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Improving the accuracy of fracture modeling in carbonate reservoirs X-field in SW of Iran

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Abstract

Fracture modeling is one of the most important steps in the study of fractured reservoirs. Due to the high cost of imaging logs and their absence in most wells of the study area, it is often attempted to use other available data to detect fractures. This paper attempts to investigate the relationship between the lithology and fractures of rocks. For this purpose, the Image, Neutron, Density, Litho-density, and NGS logs have used to simulate the lithology. Based on this feature, the studied area was divided into six homogeneity part, and the fracture probability was determined in each section to improve the accuracy of fracture modeling. Recently, an intelligent method has been proven as an efficient tool for modeling complex and non-linear phenomena. In this paper, neural network methods has been used in fracture modeling. The results show that the division of the field based on lithological studies will improves the accuracy of fracture modeling in the studied area up to 7 percent without increasing the cost of image logging.

Keywords: *Fracture modeling, Lithology, Petroleum, Neural network.*

1. Introduction

Fractures are the most important geological features that affect the production from the most carbonate reservoirs. Large volumes of hydrocarbon resources in the world are located in fractured reservoirs which are the major supplier of energy. Fractures play an important role in reservoir property and hydrocarbon migration (McQuillan 1973; Coward et al. 1998; Parnell 1998; Haneberg et al. 1999; Atilla 2000; Nian et al. 2017). Natural fracture systems have a great influence on the permeability of most carbonate reservoirs. Some hydrocarbon reservoirs with low efficiency, have a favorable production due to the transfer of liquids into wells by natural fractures. In some reserves, fractures and faults are necessary for the initial migration of hydrocarbons from source rocks (Hunt and Tucker 1992; Javadi et al. 2016; Shafiei et al. 2018). Fractures and faults are also influential factors of hydrocarbons trapping. Although fracture detection in reservoirs is an important step, it is not easy to determine how these structures affect the fluid flow of the reservoir. Due to the complexity of the fractures and the variability of their behavior in trapping, migration, and flow of hydrocarbons, their evaluation is a very complicated task (Aydin et al. 1998; Jingsong et al. 2016; Zuo et al 2019).

Each structures which are created in special geological and geomechanical conditions, have their own geometries (orientation and dimensions), distances, distributions, permeabilities and hydraulic properties that cause migration or trapping of hydrocarbons. Most joints and fractures in the upper crust are formed in conjunction with ground forces from the local construction (Pollard and Aydin 1988). They are usually found in categories that include a large number of approximately parallel joints in fractured rock units (Helgeson and Aydin 1991; Gross et al. 1995). Since these joints are confined to the boundaries of the layers, lithological unit contributions to the flow of hydrocarbon are different from each other. However, if the joints create a network of fractures that have an appropriate opening, length, distance, connection, and distribution, they can contribute to the permeation and production of the reservoir. For example, it has been proved that the joints found in the sandstone reservoir in the Piceance Basin of Colorado have caused the permeability of the reservoir rock to be 10 times higher (Lorenz et al. 1988; Eichhubi 2009).

The complex fracture process that occurs due to the changing geological conditions will create different patterns of fracture and characteristics of the natural fractured reservoirs. Most rocks are simultaneously and continuously deformed and created complex fracture systems, which is why it is not easy to identify the features of their fractures. Therefore, for the study of the fractures, it is necessary to collect a wide range of data, including geological, geophysical, petrophysical and drilling data (Gouth et al. 2006; Berre et al. 2018).

So far, many methods have been developed to study the relationship between different parameters and fractures. The equivalent fracture models based on the mimetic finite difference method yields comparable results with those based on the standard finite volume method. Whereas their accuracy is influenced by the orientations of sparsely distributed fractures. The influence of the fracture network pattern on the accuracy of equivalent

