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ARTICLE

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Optimising noise intervened data processes for inverse geoelectrical problem using adaptive neuro fuzzy inference system (ANFIS)

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ABSTRACT

Geoelectrical inversion has some problems in inverting data due to the heterogeneous behaviour of Earth. One of the major concerns in inverting the data is due to the influence of noises, which comes from the disturbance due to human interventions, atmospheric variations, and electromagnetic disturbance, etc. . In this paper, we have presented a concept of Neuro Fuzzy algorithm which can interpret the noisy data successfully. Moreover, the data were tested with artificially generated random noise, gaussian noise and missing data. Kanyakumari field region having complex geological structures and its performance is validated with a maximum threshold. Kanyakumari field region having complex geological structures is used and the performance is validated with a maximum threshold. Neuro fuzzy technique has the dominant feature of training and testing the data with utmost accuracy. These implications are made to create the specific Graphical User Interface (GUI) for the algorithm and it works well for all types of Vertical Electrical Sounding (VES) data with good performance results.

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Adaptive Neuro Fuzzy Inference System; resistivity inversion; subsurface modelling; noise intervened processing; layer model

1. Introduction

Geophysical studies show ample evidences of the successful use of the resistivity method in groundwater prospecting. The geoelectrical resistivity method is more successful in investigating groundwater studies. In electrical prospecting, the electrical currents which are sometimes naturally present in the earth, may be measured, or one may introduce currents into the ground artificially by using batteries or generators, and investigate the electrical field distribution by suitable measurements. For aquifer mapping and to estimate the subsurface features direct current resistivity methods are very useful. Vertical Electrical Sounding (VES) method is one of the best methods to study aquifers more reliably.

Due to the non-linear nature of the earth, it is difficult to estimate the subsurface parameters accurately. It is significant to note that the electrical resistivity values often vary instantaneously from one formation to the next, and hence the description of the real earth resistivity model in terms of the linear model may not be quite appropriate. Several attempts were made in the last three decades for geoelectrical resistivity inversion. The prominent inversion results were obtained from both the forward modelling techniques and direct inversion techniques. A good inversion method must simultaneously minimise the effects of data error and model parameter errors. Direct inversion techniques are trustworthy, but this too will suffer problems in generalisation. For a particular area under study with more number of training datasets available, general soft computing methods works well, but if moving towards a generalised approach, we need a specially designed algorithm for carrying out the computational methods. Geophysical prospecting methods are commonly used to estimate geological structures of earth (Wisen et al. 2004; Castilho et al. 2008; Reynolds 2011; Long et al. 2012; Arjwech et al. 2015), hydrogeological characteristics (Zahody et al. 1974; Giang et al. 2013; Trappe et al. 2019), subsoil investigations, civil engineering structure, agricultural and industrial regions. Stopinski (2003) studied the bedrock for the construction of a dam using the electrical resisitivity method. (Niedrleithinger et al. 2008) applied geophysical techniques for river embankment in Huang and Mayne. (Al-Fares et al. 2018) studied about leakage origin in Abu Baara dam using electrical resistivity tomography. (Ikard et al. 2014) characterised focussed seepage through an earth-fill dam using geoelectrical methods. Using resistivity logs, researchers are determining the reservoir characteristics (Archie 1942). Electrical resistivity survey has been implemented in various parts of the world for different purposes (ahlin et al. 2004; Friedman 2005; De carlo 2013; Asfahani 2013; Lech et al. 2016; Koda et al. 2017; Kowalczyk et al. 2017; Rabarijoely 2018). Different

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methods were applied to invert electrical resistivity data (Dahlin 2001; Loke and Dahlin 2002; Loke et al. 2003; Loke and Lane 2004)

A specially designed algorithm was implemented in this research work using the Adaptive Neuro Fuzzy Inference System (ANFIS) to invert geoelectrical resistivity data. To evaluate the performance of the algorithm, studies were carried out by adding random noise and data deletion (missing data) on the inversion of resistivity profile. In this research work, ANFIS is applied to interpret the geoelectrical resistivity data. The obtained results are compared with the available litholog of the study area.

2. Methodology

Many researchers used geophysical exploration studies using the direct current resistivity method and identified that this method is more reliable in estimating the parameters (Kosinky and Kelly 1981; Sri; Niwas and Singhal 1981; Mazac et al. 1985; Yadav and Abolfazli 1998). VES data was interpreted using curve matching procedures and other computational methods (Flathe 1955; VanDam 1964; Mooney et al. 1966; Ghosh 1971).

In general, the characteristic sounding curves are represented in multiple layers. Each of the four sets has particular properties that may be roughly classified. For H and K-type curves $\rho1> \rho2< \rho3$ and $\rho1< \rho2> \rho3$, respectively, and we may be able to draw some conclusions about relative values of $\rho1$ and $\rho3$ if the spread has been extended sufficiently. The A and Q-type curves correspond to $\rho1< \rho2< \rho3$ and $\rho1> \rho2> \rho3$, respectively (Telford 1990).

3. Geophysical method

Geophysical exploration techniques are vibrant and powerful tools that plays a vital role in the delineation of aquifer parameters in different geological formations. In particular, the Geophysical method consisting of vertical electrical sounding (VES) has been proved to know the variation of resistivity of the aquifer parameters (Rijo 1977). Schlumberger electrode array having principle advantage over several types of arrays (Figure 1) is used to study the electrical resistivity distribution of the subsurface in order to understand the groundwater conditions. The Vertical Electrical Sounding provides a non-destructive, fast and economic way to study the properties of aquifers. An important advantage of VES method is that quantitative modelling is possible using either model curves or software. The resulting models provide accurate estimates of electrical resistivity, thickness and depth of subsurface strata of the Earth. This array (what array?) is a powerful tool in the delineation of groundwater potentials because of its simple in nature and cost effective. The field procedure involves as follows: among the four electrodes that are used, the potential electrodes (M and N) remain fixed and the current electrodes (A and B) are expanded symmetrically about the centre of the spread (Figure 1,Figure 2). With very large values of current electrodes, however, it is necessary to increase the potential electrodes. Maximum half current electrodes (AB/2) separation used in this survey is 100 metres. Usually, the depth of penetration is proportional to the separation between the electrodes and varying the electrode separation provides information about the stratification of the ground. Figure 1 shows the Schlumberger electrode configuration.

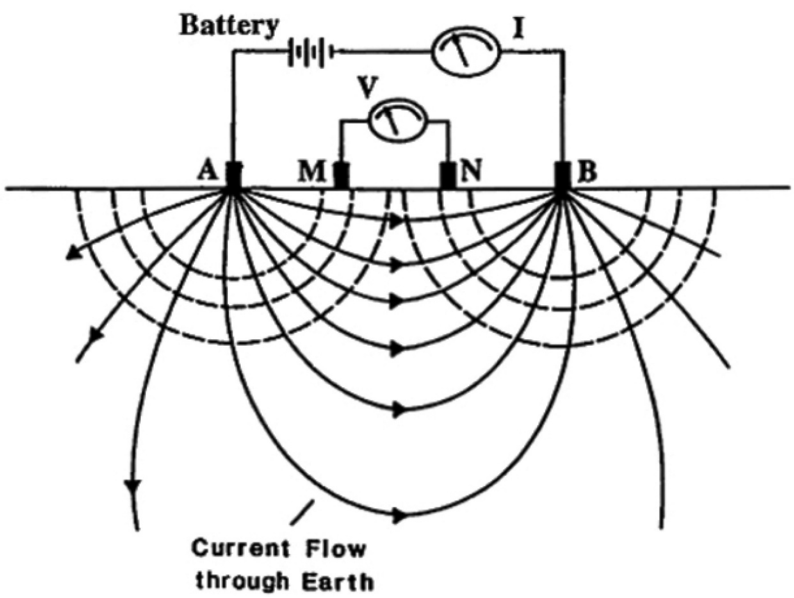

Figure 1. Schlumberger electrode configuration for geoelectrical data collection.

