PREDICTION OF FRACTURE DIP USING ARTIFICIAL NEURAL NETWORKS

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PREDICTION OF FRACTURE DIP USING ARTIFICIAL NEURAL NETWORKS

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Specially dedicated to my family and Dr. Zohreh Movahed

Al-Fatihah

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ABSTRACT

Fracture characterization and fracture dip prediction can provide the desirable information about the fractured reservoirs. Fractured reservoirs are complicated and recent technology sometimes takes time and cost to provide all the desired information about these types of reservoirs. Core recovery has hardly been well in a highly fractured zone, hence, fracture dip measured from core sample is often not specific. Data prediction technology using Artificial Neural Networks (ANNs) can be very useful in these cases. The data related to undrilled depth can be predicted in order to achieve a better drilling operation, or maybe sometimes a group of data is missed then the missed data can be predicted using the other data. Consequently, this study was conducted to introduce the application of ANNs for fracture dip data prediction in fracture characterization technology. ANNs are among the best available tools to generate linear and nonlinear models and they are 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. A feed forward Back Propagation Neural Network was run to predict the fractures dip angle for the third well using the image logs data of other two wells nearby. The predicted fracture dip data was compared with the fracture dip data from image logs of the third well to verify the usefulness of the ANNs. 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 correlation coefficients of training and test sets for the ANN model were 0.95 and 0.91, respectively. Significantly, a non-linear approach based on ANNs allows to improve the performance of the fracture characterization technology.

ABSTRAK

Pencirian retakan dan peramalan kemiringan retakan boleh memberi maklumat yang diperlukan tentang reservoir retak. Reservoir retak adalah kompleks dan teknologi masa kini kadang kala mengambil masa dan kos untuk memperoleh semua maklumat yang dikehendaki berkaitan reservoir terbabit. Perolehan teras adalah sukar bagi zon berkeretakan teruk. Dengan itu, kemiringan retakan yang diukur daripada sampel teras biasanya kurang tepat. Teknolgi peramalan data yang menggunakan Rangkaian Neural Buatan (ANNs) mungkin berguna dalam kes ini. Data pada kedalaman yang tidak digerudi boleh diramal untuk melancarkan operasi penggerudian, atau mungkin bagi sekelompok data yang tersasar, data terbabit boleh diramal menggunakan data yang lain. Dengan demikian, matlamat kajian adalah untuk memperkenalkan penggunaan ANNs bagi meramal data kemiringan retakan dalam teknologi pencirian retakan. Rangkaian Neural Buatan ialah satu daripada peralatan sedia ada yang paling baik untuk menghasilkan model selanjar dan model tak selanjar. Rangkaian terbabit ialah peranti komputer yang terdiri daripada himpunan unsur pemprosesan saling berkait yang dikenali neuron, yang terhasil daripada pentafsiran ahli sains tentang seni reka dan fungsi otak manusia. Suapan ke depan bagi Rangkaian Neural Rambatan Buatan Balik telah dilaksanakan untuk meramal sudut kemiringan retakan bagi telaga ketiga menggunakan data imej log milik dua buah telaga berhampiran. Data kemiringan retakan yang diramal kemudiannya dibandingkan dengan data imej log bagi telaga ketiga untuk menentusahkan kebergunaan ANNs. Berdasarkan keputusan yang diperoleh, kesimpulannya ialah ANNs boleh diguna dengan jayanya untuk memodel data kemiringan retakan bagi ketiga-tiga buah telaga yang dikaji. Pekali sekaitan yang tinggi dan ralat ramalan yang rendah telah mengesahkan kemampuan model ANN dalam menghasilkan ramalan yang baik, dangan pekali sekaitan bagi set latihan dan set ujian model ANNs masing-masing bernilai 0.95 dan 0.91. Akhir kata, pendekatan tak selanjar yang berdasarkan ANNs boleh meningkatkan prestasi teknologi pencirian retakan.

