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Application of artificial neural networks for prediction of Sarvak Formation lithofacies based on well log data, Marun oil field, SW Iran

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Abstract

Lithofacies identification can provide qualitative information about rocks. It can also explain rock textures which are important components for hydrocarbon reservoir description Sarvak Formation is an important reservoir which is being studied in the Marun oil field, in the Dezful embayment (Zagros basin). This study establishes quantitative relationships between digital well logs data and routine petrographic data, obtained from thin sections description. Attempts were made to predict lithofacies in 13 wells, all drilled in the Marun oil field. Seven well logs, namely, Gamma Ray (SGR and CGR), Deep Resistivity (RD), Formation Density (RHOB), Neutron Porosity (PHIN), Sonic log (DT), and photoelectric factor (PEF) as input data and thin section/core-derived lithofacies were used as target data in the ANN (artificial neural network) to predict lithofacies. The results show a strong correlation between the given data and those obtained from ANN (R^2= 95%). The performance of the model has been measured by the Mean Squared Error function which doesn't exceed 0.303. Hence, neural network techniques are recommended for those reservoirs in which facies geometry and distribution are key factors controlling the heterogeneity and distribution of rock properties. Undoubtedly, this approach can reduce uncertainty and save plenty of time and cost for the oil industry.

Keywords: *Sarvak Formation, Artificial Neural Networks, Reservoir Characterization, Lithofacies, Zagros Basin.*

Introduction

The production performance of a reservoir considerably depends on the characterization of the reservoir. One of the main goal of geologic studies is to apply suitable mathematical and statistical procedures to obtain reliable information about reservoirs (e.g. lithology, porosity, density, hydraulic conductivity, electric resistivity, salinity, and water/oil saturation), using either surface or borehole measurements. Amongst which, lithofacies identification is an important issue for reservoir characterization. Description and identification of lithofacies are essential, as they provide qualitative information about reservoirs which are, in turn, composed of various lithofacies, each of which has its own porosity-permeability characteristics (Negi *et al.*, 2006). Conventional methods, e.g. manual examinations of core and thin sections in enormous boreholes require lots of efforts, time, and cost a huge amount of money. Alternative methods are the computer-based intelligence methods (e.g. neural network, fuzzy logic, genetic algorithm, etc.), which could be utilized to provide reliable results (Nikravesh *et al.*, 2003). Artificial neural networks are well appreciated in reservoir characterization because of their advantage in extracting nonlinear relationships between a sparse set of data (Banchs & Michelena, 2002). Such methods were successfully applied to predict lithofacies from logs (Saggaf & Nebrija, 2003a; Bohling & Dubois, 2003; Maiti *et al.*, 2007; Qi & Carr, 2007), estimate logs response for missed intervals (Saggaf & Nebrija, 2003b), and predict porosity and permeability from 3D seismic data (Wong *et al.*, 1998; Trappe & Hellmich, 2000; Ali and Chawathe, 2000; Lee *et al.*, 2000; Ligtenberg & Wansink, 2001; Mathisen *et al.*, 2003; El-Sebakhy *et al.*, 2012). They are also used for earthquake prediction (Feng *et al.* 1997), textural identification of carbonate (Marmo *et al.*, 2005), shale identification and prediction (Wang & Carr, 2012), and fractured reservoir characterization (Ouenes, 2000). This study attempts to apply a back propagation neural network program to predict lithofacies of the Sarvak Fm. based on well logs data in the Marun oil field.

Geologic setting

The Sarvak Fm. (Albian to Turonian) is one of the most prolific oil reservoirs in southwest Iran, in the Zagros basin (James and Wynd, 1965; Motiei, 1993; Fig. 1). The Zagros basin predominantly comprises thick intervals of carbonates, mudrocks, and subordinate evaporitic horizons. These successions are characterized by a marked reduction in siliciclastic influx, the development of a carbonate platform to intra-shelf basin topography, and deposition of basinal source rocks somewhere in the basin. The sediments of the Sarvak Fm. were deposited on platform and within the intrashelf basin on the passive margin of the Arabian Plate (Ziegler, 2001). The complex tectonic history of the Zagros basin and Arabian Platform (Alavi, 2004; Sepehr and Cosgrove, 2005; Casini *et al.*, 2011) led to wide variations in reservoir characteristics of the Sarvak Fm. and its equivalents (Rahimpour- Bonab *et al.*, 2012), which brought the formation of intrashelf basins and paleohighs in the SW sector of the Zagros basin (including the Dezful Embayment). The study area is located at the Dezful Embayment (SW Iran), a subdivision of Zagros fold- thrust belt. In this part of the Zagros basin, the Sarvak Fm. is an important reservoir along with the overlying Ilam Fm. which comprises the upper part of the Bangestan group (Fig. 2).

