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A New Technique to Predict the Fractures Dip Using Artificial Neural Networks and Image Logs Data

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Graphical abstract

Abstract

Fractures provide the place for oil and gas to be reserved and they also can provide the pathway for them to move into the well, so having a proper knowledge of them is essential and every year the companies try to improve the existed softwares in this technology. In this work, the new technique is introduced to be added as a new application to the existed softwares such as Petrel and geoframe softwares. The data used in this work are image logs and the other geological logs data of tree wells located in Gachsaran field, wells number GS-A, GS-B and GS-C. The new technique by using the feed-forward artificial neural networks (ANN) with back-propagation learning rule can predict the fracture dip data of the third well using the data from the other 2 wells. The result obtained showed that the ANN model can simulate the relationship between fractures dips in these 3 wells which the multiple R of training and test sets for the ANN model is 0.95099 and 0.912197, respectively.

Keywords: Fractures; oil and gas reservoirs; Image logs

Abstrak

Patah menyediakan tempat untuk minyak dan gas sebagai dirizabkan dan mereka juga boleh menyediakan laluan bagi mereka untuk bergerak ke dalam telaga , sehingga memiliki pengetahuan yang betul daripada mereka adalah penting dan setiap tahun syarikat-syarikat cuba untuk memperbaiki perisian wujud dalam teknologi ini . Dalam karya ini , teknik baru diperkenalkan untuk ditambah sebagai suatu permohonan baru kepada perisian wujud seperti Petrel dan perisian geoframe . Data yang digunakan dalam kerja-kerja ini adalah log imej dan log geologi yang lain data telaga pokok di Gachsaran lapangan, beberapa telaga GS- A, J -B dan J -C. Teknik yang baru dengan menggunakan rangkaian galakan hadapan tiruan neural (ANN) dengan sokongan pembiakan peraturan pembelajaran boleh meramalkan data patah dip yang ketiga juga menggunakan data dari yang lain 2 telaga. Keputusan yang diperolehi menunjukkan bahawa model ANN boleh mensimulasikan hubungan antara keretakan harga rendah dalam 3 telaga yang R dibahagikan dengan latihan dan ujian set untuk model ANN adalah 0,95099 dan 0,912197 , masing-masing .

Kata kunci: patah ; Minyak dan gas takungan ; log imej

1.0 INTRODUCTION

In geology, fractures are the features that have been created in rocks and they have the different dip from the rocks / layers structural dip so they can be recognized. The way that they will be created is due to the movements in original rocks and these movements are due to one or more forces in place. These forces can be originated from the faults, folds, diapirisms, plate movements and so on. Recognizing the fractures has always been an important matter for geologists and many methods have been created to do this task [1,2,3].

Fracture characterization means identifying the fracture type, fracture strike, fracture dip, fracture azimuth, fracture aperture, fracture occurrence, fracture density, etc. Using the data from the fracture characterization, the fracture model can be created to have a better understanding of the fracture system with oil and gas reservoirs [4,5,6].

Artificial neural networks are among the best available tools to generate nonlinear models. Artificial neural networks are parallel computational devices consisting of groups of highly interconnected processing elements called neurons. Artificial neural networks (ANN), inspired by the scientists interpretation of the architecture and functioning of the human brain [7].

Gachsaran field is located in southwest of Iran (Figure 1) with an anticline structure, made of anhydrite/salt, 80 km long, 300 m-1500 m thickness, 8-18 km wide; it provides an excellent seal for Asmari, Pabdeh, Gurpi and the other reservoirs (Figure 2) [8].

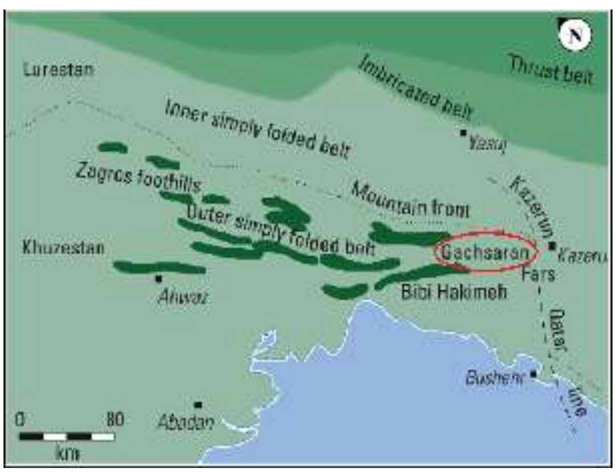


Figure 1a Location of the Gachsaran oil field [2]; b) UGC map the of Gachsaran field and the studied wells