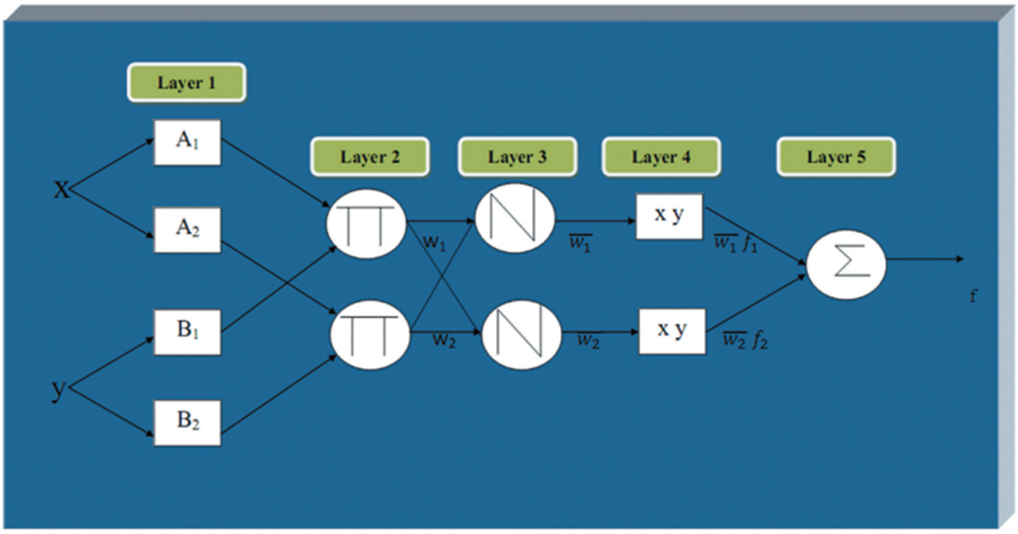

Figure 2. ANFIS architecture.

4. Fundamentals of ANFIS – theory and applications

The intelligent neuro fuzzy inference technique for data analysis and interpretation are becoming more powerful tools for making breakthroughs in the science and engineering fields by transforming the data into information and information into knowledge in recent days. Masoud Nikravesh (2004) applied intelligent techniques in the oil and gas industry for multipurposes such as risk management, uncertainty analysis and interpretation of geological data. Yasala Srinivas (2013) applied the ANFIS model to find the lithology of the study area. The last decade has witnessed significant advances in inverting geosciences data with associated characteristics. This has been made possible through improvements in data integration and quantification of uncertainties.

Neuro-fuzzy modelling is a technique for describing the behaviour of a system using fuzzy inference rules within a neural network structure. The model has a unique feature in which, it can express linguistically the characteristics of a complex non-linear system. Geoelectrical resistivity inversion problem was analysed using the ANFIS model, which produces less mean square error (Srinivas et al. 2012a, 2012b; Stanley Raj et al. 2014, 2015). The fuzzy modelling was first explored by Takagi and Sugeno (1985) and later ANFIS network was developed by Jang (1993).

In the present work, the electrical resistivity data collected using the VES (Vertical Electrical Sounding) method is used for training the dataset. The data collected from the field is the apparent resistivity, while on interpretation the subsurface parameters viz., resistivity and thickness of the individual layers are obtained. Trained data set is the reference data for interpreting the subsurface layer parameters of the earth. This dataset will be used to train ANFIS by adjusting the membership function parameters that best model this data, which suits best for this data.

The inherent problems in geoelectrical resistivity inversion that are to be overcome are as follows. Precautions to be taken while analysing the geoelectrical resistivity inversion data.

- Inadequate data and field errors/noises are also to be considered while evaluating the subsurface strata of the earth.
- Framing the appropriate algorithm for inversion is the most important section involved in applying these tools.
- Moreover, moving to a generalised approach on inversion, one should be very careful in validating the results with different field data.

The application of ANFIS algorithm for the inversion of VES data is demonstrated with different field datasets. Here, the ANFIS algorithm provides the necessary database needed for interpretation. Moreover, the best model of the trained database fits with the apparent resistivity of the field curve. The corresponding layer model is produced as an output with lowest root mean square error in a particular number of epochs.

4.1. ANFIS methodology

Initially, the data have been subjected to a certain degree of membership grade so that at each iterations the firing strength will decide the consequent parameters.

ANFIS system consists of five layers; Output of each layer is symbolised by $O_{1,i}$ with i is a sequence of nodes and 1 is the sequence showing the lining. Here is an explanation for each layer (Jang 1993), namely:

4.2. Layer 1

Serves to raise the degree of membership and the membership used here is Gaussian membership function.

$O_{1,i} = \mu_A(x),\ i = 1,2 \ldots .(1)$

and

$O_{1,i} = \mu_B(y),\ i = 1,2. \ldots .(2)$

with x is the AB/2 values and y is the apparent resistivity values chosen as the input for the i-th node for training, whereas, AB/2 and apparent resistivity values of synthetic data have been chosen as input and the corresponding true resistivity and depth values have been chosen as output values for the i-th node

$$f(x,\ \sigma;\ c) = e^{\frac{-(x-c)^2}{2\sigma^2}}$$

by $\{\sigma$ and $c\}$ are the parameters of membership function or called as a parameter premise. σ signifies the cluster bandwidth, and c represents the cluster center.

4.3. Layer 2

Serves to evoke *firing-strength* by multiplying each input signal.

$O_{2,i} = w_i = \mu_A(x)\ \mathrm{x}\ \mu_B(y),\ i = 1,\ 2. \ldots .(3)$

4.4. Layer 3

Normalizes the *firing strength*

$O_{3,i} = \overline{w} = \frac{w_i}{w_1+w_2}, i = 1,2. \ldots .(4)$

4.5. Layer 4

Calculates the output based on the parameters of the rule *consequent* $\{p_i,\ q_i$ *and* $r_i\}$

$O_{4,i} = \overline{w_i} f_i = \overline{w_i}(p_i x + q_i y + r_i). \ldots .(5)$

4.6. Layer 5

Counts the ANFIS output signal by summing all incoming signals will produce

$\sum_i \overline{w_i} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \ldots .(6)$

ANFIS uses the input data scaling by *xbounds = [min max]* command used in MATLAB software which represents the scaling parameter of the input function that varies between minimum to maximum value of the data point. Each data point is scaled for pre processing of training initially by normalising it.

5. Results and discussion

Many hybrid systems can be built on the combining platform of neural networks, fuzzy logic and neuro fuzzy networks. For example, fuzzy logic can be used to combine results from several neural networks; although some hybrid systems have been built, this present work has attained promising results when combining the fuzzy logic and neural networks. The field validation proves that this algorithm can have a bright future for estimating many non-linear problems. The field data chosen is from one of the four taluks in Kanyakumari district, located in the southern tip of India. The total region of Agastheeswaram taluk covers 279.4 km^2. It lies between the latitude 77°18′ 45″ E to 77° 35′15″ E and 8°4′ N to 8°13′45″ N longitude. The area is underlain by the crystalline rocks like gneiss and charnockite of Archaean age. Along the coast the sands of recent origin are noticed. The geology map (Figure 3) of the study area is obtained from Geological Survey of India (GSI 2005). The peninsular gneisses occupy the largest area in the district. The general trend of the strike of this area is in the N-NW to S-SE direction. Garnetiferous silliminate, graphite gneiss and garnet biotite gneiss are the two major groups identified in Kanyakumari district.