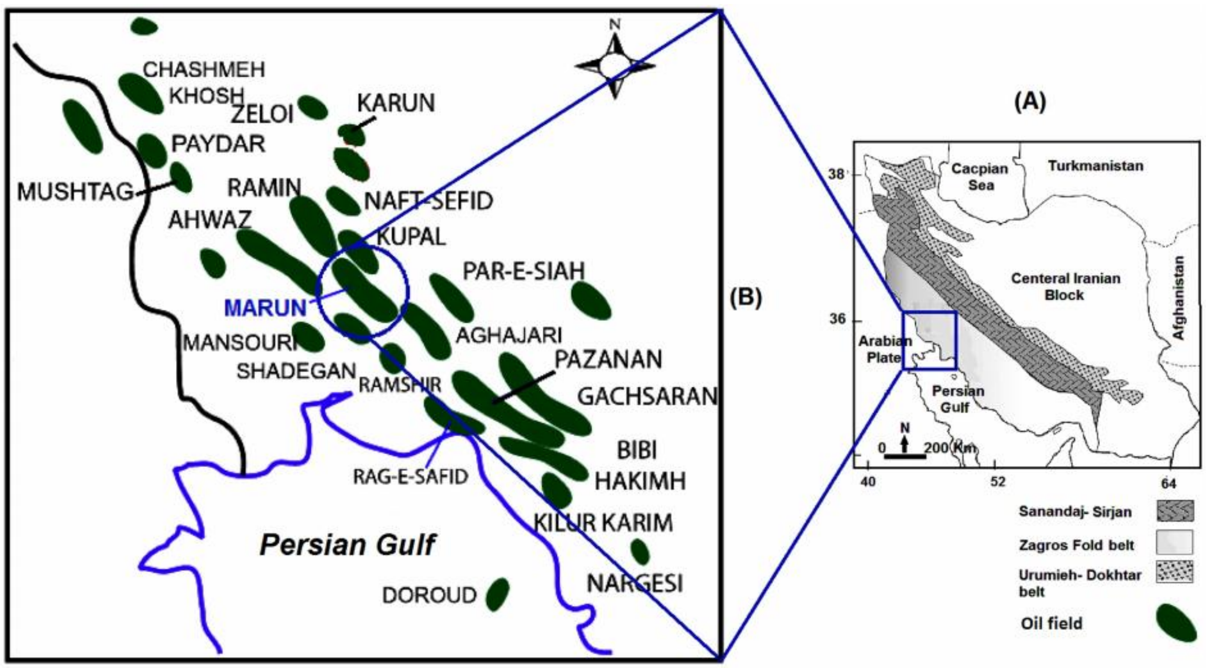

Figure1. (A) Generalized structural provinces of Iran, and (B) Location map of the study area

Lithostratigraphy

The Sarvak Fm. was deposited in a shallow marine environment during Albian to Turonian (Motiei, 1993), which passed into a lower-energy setting toward Fars and the Persian Gulf. However, in the northwestern area of Lurestan and toward Iraq, the Sarvak Fm. interfingers with the Garau Fm (Bordenave, 2002). The nature of the upper boundary of the Sarvak Fm. is variable (Fig. 2).

Deposition of conglomerates, breccias, iron oxides, and accompanied disconformities in the upper part of the Sarvak Fm. are evidence of local uplift during the Late Cenomanian to the Turonian. The lower boundary of the Sarvak Fm. with the Kazhdumi Fm. is conformable and gradational and is marked by a pronounced change from the shales of Kazhdumi Fm. to the limestones of Sarvak Fm. (James & Wynd, 1965).

Methods and Materials

Neural network analysis provides a method to constrain lithofacies from the well logs. ANN is analogous to biological nervous systems and consists of an input layer, hidden layers, and an output layer (Fausett, 1994). Neural networks are often used when the relationships of parameters are too complicated or require too much time to solve via conventional methods (Aminian & Ameri, 2005). Neural networks can discover highly complex relationships between several variables. A neural network works as a learning process from provided information, trains the data to form certain patterns for each subject, then predicts targets with the output model. In this study, we used a single-layer neural network (back-propagation) to predict the lithofacies from log data. The most widely used learning algorithm for training of the neural network is the back-propagation learning algorithm (Lim, 2003).

The architecture of an ANN includes a large number of neurons organized in different layers, so the neurons are in a succession connected by means of adjusting weights (Fig. 4). The ANN learns by repeated adjusting of the weight of inputs until the results are similar to the correct outputs of the training set.

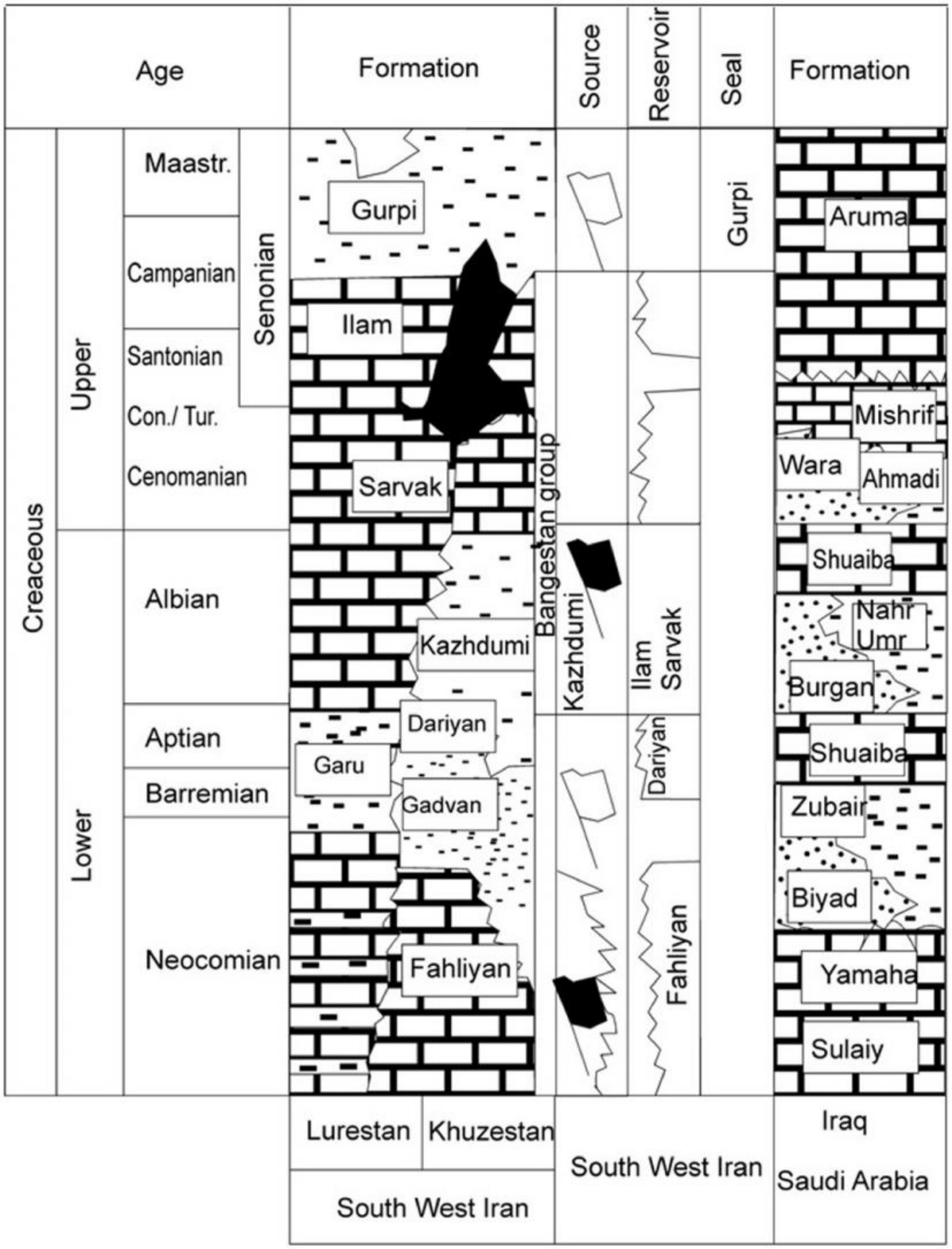

Figure 2. Stratigraphic chart of the Cretaceous system of southwest Iran and adjacent areas (Bordenave, 2002)