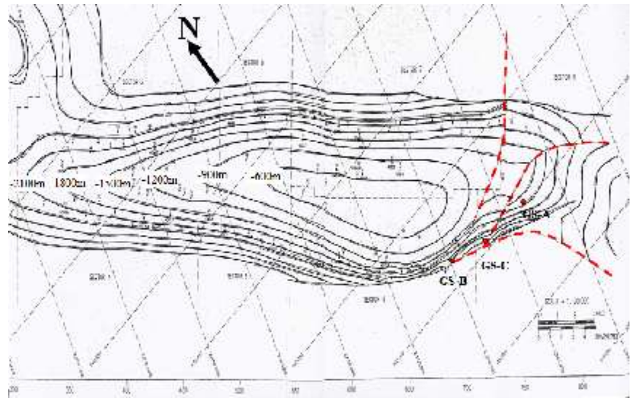


Figure 1b UGC map of the Gachsaran field and the wells number GS-A, GS-B and GS-C

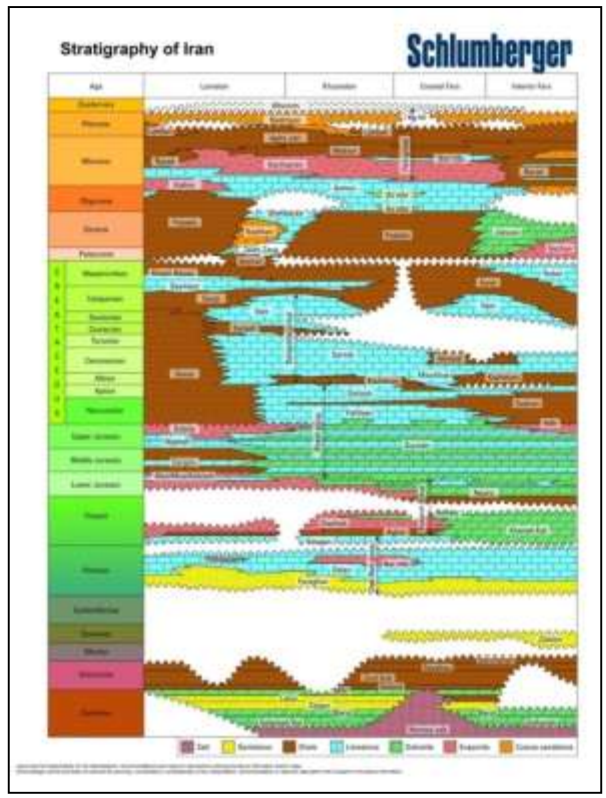


Figure 2 The location of Gachsaran oil field overlying the Asmari, Pabdeh, Gurpi and the other reservoirs, and stratigraphic nomenclature of rock units and age relationships in the Zagros basin [9]

In this work, 3 wells located in Gachsaran oil field are selected, and the data for this work are image log data in cooperation with the other geological logs. These wells are close to each other and the data for this work are from the depth 2500-2690m. The ANN is used to create a model from the existed fracture dip data in these tree wells and then by using this model, the fractures dip will be predicted. Finally, the result from ANN and the real logs data will be compared in order to validate the new technique.

2.0 A REVIEW OF ARTIFICIAL NEURAL NETWORKS APPLICATIONS IN FRACTURE CHARACTERIZATION AND MODELING TECHNOLOGY

Recently, Artificial Neural Networks (ANN) technology is being used in the field of fracture characterization and modelling technology because of the application that it has to predict the data. Usually, in oil and gas industry the engineers face the lack of data due to the complex structure of fractured reservoirs. In these cases, the ANN can help them to predict the missed data using the other data. The ANN can create a model using the measured data to predict the other data that is very helpful in oil and gas industry because this industry is data based industry. Oil and gas industry from the beginning of the oil exploration until the production and transferring the oil and gas in refinery units is all based on data that most of these data are underground data. These underground data are gained by using logging tools, cores, well testing, production data and so on that in some cases logging tools or other tools miss the data measurement in a specific depth so ANN can help to recover these unmeasured data. Sometimes ANN can be used to test the data, in this case the data will be given to ANN and the data that want to be tested will not be given to ANN so ANN will predict them then these data can be compared to the real data calculated by tools.