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fracture models. The relative difference between the equivalent fracture model and the discrete fracture model is 1 % - 3 %. The equivalent fracture model with the mimetic finite difference method yields a smaller relative difference than that with the finite volume method. However, based on the same grid block dimension and the petrophysical parameters, when the fracture pattern changes from parallel to non-parallel, the relative difference increased to 5% - 7% (Chen et al. 2017). The use of image logs and their relationship with other logs can help to identify the network of fractures. The determination of linear and nonlinear regression between logs can be used to improve the accuracy of fracture modeling. In order to find a generalized estimator, a unique normalization method are developed, and by using it, a non-linear regression has been found which estimates fracture density with correlation coefficient of higher than 80%. The resultant regression has the capability of generalization in the studied field (Tokhmchi et al. 2010).
The reservoir zoning approach based on lithological units can improve fracture modeling accuracy. One of the models used in this regard is the ARX model (Shiri et al. 2012). Another method for extracting information from the data obtained from the logs is the Parzen and wavelet combination method. The results of the study showed that the wavelet transform and the Parzen classification were the best combination techniques used for vuggy zones detection. According to the results, the method can be generalized with a total accuracy of 52–99% (average 75%) (Asgari Nezhad et al. 2014).
Image logs are kind of modern loges that can be used for detecting fractures crosscutting with the well (Khoshbakht et al. 2012). Therefore, determining the relationship between these logs and other available data can greatly help to improve the fracture model.
Due to the fact that lithology is one of the factors affecting the fracture network, the study of lithology and its relationship with fractures can improve the fracture modeling accuracy. since, its possible to determine the lithology in all wells using petrophysical methods, it is possible to predict the changes in fractures due to lithological changes in the field (Aghli et al. 2016) based on determined relationship between lithology and fractures. This will be valuable when the FMI and FMS data are not available for wells.
In this paper, this relationship is examined and the results are presented. In this study, geostatistical methods and neural network methods have been used. The study area is located in the southwest of Iran. The recognition of features related to basement tectonics and realization of their implication in the control and modification of geological processes are important adjuncts to the search for hydrocarbon accumulations in this region (Rahnama-Rad et al. 2009). The field is parallel to the general folding of the region (northwest - south east). In order to verify the field, 24 wells were drilled in it. Image logs were provided in two of the wells and core information is available in six of the wells. The aim of this study is investigating the relationship between lithology and fractures in these two wells and to use the results in other wells.

2. Methodology

2.1. Used data

The fracture model is mainly made using static data such as image logs and cores. Using existing data can play an important role in improving the model accuracy and reducing fracture modeling errors. The lithology of studied area is mainly composed of limestone, dolomite, anhydrite and shale. According to the above combination and modeling simplification, it was decided to define 6 main lithological units this area (Table 1). According to the table 1 to simplify and prevent the increase in the number of lithologies the Carbonate has been used for dolomite, limestone or a combination of these two (codes 2 and 4). The lithology of limestone-dolomite (code 5) is also composed of a considerable amount of lime and dolomite.

Table 1: Petrology defined for study area and their code

Lithology	code	Color
Limestone	0	Blue
Dolomite	1	Purple
shaly carbonate	2	Gray
Anhydrite	3	Green
Anhydritic carbonate	4	Yellow
Dol-limestone	5	Red

2.2. Neural network

An artificial neural network is a data processing system that is thought of as a human brain. In this network data processing is handled by small and large processors that deal with each other in an interconnected and parallel network to solve a problem. Different methods have been designed to construct problem-solving by the neural network. Here the training method with the supervisor is used. In this method, for each category of input patterns, the corresponding outputs are also shown to the network and weights are changed until the difference between the output of the network and the training patterns of the desired outputs is as acceptable as the error. The goal is to design a network that first learns using existing educational data and then by providing a vector input to the network which may or may not has already been acquired by the network Class is detects. Such a network is widely used for pattern recognition tasks. The following data was used as the network input:

- Image log

The image logs are one of the most powerful tools for exploration, drilling and development of oil reservoirs.

- Sonic logs

One of the most important markers of fractures is the vibration of sound waves inside and around the well.

- Neutron log

Neutron diagrams by measuring the amount of neutron capture generated from a neutron source measured the ionic concentration of hydrogen in the formation. This graph calculates the total porosity and in the presence of an open fracture present an anomaly in this chart.

- Density log

In this type of diagram, the formation density which is a function of rock type and porosity, is measured by gamma radiation by the device and the gamma radiation recorded from the formation is measured.

- Litho density log

This tool is known as the photoelectric diagram and can use to identify the mineralogy of the formation. Determination of photoelectric absorption cross-section using LDT tool can be used in wells drilled with barite to detect mud flood and the rate of mud thinning in low porosity zones.

- Natural Gamma Spectrometry (NGS)

In addition to measuring total radioactivity, NGS charts measure the energy level of gamma rays emitted from the formation. In fractured reservoirs, increase of gamma rays or shale line without increasing shale volume may be observed due to the deposition of uranium salts at the fractures-due to rotation of hydrothermal waters or groundwater. Therefore, uranium peaks can be used to diagnose fractures.