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LIST OF ABBREVIATION

ANN	-	*Artificial Neural Network*
BS	-	*Bit Size*
C1	-	*Caliper Pair 1-3*
C2	-	*Caliper Pair 2-4*
CGR	-	*Gamma Ray (Corrected)*
CKH	-	*Core Horizontal Permeability*
COND.CONNECTED.SP	-	*Conductive Connected Spots*
COND.PATCHES	-	*Conductive Patches*
COND.ISOLATED.SPOT	-	*Conductive Isolated Spots*
CPOR	-	*Core Porosity*
CS	-	*Cable Speed*
DEVI	-	*Borehole Deviation Angle (deg)*
DYNAMIC	-	*Sliding Window Normalization*
EMEX	-	*Measurement Control Voltage*
FMI	-	*Full bore Formation Micro Imager Tool*
FRACTURE APERTURE	-	*Aperture of Fractures*
FARCTURE DENSITY	-	*Number of Fractures Per Meter*
FRACTURE POROSITY	-	*Porosity of Fractures*
GEOLOG	-	*Geological Lithozones*
GPIT	-	*General Purpose Inclinometry Tool*
HAZI	-	*Borehole Deviation Azimuth (deg)*

HC BEDDING	-	*High Confidence Bedding*
HDRS	-	*Deep Resistivity*
HGR	-	*Gamma Ray*
HMRS	-	*Shallow Resistivity*
ILD	-	*Deep Resistivity (Deep Induction)*
ILM	-	*Shallow Resistivity (Shallow Induction)*
LQC	-	*Log Quality Control*
LC *BEDDING*	-	*Low Confidence Bedding*
LR	-	*Learning Rate*
MDT	-	*Modular Formation Dynamics Tester Tool*
MO	-	*Momentum*
NPHI	-	*Neutron Porosity*
OBMI	-	*Oil Base Mud Imager*
P1AZI	-	*Pad 1 Azimuth (deg)*
PE	-	*Photoelectric Factor*
PEFZ	-	*Photoelectric Factor*
PERM	-	*Permeability from FMS*
PERM.INDEX	-	*Raw FMI Permeability Indicator (Mobility)*
PEX	-	*Platform Express*
PHIS	-	*Secondary Porosity*
PHIT_FMI	-	*Average High-resolution Porosity from FMI*
PIGE	-	*Shale Corrected Log Porosity*
POR_HIST	-	*Porosity Histogram*
PP	-	*Pad Pressure*
RES.SOPTS	-	*Resistive Spots*
PES.PATCHES	-	*Resistive Patches*

Rc	-	*R is the correlation coefficient and C refers to the carbiration set*
R^2c	-	*R^2 is the correlation coefficient and C refers to the carbiration set*
R^2t	-	*R^2 is the correlation coefficient and t refers to the test set*
Rt	-	*R2 is the correlation coefficient and t refers to the test set*
RHOZ	-	*Formation Density*
RLA3	-	*Shallow Resistivity*
RLA5	-	*Deep Resistivity*
SPOR	-	*Secondary Porosity from FMI*
STATIC	-	*Fixed Window Normalization*
TENS	-	*Tension*
TNPH	-	*Porosity from Neutron Log*
UBI	-	*Ultrasonic Borehole Imager tool*
WALL	-	*Borehole Wall*
XPT	-	*Xpress Pressure Tool*

LIST OF SYMBOLS

	-	High Confidence Bedding
	-	Low Confidence Bedding
	-	High Confidence OBMI Bedding
	-	Low Confidence OBMI Bedding
	-	High Confidence UBI Bedding
	-	Low Confidence UBI Bedding
	-	Minor Open fractures
	-	Major open fractures
	-	Medium open fractures
	-	Closed fracture
	-	Continuous open fractures
	-	Discontinuous open fractures
	-	Fault

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CHAPTER 1

INTRODUCTION

1.1 Background

Fractures in subsurface reservoirs are known to have significant impacts on petroleum reservoir productivity. Quantifying their importance, however, is challenged by limited subsurface observations, and intense computations for modelling and upscaling. In carbonate reservoirs, the permeability field is commonly influenced by the presence of fracture networks. Detailed fracture characterization then becomes crucial in order to improve our ability to predict the flow behaviour in subsurface reservoirs (Cappa et al., 2005).

In Geology, a fracture is defined as any separation in a geologic formation, such as a joint or a fault that divides the rock into two or more pieces. It is a surface along which a loss of cohesion in the rock texture has taken place. The orientation of the fracture can be anywhere from horizontal to vertical. The rough surface separates the two faces, giving rise to fracture porosity. Fractures are caused by stress in the formation, which in turn usually derives from tectonic forces such as folds and faults. These are termed natural fractures.

