# Application of artificial neural networks in fracture characterization and modeling technology

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*Abstract:* - Fracture characterization and modeling technology can characterize the fractures of naturally fractured reservoirs. In this work, a novel application of Artificial Neural Networks (ANNs) will be introduced which can be used to improve this technology. The new technique by using the feed-forward ANN with back-propagation learning rule can predict the fractures dip inclination degree of the third well using the data from the other two wells nearby. The result obtained showed that the ANNs model can simulate the relationship between fractures dips in these three wells which the multiple R of training and test sets for the ANN model are 0.95099 and 0.912197, respectively.

*Key-Words:* - Fracture characterization and modeling; Artificial Neural Networks; Dip inclination degree

## 1 Introduction

In geology, fractures are the features that have been created in rocks and they have the different dip inclination angle 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].

Artificial Neural Networks (ANNs) are among the best available tools to generate nonlinear models. ANNs are parallel computational devices consisting of groups of highly interconnected processing elements called neurons, inspired by the scientists interpretation of the architecture and functioning of the human brain [6].

Recently, ANNs are 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 ANNs can help them to predict the missed data using the other data.

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.

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. used ANN to predict the natural fracture porosity from well log data. They show of 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. They arranged the log data inputs as their influence on natural fracture porosity [7].

Adibifard et al. used ANN to predict the reservoir parameters in naturally fractured reservoirs using well test data. They used the theoretical pressure derivative curves to train the ANN and they used the different training algorithms to train the ANN. 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 [8].

Xue et al. used a combination of the ANN and genetic algorithms to predict the fracture parameters in low permeability reservoirs. They designed genetic algorithm back propagation neural network to predict the deep-shallow laterolog curves and micro-electrode logging curves [9].

Malallah et al. used ANN to predict the fracture gradient coefficient in one of the middle eastern fields. 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 [10].

Jafari et al. used ANN to predict the equivalent fracture network permeability. 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 [11].

Aifa et al. used ANN to prove the relation between magnetic susceptibility and petrophysical parameters in the tight sand oil reservoir of Hamra quartzites. 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 [12].

Yanfang et al. used hybrid simulation with ANN and data analysis techniques to do the refracturing candidate selection. They used the ANN 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 [13].

Darabi et al. 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 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 [14].

Foroud et al. used ANN to do the history matching based on global optimization method for one of the Iranian fields. 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 [15].

Ouahed et al. used ANN to characterize naturally fractured zones for one of the Algerian fields. 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 [16].

Boadu used ANN and petrophysical models to predict the oil saturation from velocities. 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 ANN as an inversion tool [17].

Irani et al. 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 [18].

In this study 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.

## 2 Materials and Methods

Gachsaran field with thickness of 80 km long and 8-18 km width contains fractured formations of Asmari, Pabdeh, Gurpi and Khami. Asmari formation of the field contains carbonate, marly shale and vaporized marls which are sounded from top by Gachsaran anhydrite/salt formation (Fig. 1) [19].

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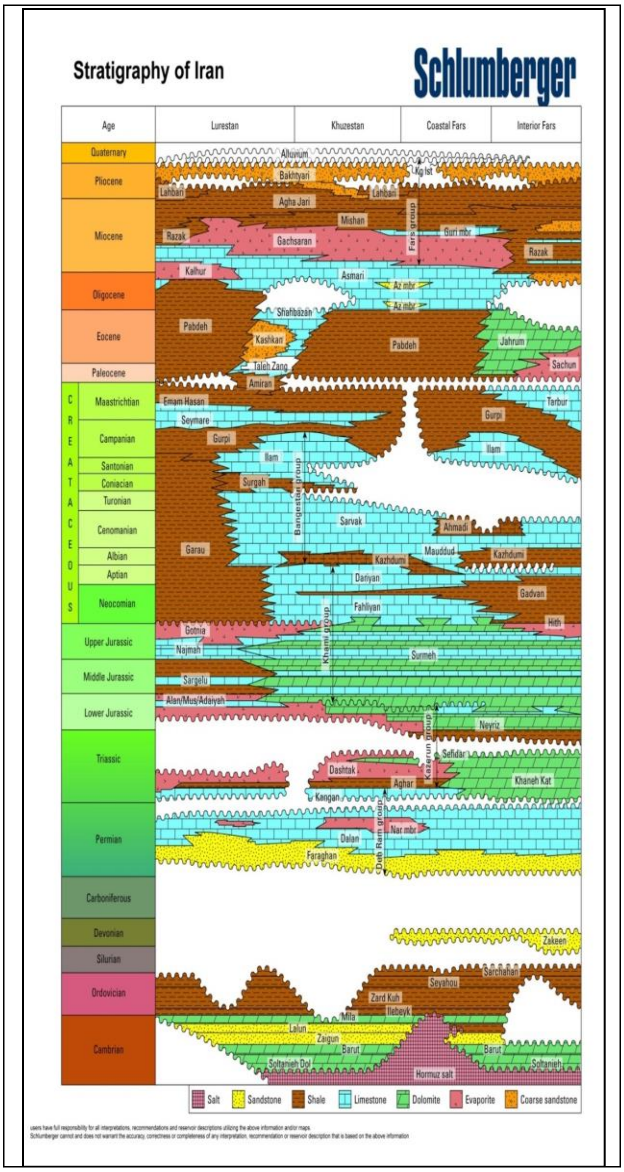