The groundwater occurs in almost all the geological formations like crystalline rocks, sedimentary formations and quaternary alluvium and beach sands. The groundwater occurrence in the hard rock region is limited to the weathered mantle of thickness 10–35 m below ground level. The weathered thickness in hard rock regions is discontinuous both in space and depth. Hence, the groundwater potentiality is influenced by the intensity of weathering. In the sedimentary formations having alluvial deposits, the water table is very shallow which is up to a maximum depth of 10 m (PWD 2005). Field data chosen from the sounding location 77.51397 E and 8.108833 N. Figure 4 shows the corresponding multilayer model. Figure 5 shows the regressed layer model. Figures 6 and 7 show the ANFIS rule architecture and membership functions, respectively. Figure 8 shows the geoelectric section of the corresponding layer model.

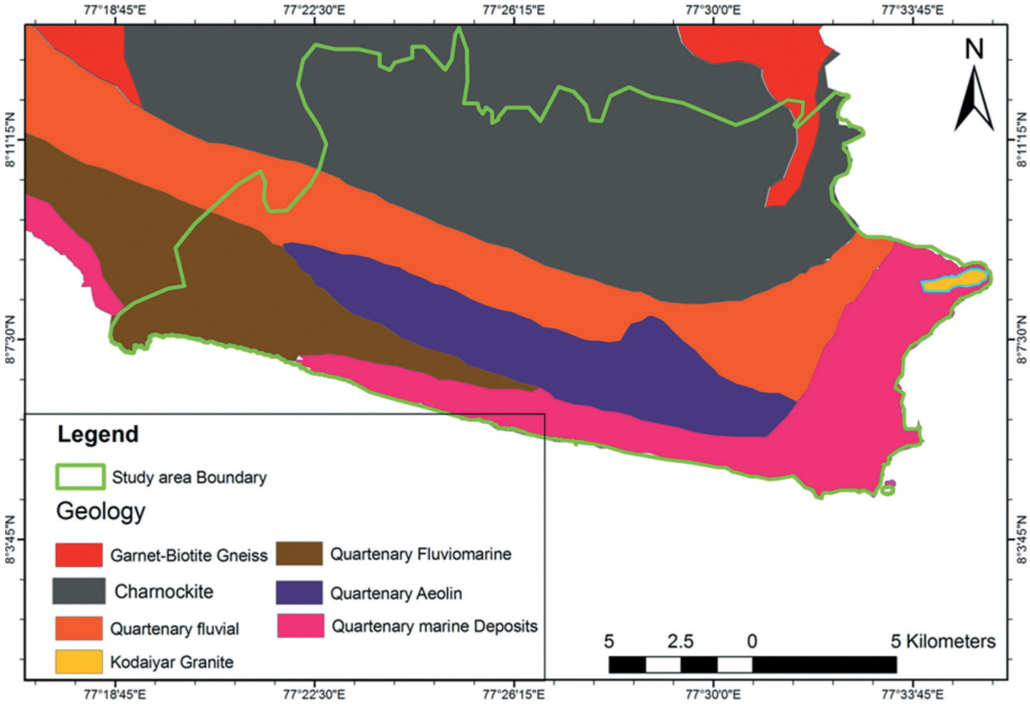

Figure 3. Geology map of the study area (redrawn after GSI 2005).

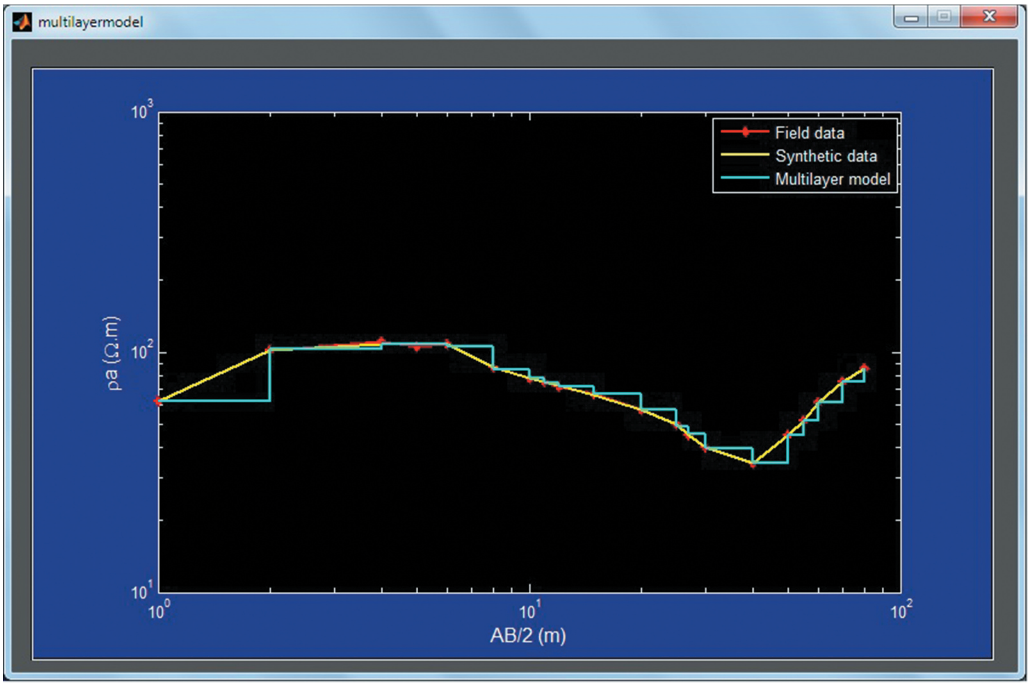

Figure 4. Obtained multilayer model inversion of ANFIS algorithm.

5.1. Performance evaluation of algorithm

The performance of the algorithm has been evaluated by three methods

a) Adding random noise to the data

b) Missing data values to the original field data

c) Adding gaussian noise to the data

5.2. A) Adding random noise to the data

It is very necessary for a system to be fault tolerant and immune to noise system to enhance the performance of any problem which is taken into account. Soft computing techniques would be the better tool to estimate the subsurface features more clearly than any other conventional methods. More positively, the soft computing inversion involves the knowledge-

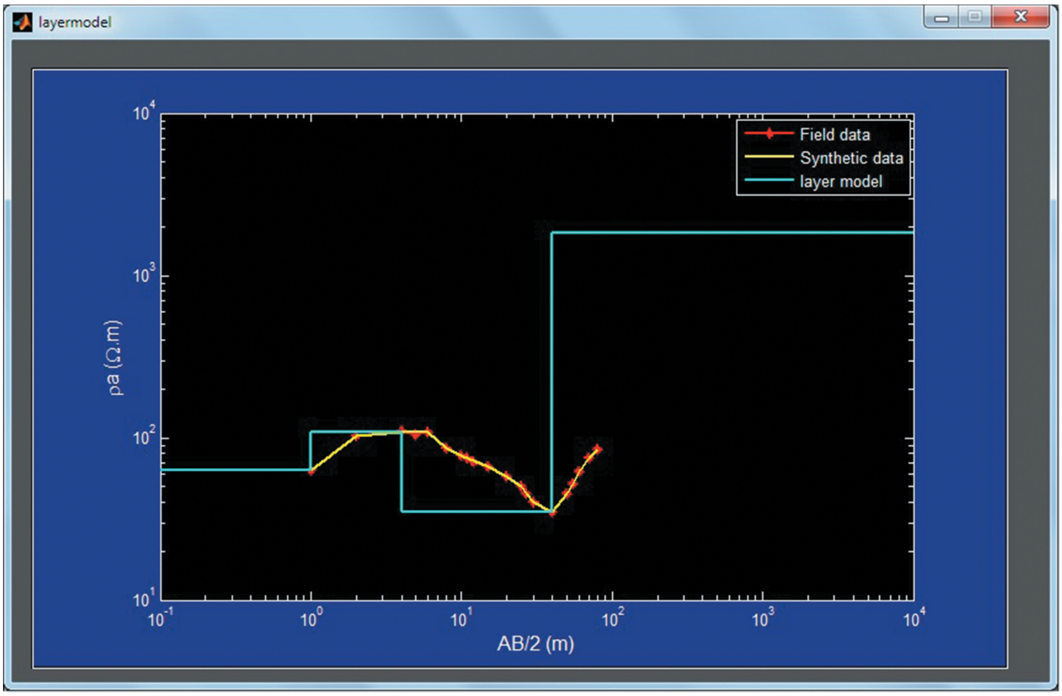

Figure 5. Obtained regressed layer model inversion of ANFIS algorithm.

