Petroleum & Coal
ISSN 1337-7027

Available online at www.vurup.sk/petroleum-coal
Petroleum & Coal 55 (3) 254-260, 2013

STOCHASTIC FRACTURE NETWORK MODELING USING INTEGRATED RESERVOIR DATA IN ONE OF IRANIAN NATURALLY FRACTURED RESERVOIRS

Ghafoor Karimi, Ali Mohammad Bagheri, Mehdi Bahremandi, Fariborz Talebi,
Amir Abbas Askari, Iraj Maddahi

NIOC-Research Institute of Petroleum Industry, E-mail: karimigh@ripi.ir

Received June 11, 2013, Accepted September 30, 2013

Abstract

The objective of the study was to perform a Stochastic Fracture Modeling study on a case study field, including investigation of fracture intensity distribution and generation of parameters that are required for dynamic simulation of naturally fractured reservoirs (NFR). Emphasis was put on the characterization of a case study with a strongly seismically driven field, including the use of seismic attributes for fracture prediction.

In summary, the activities that were carried out included: Review of regional and reservoir geology, Seismic interpretation and seismic data analysis and Fracture modeling.

In the field case study, the occurrence of natural fractures is clearly related to the structural deformation. There are also faults that are traversing the hinge of the structure; exhibiting strong control on fracture intensity. The area of maximum fracture intensity is the hinge of the fold, with local maxima being situated in the immediate proximity of the faults.

Key Words: Stochastic fracture Modeling; Fracture Indicator; Geomechanics; Fracture Drivers.

1. Introduction

A continuous fracture modeling study was performed for the oil and gas field using the commercial software. The workflow of this modeling was divided into five distinct parts:

1. Analysis and Derivation of Fracture Indicators, the available data that potentially have some association with fracture intensity are analyzed for their suitability as fracture indicators. Also, it was attempted to combine various data sources in order to obtain optimized fracture indicator logs. For the case study field, the low data density proved to be a challenge in the selection and creation of meaningful fracture indicators.
2. Construction of a 3D Geomodel.
3. The Geomechanics section deals with the deformation mechanism identification and the generation of geomechanical parameters for fracture modeling.
4. Identification and Ranking of Fracture Drivers, fracture drivers such as structural derivatives and seismic attributes are investigated for possible associations with fracture intensity.
5. Stochastic Fracture Modeling includes the modeling of fracture intensity, fracture permeability and other parameters that are relevant for dynamic simulation, such as matrix block size and directional permeability.

2. Analysis and Derivation of Fracture Indicators

Fracture indicators that are derived from cores or BHI logs are referred to as static fracture indicators. The analysis of core data and the interpretation of BHI logs can be used as a starting point to obtain fracture indicator logs. Static fracture indicators provide insight into numerous parameters that are considered as important for fracture modeling, such as: 1. Fracture intensity, 2. Mechanical layer thickness, 3. Impact of lithology and 4.Impact of porosity.

Dynamic fracture data are an important source of information, as these take into account only those fractures that are open and allow fluid flow. The most common dynamic fracture indicators are: 1. Mud loss, 2. Productivity index, 3. Production logs and 4.Well tests

3. 3D Geomodel

In discrete fracture modeling, geomodel was used as the grid in input data. Both the reservoir geometry and petrophysical parameters were important factors in the fracture modeling workflow. In this case all wells data such as wells location, trajectory, raw and evaluated logs were imported to construct the Stratigraphic model, then all Seismic data such as UGC, faults, Acoustic Impedance cube were incorporated to build the structural model and the geostatistical analysis was done and SIS and SGS methods were used to construct the properties models.

4. Field Geomechanics

Geomechanical analysis plays a major role in any fracture modeling project. Strain and stress imposed on a geological structure often cause increased fracturing at the location of high stress and strain. In combination with other geological fracture drivers (porosity, lithology, mechanical layer thickness), the knowledge of stress and strain can provide valuable information for fracture prediction.