Naturally fractured reservoirs are elusive systems to characterize and difficult to engineer and predict. It is important to establish some basic criteria for recognizing when fractures are an important element in reservoir performance and to recognize the nature and performance characteristics of a naturally fractured reservoir. Fractures occur in preferential directions, determined by the direction of regional stress. This is usually parallel to the direction of nearby faults or folds, but in the case of faults, they may be perpendicular to the fault or there may be two orthogonal directions (Crain, 2015).

Naturally fractured reservoirs contain a significant amount of the world’s remaining oil and gas reserves (World Energy Outlook, 2006). Mostly, naturally fractured reservoirs are associated with brittle rocks. Natural fractures are more common in carbonate rocks. However, there are also authors who argue that all sedimentary rock reservoirs contain natural fractures to some extent (Nelson, 2001).

Natural fractures in reservoir rocks contribute significantly to productivity. Therefore, it is important to glean every scrap of information from open hole logs to locate the presence and intensity of fracturing. Even though some modern logs, such as the formation micro-scanner and televiewer, are the tools of choice for fracture indicators, many wells lack this data.

Most natural fractures are more or less vertical. Horizontal fracture may exist for a short distance, propped open by bridging of the irregular surfaces. Most horizontal fractures, however, are sealed by overburden pressure. Both horizontal and semi-vertical fractures can be detected by various logging tools. In sedimentary basins, the fracture orientations are dominated by structural patterns. Fractures open at depth tend to be oriented normal to the direction of minimum in-situ compressive stress.

The characterization of fractured rock formations, specifically their fluid conductivity properties, has application in petroleum production. By far the most potentially conductive elements of a formation are its laterally connected, discrete fracture systems, as permeability upper bounds of an extensive discrete fracture system may be orders of magnitude larger than that of porous media.

Fracture characterization means identifying the fracture type, fracture density, fracture aperture, fracture dip, fracture strike, fracture azimuth and any other relevant information about the primary and secondary fractures. By using the data gained from fracture characterization, a fracture model can be created in order to have the better understanding of the fracture system (Sirat, 2013). The characterization of these local, high conductivity geologic elements, is therefore critical, albeit extremely difficult, due to their illusive geometry.

Fracture characterization is important in oil and gas industry because of the significant role that fractured reservoirs play in an industry. The large amount of oil and gas reserves are placed in these reservoirs and having enough knowledge of fracture system is an essential matter as such that fracture characterization and modelling technology are the key for oil and gas exploration objective. Fractures can be characterized using core data, fluid flow data, and well test data and so on but, the most advanced technology to characterize the fractures is by means of image log technology.

Image log tools are advanced tools including Formation Micro Scanner (FMS), Oil-Base-Mud Imaging (OBMI), Ultrasonic Borehole Imager (UBI) and Formation Micro Imager (FMI). They can provide images from the well so that by using these images the fracture characterization job can be done properly, but the problem is that if there is a lack of input data the softwares using image log data can not do the fracture characterization properly.

The conventional fracture characterization softwares that use the image log data such as Petrel and Geoframe will receive all the input data and will give the information about the fracture system. But they can not be useful if there is a lack of input data or if they want to predict the fracture system for other undrilled wells.

For instance, if there is a field with a few wells and in one of them there is not any fracture dip data, or another case is that if data from one of the wells are missing in some depth, or another case that if the engineers are not sure about the interpreted data from the logs or samples, these tools will have difficulties to do the fracture characterization. In this case Artificial Neural Networrks (ANNs) are useful because they can predict the fracture system for un drilled wells and also if there is a lack of input data they have this ability to cover this lack using the other input data.

ANNs are among the best available tools to generate linear and nonlinear models. ANNs are computational devices consisting of groups of highly interconnected processing elements called neurons. ANNs inspired by the scientist's interpretation of the architecture and functioning of the human brain. The new technology of ANNs have been used in other sciences and fields to predict the data and the future of ANNs are very wide (Foroud et al., 2014).