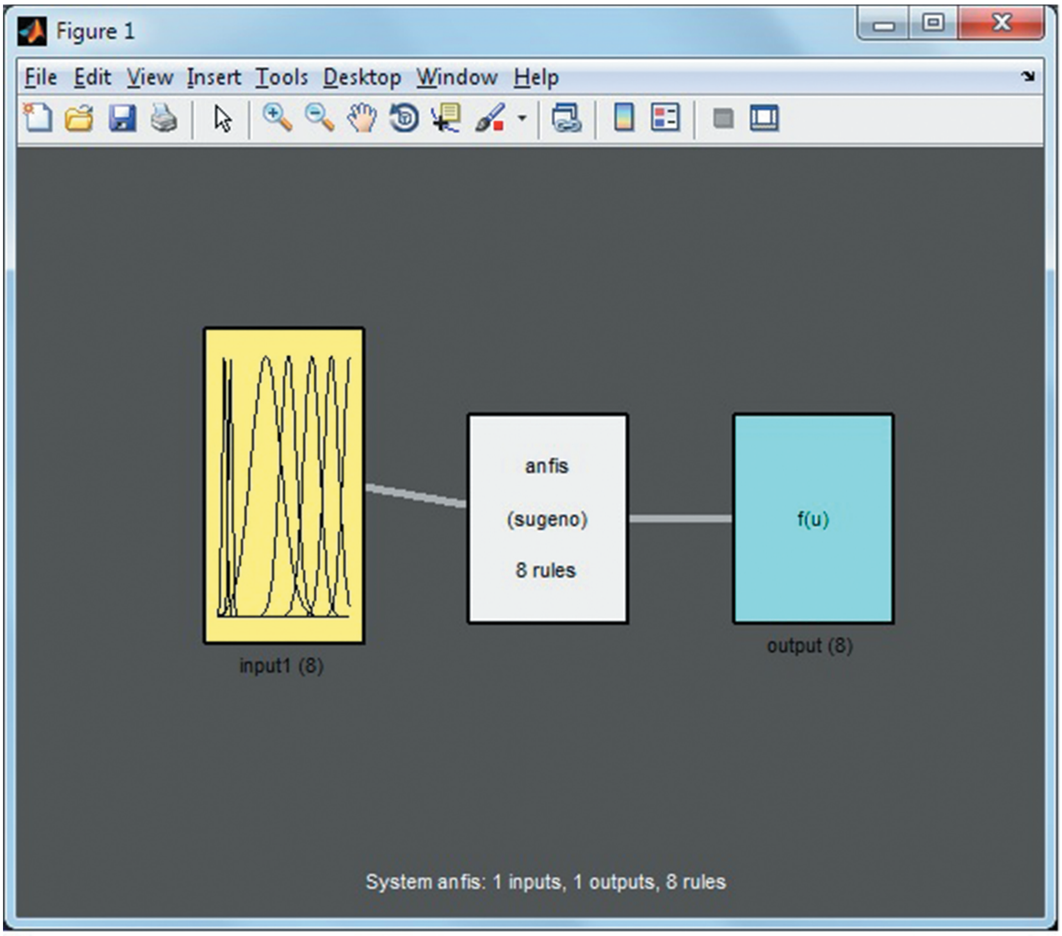

Figure 6. ANFIS rule architecture.

based approach, which proclaims the self-dependent and pertaining algorithm to solve complex problems more easily. In this research work, random noises were added to the original field data with 5%, 10%, 20% and 40% to check the performance of the algorithm. The results are shown in Figures 9, 10, 11 and 12, respectively, for corresponding the noise percent added. The results demonstrate that the layer model inversion has

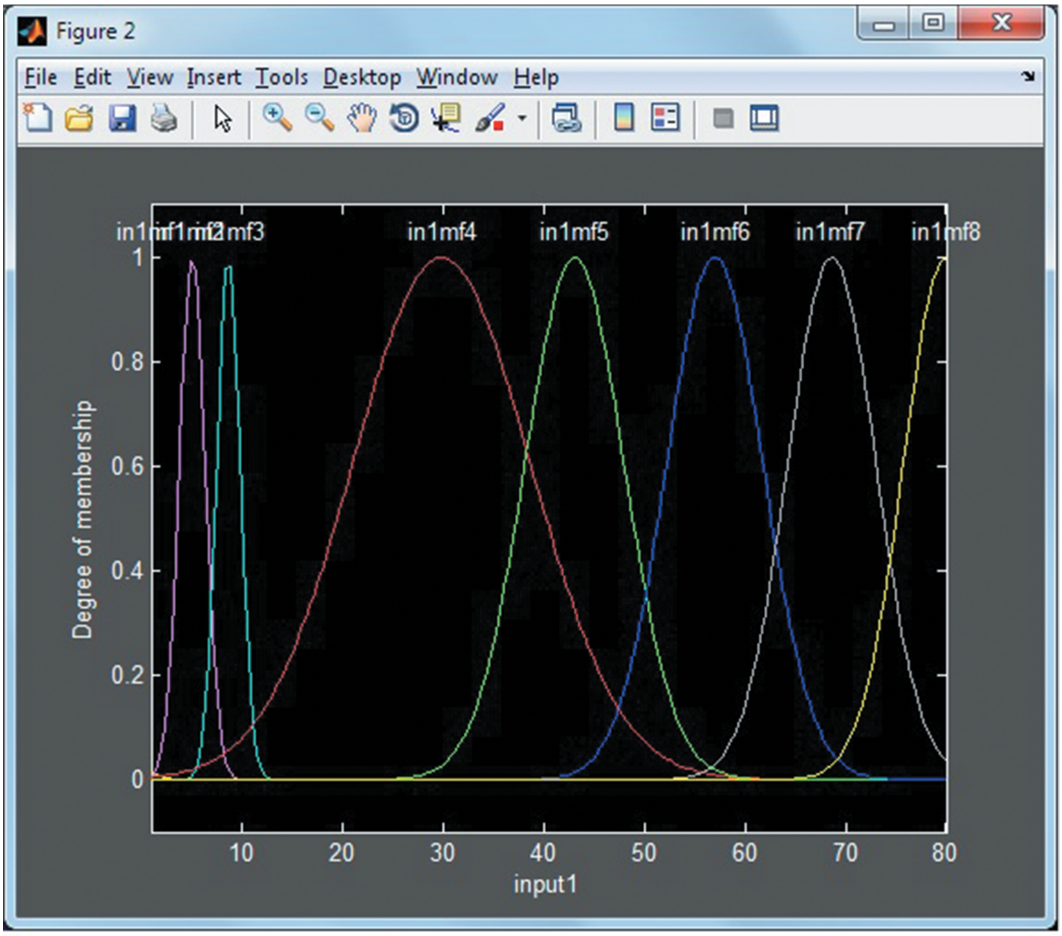

Figure 7. Membership functions mapped between the input and output data.