Sometimes engineers don't have the availability of the fracture characteristics of the all well depths so in these cases they will use the data from the logged depth to predict the unlogged depth. ANN by predicting the data can save costs and time for engineers and it also can be used to test the logged data. By developing the ANN technology every year the companies try to use this technology in oil and gas industry because of the benefit that this technology has in term of costs and time saving.

ANN uses computer programs that are written in C, C++, Matlab and other computer languages and they follow the human brain application. The human brain is made of millions of neurons that these neurons help the brain learn the knowledge and later on use this knowledge to calculate the other problems. ANN also can be trained by existing data and then can be used to calculate and predict the data.

Numbers of studies have been done recently in this field that engineers tried to use this useful technology in fracture characterization and modelling. Zerrouki et al. (2014) used ANN to predict the natural fracture porosity from well log data. In this job, they show the useful application of ANN to predict natural fracture porosity when transit time is lacking by the good result that they obtained from the correlation between the experimental results and natural fracture porosity log results. In this job, they arranged the log data inputs as their influence on natural fracture porosity [10].

Adibifard et al. (2014) used ANN to predict the reservoir parameters in naturally fractured reservoirs using well test data. In this job, they used the theoretical pressure derivative curves to train the ANN and they used the different training algorithms to train the ANN. In this job, the optimum number of neurons for each algorithm were obtained through minimizing Mean Relative Error (MRE) over test data. They showed that the Levenberg–Marquardt algorithm has the lowest MRE [11].

Xue et al. (2014) used a combination of the ANN and genetic algorithms to predict the fracture parameters in low permeability reservoirs. In this job, they designed genetic algorithm back propagation neural network to predict the deep-shallow laterolog curves and micro-electrode logging curves [12].

Malallah et all. (2005) used ANN to predict the fracture gradient coefficient in one of the middle eastern fields. In this job, they used a new simple mechanism for fracture gradient prediction as a function of pore pressure, depth and rock density. Their job is valuable because of the importance of the fracture gradient estimation in oil and gas industry, especially in drilling operations [13].

Jafari et al. (2012) used ANN to predict the equivalent fracture network permeability. In this job, they showed that fracture density, fracture length and fracture orientation can be used to estimate the fracture permeability using ANN. They showed that the correlation obtained from this method can be used to calculate equivalent fracture network permeability in 2D and 3D models [14].

Aifa et al. (2014) used ANN to prove the relation between magnetic susceptibility and petrophysical parameters in the tight sand oil reservoir of Hamra quartzites. In this job, they calculated a non-linear relation between magnetic susceptibility and petrophysical parameters using ANN. They used an ANN structure of 25 neurons in hidden layer with the correlation coefficient (R) equal to 0.907 [15].

Yanfang et al. (2014) used hybrid simulation with ANN and data analysis techniques to do the refracturing candidate selection. In this job, they used the artificial neural networks with back propagation algorithms to predict the post fracture production. They used the independent variables against production performance for several wells and they calculated the correlation coefficient of these wells using ANN. Each selection that has the lowest correlation coefficient can be the best selection of refactoring job in any field. This method can be used in any field that has the potential of post fracturing job and can reduce the risk of operation [16].

Darabi et al. (2010) used ANN to do the 3D fracture modelling job in the Parsi oil field of Iran. The Parsi oil field is a naturally fractured reservoir in south of Iran and in this job they calculated the fracture index of this field using ANN and some geological and geomechanical parameters including shale volume, porosity, permeability, bed thickness, proximity to faults, slopes and curvatures of the structure [17].

Foroud et al. (2014) used ANN to do the history matching based on global optimization method for one of the Iranian fields. In this job, using ANN based method they developed a history matching process in this field and they proved that the ANN is useful for numerical simulation for history matching process. They generated multiple history matching scenarios that by comparing them the best scenario can be selected. Optimum production scenario can help the field to have the best recovery factor and without any further operation can products for years with a high production rate [18].