To estimate the strain of a structure, it is required to know both the pre-deformed state of the structure and the deformation mechanism. If the pre-deformed state of the system is not known, it is commonly assumed that the layers were deposited parallel and horizontally.

For folded structures, three types of post sedimentary deformation mechanisms are typically defined:

Flexural slip deformation is a simple shear deformation, caused by the slipping of strata along bedding planes in combination with a simultaneous flexure of the strata. Flexural slipping is characterized by the fact that bed thickness does not change during deformation.

Buckling is thought to occur by buckling of a surface and its confining volume. Folds that were deformed by a buckling mechanism are typically characterized by a thinning of the limbs and a thickening of the hinge zone (similar folds).

Mass displacement occurs when the deformation cannot be accommodated by flexural slipping or buckling. In this case, rocks are generally removed from the path of stress by pressure dissolution. Pressure dissolution is a metamorphic reaction in which rocks shorten by dissolving some of their constituents.

The geomechanical analysis of the field case study was conducted analogously to the activities, such as investigation of deformed and flattened structural cross-sections, deformation type identification and calculation of slope and curvature of the reservoir structure.

5. IDENTIFICATION AND RANKING OF FRACTURE DRIVERS

Fracture drivers are geological parameters that are associated with fracture intensity. Fracture intensity and orientation are primarily the result of stress and strain, which in turn depend on several factors, such as depth, layer thickness, tectonic history and structure.

Major factors that are strongly associated to the mechanics of rock fracturing and thus fracture intensity in a reservoir are: 1. Reservoir structure, 2. Bed thickness, 3. Lithology, 4. Distance to faults and 5. Seismic attributes.

The fracture drivers that were investigated for the case study field were the reservoir structure and its derivatives, distance to faults and seismic attributes. During the investigations indicating an association of fracture intensity with lithology and porosity were made. However, neither porosity nor lithology can be mapped spatially with a reasonably high degree of confidence to use these parameters as fracture drivers. Basic investigations showed that all parameters, except the interval amplitude and the instantaneous interval amplitude attribute, that were considered as fracture drivers are basically suitable for fracture modeling. However, for none of the investigated parameters a clear linear relationship with fracture intensity could be established. Interval instantaneous amplitude and interval amplitude both exhibit a strong correlation with geopressure and were therefore excluded from further investigation.

The ranking of drivers showed that the structural derivatives are the most relevant fracture drivers. Seismic attributes and distance to faults play only a subordinate role.

Table 1 Ranking of field case study drivers

Ranking	Attribute	Relevancy(%)
1	Slope N-S	100
2	Curvature NW-SE	75
3	Curvature NE-SW	62
4	Slope NW-SE	57
5	Slope NE-SW	48
6	Distance to Faults	39
7	Geopressure	36
8	Structure	31

6. STOCHASTIC FRACTURE MODELING

The stochastic fracture modeling phase consists of three distinct phases:

1. Neural network modeling
2. Fracture analysis
3. Stochastic fracture properties modeling

The stochastic fracture modeling of the field case study included the generation of a fracture intensity model, fracture analysis as well as stochastic fracture permeability and fracture porosity modeling. Fracture intensity modeling was based on the ranked fracture drivers and the fracture count logs.

Fracture intensity is generally high on the hinge of the fold, with its local maximum in the immediate proximity of the faults. A gradual decrease in fracture intensity towards the limbs could also be observed. Fracture intensity is generally high on the hinge of the fold, with its local maximum in the immediate proximity of the faults. A gradual decrease in fracture intensity towards the limbs could also be observed.

Fracture analyses included especially the generation of probability maps, computation of fracture orientation and calculation of matrix block size. The generated probability maps indicate that the probability of high fracturing is very high on the hinge of the fold, particularly in the vicinity of the faults. It was also found that the probability of moderate fracturing is high throughout the field. The dominant fracture orientation in the case study field is in north-south direction. On the hinge of the fold, the fracture orientation is partly strongly influenced by the strike direction of the faults, which is sub parallel to parallel to the hinge of the structure. Fracture orientation and fracture intensity were used to calculate matrix block length. Matrix block length varies from 1.7 meters in north-south direction to 3.3 meters in the vertical direction.