The database to be introduced to the neural network consists of three groups: training, test, and verification. The training set is used to train and create the network. The actual output of the training set data is used to develop the weights in the network. The test set is used to evaluate the predictive ability of the network. This is also ensuring that the network would not memorize the data. The verification set is used to evaluate the accuracy of the newly built network by providing the network with a set of data it has never faced. As a result of the non-linear weighting, the neural network can handle very complex problems. The training phase was performed by back-propagation learning algorithm. In general, we suppose there are "n" number of inputs (x_1, x_2, x_3, ……. x_n) and one output; the output (y) could be presented by the following relationship (equations 1 and 2):

$$Y = f(net) = f\left[\sum_{i=1}^{n} wx\right] \quad (1)$$

and

$$net - w_x^t = w_1x_1 + w_2x_2 + .w_nx_n \quad (2)$$

where f(net) refers to activation or transfer function and w_n is the weight vector. In this study the transfer function was tansig and logsig and the architecture of the artificial neural network built for this study was 7, 22, 7.

ANN is similar to the neural system of the human mind. ANN comprises of numerous processors (artificial neurons) which are designed to transfer the signals (Bhatt & Hell, 2002). These artificial neurons could be trained to learn, remember and apply the results after their training in a manner similar to human beings' mental system. ANN is broadly applied in engineering, medical sciences, as well as petroleum industries including log interpretation, reservoir characterization, and secondary recovery (Mohaghegh & Ameri, 1995). The numbers of the layers transform the function of individual layers and the numbers of the neurons; moreover, their connections are controlled by the structure of the AAN. The neurons are organized in a layered structure, so each layer is responsible for a distinct action. The input layers obtain the data and transfer them to the middle layer. The middle (or hidden layer) could process and analyze these data (Figs. 3 and 4). The output layer gets the results of the middle layer, gives them a meaningful form, and feeds them back to the system. The most important part of the network is the processors which are composed of combined and transfer functions. The combined function can multiply various inputs by their relevant weight, and then combine the results to produce a digit. The effect of the weight of any link is similar to the synopsis of biologic neurons (Aminzade & de Groot, 2006). The processors have a non-linear function which is called the transfer function. The output of the combined function is used as the input for the transfer function. The transfer functions comprise of sigmoid Tangent (Tansig), sigmoid logarithm (Logsig), and linear purline function (Purlin). The relative function between artificial neurons and the biologic counterpart is expressed in Equation (3). In most cases, a neural cell has an extra input which is called Bias. Figure 3 is a mathematical model of a neural cell in which the combined function, the transfer function, weight of each input, and bias are illustrated.

$$y = a[\sum(w_i\, x_i)] \quad (3)$$

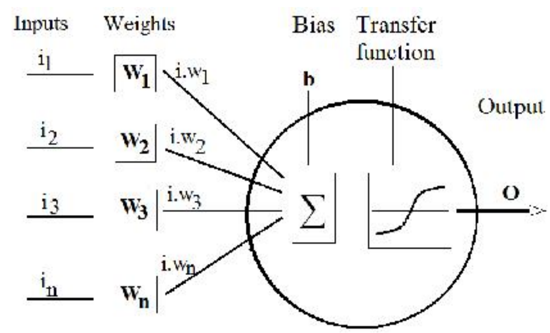

Figure 3. Mathematical representation of a neural cell in the network

Weights and bias could be adjusted in a network to facilitate the network for better recognition of the algorithms. If the sum weights of the input signals exceed the value of b in Equation (4), the neurons would be excited (Aminzade and de Groot, 2006).

$$O = \sum W_i\, X_i - b \quad (4)$$

There are two types of neural networks according to the nature of the connection between knots. These are called Feed-forward networks and Feed-back networks. The latter is normally used in oil industries, particularly for reservoir petrophysic characteristics (Saggaf & Nebrija, 2003a, b).

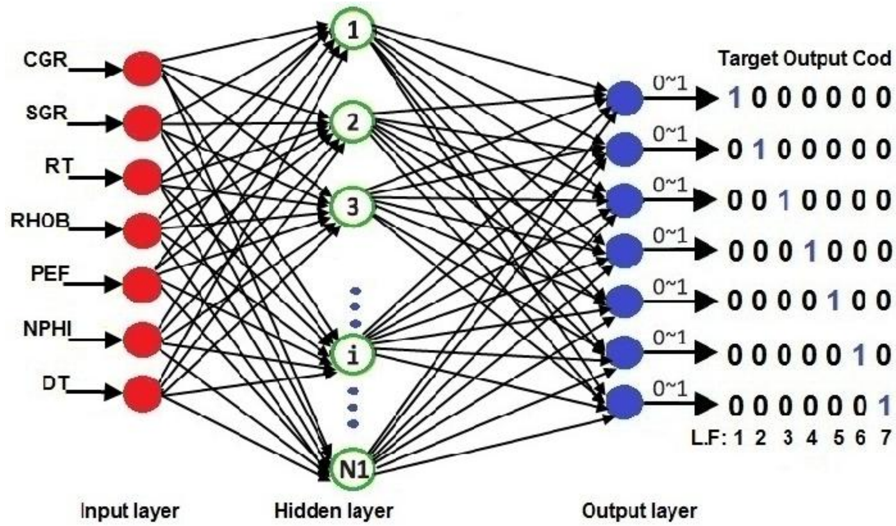

Figure 4. Architecture of the artificial neural network built for this study

Available data

Digital well logs (CGR, DR, RHOB, NPHI, RT, and PE) were assembled from 13 wells in the Marun oil fields. A total of 350 m of the cored interval of the Sarvak Fm. from well #305 was described. Core interpretations include lithofacies type, depositional fabric (described in terms of Dunham, 1962 classification), grain size, type of porosities, and fossil content. The data of well #123 were used for the verification of the results.