**Fig. 1:** The location of Gachsaran formation overlying the Asmari, Pabdeh, Gurpi and the other reservoirs; stratigraphic nomenclature of rock units and age relationships in Zagros basin [20].

Principles, functioning and applications of artificial neural networks have been adequately described elsewhere [21]. 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). 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.

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 (Fig. 2).

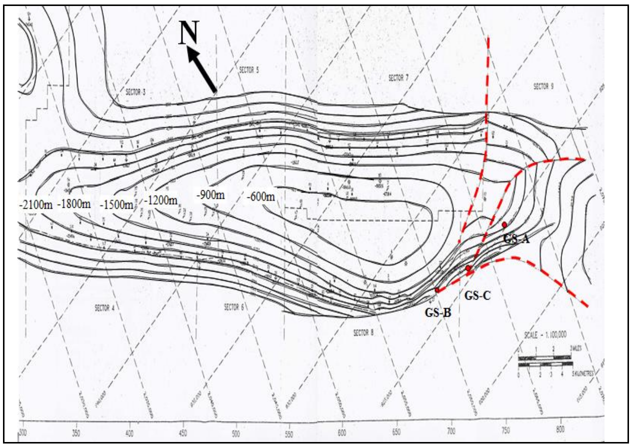



**Fig. 2:** Map of the Gachsaran field and the three study wells, GS-A, GS-B and GS-C.

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. Fig. 3 to 6 are given to show the data used for this work.