2.3. Combine data and modeling

The preparation of the 3D lithology model has many applications in geological sciences. One of these applications is the use of lithology and fracture relationship in improving the fracture model. For this purpose, this paper examines this relationship and its application. At first, raw data was analyzed to obtain a proper understanding of their profile and distribution. One of the charts that provides proper information on the vertical distribution of lithology is the probability curves which are located in the place of all wells for all layers and zones. In this curves, the percentage of lithology for each individual layer was calculated. As a result, the topography has been removed and therefore it will be suitable for stratigraphic and sedimentary interpretation. Subsequently, according to the modeling methods, the data were scaled up to the large reservoir network and then analyzed. In this process, any lithologic code which has the most repetition in a cell was selected for the cell. The average height of each layer in this study is 3 meters and there are 6 data for each 15 centimeters, so at scale up stage, the average of all 18 lithology codes was converted to a code and attributed to the corresponding cell. Using the main logs that represents lithological changes (Neutrons, Density, Photoelectric factor, Gamma and Sonic) and also the definition of six classes that are equivalent to six lithologies defined in wells, the neural network was trained. Finally, for all the wells and intervals that the above logs were available, lithology was determined using multi-layer perceptron neural network (Fig 1).

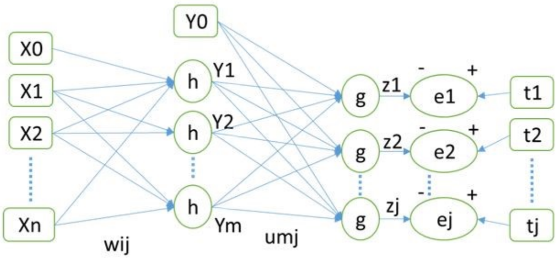

Fig 1. Multi-layer perceptron neural network structure used in this study (Bishop 1997)

The data were calculated using the following formulas in the neural network, the process of which is shown in Fig 1.

- X0 … xn: data of logs
- Wij: weight o data
- $s_m = \sum_{i=0}^{n} x_i \times w_{im}$
- $y_m = h(s_m)$
- $h(s_m) = tgh(s_m) = \dfrac{e^{s_m} - e^{-s_m}}{e^{s_m} + e^{-s_m}}$
- $p_j = \sum_{m=0}^{M} y_m \times u_{mj}$
- $z_j = g(p_j)$
- $SSE = \sum_{l=1}^{N} e_l^2$

In this study, a complete analysis was performed for all zones and all lithologies. In the probabilistic modeling, due to the introduction of uncertainty into the model, the initial distribution of data in the final model will be largely preserved. One of the methods used to control the modeling quality is to compare the initial histogram of the data in the wells, with the histogram of the data after scale up and histogram. In this study, this method was used to examine the results. At the end, in order to compare the statistics of lithology and fracture, cross-platform fractures and lithology codes were plotted (Fig. 8).

3. Discussion

Before lithology modeling, it is necessary to analyze the raw data in order to obtain a proper understanding of their specifics and distribution. One of the charts that provides proper information about the vertical distribution of lithology is the probability curves that are plotted for all layers and zones in the area of all wells. In this chart, the percentage of lithology for each individual layer is calculated and, as a result, the topographic effect is eliminated in order to be suitable for stratigraphic and sedimentary interpretation.

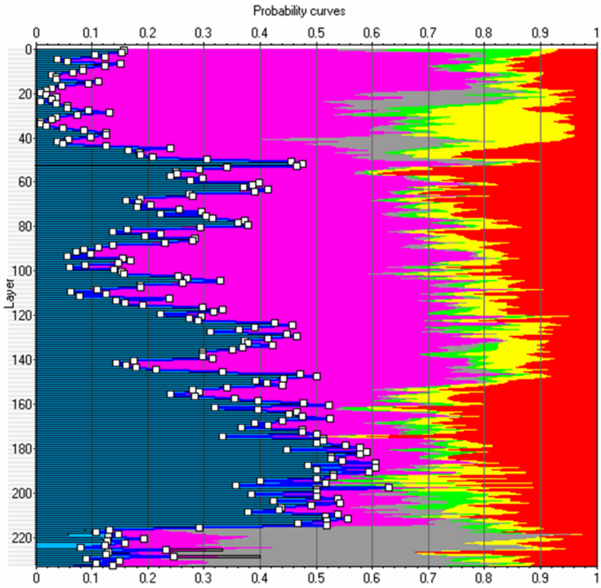

Fig 2. Lithology prospect diagram for different layers at the site of all wells for which lithology has been defined

Fig 3. scale up lithology in the reservoir network

On the other hand, in the 3D modeling of lithology, a similar vertical distribution can be reconstructed. In figure 2, the probability curve for all studied layers is shown. It should be noted that this chart is before the modeling, and it is only related to the location of the wells.