Lithofacies classification and depositional environments

Seven major lithofacies were recognized based on petrographic examinations of thin sections from cores of well #305 of the Sarvak Fm. in the Marun oil field. The depositional environment and detailed microfacies analysis of the Sarvak Fm. were described by several researches (e.g., Taghavi *et al.*, 2006; Beiranvand *et al.*, 2007; Farzadi & Hesthmer, 2007; Ghabeishavi *et al.*, 2010; Hajikazemi *et al.*, 2010, 2012; Razin *et al.*, 2010; Rahimpour-Bonab *et al.*, 2012; Asadi Mehmandosti *et al.*, 2013). Seven major lithofacies (Fig. 5) are recognized as: (1) dolomudstone, (2) floatstone, (3) wackestone, (4) boundstone, (5) mudstone, (6) ooid grainstone, and (7) packstone, deposited in 5 distinct facies belts on a carbonate shelf including tidal zone, restricted lagoon, open lagoon, shelf margin, and open marine. Our interpretation is almost similar to those previously published for the Sarvak Fm.

Here is a brief description of these 5 facies associations. Facies association 1 includes dolomusdstone/ mudstone lacking biota or sparse bioclasts, which was deposited on a tidal flat/supratidal zone. Facies association 2 includes peloid Packstone/ grainstone and bioclast-peloid wackestone to packstone. Green algae, milliolids and some rounded intraclast imply a lagoonal setting. Low faunal diversity and well-preserved peloids suggest a somewhat restricted lagoon. Facies association 3 includes bioclast floatstone to wackestone with abundant rudistid bioclasts and benthonic foraminifera. This is corralatable to SMF No. 8 of Flugel (2010), which indicates an open lagoon. Various bioclasts include large benthonic formas (*pseuduhyponinis sp., pseudolithonella richelli, prealveolina sp., nezzazata sp, ostracoda,* coral and rudist clasts). Facies association 4 comprises of two microfacies (ooid grainstone and coral boundstone to floatstone). Some large intraclast and echinoids are also present. This lithofacies represents a platform margin oolithic/ bioclastic buildup. Facies association 5 is composed of sponge spicule bearing planktonic foraminifera packstone to wackestone. This lithofacies was deposited in an open marine setting.

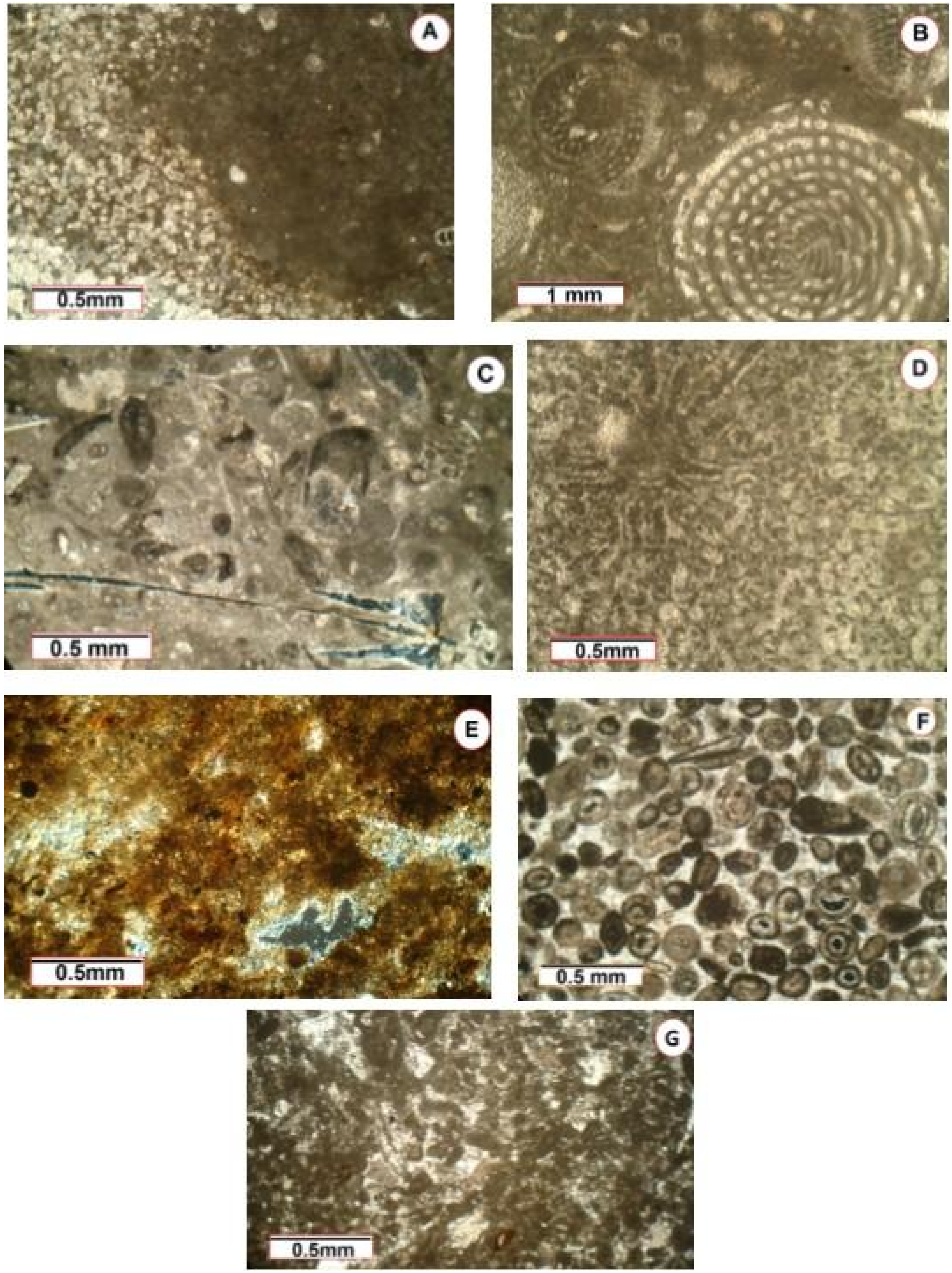

Figure 5. Photomicrograph of seven lithofacies types recognized from Sarvak Fm. in well # 305, Marun oil field (A) dolomudstone; (B) floatstone; (C) wackestone; (D) boundstone ,(E) mudstone, (F) ooid grainstone and (G) packstone

Statistical data analysis

SGR, CGR, RT, NPHI, RHOB, DT, and PEF are available well logs in the Marun oil fields. Statistical analyses were performed (Table 1) and the results were used to evaluate the predictor variables for the neural network.

