysical survey in order to obtain subsurface information in high resolution. Typically, electrical methods have operating frequencies within range from direct current (DC) to > 1GHz for obtaining information about the subsurface structure and composition [1]. Electrical information can be used to characterize the geophysical location and properties qualitatively, to get information for examples about location of faults and fractures.

Electrical resistivity or Direct Current (DC) resistivity method has significant potential in geophysical applications as well as Induced Polarization (IP) method. This method determines the spatial distribution of low-frequency resistive based on characteristics of soil [2]. IP method is based on capacitive measurement. However, electrical resistivity methods are widely used in geophysical applications as compared to IP method. Electrical resistivity methods have several advantages such as easy to implement, inexpensive instrumentations and widely available data processing tools. The most important advantage of this method is the relationships of properties between electrical resistivity and geophysical location are well established. The limitation of IP method in geophysical application is due to complex procedure in data acquisition and parameter interpretation is not fully understood [3].

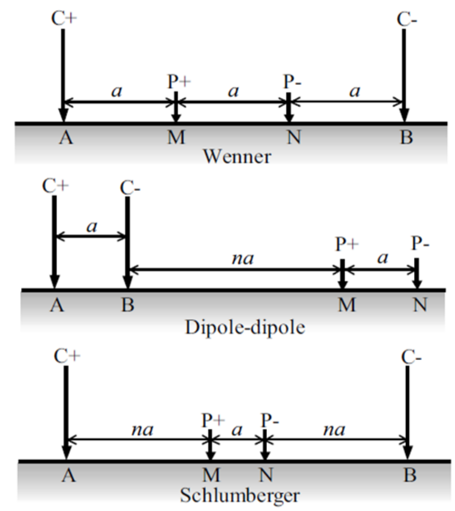


Figure 1 Example of electrode configurations [2]

In electrical resistivity method, four-electrode measurements technique is used in the geophysical field. This technique is known as Wenner four-pin approach [4] and being used to determine the spatial variation of resistivity in the field. The deployment of electrodes in field can be placed either in boreholes or ground surface. In order to introduce an electrical circuit in the field, two electrodes are deployed to act as current source and current sink. The potential difference measurement between remaining two electrodes permits determination of an apparent resistivity. Inverse method is introduced to determine an image of geophysical subsurface based apparent resistivity measurement. Besides of Wenner four-pin approach, other commonly used configurations are such as pole-pole, pole-dipole, dipole-dipole, and Schlumberger configuration. Figure 1 shows electrode configuration for Wenner, dipole-dipole and Schlumberger approach. In the figure represents the poles for injecting the current and P represents the poles for measuring the potential different.

Ground penetrating radar (GPR), a non-invasive method, is based on wave propagation that allows for quick responses. In recent years, this method has been widely used in hydro geological surveys because GPR wave has properties of highly sensitive to the presence of water [5]. The unique GPR properties towards water also makes GPR is effective to delineate zones that has water movement [6]. The idea of GPR is based on electromagnetic (EM) theory. Electrical and magnetic properties plays significant role in determining GPR behaviors and applications. The measurement is based on reflection categories which use transmitter and receiver. However, there are several limitations of GPR methods such as it is best used in low electrical conductivities field area only, it is limited in areas that have high signal attenuation, and it needs for complex data analysis and interpretation.

Electromagnetic Induction (EM) is a method that efficient and effective in surveying of very large areas. In geophysical surveying, airborne electromagnetic (AEM) is the most commonly used method. It measures the apparent electrical conductivity of the ground to depths ranging from a few to a few hundred meters, depending on the instrument chosen and the ground conductivity [7]. Frequency domain EM (FDEM) requires the transmitter coil to operate at fixed frequency continuously. Airborne based FDEM surveys are normally done using several coil pairs and being towed by a low flying aircraft. Data obtained from airborne FDEM are then being processed to produce image of apparent conductivity. Time domain EM (TDEM) measures the decay of a transient, secondary magnetic field produced by currents induced to flow in the ground by termination of a primary electric current flowing in a transmitter loop [7]. This method deployed by fixed wing aircraft. The shape and strength of the transient signal are being processed to obtain the depth variation and apparent ground conductivity.