Ouahed et al. (2005) used ANN to characterize naturally fractured zones for one of the Algerian fields. In this work, they used a feed forward Back Propagation Neural Network (BPNN) to predict the fracture intensity maps of this field and then a mathematical model was applied to calculate the fracture network maps [19].

boadu (2001) used ANN and petrophysical models to predict the oil saturation from velocities. In this job, he trained the ANN using the simulated data based on the petrophysical model. He calculated the oil saturation degree from velocity measurements of unconsolidated sediments at a laboratory scale using a petrophysical model and artificial neural network (ANN) as an inversion tool [20].

Irani et al. (2011) used a hybrid artificial bee colony-back propagation neural network to reduce the drilling risk by predicting the bottom hole pressure in underbalanced drilling conditions. Their results showed that carefully designed hybrid artificial bee colony-back propagation neural network outperforms the gradient descent-based neural network [21].

In this work a feed forward Back Propagation Neural Network (BPNN) will be used to predict the fractures dip angle for the third well using the image log and other geological log data of the two other wells nearby. The new method can save costs and time in drilling and production operations. It can reduce the risk of drilling operation and post fracturing job. It can be also used in real time logging operation and many other benefits that in next chapters will be mentioned.

3.0 MATERIALS AND METHODS

Principles, functioning and applications of artificial neural networks have been adequately described elsewhere [22]. A three-layer feed-forward network formed by one input layer consisting of a number of neurons equal to the number of descriptors, one output neuron and a number of hidden units fully connected to both input and output neurons, were adopted in this study. The most used learning procedure is based on the back propagation algorithm, in which the network reads inputs and corresponding outputs from a proper data set (training set) and iteratively adjusts weights and biases in order to minimize the error in prediction. To avoid overtraining and consequent deterioration of its generalization ability, the predictive performance of the network after each weight adjustment is checked on unseen data (validation set). In this work, training gradient descent with momentum is applied and the performance function was the mean square error (MSE), the average squared error between the network outputs and the actual output.

In this work, tree wells are selected (X1=well number GS-A, X2=well number GS-B, Y=well number GS-C) which are logged with FMI (Formation Micro Imager) and OBMI (Oil Base Mud Imaging) tools. The data are from the depth 2500-2690m that for every 5 meters the average is used that for every input and output there will be 38 raw data. In this depth all the 3 wells are in Asmari reservoir, so that the fractures dip for these wells will change at a same rate by changing the depth due to the forces that will create the fractures. Therefore, by using the existed data for these 3 wells, the fracture dip model will be created using the ANN, then this model will be used in order to predict the fracture dip for the third well (Y, Well number GS-C) and finally the validation will be done between the fractures dip data from ANN model and the fracture dip data from the logs. Figures 3 to 6 are given to show the data used for this work.

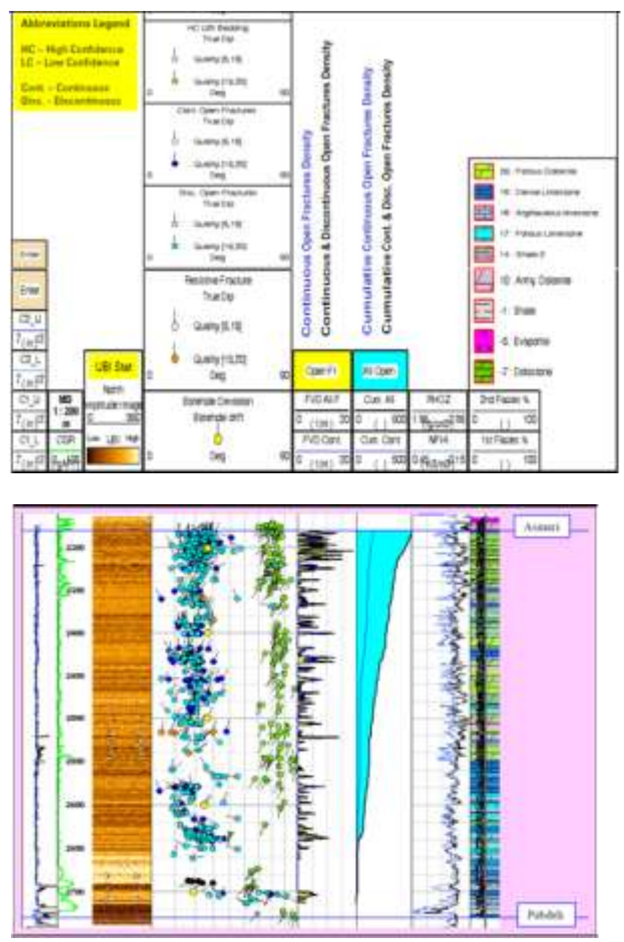
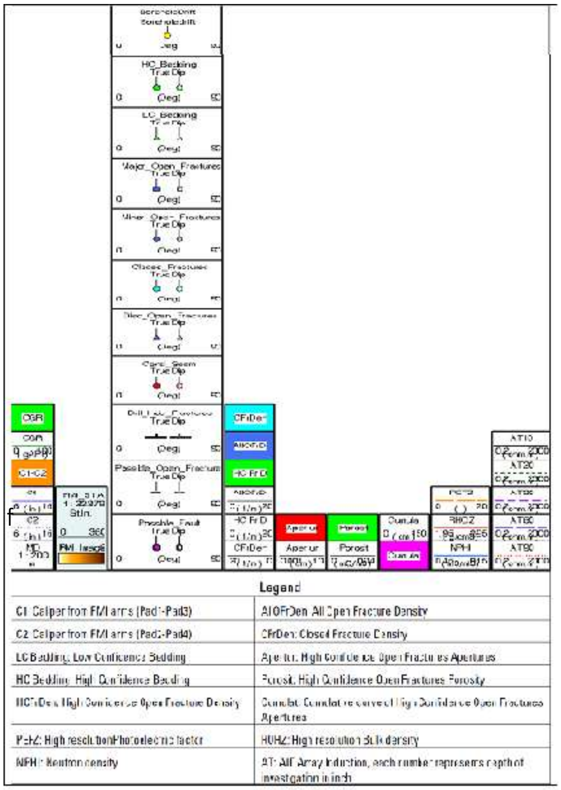