The histograms of SGR and CGR show that the grainstone facies (lithofacies 6) has SGR and CGR logs value, varying from 15 to 20 and 8 to 12 API units respectively, whereas values vary between 5 to 10 and 4 to 8 for the rest of the lithofacies respectively (Figs. 6, 7). In terms of resistivity, mudstone facies (lithofacies 5) has relatively high values (Fig. 8). As shown in Figure 8, the floatstone facies (lithofacies 2), packstone facies (lithofacies 7), and boundstone facies (lithofacies 4) display various RT values.

Table 1. Value ranges of well logs data in the Marun oil field

Lithofacies	SGR (API)	CGR (API)	NPHI (v/v)	RHOB (gr/cm³)	DT (µs/ft)	PEF (B/E)	RT (mΩ)
Dolomudstone	10-15	4-6	0.2-2.1	2.54-2.61	54.6-61.5	4.92-4.94	158-58.4
Floatstone	0-30	4-14	-0.5-5	4.4-2.74	48.7-96.5	4.88-4.96	33-2000
Wackestone	5-25	4-16	0.3-2.3	2.62-2.72	51.5-56.3	4.92-5	17.9-200
Boundstone	0-15	4-10	0.4-2.7	2.64-2.7	47-61.5	4.92-4.96	131-2000
Mudstone	10-20	4-8	0-3	2.6-2.74	51-56.1	4.88-4.96	2000
Grainstone	10-25	4-12	4.6-11.68	2.54-2.6	60-66.02	4.86-4.88	12-352
Packstone	5-35	2-16	0.2-13.9	2.45-2.73	52.7-71.2	4.88-4.96	9.3-2000

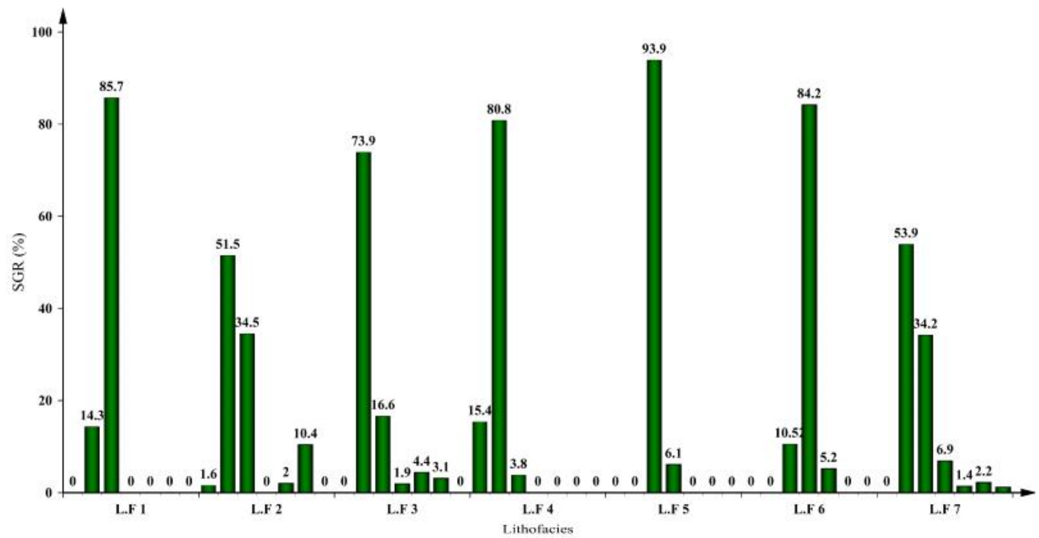

Figure 6. Histogram of SGR vs. lithofacies

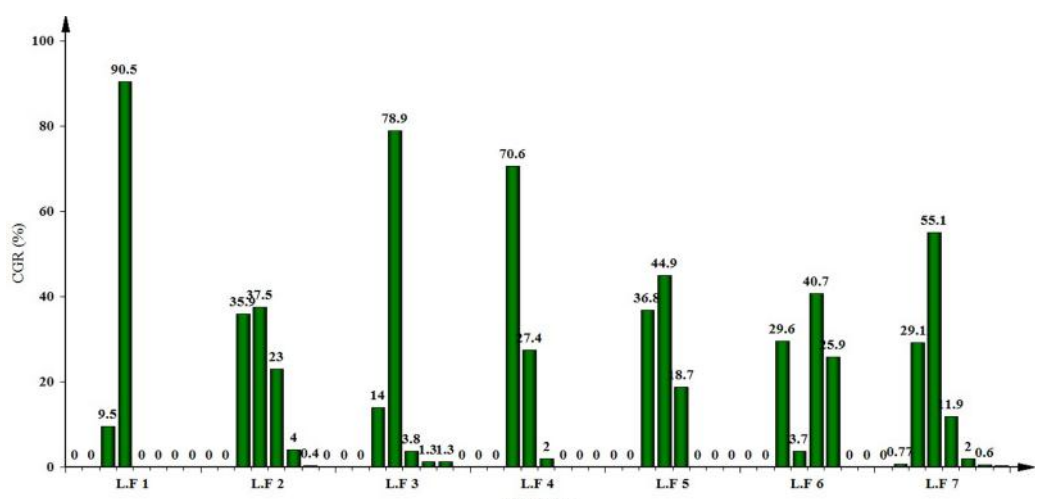

Figure 7. Histogram of CGR vs. lithofacies

The average distribution of the sonic and neutron log-derived porosity of these lithofacies shows that the ooid grainsone (lithofacies 6) has a mean of 34% and maximum calculated porosity, compared to the other lithofacies (Fig. 9), whereas lithofacies 4 has the minimum porosity (ave. 26.6%). Although lithofacies of the Sarvak Fm. show significant overlap, individually they represent relatively distinctive well log responses. The overlap in log response is well demonstrated in the cross plot of DT vs. RHOB and CGR (Fig. 10).