2.2 Imaging Techniques

Recently, there are up to 3-dimensional techniques for constructing the geophysical mapping. One-dimensional (1-D) technique of surveying can be divided into two main methods; profiling and vertical electrical sounding (VES). Profiling method requires a constant spacing array of electrodes to move along a line and the variation is plotted against profiled distance. The VES method requires the electrode separations around a mid point to be increased by a logarithmic distribution in order to find the layering of strata [8].

Two-dimensional (2-D) technique of surveying is introduced as a result of tremendous advent of data acquisition automation and inversion in recent years. 2-D resistivity method requires many data that need to be recorded with different electrode separations along a line. Thus, in practical implementation, system with automated multi-electrode data acquisition is important to acquire a dense data and reduce structure complexity in the ground [8].

Data produced by automated multi-electrode system are in large amounts and requires further data handling and processing. Inversion technique or automatic inverse numerical modelling that based on finite difference and forward calculation technique using finite element method have been developed to process this large amount of data.

The three-dimensional (3-D) technique of surveying is done by laying out a grid of electrodes and measurements are taken with electrodes aligned in different directions [8]. This 3-D technique has the same principles as 2-D in term of data interpretation. The high number in electrodes combinations and bigger grid size contributes time consuming and requires advances multichannel instrument to acquire data through data acquisition. Practically, in some cases, measurements are made in one direction only. 3-D data sets consists a number of parallel 2-D lines. However, the quality of this type of 3-D case is poorer compared to complete 3-D survey [9].

2.3 Inversion Process

The measured data from geophysical surveys are indirectly related to certain earth physical properties. Thus, these data must be solved in systematic manner in order obtain estimate model that close to actual model. This problem solving technique is known as inverse problem. Unlike the forward model, the inverse problem is more difficult to solve. Reconstruction model from the data will require unknown function property and infinite principles considerations. Figure 2 illustrates short definition of forward problem and inverse problem.

From literature, there are various technique proposed by the researchers in order to solve inverse problem. Linear regression, least squares and normal equation method are the most basic technique used in solving inverse problem [10]. Throughout history, geophysical inverse method requires significant improvement that increase computer needs. With the help of computational facilities, research on optimization of the fundamental technique rises rapidly. Computational intelligence methods such as Neural Network (NN), Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) have been explored to address this issue.

In neural network implementation, synthetic data are used to train the proposed network. A feed forward back propagation network shows excellent results in which the estimated model is closed to real parameter model [11]. The radial basis function network (RBFNN) computational capability appears to be very efficient and able to estimate true resistivity in very small error [12].

PSO technique also contributes to small error between estimated model and actual model solutions (Ranjit Shaw, 2007). PSO performance and ability are successfully compared to other known global optimization algorithm in respective to curve convergences. PSO resulted in very impressive convergence rate and faster than Binary Ginetic Algorithm (BGA) and Simulated Annealing (SA) [13].

Gauss-Newton and Quasi-Newton technique are used to improve least square calculation by means of inversion of data sets. Gauss-Newton method is used to recalculate the Jacobian matrix for all iterations and Quasi-Newton method is used in order to reduce computational time. Combination both of this method resulted in reduction of computational time and satisfactory with small error [14].

3.0 METAMODEL APPROACH FOR 2-D RESISTIVITY INVERSE PROBLEM

3.1 Neural networks based metamodel

Metamodeling, or also called as surrogate model, is a modelling method used especially for a complex system in which the dynamic model of the system is not necessarily known but its input and output is important to build the model relationship. Metamodel has been successfully used in many fields where complicated computer models of an actual system exist but they may require a considerable amount of running time. Models involving finite element and fluid dynamics analysis or multi-objective optimisation algorithms with many parameters are some typical examples. There exist a number of metamodeling techniques, such as neural networks [15][16], Multivariate Adaptive Regression Splines (MARS)[17], Response Surface Modeling (RSM)[18], etc. Nevertheless, there is no conclusion about which model is definitely superior to the others.