Figure 3 Summary of fracture analysis results of well number GS-A



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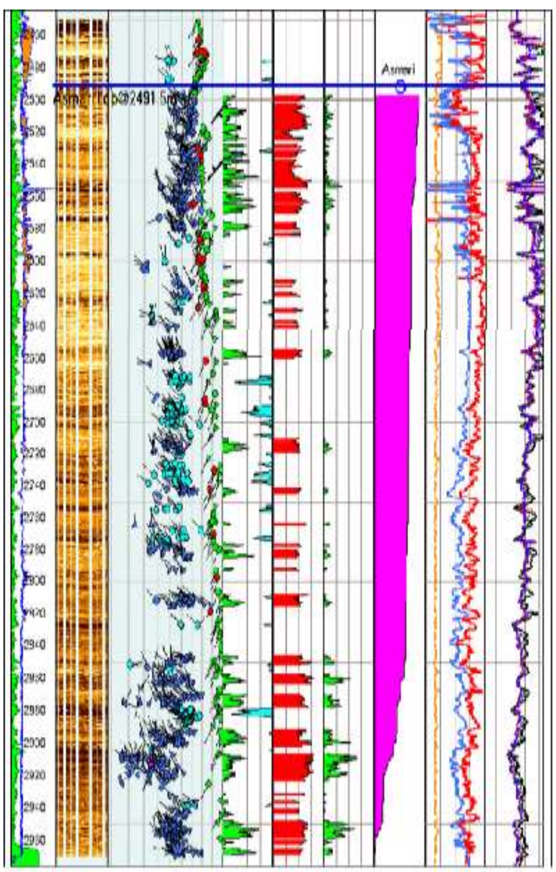