In modeling process, the data must be scaled up in reservoir network and then must be thoroughly analyzed. Figure 3 shows scale up lithologies in the reservoir network for the study area. As shown in this figure, good 3D modeling has been achieved due to the high number of data and proper dispersion. In this study, lithology was identified using available logs. For this purpose, the Neutrons, Density, Photoelectric factor, Gamma and Sonic logs used to characterize lithological changes. Six classes were defined for lithology. Finally neural network was trained, for studied area where the above logs were available. Then the lithology was determined and acceptable results were obtained.

The lithology obtained from the neural network in the first column from the right, the linguistics interpreted by the interpreter in the second column and the logs in the subsequent columns are shown in figure 4. As seen in this figure lithology obtained from the neural network have acceptable adaptations to the interpreted lithology. The SIS algorithm (Sequential Indicator Simulation) was used and the lithology probability was simulated as shown in figure 5. In this model, the vertical distribution of data is preserved. Due to the uncertainty of the areas with lower data they not used in geological interpretations. Because of the characteristics of probabilistic simulations, the resulting model is non-homogeneous and there is severe changes in the boundary between lithologies. However, probabilistic modeling also has some advantages including due to the introduction of uncertainty into the model the initial distribution of data in the final model will be largely preserved.

One of the methods used to control the modeling quality is to compare the histogram of the initial data, with the histogram of the scale up data and the modeling histogram, as shown in figure 6. In figure 5, six codes from 0 to 5 represent the six petrography given in Table 1. As seen in this figure, there is a good similarity between the distributions of data in these three stages. In figure 7, which is constructed along the axis of the structure, the heights or the old lines and the hills around them are well defined.