Fracture porosity and fracture permeability from interpreted well tests were applied to generate stochastic porosity and permeability models. Maximum fracture porosity and fracture permeability are located in the proximity of the faults on the hinge of the structure. Average fracture permeability is 6300 mD, average fracture porosity is 0.16.

6.1 Neural network modeling

Based on the fracture indicators and the ranked fracture drivers, a set of stochastic fracture models is created using a back-propagating neural network. A neural network was done as primarily an artificial intelligence tool, which recognizes patterns based on integration of known parameters and was therefore a data driven approach.

The fracture count logs that were generated for Well-1, Well-13, Well-19 and Well-42 were used to provide training and testing data sets for neural network modeling.

Several configurations of the neural network parameters were tested; the best results could be achieved by using 50 % of the input data set for training and testing purposes. The necessity to use a relatively small training data set was imposed by the limited number of input data. Only by reducing the size of the training data set it was possible to obtain a reasonably big testing data set to assess the quality of the estimation model. The training testing correlation coefficient was set to 0.7, the testing correlation was set to 0.3. However, with the selected configuration, testing correlation coefficients in excess of 0.5 could be achieved.

Using the above described configuration, ten fracture model realizations were generated. The quality of every realization was assessed by cross-plotting the training and testing results. In the generated realizations, three best realizations were picked for further use. The respective training and testing cross-plots are documented in Figure 1, Figure 2 and Figure 3.