In this work, neural network metamodels are proposed to approximate the resistivity inversion mapping for the apparent resistivity values obtained from electrical sounding measurements, in which two topologies are proposed; the radial basis function neural network (RBFNN) and the multi-layer perceptrons (MLP) neural network . These two topologies are widely used in solving function approximation and pattern classification. The RBFs were first used in 1988 to design Artificial Neural Networks [19], with two layers: a hidden layer of radial basis function and a linear output layer. The input of the network is typically nonlinear, whereas the output is linear, representing the weight sum from the hidden neurons. By denoting *R* the number of inputs while *Q* the number of outputs, the output of RBFNN, e.g. for *Q* = 1, is calculated as

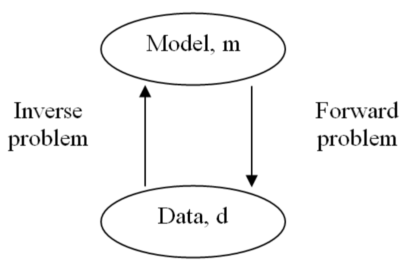


Figure 2 Forward problem and inverse problem

$$\eta^1(x,w) = \sum_{k=1}^{S1} w_{1k}\phi\left(\|x - c_k\|_2\right), \qquad (1)$$

where $x \in \Re^{R\times 1}$ is an input vector, $\phi(\cdot)$ is a basis function which $x - c_k = r$ is the scalar radius, $\|\cdot\|_2$ denotes the Euclidean norm, w_{1k} are the weights in the output layer, $S1$ is the number of neurons (and centres) in the hidden layer and $c_k \in \Re^{R\times 1}$ are the RBF centres in the input vector space. The output of the neuron in a hidden layer is a nonlinear function by means of Gaussian based radial basis function that is given by:

$$\phi(x) = e^{-\frac{\|x-c_k\|^2}{\sigma^2}}, \qquad (2)$$

where σ is the spread parameter of the RBF. For training, the least squares formula was used to find the second layer weights while the centers are set using the available data samples.

The MLP architecture is another feed-forward type of neural network architecture where it has no feedback loops inside the network. Generally, the architecture contains of input layer, hidden layer and output layer. The neurons inside the network are connected in unidirectional connection between them. This network has static properties since the output only depends on the present input. Equation (3) represents the output equation of feed-forward neural network.

$$y_{net} = \sum_{i=1}^{n} x_i w_i + w_o$$

where:

y_{net} = output
x_i = neuron signal
w_i = weight of neuron signal
w_o = weight of bias internal to the neuron

The MLP network has several important components such as neurons, activation vector, signal function, learning rule and environment. Activation vector involves activation signal of the individual neurons. Back-propagation learning algorithm is used in feed-forward neural network learning rule. The component of environment covers neural network operations such as deterministic (noiseless) and stochastic (noisy). The signal function components of neural network involves variety of signal such as binary threshold, bipolar threshold, linear, sigmoid, hyperbolic tangent, Gaussian and stochastic. Here, we will employ sigmoid and linear signal function in the analysis.

3.2 Generation of Synthetic Data

The dataset of the DC resistivity survey is supposed to be collected from the site measurement. However, in simulation study, these dataset could be generated synthetically using open source software known as RES2DMOD, which is invented by M.H Loke [20]. Many scholars have been using this software for research purpose. It was developed based on actual field measurement but several potential factor need to be considered in real application such as electrode accuracy and random noise. This software uses finite element forward modelling technique to calculate the apparent resistivity for a 2-D subsurface model based on user defined.

In this work, synthetic data generations are based on hybrid Wenner-Schlumberger electrode configuration with the number of electrodes of 36. The 2-D subsurface model used in this work is based on *single_block.mod* model which available in RES2DMOD software. The model used in this work has a homogenous medium of 100 Ωm with an embedded anomalous body of 1000 Ωm. The selection of proposed model has a high resistivity values in order to train the proposed techniques for high resistivity contrast region. Finite-element algorithm is used to calculate apparent resistivity and generate the 2-D synthetic datasets. A total of 16 training dataset and four testing dataset are generated using this software. The locations of the anomalous body or buried object in each training dataset as well as testing dataset are changeable and different in term of their positions.

There are two important files that need to be generated from this software; the *.*dat* file and the *.*txt* file. The *.*dat* file contains information of horizontal distances, electrode spacing, number of data level and apparent resistivity value represents in four column respectively. While, for *.*txt* file, three column of information are generated; x-location, z-location and true resistivity value respectively. The four column matrix of *.*dat* file is then converted into three column matrix in order to represent information of horizontal location (in meter), depth of datum (in meter) and apparent resistivity (in ohm.meter), respectively. This data is used as the input matrix, *P* to the proposed techniques. For *.*txt* files, the three column matrix is converted into one column matrix that contains information of targeted resistivity value (in ohm.meter) and later being used as target matrix, *R* in proposed techniques. These data conversions are done by using prepared MATLAB m-file.