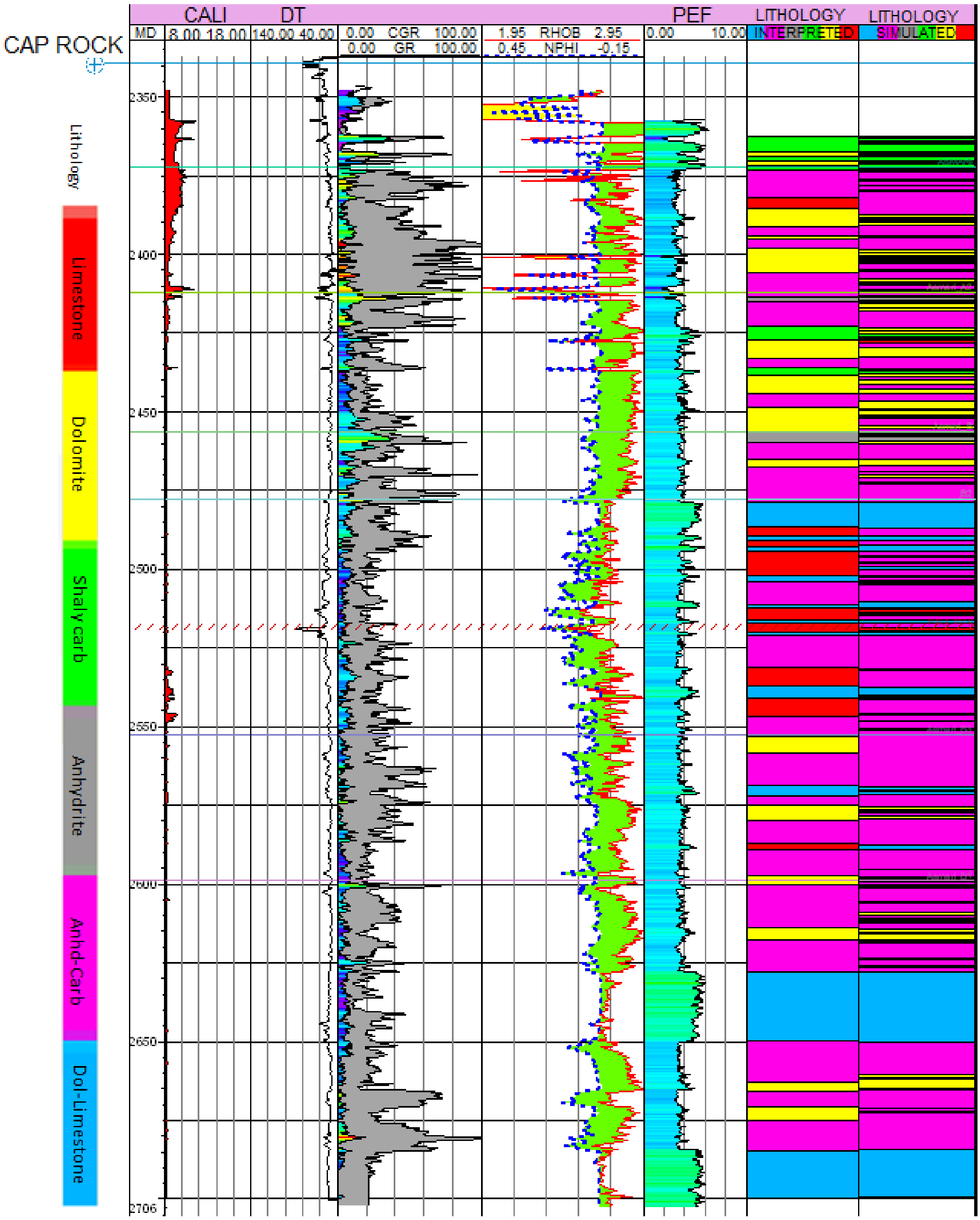

Fig 4. logs and lithology interpreted by the interpreter and lithology computed by the neural network

Since the amount of dolomite in the southern edge of the anticline is greater than the northern edge and because dolomite is more brittle therefore, the degree of fracture in the southern edge is higher. It is worth noting that some dolomitization may be related to the fracture. This means that the flow of fluid through fractures leads to secondary dolomitization which occurs after folding. The next step is to compare the lithology and fracture statistics. Cross-Plot of the severity of fractures and lithology codes were plotted as shown in figure 8.

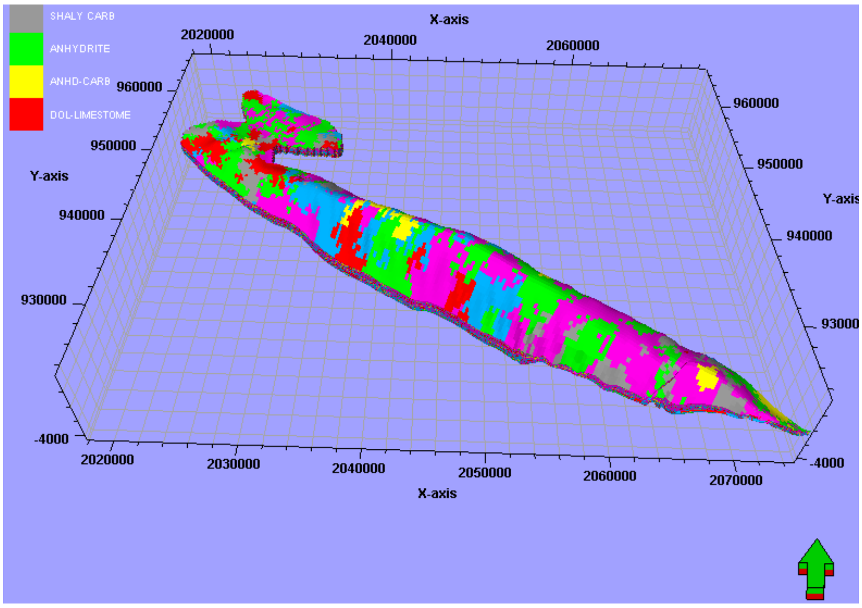

Fig 5. 3D lithology mode prepared by simulation algorithm

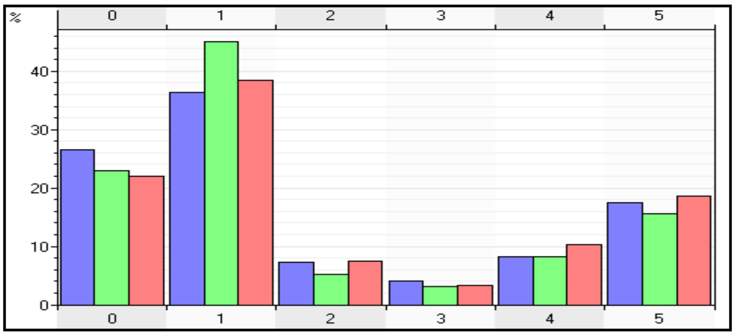

Fig 6. lithology histogram at the site (red), after scale up (green) and after being modeled (blue)