In this study, a novel application of ANNs will be introduced and verified using the image logs data of the three wells, located in one of the naturally fractured reservoirs. A feed forward Back Propagation Neural Network (BPNN) will be run to predict the fractures dip angle for the third well using the image logs data of the two other wells nearby. The predicted data will be compared with the image logs data of the third well to verify the usefulness of the ANNs in fracture characterization and modelling technology.

1.2 Statements of the Problem

i. Core analysis usually focuses on the worse portion of the reservoir due to the fact that core recovery has rarely been well in a highly fractured zone, therefore, fracture dip measured from core sample is often not characteristic. There are some limitations in the core technique such as high expensive, unidirectional and low recovery in fractured zone.

ii. Data prediction in complicated fractured reservoirs has always been an important issue for engineers in oil and gas industry, and every year companies are trying to find new ideas to improve this important matter. By predicting the data, the decision for next step and planning for future work will be more reliable and operational.

iii. Sometimes a group of data is missed or the data is related to undrilled depth .This data can be predicted can be predicted using the other data in order to achieve a better drilling operation. Data prediction technology using ANNs can be very useful in these cases.

iv. The application of ANNs in oil and gas industry is not very wide same as the other sciences. Consequently, this study is conducted to introduce the application of ANNs for data prediction in fracture characterization and modeling technology.

1.3 Objectives

The objectives of the research are:

a) To Characterize fractures in wells (GS-325, GS-264 and GS-245) for selecting best fracture data and better data match for ANN modeling technology.

b) To predict the fracture dip in third well by using data from 2 other wells in ANN model.

c) To improve ANN application in fractured reservoirs and determining the suitable ANN type.

d) To adapt the ANN applications in fracture dip predictions.

e) To validate the value of fracture attribute from image logs.

1.4 Scopes

The scope of this study are:

i. Interpreting the image log data FMS, FMI, OBMI, UBI) and petrophysical logs of the three wells with (GS-264 between GS-245 with 3 km distance and GS-325 with 5 km distance).
ii. Selecting a good fractured reservoir data (Asmari reservoir which is a carbonate reservoir).
iii. Using Fracture dip as input for Neural network Analysis.
iv. Finding the suitable type of ANNs (BPNN) for this study.
v. Writing the computer programs using ANNs method.
vi. Applying the image logs data in computer programs.
vii. Predicting the fractures dip angle of the third well using the image logs data of the two other wells nearby.
viii. Comparing the predicted data by ANNs and actual data of image logs for the third well.
ix. Verifying the usefulness of image log fracture data and ANNs to predict the dip.

1.5 Significance of Study

The following significant of study are consequently delineated as below:

i. Naturally fractured reservoirs play an important role in oil and gas industry and this study will introduce the new application of ANNs to predict fracture dip for better understanding of the fracture system in this kind of reservoirs.
ii. An ANN has many known benefits and along the best feature is the ability to learn from the input data. ANNs can save both time and money because it takes data samples rather than a complete set of data to obtain the solutions and it can simply estimate the best and shortest way to solve the problems by employing the previous data

and creating the most effective model. ANNs use the simple mathematical models to increase the data analysis technology, and scientists believe that it can be effective in any single technology and method, but it takes time for researchers to find the way to apply them in different aspect of the sciences and engineering applications.

iii. ANNs are made to solve the hardest tasks that the other computer programs and methods are unable to solve using the unique structure that are patterned from the human brains. One of these tasks is speech recognition using the similar method for handwriting recognition using more complicated programs. ANNs will be more complicated when the task is more difficult and every year these tasks had become more complex and comprehensive. Modern technology is aiming to simulate the actual human brain abilities using ANN technique.

iv. According to the obtained results, it is concluded that the ANNs 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.

v. The time and cost that can be saved by this method cannot exactly be estimated and it depends on the situation. It depends on the type of the well if it's horizontal or deviated and also the place that well is located, if the access to the well is easy or difficult. It also depends how much depth is going to be drilled and logged. Subsequently, an exact estimate of cost and time that will be saved using this method cannot be estimated.

vi. In distinction, there tends to be a suspicion and even a suspicion of those logging tools that make measurements which impend to imitate or even replace the cores. Consequently, image logs are more valuable to study the subsurface fractures in these such cases and the logs which come closest to accomplishing this are the high resolution image logs.