The synthetic data sets (input data, target data and test data) are then normalised to the range of [0, 1] by using the mapminmax function in MATLAB, to allow the neural networks activation function to squash all incoming data and to make the computer model execution more efficient.

Table 1 Statistical analysis for radial basis function neural networks

spread	*RMSE*	*MAE*	R^2	d_2	Time (min)
0.1	0.181	0.033	-0.02	0.11	0.29
0.2	0.185	0.036	0.16	0.38	0.30
0.3	0.146	0.025	0.33	0.61	0.32
0.4	0.264	0.055	-0.50	0.48	0.51
0.5	2.030	0.178	-126.98	0.01	0.74
0.6	8.656	0.848	-2325.37	0	1.45
0.7	23.054	2.481	-16494.60	0	5.41
0.8	46.91	5.594	-68314.70	0	18.39
0.9	80.494	10.347	-201083.00	0	42.37
1.0	123.815	17.386	-475799.00	0	69.82

3.3 Neural Networks Training

The neural networks metamodel will be trained with several training iterations to achieve a prescribed mean square error (MSE) threshold. The designed network is tested on several test sets, which have not been used during the training stage. To review this section, the proposed algorithm for the 2-D resistivity mapping is summarised as follows:

1) Define the initial input data, *P*, from the *(*.dat*) file.
2) Define the initial target data, *T*, from the *(*.txt*) file.
3) Normalise the input and output of the training data set.
4) Fit the neural network (for both cases: RBF and MLP) using P and T until reaching the prescribed MSE threshold.
5) Define a testing data set, *R*.
6) Evaluate the designed network in (4) using the normalised testing data sets of *R*.
7) Calculate system error, which is the difference between output in (6) and the target testing data. If the error is less than prescribed goal, stop the process and plot the inversion results. Otherwise go to step 8.
8) Set the new iteration number. Add a new input and target data set (by changing the anomalous body location and distance between electrodes) to the previous training set, and return to step 3.

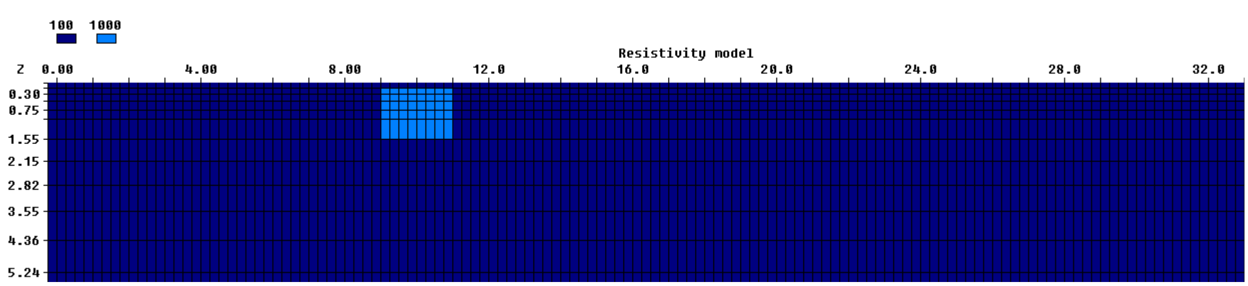


Figure 3 Model used to generate synthetic resistivity dataset

3.4 Performance Indicator

The validation method is important in evaluating performance of the proposed neural network. The proposed neural network provides the predicted model that respect to the actual model. Therefore, the accuracy of the predicted model must be as closed as possible to the actual model. In this work, several statistical analysis are used to measure the errors such as Root Mean Square Error (*RMSE*), Mean Absolute Error (*MAE*), determination coefficient (R^2) and index of agreement (d_2).

3.5 Reconstruction Image

The reconstruction image is done in two-dimensional with the predicted true resistivity obtained from neural network model. The x-axis was set to horizontal location and the y-axis was set to depth of datum. The predicted true resistivity was interpolated to fit in the surface of x-axis and y-axis. In this work, there are three image reconstructions have been developed; interpolation plot of measurement data, inversion data and actual data in which the code is written in the Matlab environment.