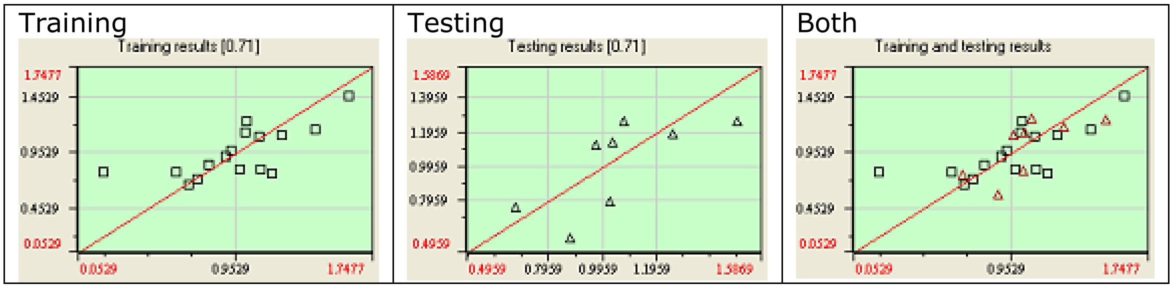

Figure 1 Training and testing results of realization 1

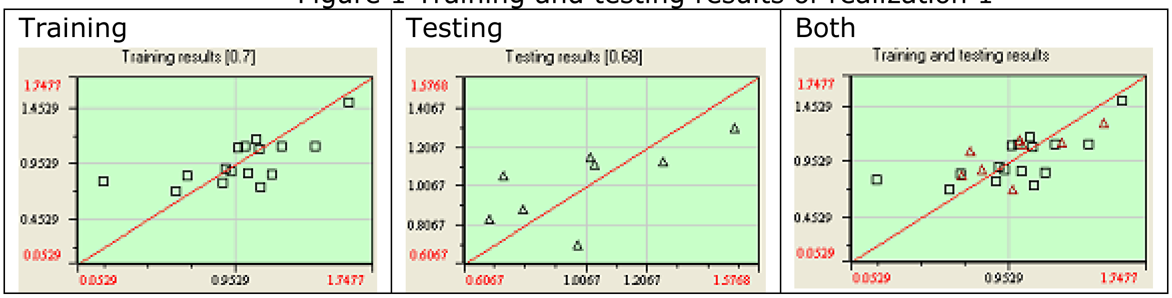

Figure 2 Training and testing results of realization 2

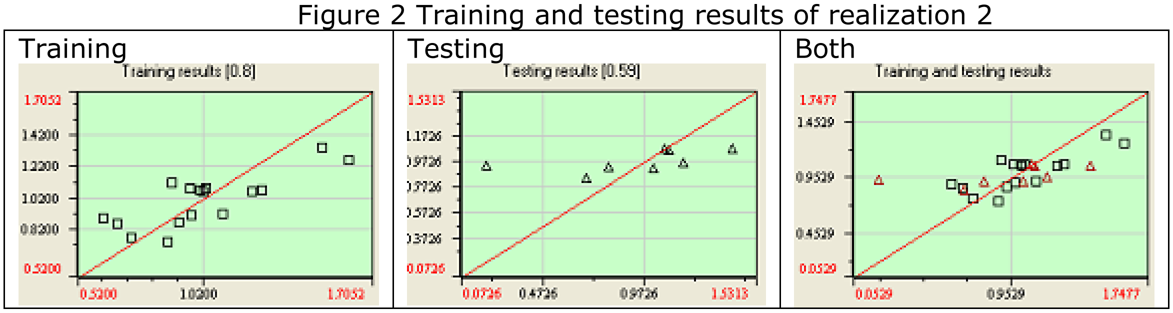

Figure 3 Training and testing results of realization

As none of the three realizations shows any outlying or anomalous patterns, all three realizations can be used for further analysis of the modeled fractures with big confidence (Figure 4).

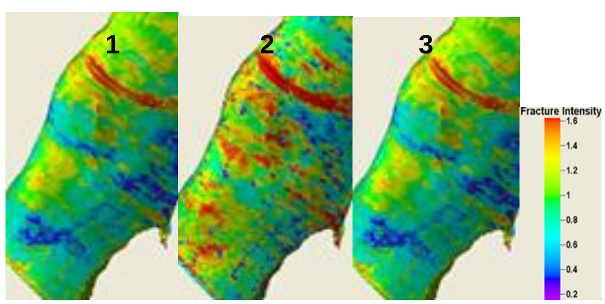

Figure 4 3D view of fracture intensity on 3 realization

6.2 Fracture analysis

The selected realizations were used to perform further investigations and analyses on the fracture intensity distribution. The following tasks were carried out:

- Generation of an average fracture model
- Probability analysis of average fracture model
- Investigation of fracture anisotropy
- Computed matrix block size
- Discrete fracture network modeling(DFN)

6.2.1 Average fracture model

An average fracture model was created based on the three selected models by calculating the arithmetic mean of fracture intensity for every grid block. The purpose of generating average fracture model is to filter out some of the random components that are always present in stochastic modeling methods.

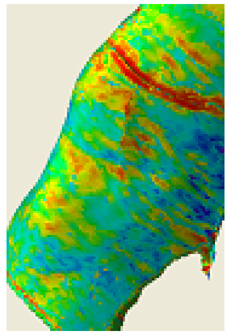

Figure 5 3D view of average fracture model

6.2.2 Probability analysis of average fracture model

Probability maps were generated for fracture intensity cut-offs of 1 and 0.5. Figure 6 shows the probability map that was generated with cut-off 1. The probability map that was generated with cut-off 0.5 is displayed in Figure 7.