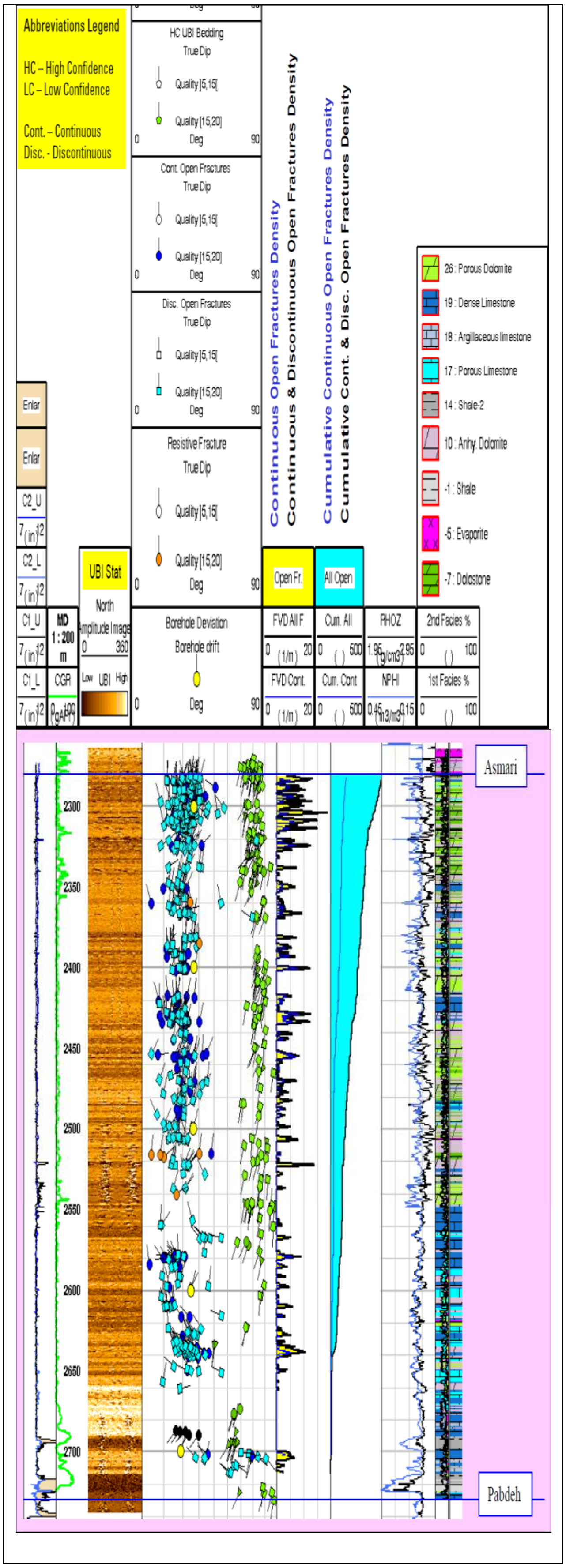
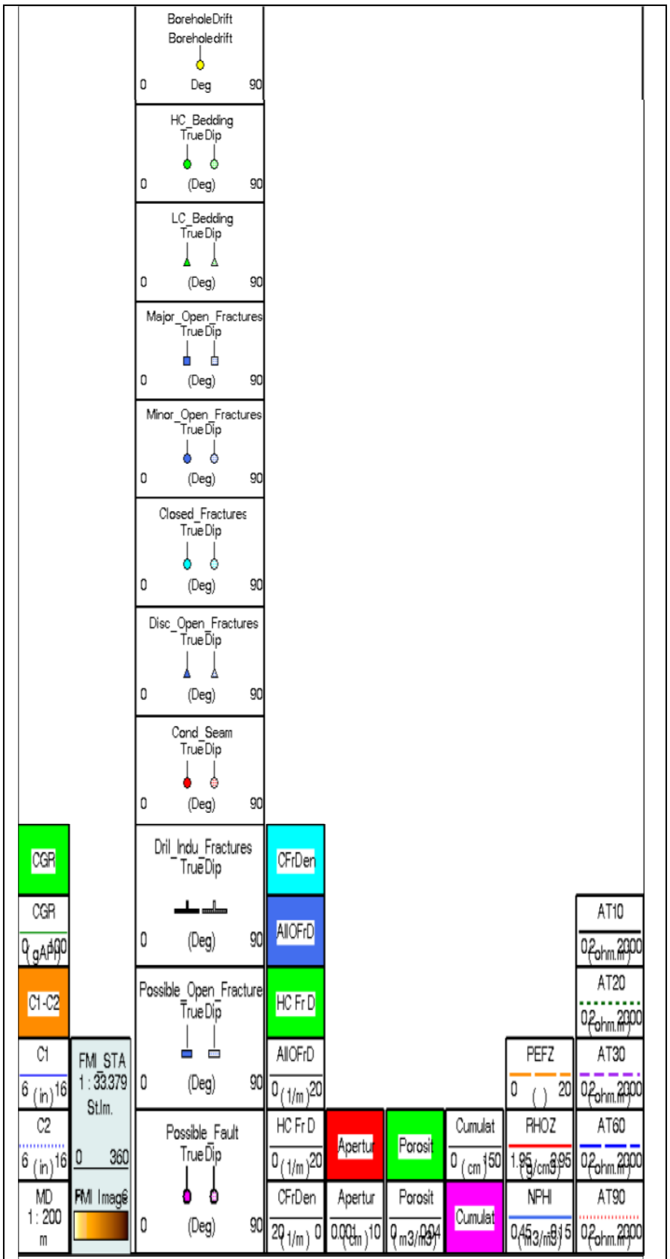



**Fig. 3:** Summary of fracture analysis results of well number GS-A.




| Legend | |
|---|---|
| C1: Caliper from FMI arms (Pad1-Pad3) | AllOFrDen: All Open Fracture Density |
| C2: Caliper from FMI arms (Pad2-Pad4) | CFrDen: Closed Fracture Density |
| LC Bedding: Low Confidence Bedding | Apertur: High Confidence Open Fractures Apertures |
| HC Bedding: High Confidence Bedding | Porosit: High Confidence Open Fractures Porosity |
| HCFrDen: High Confidence Open Fracture Density | Cumulat: Cumulative curve of High Confidence Open Fractures Apertures |
| PEFZ: High resolutionPhotoelectric factor | ROHZ: High resolution Bulk density |
| NPHI: Neutron density | AT: AIT Array Induction, each number represents depth of investigation in inch |