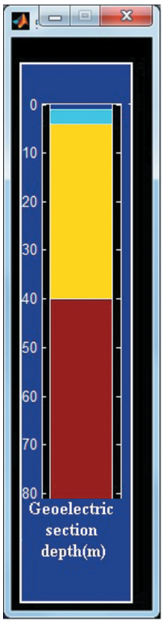

Figure 8. Geoelectric section of the corresponding layer model.

been oscillating while increasing the noise percent. Finally, by adding above 50% noise, the system becomes unstable. For fixing the solution, ANFIS tries to fix the membership functions of different range and the number of rules increment as shown in Table 1. Thus, it proves that the entire algorithm itself oscillates for fixing the layer model, the litholog information of the log doesn't vary to maximum error percent. This verifies the ANFIS algorithm tries to maintain the linearity throughout the program by adjusting the membership function (gaussian membership function is used here). It takes much time in fixing the layer model when increasing the noise percent. But the result showed that only below 20% noise level, the system can interpret the layer model more quickly and efficiently with minimum error percent. So for rapid inversion of optimising the problem, the system should have maintained the noise percent below the respective value.

5.3. B) Missing data values (by random data deletion)

The performance of the algorithm was further tested by random data deletion. Similar to the noise intervened data, the system is subjected to missing data

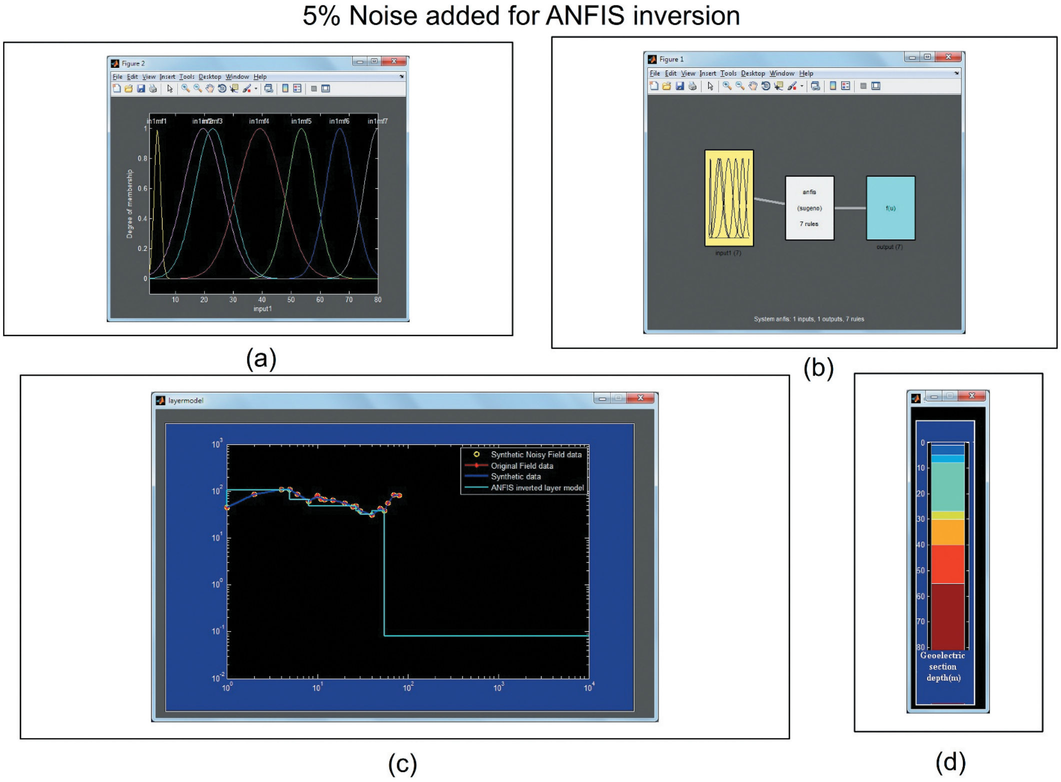

Figure 9. Layer model inversion result for five percent random noise added to the input data.

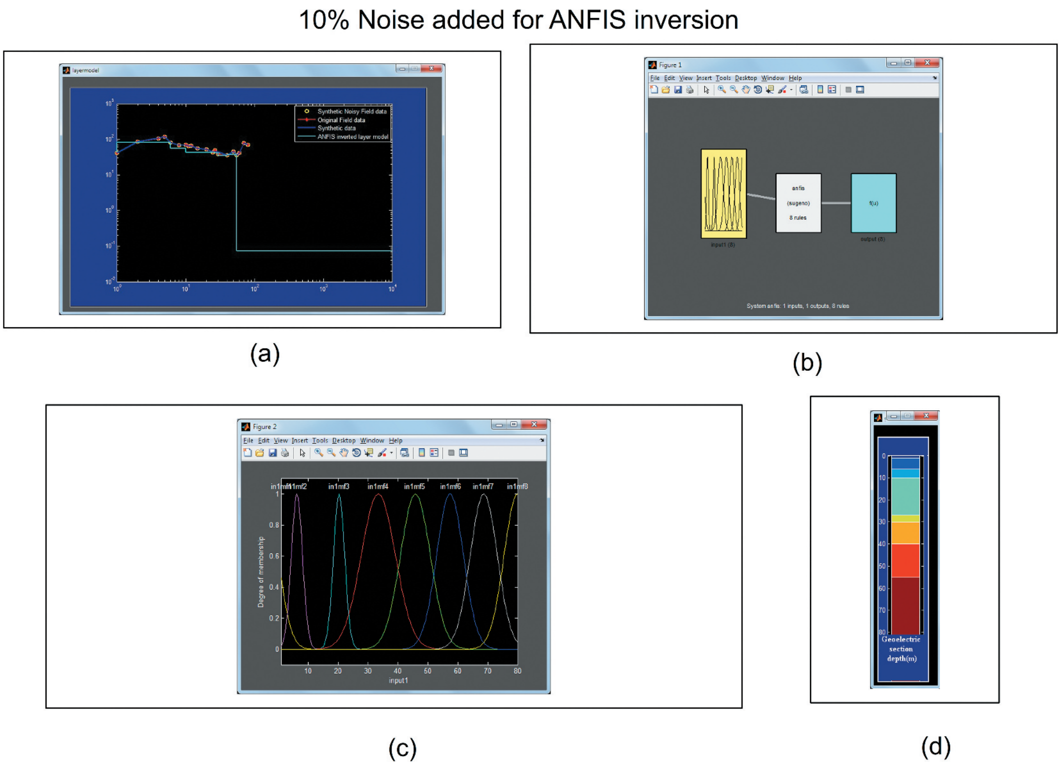

Figure 10. Layer model inversion result for ten percent random noise added to the input data.

values by removing the data randomly from the original filed data which is feed as an input.

When 20% of data missing is made, it doesn't bring a major problem for inversion. It performs well at this particular stage. But while going beyond the 20% missing data, the system subjected to oscillation and takes more time for fixing the result. The system cannot interpolate the nearby missing values of the data when the missing data level reached 40%. This result is not similar to the noisy data result