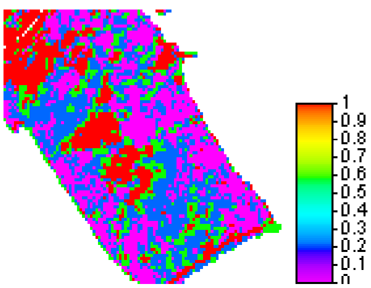

Figure 6 Probability map for a fracture intensity cut-off of 0.5

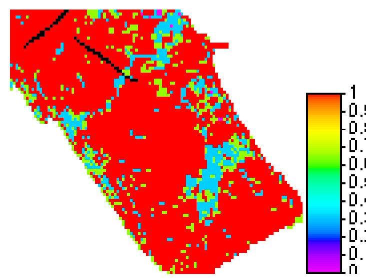

Figure 7 Probability map for a fracture intensity cut-off of 0.5

6.2.3 Fracture anisotropy map

Fracture anisotropy maps were generated for all layers of the fracture model. Due to the very similar fracture intensity distribution throughout the reservoir interval, also the fracture anisotropy patterns are practically identical. Therefore, description of fracture anisotropy in this section will be limited to the uppermost reservoir layer, but the observations can be considered as valid for all other layers of the fracture model.

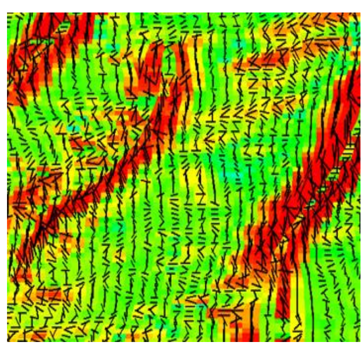

Figure 8 Fracture anisotropy map for layer 1 in close-up views

6.2.4 Computed matrix block size

The matrix block size is a characteristic coefficient of a fractured reservoir. It is used to calculate the shape factor σ, which is applied in the dynamic simulation of fractured reservoirs to calculate the mass transfer coefficient between matrix blocks and the surrounding fractures. Based on fracture intensity and fracture orientation, matrix block size was computed. It was found that matrix block length is generally the largest in the vertical direction and the smallest in north-south direction. Average matrix block length in the three main directions are summarized in Table 2.

Table 2 Average matrix block lengths

Direction	North-South	East-West	Vertical
Matrix Block Length, m	1.84	3.1	3.45

6.2.5. Discrete fracture network modeling (DFN)

The idea behind traditional Discrete Fracture Network (DFN) modeling is that the fractures are represented on an individual basis and that fluid flow behavior can be predicted from the fracture geometries and data on the transmissibility of individual fractures. The output of the DFN is equivalent fracture parameters (fracture permeability, matrix block size) that can be used with any fractured fluid flow simulator.

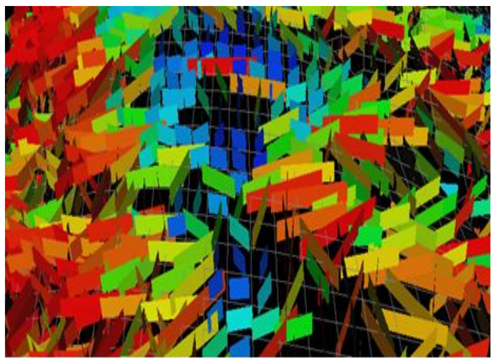

Figure 9 Close-up of discrete fracture model

6.3. Stochastic fracture properties modeling

Fracture permeability and porosity are parameters that exhibit the strongest influence on the dynamic properties of a fractured reservoir. Also for dynamic simulation, it is required that the fracture permeability and porosity are known. Fracture properties can be estimated from various sources, such as cores, BHI logs, outcrops and well tests.

Well tests, however, provide a measure of fracture permeability on a larger scale and do not only take into account the permeability of individual fractures, but also the connectivity and flow path tortuosity, which also influences the permeability of a fracture network.

Fracture porosity obtained from well tests is used to generate calibrated porosity logs at the wellbores. These logs are then used along with generated fracture intensity models to create a stochastic fracture porosity model.