**Fig. 4:** Header for figure 5.

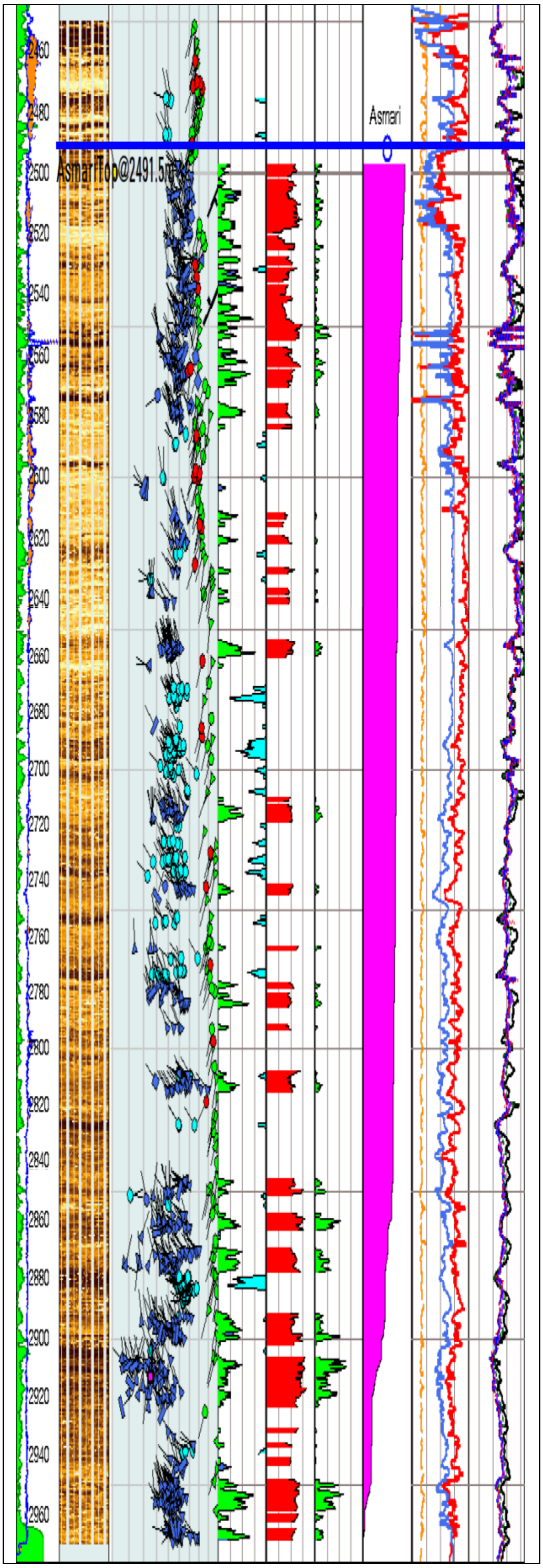



**Fig. 5:** Summary of fracture analysis results of well number GS-B.

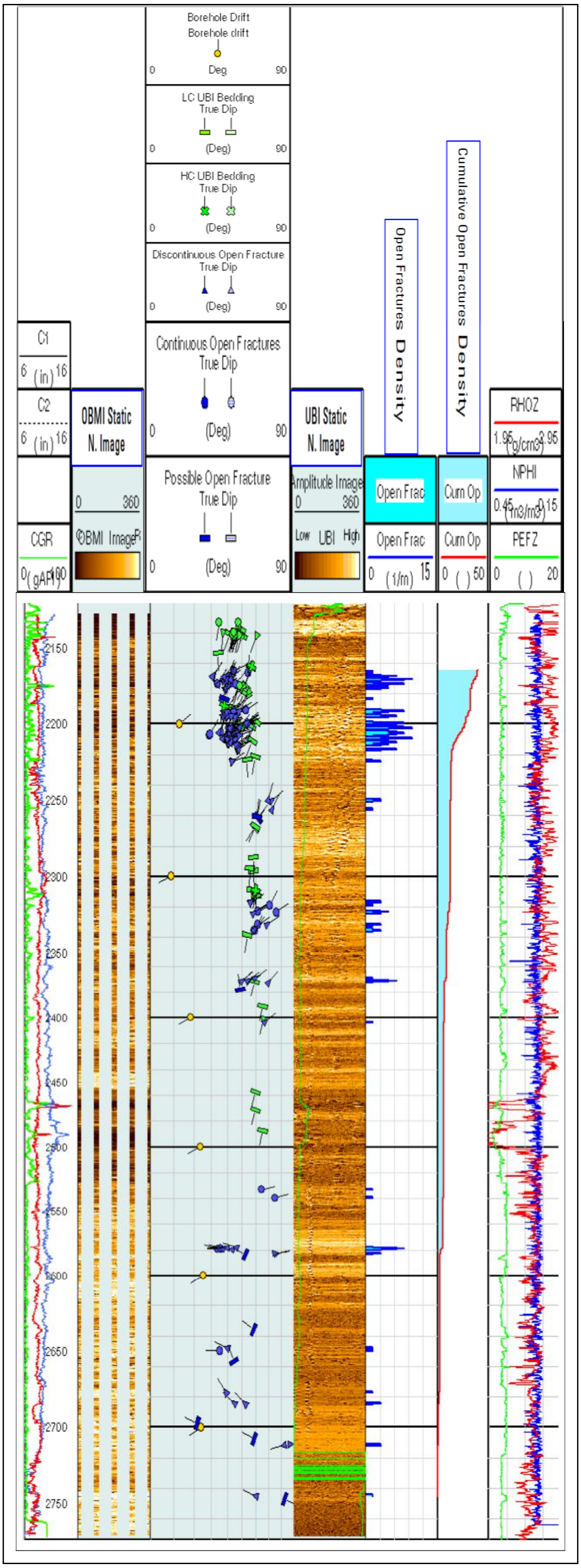



**Fig. 6:** Summary of fracture analysis results of well number GS-C.

# 4 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 Fig. 7 where computed or predicted fractures dip values are plotted against the corresponding logs data. Fig. 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.

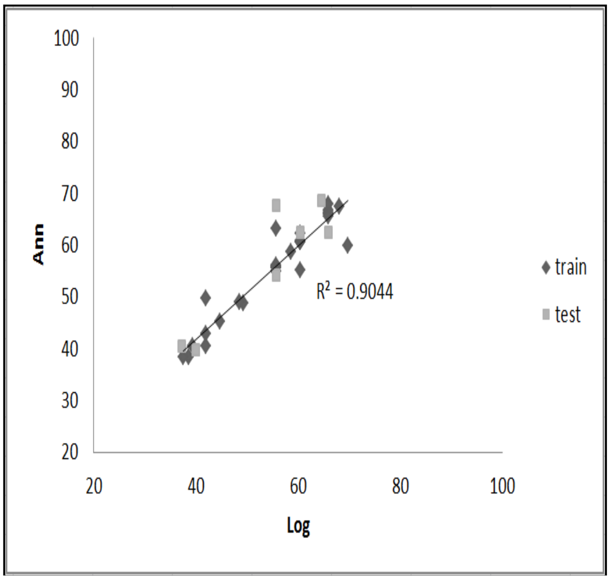



**Fig. 7:** Plots of predicted values estimated by ANN modeling versus Log values.

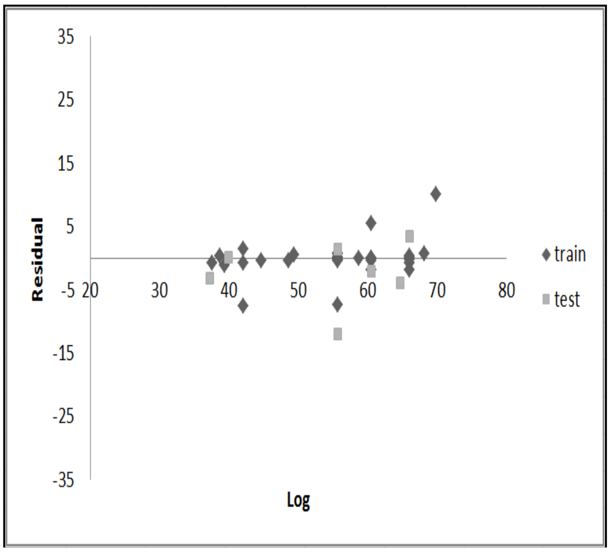



**Fig. 8:** Plots of residual versus Log values in ANN model.

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.

| No. | X1 GS-A | X2 GS-B | Y( Log) GS-C | Y(ANN) GS-C |
|---|---|---|---|---|
| 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 $R^2$ are the correlation coefficient.

| $R^2$t | $R^2$c | Rt | Rc | Model |
|---|---|---|---|---|
| 0.8321 | 0.9043 | 0.9122 | 0.9510 | ANN |

# 5 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 three 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.

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