20% Noise added for ANFIS inversion

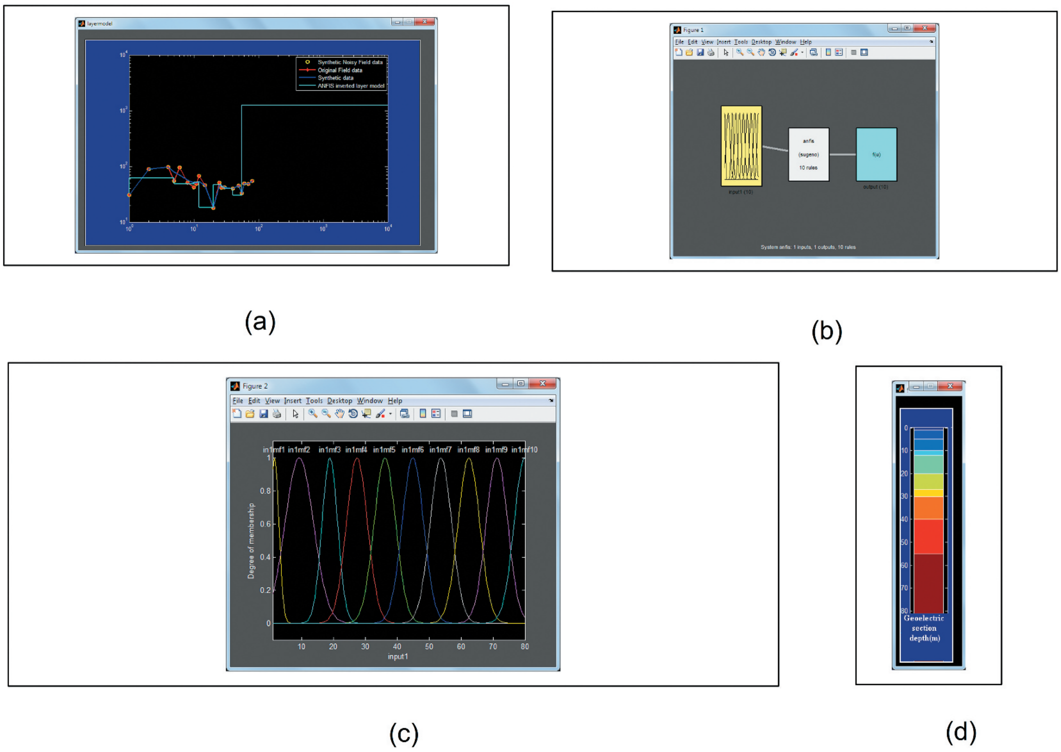

Figure 11. Layer model inversion result for twenty percent random noise added to the input data.

40% Noise added for ANFIS inversion

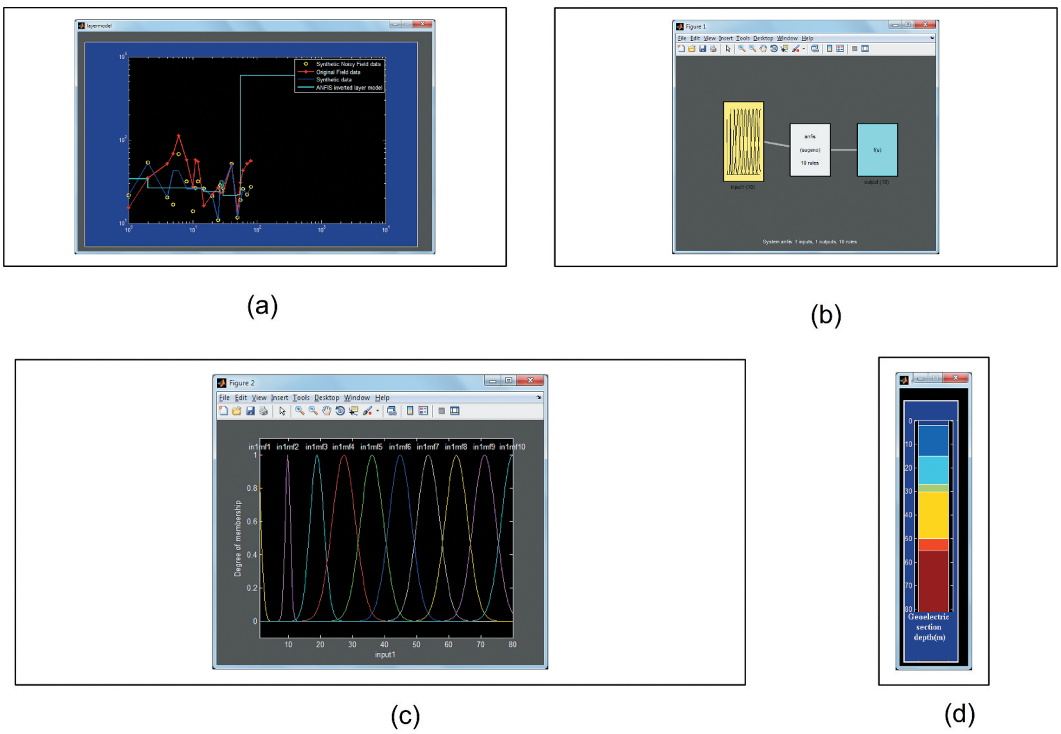

Figure 12. Layer model inversion result for forty percent random noise added to the inputdata.

because in the earlier attempt the performance of the algorithm was maintained constantly up to 40%. The constraint in missing data interpretation is that, when it goes beyond the 20% missing data values, more number of data has to be added to retrieve the information clearly. This is the prominent result that this kind of interpretation is directly proportional to the number of data. More the number of data, the error percent is low and the inversion hails more performance.

Table 1. Random noise added for ANFIS inversion showing the performance.

S. No.	Percentage of random noise added	True Resistivity (in Ohm-m)	Depth (in m)	Error Percent (RMSE)	Computational Time (in sec)	Number of rules framed while ANFIS inversion
1	5%	44.8704	1	0.950	6.866	7 rules
		105.851	5			
		65.7963	8			
		47.6943	27			
		38.0296	30			
		31.577	40			
		37.600	55			
		0.0795				
2	10%	41.268	1	1.381	21.668	8 rules
		81.988	6			
		54.652	10			
		43.223	27			
		42.042	30			
		35.151	40			
		36.674	55			
		0.073				
3.	20%	33.229	1	6.26925	21.6611	10 rules
		62.365	5			
		48.666	10			
		51.779	12			
		18.136	20			
		47.056	27			
		42.031	30			
		39.820	40			
		30.330	55			
		1234.93				
4.	40%	33.994	2	6.44922	21.7359	10 rules
		26.332	5			
		23.730	27			
		32.296	30			
		21.416	50			
		22.22	55			
		594.02				
5.	<50%	ANFIS System Unstable				

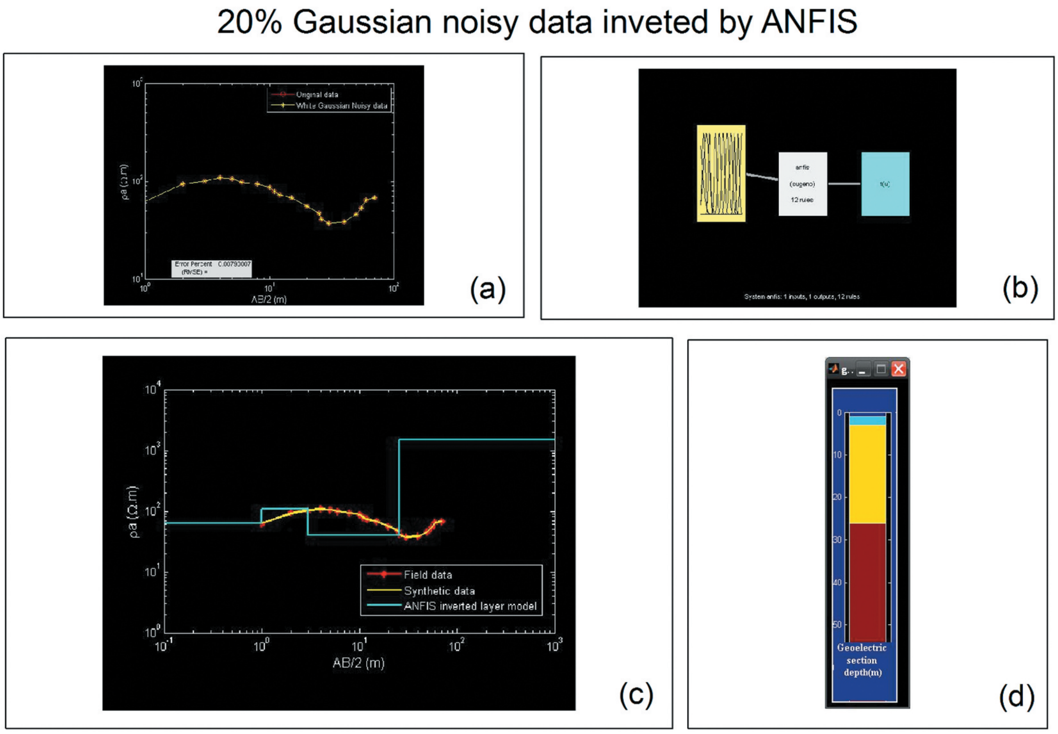

Figure 13. Layer model inversion result using ANFIS for 20% gaussian noise added to the input data.