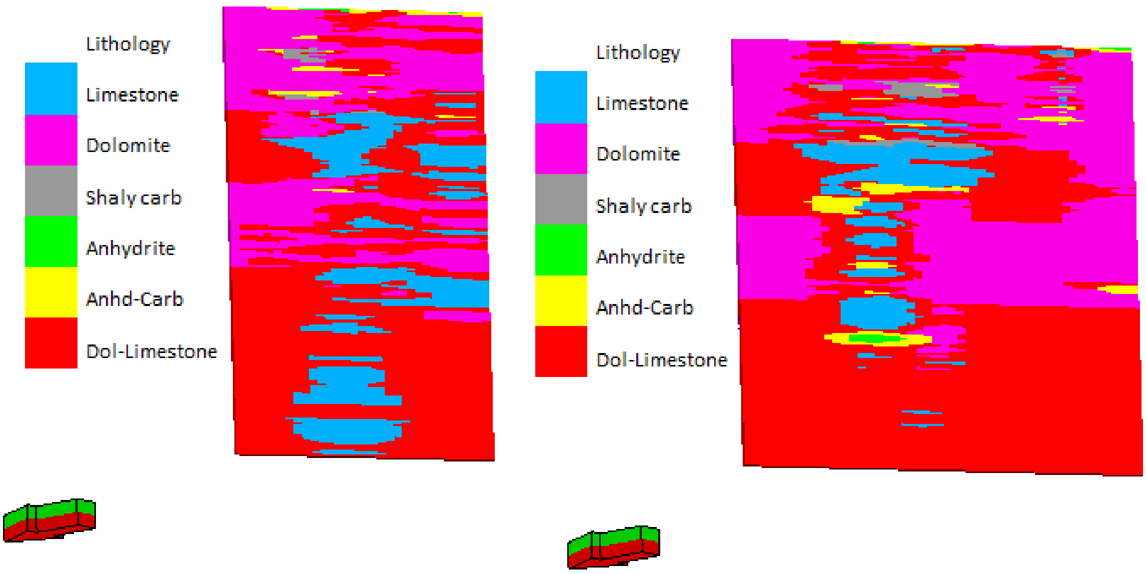

Fig 7. Extracted and horizontal image of the lithological model along 25(left), 10(right) degree