4.0 RESULTS AND DISCUSSION

Firstly, synthetic data of different homogeneous mediums need to be generated for the purpose of training and testing the proposed models. Series of different position of anomalous bodies are investigated in this work. For example, for one anomalous body as referred to Figure 3, the difference in colour shows the variance in term of resistivity; the anomalous body was represented by light blue colour having resistance of 1000Ω.m, whereas the dark blue colour represents the homogenous medium with resistivity of 100Ω.m. In each of the synthetic data set consists of 240 datum points, hence for the purpose of training, the number of datum points for training dataset has been set to 3840 (i.e. combination of 16 sets of synthetic data of different combination of anomalous positions).

4.1 RBF Networks Evaluation

A structure of RBF neural networks is proposed in solving the inverse problem. The spread parameter of RBF networks has been varied within the range of 0.1 to 1, which will affect the network performance. Several analyses were carried out in order to verify the networks performance based on set of performance indicators. For *RMSE* and *MAE*, the closer the value to zero indicates better result, while for R^2 and d_2, the closer the value to one provides better performance.

Table 1 shows statistical analysis of the radial basis function neural network for two anomalous body test model. From this statistical analysis, spread value of 0.2 and 0.3 shows acceptable performance. In term of RMSE and MAE analysis, spread value of 0.3 has smaller value that closes to zero as compared to spread value of 0.2. For analysis of R2 and d2, spread value of 0.3 has larger value that close to one as compared to spread value of 0.2. Both have almost similar computational training time of 0.3 minutes. Thus, spread value of 0.3 is proposed as the best parameter value for radial basis function neural network. All computational times (to complete Step 1 to 8 as described in the previous section) are based on the simulations using INTEL® Core i5 PC.

4.2 MLP Networks Evaluation

For MLP networks, series of trial approach have been conducted to determine the number of hidden neuron in hidden layer and type of training functions. The number of hidden neurons was varied in the range of 1 to 50 neurons. The training functions that are being tested in this work include 'trainlm', 'trainbr', 'trainrp' and 'trainscg'. Similar to RBF neural network, various statistical analyses were performed in order to determine MLP network performance and they are interpreted into graphs form. For examples, Figure 4(a) and 4(b) show results of series of statistical analysis for *RMSE* and R^2 against number of hidden neurons and training functions based on two anomalous body test model. In Figure 4(a), the RMSE performance of 'trainrp' and 'trainscg' are better during range number of hidden neurons from 1 to 25 as compared to the other two training functions. As

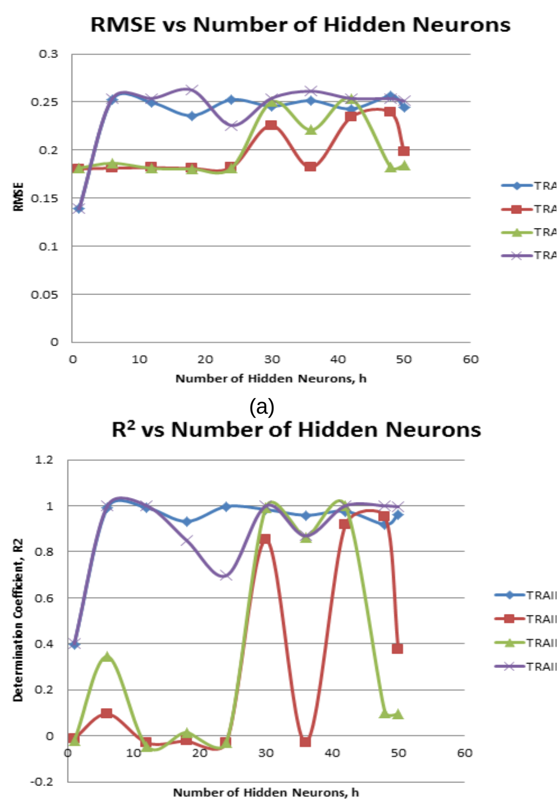


Figure 4 MLP networks performance; (a) *RMSE* versus number of hidden neurons, (b) R^2 versus number of hidden neurons

the number of hidden neuron is greater than 25, the *RMSE* performance of these four training functions is almost similar.