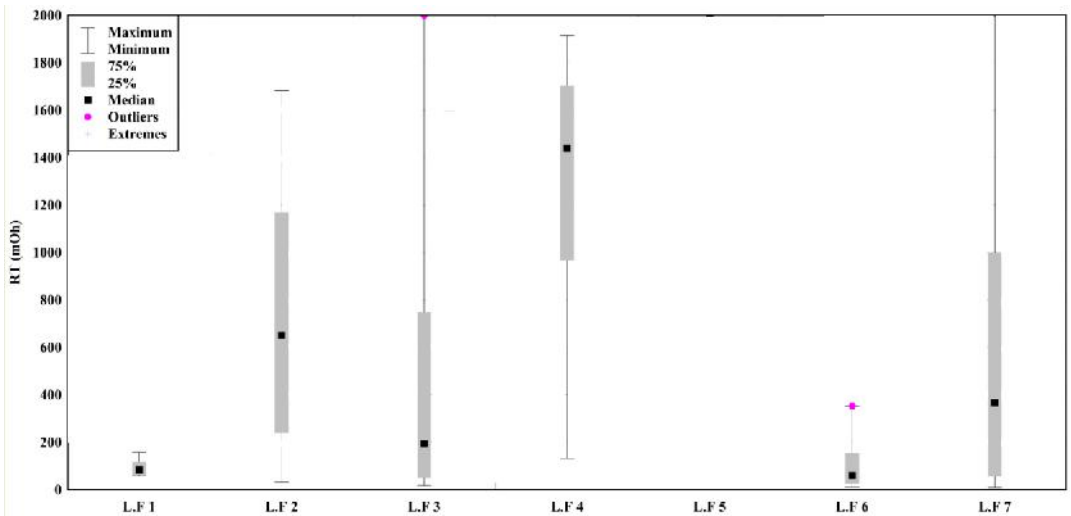

Figure 8. box plot of RT and porosity vs. lithofacies

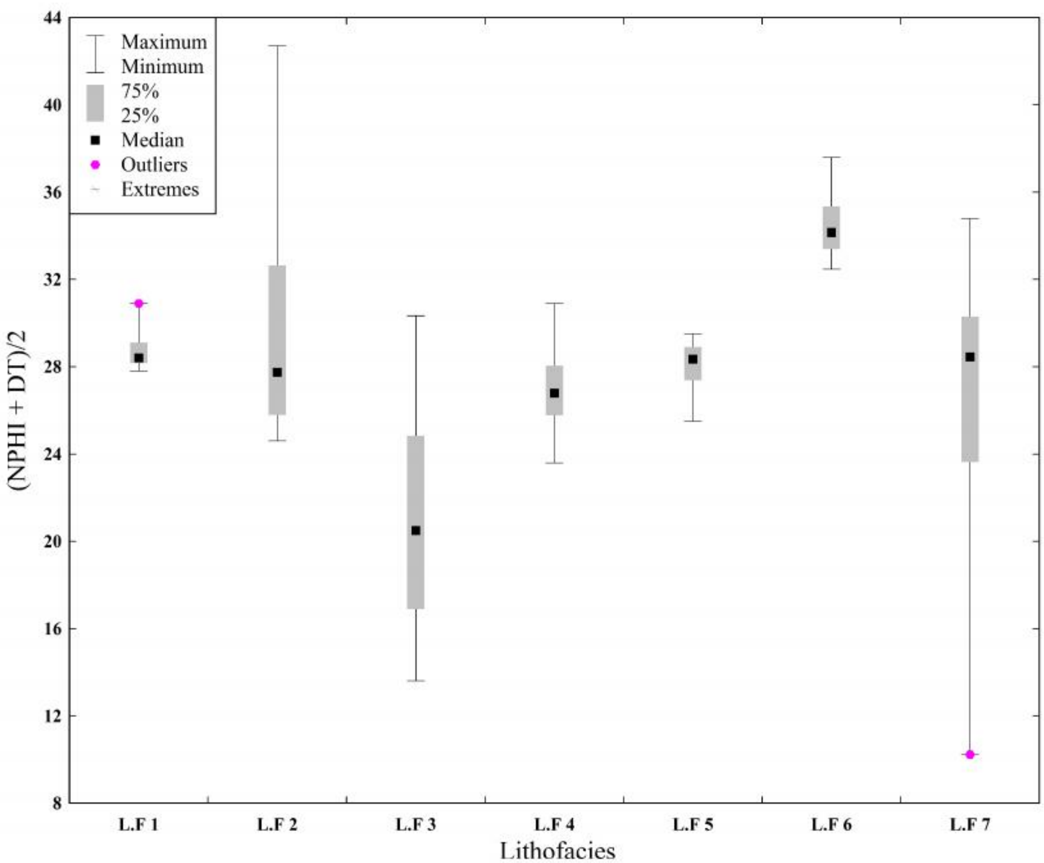

Figure 9. box plot of porosity vs. lithofacies

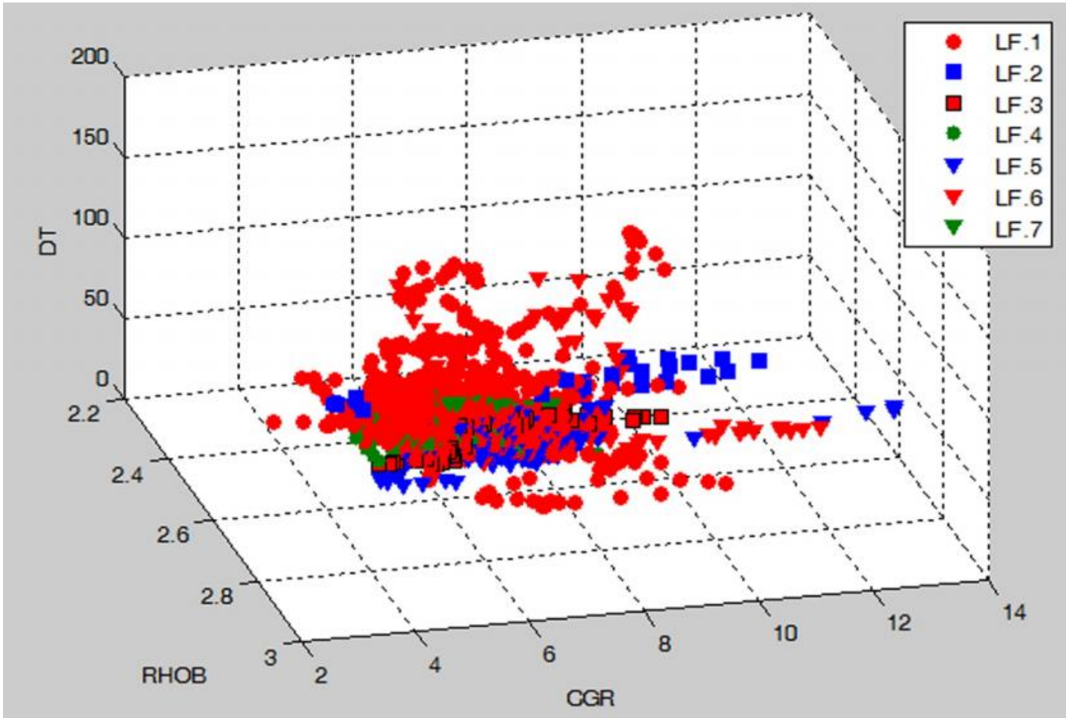

Figure 10. Cross plot of DT vs. RHOB and CGR

Results

Core lithofacies were chosen as target to the ANN. The training process of the ANN involved selection of the structure (i.e. number of layers, number of neurons, types of activation functions, etc.) and the updating of the weights and biases, which were performed by several learning algorithms.

ANN, with one hidden layer, was chosen by established practice. Since there are seven inputs with only one output, the structure of the input and output layers is fixed. Hidden neurons with tansig (nonlinearity) and output neurons with tansig activation were chosen. The neural network was trained to predict lithofacies of the Sarvak Fm. Performance of trained ANN could be evaluated by the post-training process which has been designed for this type of analysis. The expected correlation coefficient of those parameters should be close to unity if targets (core-derived lithofacies) and outputs are in good accordance. In this study, reasonable results are obtained, as the correlation coefficient between output data and targets is close to 1, which indicates the efficiency and robustness of this method. Figure 12 represents the correlation coefficient of training that is equal to 0.96% (Fig. 11A).