Figure 5 Summary of fracture analysis results of well number GS-B

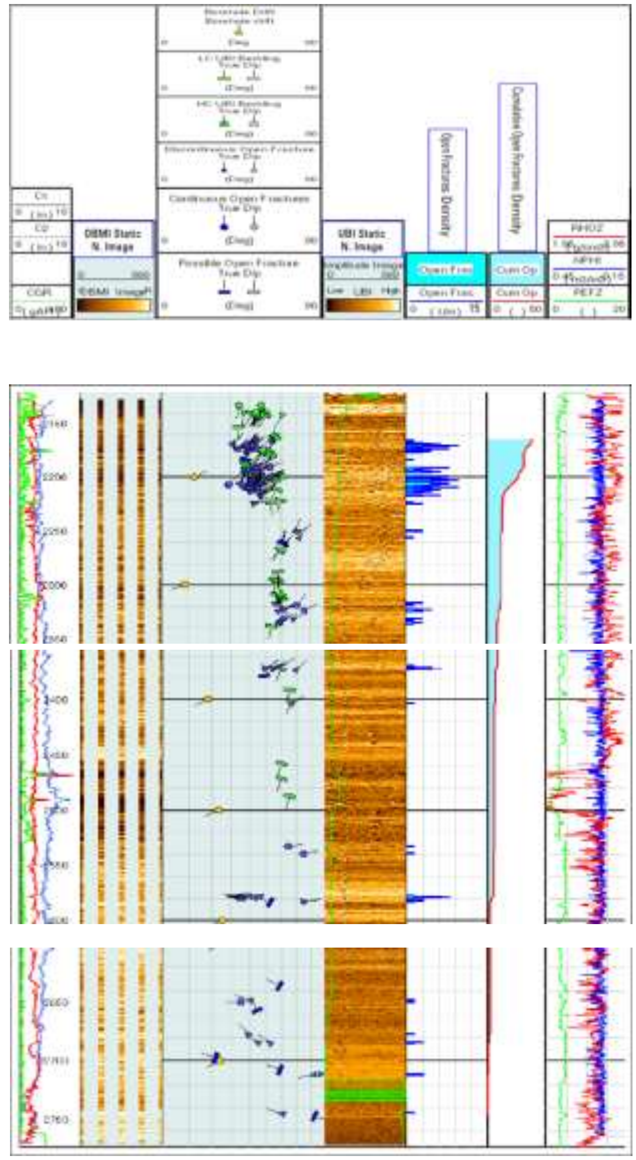

Figure 6 Summary of fracture analysis results of well number GS-C

4.0 RESULTS AND DISCUSSION

4.1 ANN Optimization

A three-layer neural network was used and starting network weights and biases were randomly generated. Fractures dip data of the wells number GS-A (X1) and GS-B (X2) from the depth 2500-2690m were used as inputs of network and the signal of the output node represent the fractures dip data of the well number GS-C (Y) from the same depth. Thus, this network has two neurons in input layer and one neuron in output layer. The network performance was optimized for the number of neurons in the hidden layer (hnn), the learning rate (lr) of back-propagation, momentum and the epoch. As weights and biased are optimized by the back propagation iterative procedure, training error typically decreases, but validation error first decreases and subsequently begins to rise again, revealing a progressive worsening of generalization ability of the network. Thus training was stopped when the validation error reaches a minimum value. Table 1 shows the architecture and specification of the optimized network.

Table 1 Architecture and specification of the generated ANN model

No. of nodes in the input layer	2
No. of nodes in the hidden layer	9
No. of nodes in the output layer	1
learning rate	0.4
Momentum	0.1
Epoch	17000
Transfer function	Sigmoid

4.2 Results of ANN Analysis

The fracture dip model provided by the optimal ANN is presented in figure 7 where computed or predicted fractures dip values are plotted against the corresponding logs data. Figure 8 shows a plot of residuals versus the observed fractures dip values. The substantial random pattern of this plot indicates that most of the data variance is explained by the proposed model.