As shown in Figure 4(b), the training functions of 'trainbr' and 'trainlm' shows very good performance that close to one for all number of hidden neurons. The other two training functions have almost zero value during range of number of hidden neurons from 1 to 25. In another evaluation of computational time, the 'trainbr' outperforms another three training functions. Overall, from the statistical analysis, the best performance obtained when the number of hidden neurons of 30 and training function of 'trainlm' are used.

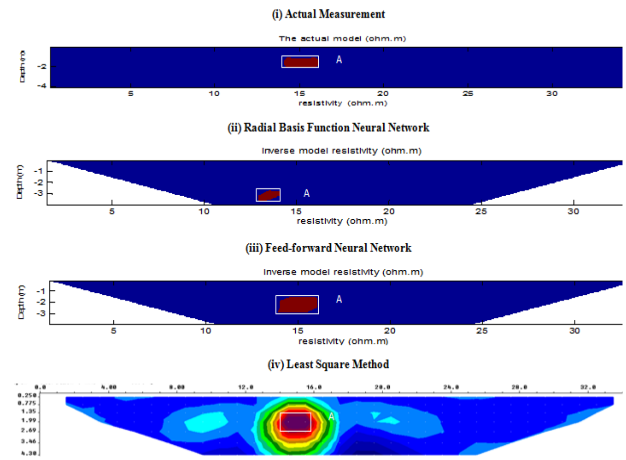
4.3 Comparative Analysis

In this work, the least square (with smoothness-constrained) technique is used as a benchmark for this study. This inversion technique is a well-known conventional approach which available in the RES2DIN software (with the latest version 3.59), whereby it is claimed to give the inversion closely corresponding to reality.

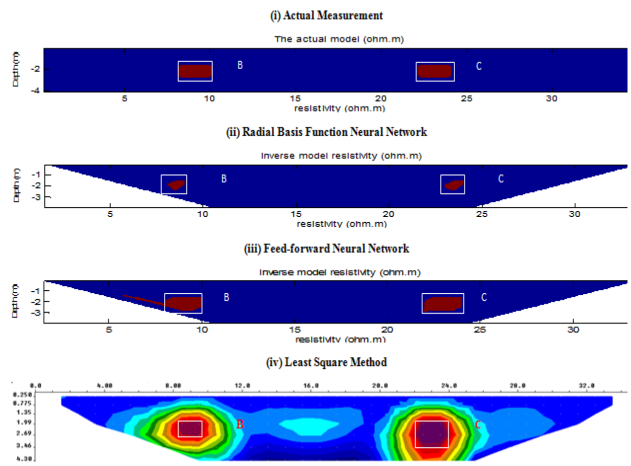
The dimension of anomalous body of each inversion technique is compared analytically in term of horizontal dimension, vertical dimension, percentage error of horizontal dimension and percentage error of vertical dimension. The best configuration of each inversion technique is used in this comparative study. For radial basis function neural network technique, the chosen spread value is 0.3 and mean square error of 0.000001. For multilayer perceptron neural network (or also known as feed-forward neural network), the best configuration used is when the number of hidden neuron of 30 and training function of Levenberg-Marquardt back-propagation training algorithm. Least square method with the smoothness-constrained is chosen as configuration for conventional approach.

Figure 5(a), (b) and (c) show examples of comparison results between each inversion technique by using graphical user interface mapping, for one, two and three anomalous bodies, respectively. From Figure 5(a) and (b), all the inversion techniques were able to map to anomalous body at the exact position. However, the vertical and horizontal dimensions of each technique give different accuracy. However, Figure 5(c) shows that only feed-forward neural network technique is able to predict the anomalous bodies at respective positions. It also shows that radial basis function neural network resulted in poor performance as compared with the other two techniques. In term of robustness, feed-forward neural network is more robust since this technique can map most of the anomalous body being tested in the test model. A similar trend as given in Figure 5(c) will be obtained if the number of anomalous bodies is increased.