Attempts were made to test the ANN model through the evaluation of 350 core-derived data. Many sensitivity analyses were carried out in order to optimize the model in terms of the number of hidden neurons, activation function, and learning algorithm parameters. Figure 11 B shows the good correlation coefficient of testing (0.95%) and the correlation between the core lithofacies and the ANN predicted lithofacies (Fig. 12). This high value means the interpretations are well supported by realistic core-derived data, as was expected.

In order to validate the predicted lithofacies by ANN, the core of 120 m interval of the well #123 in the Marun oil field was examined and the results were compared with the lithofacies predicted by ANN (Fig. 13). The correlation coefficient between the core lithofacies and the ANN-predicted lithofacies are presented in (Fig. 14). Obviously, there is a strong relation between these variables as the high value of R^2 (0.899) supports our proposed approach.

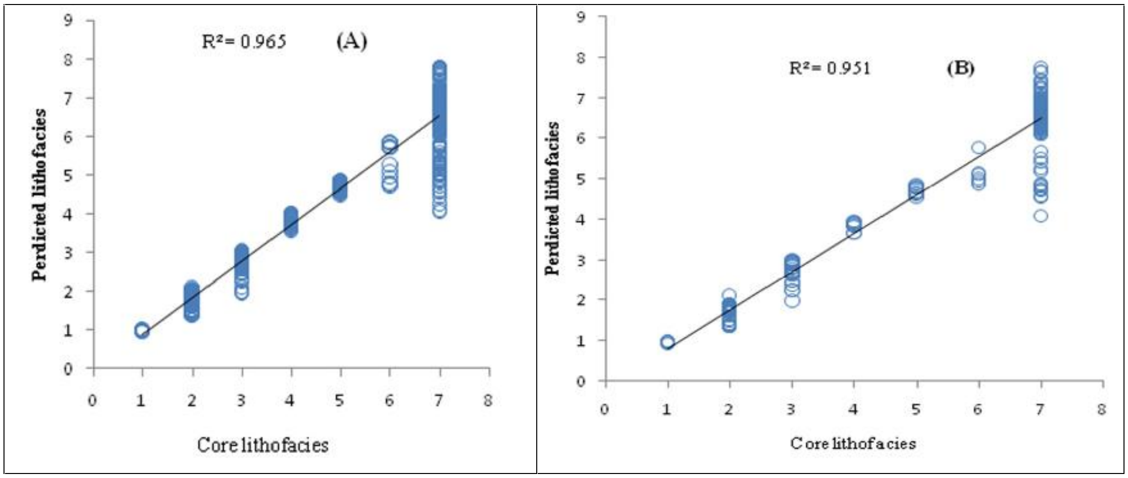

Figure 11. A and B cross plot of core derived lithofacies vs. predicted lithofacies from ANN training (A) and test (B)