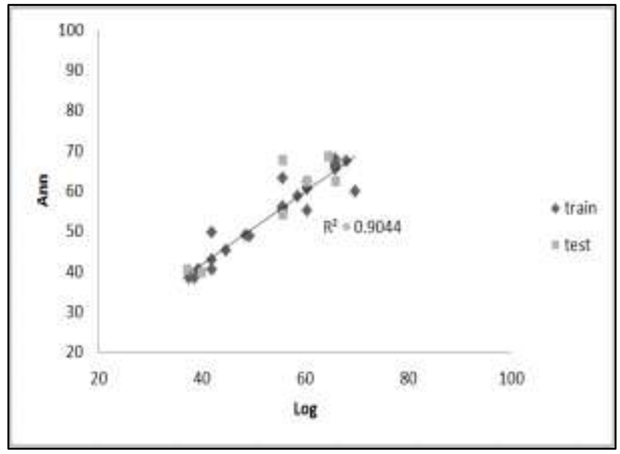

Figure 7 Plots of predicted values estimated by ANN modeling versus Log values

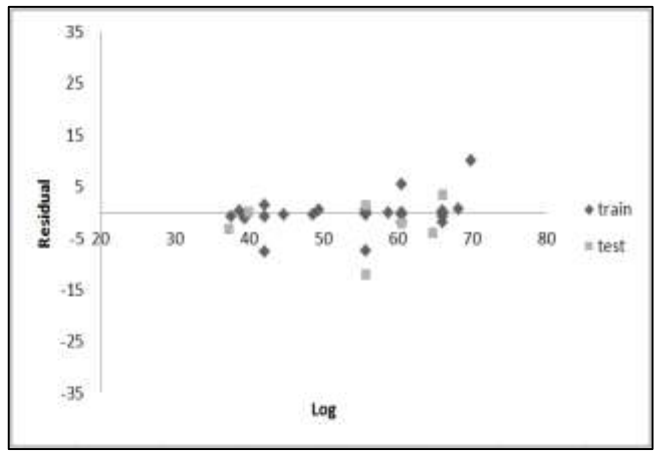

Figure 8 Plots of residual versus Log values in ANN model

The agreement between computed and observed values in ANN training and test sets are shown in TABLE 2. The statistical parameters calculated for the ANN model are presented in TABLE 3. Goodness of the ANN-based model is further demonstrated by the high value of the correlation coefficient R between calculated and observed fracture dip values 0.95099 and 0.912197 for training and test set, respectively.

Table 2 Data set of Log and ANN predicted values

Number	X1=Well number GS-A	X2=Well number GS-B	Y(Log)=Well number GS-C	Y (ANN)
Training set				
1	15.02287	43.86901	66.00388	66.77455
2	19.60213	54.85579	69.87629	59.90119
3	21.40582	51.90308	60.48607	60.578
4	17.88913	48.79102	38.70773	38.31932
5	14.96191	48.80968	55.68631	56.06223
6	30.50044	56.57765	66.00388	66.25523
7	29.61569	52.24769	55.68631	55.65638
8	24.06834	39.36527	58.68378	58.76799
9	21.49609	38.31668	37.63248	38.34297
10	18.5875	55.29606	42.04851	49.68509
11	39.5079	39.43705	48.62855	49.08314
12	8.84677	26.6485	55.68631	55.9497
13	17.50261	53.36557	66.00388	65.89331
14	20.84588	49.06684	60.48607	55.0873
15	21.9419	48.34997	55.68631	63.10661
16	39.5079	50.15751	42.04851	42.76785
17	15.6683	40.39614	55.68631	54.94827
18	21.40582	55.5377	60.48607	62.28648
19	27.94638	41.234	49.36781	48.81897
20	21.80695	53.16415	66.00388	67.90041
21	9.6602	41.82537	44.71148	45.14847
22	13.53298	33.18401	55.68631	55.61652
23	36.02494	51.40393	60.48607	60.4766
24	27.34866	55.10685	66.00388	65.58337
25	39.5079	48.21539	42.04851	40.58616
26	25.36997	48.34614	55.68631	54.94786
27	35.42421	37.06236	60.48607	60.57065
28	13.22259	47.75132	68.10967	67.42169
29	20.76198	25.2531	55.68631	55.75746
30	39.5079	47.94378	39.38554	40.518
31	21.40582	42.54467	60.48607	60.80671
Test set				
32	18.91059	53.80449	66.00388	62.56506
33	27.95822	54.51646	64.63335	68.58759
34	14.55485	48.18651	60.48607	62.57261
35	20.62757	40.39614	55.68631	54.16414
36	12.31543	48.79925	55.68631	67.60181
37	37.61452	41.64024	39.9623	39.8287
38	39.5079	47.17748	37.22468	40.38719

Table 3 Statistical parameters obtained using the ANN model; c refers to the calibration (training) set and t refers to the test set; R and R2 are the correlation coefficient

R^2t	R^2c	Rt	Rc	Model
0.8321	0.9043	0.9122	0.9510	Ann

5.0 CONCLUSION

Fracture modeling was performed on tree wells using ANN that predicts the fracture dip values of the third well using the fracture dip data of the other two wells. According to the obtained results, it is concluded that the ANN can be used successfully for modeling fracture dip data of the tree studied wells. High correlation coefficients and low prediction errors obtained confirm the good predictive ability of ANN model, which the multiple R of training and test sets for the ANN model is 0.95099 and 0.912197, respectively. A non-linear modeling approach based on artificial neural networks allows to significantly improve the performance of the fracture characterization and modeling technology, so this technique can be added to the existed softwares such as Petrel and Geoframe softwares.

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