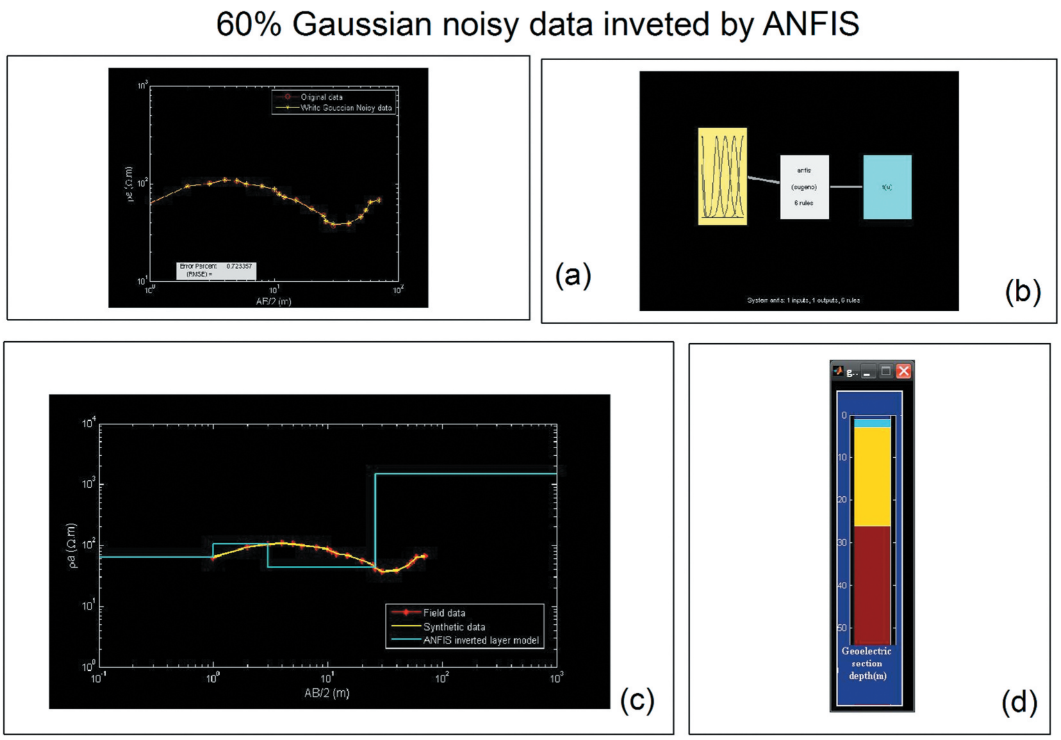

Figure 14. Layer model inversion result using ANFIS for 60% gaussian noise added to the input data.

Thus, the ANFIS performance level on comparing to noisy data and missing data interpretations are pretty good. At each and every stage the performance level has been checked with Root Mean Square Error (RMSE). The algorithm itself possibly tries to reduce the error percent and it is legible to work in this platform to interpret such data than to rely on a conventional approach.

5.4. C) Adding gaussian noise to the data

In most of the geophysical inversion techniques, we will perpetually suffer several kinds of noise which are observed from the field and distort the original data. In this attempt, gaussian noise was added to the original data step by step from 10% to 80% and the results were studied in the case of ANFIS inversion. This proves the stability of the algorithm and its robustness when it is subjected to numerous attempts of noise intervened data training.

In previous attempts by various researchers, the problem of generalisation and choosing initial model parameters in resistivity inverse problems was difficult (Ghosh 1971; Zohdy 1989; Qady and Ushijima 2001; Singh et al. 2005; Ekinci and Demirci 2008; Carlos et al. 2000). Maiti et al. (2011) tried a hybrid Monte-Carlo-based approach with neural networks for inversion of data in forward modelling technique. But in direct inversion, this algorithm proves to be the worthwhile in inverting the layer model quickly and efficiently. This effort was made successful when the inversion of data with the present algorithm was compared with the conventional data interpretation. Figures 13, 14 15 16 17 18 and 19 show the gaussian noise added to the original resistivity data with Signal to Noise Ratio (SNR) is 20%, 60% and 80% respectively. Above 50% the ANFIS system is unstable. Thus, it is revealed that the data within 50% of noise can be interpreted successfully by the designed ANFIS algorithm.

After this research, the data chosen from the Kanyakumari field was taken to invert using this well-performed algorithm. Profile 1 has been chosen in the Latitude, Longitude of VES 1–8° 7′ 34.7988″ N and 77° 20′ 0.0240″ E, VES 2–8° 7′ 31.4004″ N and 77° 20′ 17.4120″ E, VES 3–8° 7′ 27.5016″ N and 77° 20′ 37.5000″ E, VES 4–8° 7′ 24.6000″ N and 77° 20′ 52.9080″ E, VES 5–8° 7′ 17.7996″ N and 77° 21′ 33.9840″ E. The inversion result with pseudo cross-section and thickness of the subsurface layer is shown in Figure 16. Tables 2 and 3 show the respective profile for ANFIS inverted result and its longitudinal resistivity variations, respectively.

5.5. Error estimation

L1 norm error estimation is used to minimise the errors while iteration. This method finds applications in many fields because of its robustness compared to L2-norm. L2-norm squares the error and thus the model is much more sensitive in the case of applying noisy data. If the amount of noise present in the data is above a certain percentage as calculated from the gaussian noise observations in this study, then the model will be unstable in such cases.

Overfitting problems in ANFIS are avoided by fixing the permissible error percentage to

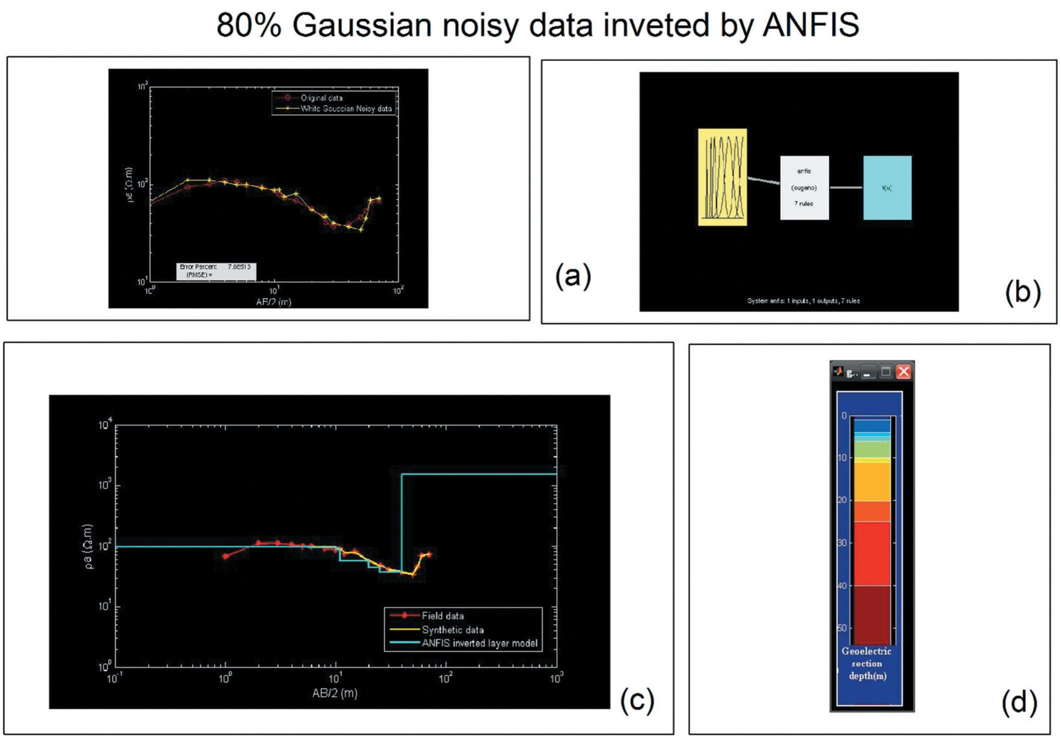

Figure 15. Layer model inversion result using ANFIS for 80% gaussian noise added to the input data.