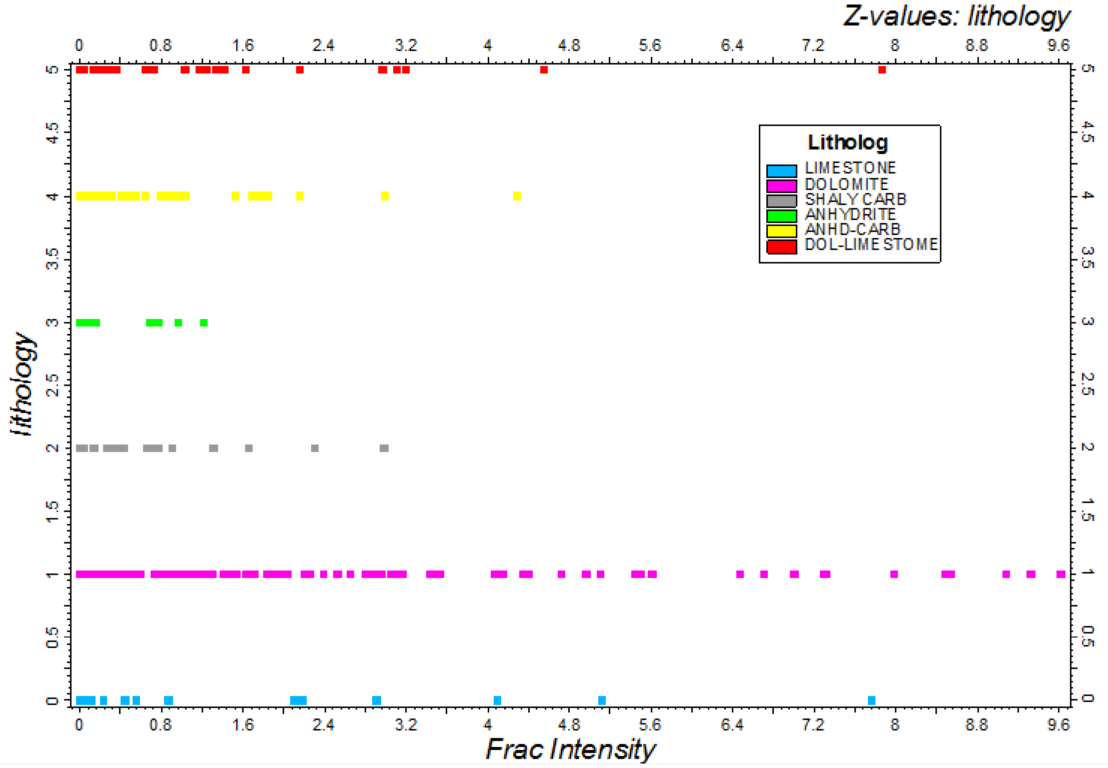

Fig 8. Cross-plot fractures and lithology codes

It is clear that the lithology code 1, which is related to dolomite, has the highest and most extensive fracture intensity values. Lithology codes 5 and 0 are related to limestone-dolomite and limestone have intermediate fracture. The least fractures are observed for anhydrite (code 3), which is less than 2. Lithology of shale carbonate and carbonate anhydrite (codes 2 and 4, respectively) also show lower fracture severity. As a result, it is known that lithology can be one of the factors controlling fractures in the field. After entering the model made from lithology into the fracture modeling process, the accuracy of the final model of the fracture improved by seven percent. This shows that studying individual parameters in fractures separately and modeling them can help to improve the accuracy of fracture modeling. The studies have shown that increasing the accuracy in modeling is different depending on the method and data used, and all or some of the existing methods can be used depending on the purpose of the studies to improve accuracy.

4. Conclusion

Image logs are one of the important data in the study of fractures. Due to the lack of image logs in most wells in the studied area, it is necessary to study fractures using other available information. In this paper, lithology and its relationship with fractures in southwestern of Iran have been investigated. For this purpose, lithology was determined using neural network method and information from various existing logs. The lithology derived from the well information provided a good connection with the lithology of the interpreters. Then, the relationship between obtained lithology and fractures was investigated in the wells where fracture data were available. The results showed a good correlation between lithology and fracture. For example, the fracture severity in dolomite showed the highest and in the anhydride showed the lowest value, and these values were observed in all wells. As shown in this paper, lithology is one of the factors that controls the fracture. Given the fact that it is possible to determine the lithology in most wells, its use can improve the accuracy of the model. According to the results of this study, this accuracy can be up to 7%. The increased accuracy of modeling in some of the proposed models is presented in the Introduction section, which this increase in accuracy is acceptable compared to them. It is recommended to improve the accuracy of the model by using these results and introducing lithology in fracture modeling and other effective parameters that investigated and modeled before final fracture modeling.

References

Aghli G, Soleimani B, Moussavi-Harami R, Mohammadian R (2016) Fractured zones detection using conventional petrophysical logs by differentiation method and its correlation with image logs, *Journal of Petroleum Science and Engineering* 142:152-162.

Asgari Nezhad Y, Tokhmechi B, Kamkar A, Sherkati S, Kavousi K, Jamali A (2014) A combined Parzen-wavelet approach for detection of vuggy zones in fractured carbonate reservoirs using petrophysical logs, *Journal of Petroleum Science and Engineering* 119:1-7.

Atilla A (2000) Fractures, faults and hydrocarbon entrapment, migration and flow, *Marine and Petroleum Geology* 17:797-814.

Aydin A, Myers R, Younes A (1998) Faults: Seal or Migration Pathways?, Neural Networks for Pattern Recognition, *Oxford University Press*, 5:508.

Berre I, Doster F, Keilegavlen E (2018) Flow in fractured porous media: A review of conceptual models and discretization approaches, *Transport in Porous Media* 130(1):215-36.

Bishop C (1997) Neural Networks for Pattern Recognition, *Oxford University Press*, 508.