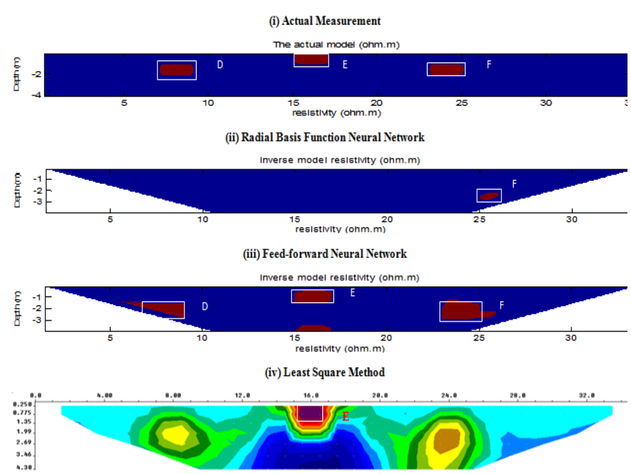
The comparative result for one, two and three anomalies is summarised in Table 2, 3 and 4, respectively. Table 2 shows dimension comparison for one anomalous body for each proposed technique based on Figure 4(a). Feed-forward neural network method has the lowest percentage error for



(a)



(b)



(c)

Figure 4 Comparison results: (a) one anomalous body, (b) two anomalous bodies, and (c) three anomalous bodies

Table 2 Comparison for the dimension from the inversion results for one anomalous body

	Methods	Horizontal dimension (m)	% error	Vertical dimension (m)	% error
Anomalous *A*	RBFNN	1.19	43.6	0.86	14
	FFNN	2.02	4.27	1.33	33
	Conventional	1.46	30.81	0.67	33
	Actual parameter	**2.11**		**1.00**	

Table 3 Comparison for the dimension from the inversion results for two anomalous bodies

	Methods	Horizontal dimension (m)	% error	Vertical dimension (m)	% error
Anomalous *B*	RBFNN	0.95	54.97	1.00	22.48
	FFNN	2.02	4.27	1.33	3.1
	Conventional	1.32	37.44	0.87	32.56
	Actual parameter	**2.11**		**1.29**	
Anomalous *C*	RBFNN	0.95	54.97	1.00	22.48
	FFNN	2.02	4.27	1.33	3.10
	Conventional	1.55	26.54	1.41	9.30
	Actual parameter	**2.11**		**1.29**	

Table 4 Comparison for the dimension from the inversion results for three anomalous bodies

	Methods	Horizontal dimension (m)	% error	Vertical dimension (m)	% error
Anomalous *D*	RBFNN	0	100	0	100
	FFNN	2.02	4.27	1.33	33
	Conventional	0	100	0	100
	Actual parameter	**2.11**		**1.00**	
Anomalous *E*	RBFNN	0	100	0	100
	FFNN	2.02	4.27	1.06	6
	Conventional	1.31	37.91	1.22	22
	Actual parameter	**2.11**		**1.00**	
Anomalous *F*	RBFNN	1.01	52.13	0.71	29
	FFNN	2.02	4.27	1.47	47
	Conventional	0	100	0	100
	Actual parameter	**2.11**		**1.00**	

horizontal dimension of 4.27% and shares same percentage error for vertical dimension with conventional method. A very high percentage error is recorded in horizontal dimension by radial basis function and conventional method.

The comparison result in Table 3 is based on Figure 4(b). Again, feed-forward neural network method shows better performance as compared to the other two methods. For both anomalous body of B and C, feed-forward neural network recorded has the lowest percentage error for horizontal and vertical dimensions. From Table 4, it is shown that radial basis function and conventional method only able to map one anomalous body, out of three. Feed-forward neural network method has the ability to map all the anomalous body with very small percentage error for horizontal dimension. However, for vertical dimension percentage error, this method shows poor performance for anomalous body D and F.

5.0 CONCLUSION

This work has presented two proposed techniques for two dimensional apparent resistivity mapping for subsurface investigation application which are radial basis function neural network and feed-forward neural network (i.e. multilayer perceptron). In this study, the apparent resistivity values are generated synthetically from known models by using RES2DMOD software. These values are used in training the proposed network technique to indicate the ability of the proposed network to interpret and predict the target or output based on the given input. Several of statistical analyses have been conducted to evaluate the proposed network. A major analysis in this study is to compare the performance of the proposed networks with the existing conventional method. The conventional method used in this study is least square with the smoothness-constrained generated by commercial software of RES2DINV. This comparison is based on horizontal dimensions and vertical dimensions of the tested anomalous body. In general, all the methods used in this work are able to give the acceptable dimension as compared to the actual parameter, however, in average the feed-forward neural network contributes a lesser error than the conventional method and radial basis function method.

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