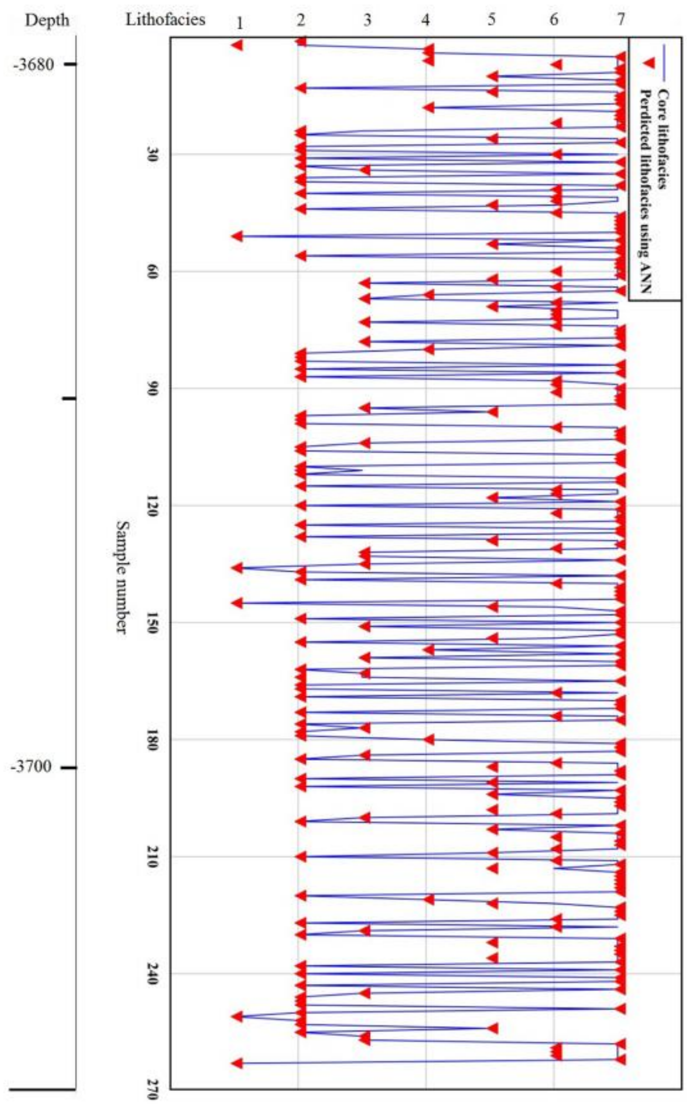

Figure 12. Predicted lithofacies from ANN testing and core-derived lithofacies

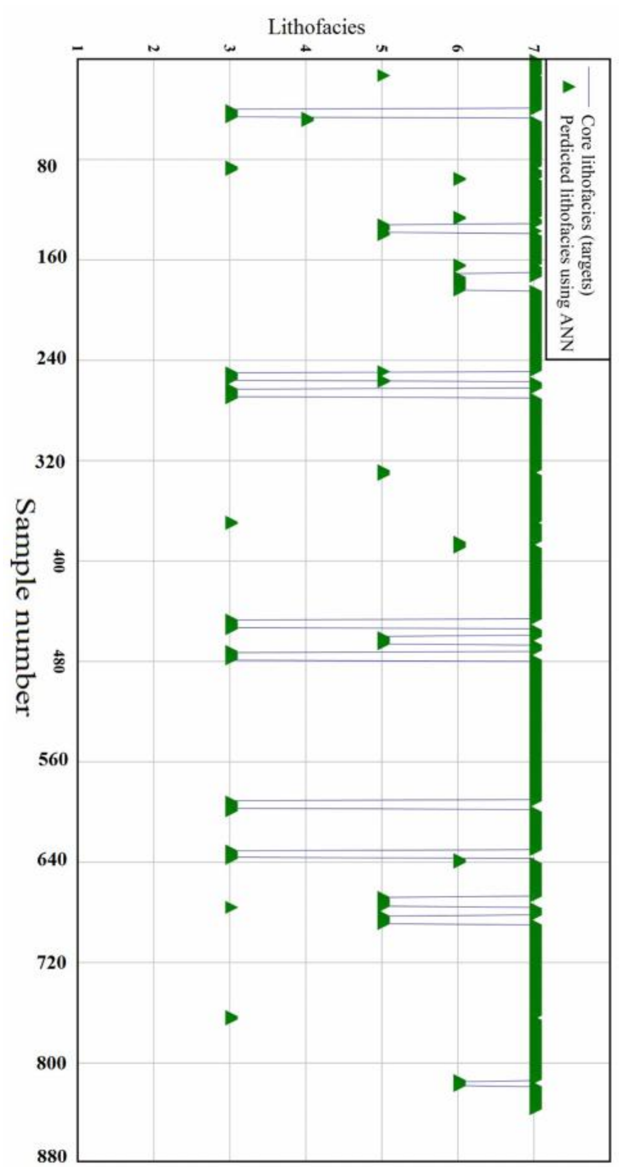

Figure 13. Predicted lithofacies from the ANN validation process and core-derived lithofacies

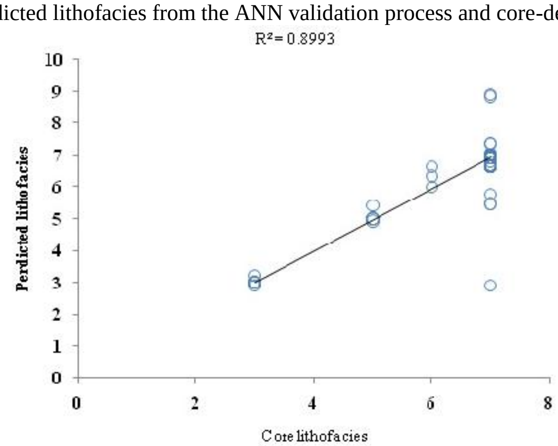

Figure 14. Cross plot of core lithofacies of well# 123 of the Marun oil field and predicted lithofacies from the ANN validation

Conclusions

Lithofacies identification and classification is vital in reservoir characterization. This study attempted to use core and well log data to identify and predict lithofacies by neural network. A total of 350 m core of the Sarvak Fm. from well #305 were described. The results of the predicted lithofacies were compared to actual lithofacies in test and validation process. Their accuracy was calculated as equal to 95% and 89% and their MSE equal to 0.293 and 0.403, respectively. The following conclusions are obtained: the described core lithofacies display a significant accuracy of lithofacies prediction in comparison to neural network models in carbonate reservoirs in the Marun oil field. This approach provides a method to predict the characteristics of lithofacies in carbonate reservoirs. The prediction of lithofacies by the neural network from well logs could improve our understanding of the facies distribution and the patterns of carbonate reservoirs and would save the time and cost of exploration.

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