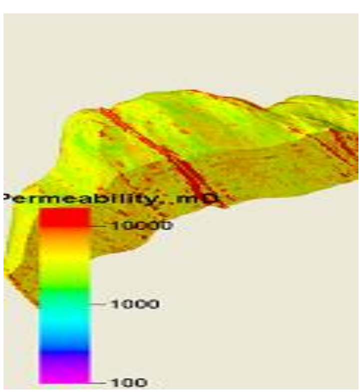

Figure 10 Fracture permeability model

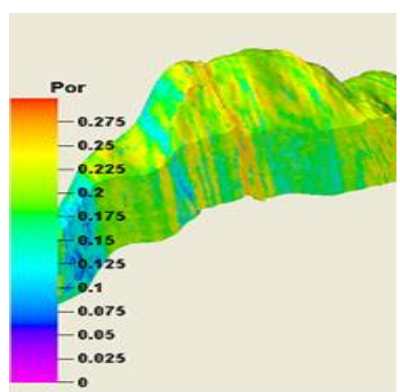

Figure 11 Fracture porosity model

7. Conclusions

With this study a consistent workflow could be presented that not only enables fracture characterization tightly coupled to seismic data, but also allows a direct and fast evaluation of the applicability of the available input data and hence strongly reflects the reliability of the generated fracture network and its properties.

The individual deliverables of this study are:

- A comprehensive characterization workflow allowing to incorporate data of all scales and various sources in a consistent manner.
- For the field case study it could be shown that the available seismic data and the derived attributes provide an appropriate mean to create consistent fracture intensity and fracture property models.
- For that case an additional strength of the workflow is demonstrated; that is the potential to quantify the data sufficiency as well as assessing the reliability of the resulting models in a fast and simple manner.

The results form a basis for a regional fracture model that should be enhanced step by step by integrating additional data from neighboring fields. For the field case study, geomechanical parameters exert the strongest control on fracture intensity. Fracture intensity is the greatest in areas of great structural curvature, that is, near the hinge of the folds. In addition the faults traversing the field were identified to represent intensely fractured zones.

References

[1] Laribi, M., Boubaker, H, Beck,B., Chen,H.K, Amiri-Garroussi, K, Rassas, S, Rourou, A, Boufares, T, Douik, H,. Saidi, N., and Ouenes, A.: "Integrated Fracture Reservoir Charactrization and Simulation: Application to Sidi El Lilani Field, Tunisia.", paper SPE 84455 presented at 2003 SPE Annual Technical Conference and Exhibition, Denver.

[2] Zellou, A, Hartley, L.J, Hoogerduijn-Strating, E.H, Al Dhahab, S.H.H, Boom, W., Hadrami, F.: "Integrated Workflow Applied to the Characterization of a Carbonate Fractured Reservoir: Qarn Alam Field," paper SPE 81579 presented at SPE 13th Middle East Oil Show & Conference, Bahrain.

[3] Ouenes, A., Richardson, S., Weiss, W.: "Fractured reservoir characterization and performance forecasting using geomechanics and artificial intelligence," paper SPE 30572 presented at the 1995 SPE Annual Technical Conference and Exhibition.

[4] Zellou, A., Ouenes, A: "Integrated Fractured Reservoir Characterization Using Neural Networks and Fuzzy Logic: Three case studies ",Soft Computing and Intelligent Data Analysis in OilExploration, Elsevier, Amsterdam

[5] Zellou, A., Ouenes, A., Banik, A.: "Improved Naturally Fractured Reservoir Characterization Using Neural Networks, Geomechanics and 3-D Seismic," paper SPE 30722 presented at the 1995 SPE Annual Technical Conference and Exhibition.

[6] Gauthier, B., Zellou, A., Toublanc, A., Garcia, and J.M Daniel: "Integrated Fractured Reservoir Characterization: a Case Study in a North Africa Field," paper SPE 65118 presented at the 2000 European Petroleum Conference, Paris, Oct.24-25.

[7] Henk, A. and M. Nemcok, 2008, Stress and fracture prediction in inverted half-graben structures: Journal of Structural Geology, v. 30, no. 1, p. 81-97.