Chen T, Clausera C, Marquart G (2017) Efficiency and accuracy of equivalent fracture models for predicting fractured geothermal reservoirs: the influence of fracture network patterns, *Energy Procedia* 125: 318–326.

Coward M, Sezgin Daltaban T, Johnson H (1998) Structural geology in reservoir characterization, Geological Society, *Nature* 266.

Eichhubl P, Davatz NC, Becker SP (2009) Structural and diagenetic control of fluid migration and cementation along the Moab fault, Utah, AAPG Bulletin 93:653–681.

Gouth F, Toublanc, A, Mresah, M (2006) Characterization and Modeling of a Fractured Reservoir Using a Novel DFN Approach, Abu Dhabi *International Petroleum Exhibition and Conference held*, Abu Dhabi, U.A.E SPE 102165-MS.

Gross M, Fischer M, Engelder T, Greenfield R (1995) Factors controlling joints spacing in interbedded sedimentary rocks, *Geological Society (London)* 92: 215–233

Haneberg W, Mozley P, Moore J, Goodwin L (1999) Faults and subsurface in the shallow crust, American Geophysical Union, *Geophysical Monographs* 113:7-26.

Helgeson D, Aydin A (1991) Characteristics of joint propagation across layer interfaces in sedimentary rocks, *Journal of Structural Geology* 13:897-911.

Hunt D, and Tucker M (1992) Stranded parasequences on the forced regressivewedge systems tract deposition during base–level fall. *Sedimentary Geology* 81:1-9.

Javadi M, Sharifzadeh M, Shahriar K, Sayadi S (2016) Migration tracing and kinematic state concept embedded in discrete fracture network for modeling hydrocarbon migration around unlined rock caverns, *Computers and Geosciences* 91:105-118.

Jingsong P, Changgui X, Ajuan W, Yuechuan W, Bingjie W, Yonghua G, Jiangtao Z, Xin W (2016) Hydrocarbon migration caused by rupture of pressure compartment in south Liaozhong sag, Bohai Bay Basin, Offshore China. *Petroleum Exploration and Development* 43:425-434

Khoshbakht F, Azizzadeh M, Memarian H, Nourozi G, Moallemi S (2012) Comparison of electrical image log with core in a fractured carbonate reservoir, *Journal of Petroleum Science and Engineering* 87:289–296.

Lorenz J (1988) Multiwell Experiment Final Report: The coastal interval of the Mesaverde Formation, *Sandia National Laboratories Technical Report* 1131.

McQuillan H (1973) Small-scale fracture density in Asmari Formation of southwest Iran and its relation to bed thickness and structural setting, *American Association of Petroleum Geologists Bulletin* 57: 2367-2385.

Nian L, Nansheng Q, Jian C, Fangyu S, Hang W, Xuesong L, Yuanjie W, Yaxian J, Qianqian F (2017) Hydrocarbon migration and accumulation of the Suqiao buried-hill zone in Wen'an Slope, Jizhong Subbasin, Bohai Bay Basin, China, *Marine and Petroleum Geology* 86:512-525.

Parnell (1998) Dating and Duration of Fluid Flow and Fluid-Rock Interaction, Geological publication 144.

Pollard D, Aydin A (1988) Progress in understanding jointing over the past century, *Geological Society of America Bulletin* 100:1181-1204.

Rahnama-Rad J, Farhoudi G, Ghorbani H, Habibi Mood Sh, Derakhshani R (2009) Pierced salt domes in the Persian Gulf and in the Zagros mountain ranges in southern Iran and their relationship to hydrocarbon and basement tectonics, *Iranian Journal of Earth Sciences* 1: 57-72

Shafiei A, Maurice B. Dusseault, Ehsan Kosari, Morteza N. Taleghani (2018) Natural Fractures Characterization and In Situ Stresses Inference in a Carbonate Reservoir. *An Integrated Approach. Energies* 11(2):312.

Shiri Y, Tokhmechi B, Zarei Z, Koneshloo M (2012) Self-affine and ARX-models zonation of well logging data, *Physica A: Statistical Mechanics and its Applications* 391:5214-5208.

Tokhmchi B, Memarian H, Rezaee M (2010) Estimation of the fracture density in fractured zones using petrophysical logs, *Journal of Petroleum Science and Engineering* 72:206-213.

Zuo L, Tan X, Yu W, Hu X (2019) Fracture Detection and Numerical Modeling for Fractured Reservoirs, *Energies* 12:386; doi:10.3390/en12030386.