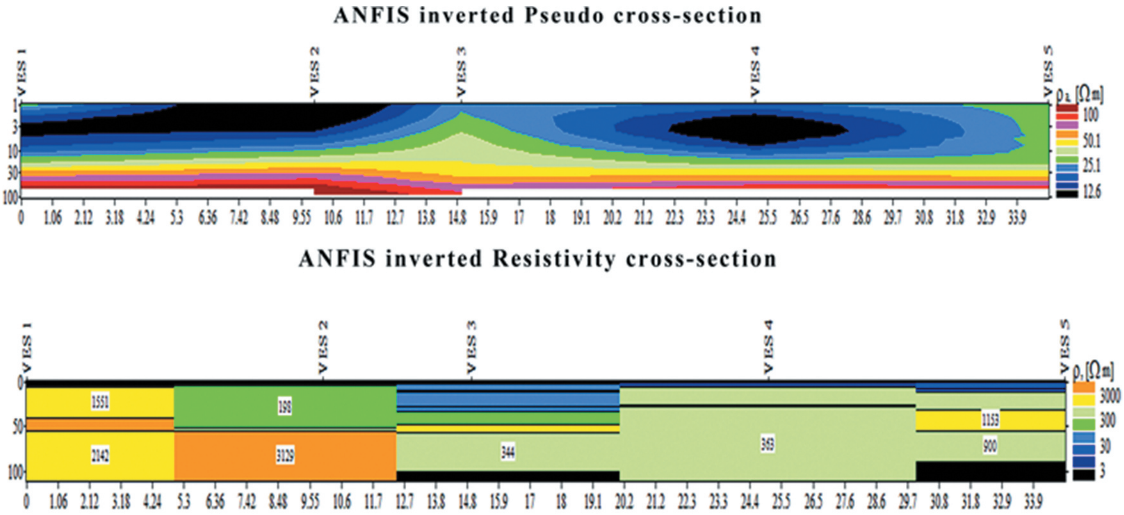

Figure 16. ANFIS inverted pseudocross section profile.

minimum (below 10% in this study). The permissible error was fixed by the user to choose the appropriate model parameters while iteration.

6. Conclusions

This kind of geophysical optimising problem including the noise and missing data values which works well with the soft computing approach. Noise and missing data are the major problems in geophysical data acquisition. Mainly, if the field area chosen to study is vulnerable or cannot be accessible clearly or more noises in the field regions, it would be better to opt for such intelligent techniques for inversion. The developments and advancements in the field of inversion which is dependable on the intelligent technique will possibly give the correct definition of the subsurface layer model. In these aspects of learning, the adaptive algorithm becomes accustomed itself for any kind of field data. The results of the research work are summarised below

1) The program concerns on the generalised inversion than the conventional ANFIS algorithm inversion. The major difference between the two approaches is, in the earlier we need more number of field data that has been subjected for network training. The solution depends on the number of datasets involved in training. But in the later part it is not necessary to have more number of data but the network itself will generate more number of datasets and it indirectly supports the performance of the algorithm. So this would be the semi-supervised algorithm. Moreover, it depends on the number of epochs which plays a major role in generating a large number of synthetic datasets necessary for inversion.

2) This research work concentrates mostly on the performance of the algorithm by considering (a) number of epochs, (b) Error percent, (c) Number of rules assigned to each iteration and (d) Computational time.

3) The algorithm framed on the generalised platform and tested with the noise intervened data and missing data values. Performance analysis was made to check the algorithms reflection on the disturbed data.

4) The tested algorithm was finally subjected to coastal data inversion and it proclaims the best algorithm for inverting any non-linear data. Thus, this algorithm would be the best noise reduction algorithm and efficient in picking the information necessary for inversion.

5) Different models can be generated while testing the ANFIS algorithm at each number of iterations within a limit of a particular error percent. The more appropriate model with less error percentage can be chosen as the reliable model.

6) In general, large number of datasets collected from a particular study area is

used to train the soft computing methods, and the remaining data is used to test. However, the training datasets are generated by changing weights and membership functions based on the field data in the present concept. Thus, this approach can be applied to invert the VES data collected from any study area.

7) The conventional geophysical inversion techniques can be improved by using a

certain kind of soft computing techniques. Increasing the number of trained datasets by increasing the number of iterations (since each iteration will produce a different layer model), the ANFIS will converge with the result and make the output to flow towards a distinctive solution. The ANFIS can also be applied

Table 2. ANFIS inverted profile.

VES No.	True Resistivity (in Ohm-m)	Depth (in m)	Error Percent (RMSE)	Computational Time (in sec)
1.	30.4699	1	0.33	23.2038
	11.0761	3		
	13.1531	4		
	12.394	5		
	71.140	40		
	65.940	55		
	2142.87			
2.	6.0756	1	0.8320	21.9926
	12.163	4		
	12.416	4.2		
	89.736	50		
	82.901	55		
	3129.36			
3.	23.313	1	0.622	21.3415
	43.67	10		
	36.801	12		
	40.878	25		
	38.099	30		
	62.101	50		
	54.671	55		
	94.199	90		
	0.0879			
4.	18.595	1	0.1713	3.9226
	8.532	4		
	36.5609	25		
	36.2502	27		
	2040.17			
5.	29.4871	1	0.4692	21.0232
	26.3768	11.8		
	68.4449	30.7		
	67.8925	55		
	127.378	90		
	0.0557			

Table 3. Longitudinal resistivity variations taken for Kanyakumari profile.

S. No.	Percentage of White Gaussian noise added	True Resistivity (in Ohm-m)	Depth (in m)	Error Percent (RMSE)	Computational Time (in sec)	Number of rules framed while ANFIS inversion
1	10	63.2419	1	0.9132	19.0667	6
		105.387	3			
		43.1823	26			
		1514.59				
2	20	63.2376	1	0.914236	29.4628	12
		106.835	3			
		40.7399	26			
		1514.54				
3	40	63.3428	1	0.939288	18.2351	10
		104.818	3			
		40.9337	26			
		1514.32				
4	60	63.5693	1	0.857434	14.9081	6
		104.792	3			
		43.0718	26			
		1503.38				
5	80	96.0535	1	6.05378	93.2999	7
		96.0535	1			
		96.1082	4			
		96.1322	5			
		95.7721	6			
		93.416	10			
		88.1523	11			
		56.4565	20			
		44.1743	25			
		36.8733	40			
		1517.35				
6	<80	**OPTIMALLY WEIGHTED ANFIS SYSTEM BECOMES UNSTABLE**				

to 2D and 3D inversion problems with certain controlling parameters such as learning rate, momentum, the number of iterations and error percent. Training database and acquiring knowledge are accomplished to the best by ANFIS algorithm. More reliable performance of ANFIS technique will have the best scope in the future for estimating many optimisation problems.

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