REFERENCES

Adibifard, M.,Tabatabaei-Nejad, S.A.R. ,Khodapanah,E. (2014). Artificial Neural Network (ANN) to estimate reservoir parameters in Naturally Fractured Reservoirs using well test data, DOI: 10.1016/ j. petrol. 2014.08.007.

Aifa,T., Zerrouki,A.A., Baddari ,K., Géraud,Y.(2014). Magnetic susceptibility and its relation with fractures and petrophysical parameters in the tight sand oil reservoir of Hamra quartzites, southwest of the Hassi Messaoud oil field, Algeria, Journal of Petroleum Science and Engineering.

Alavi, M. (2004). Regional Stratigraphy of the Zagros Fold-thrust belt of Iran. American Journal of Science, Vol.304, pp. 1-20.

Bahrami, H. , Siavoshi, J.,Parvizi, H. , Esmaili, S.,Karimi, M. (2008) . Characterization of Fracture Dynamic Parameters to Simulate Naturally Fractured Reservoirs, IPTC 11971.

Boadu, F.K. (2001). Predicting oil saturation from velocities using petrophysical models and artificial neural networks, Journal of Petroleum Science and Engineering 30 (3):143-154 · September 2001,DOI: 10.1016/S0920-4105(01)00110-3.

Borbas, T., Wendt, B., Jacques, R., Tabanou, J.R., Cheung, P., Liu, C. B., Hansen, S., Lavigne, J., Omeragic, D. , Pickens, T. (2002). Thinly Laminated Reservoir Evaluation in Oil-Base Mud: High Resolution Versus Bulk Anisotropy Measurement, a Comprehensive Evaluation. SPWLA 43rd Annual Logging Symposium. 2-5June. Paris, France.

Bosold, A., Schwarzhans, W., Julapour, A., Ashrafzadeh, A.R., Ehsani ,S.M. (2005). The structural geology of the High Central Zagros revisited (Iran), RWE Dea AG, Ueberseering 40, D-22297 Hamburg.

Cappa, F., Guglielmi, Y., Fénart, P., Merrien-Soukatchoff, V.,Thoraval, A. (2005) Hydromechanical interactions in a fractured carbonate reservoir inferred from hy-draulic and mechanical measurements. Interna-tional Journal of Rock Mechanics and Mining Sci-ences 42, 287–306.

Crain, E.R.,(2015). Crain's petrophysical handbook. https://www.spec2000.net/22-fracloc1.htm.

Darabi, D., Kavousi, A., Moraveji, M., Masihi, M. (2010). 3D fracture modeling in the Parsi oil field using artificial intelligence tools, Journal of Petroleum Science and Engineering 71 (1): 67-76, DOI: 10.1016/ j. petrol.2010.01.004.

Daungkaew S., Fujisawa, G.,Chokthanyawat, S.,Comrie-Smith, N.,Thaitong, T. (2012). Is there a better way to determine the viscosity in waxy crudes? SPE Asia Pacific Oil and Gas Conference and Exhibition, APOGCE.

Ellis, C., Wilson, P. J. (2005). Can a Neural Network Property Portfolio Selection Process Outperform the Property Market. Journal of Real Estate Portfolio Management, 11 (2), 105-121.

Hassan, G., Kurkoski, P. (2010). Zero Latency Image Compression for Real Time Logging While Drilling Applications, XP-010920710, Oceans, 2005, Proceedings of MTS/IEEE Washington, D.C., Sep. 18-23, 2005, pp. 1-6, 14 .

Hinton, G. E., Deng, L., Yu, D., Dahl, G. E., Mohamed, A., Jaitly, N., Senior, A., Vanhoucke, V., Nguyen, P., Sainath, T. N., Kingsbury, B. (2012). Deep neural networks for acoustic modeling in speech recognition: The shared views of four research groups. IEEE Signal Process. Mag., 29(6):82–97.

Foroud, T. (2014). Assisted history matching using artificial neural network based global optimization method- Applications to Brugge field and a fractured Iranian reservoir, Journal of Petroleum Science and Engineering.

Goel, S. and Tang, X. (1989). Brace Fractures and Analysis of Phase I Structure, Journal of Structural Engineering 115 (8) ·

Guerriero, G., Mazzoli, S., Iannace, A., Strauss, C. (2012). A permeability model for naturally fractured carbonate reservoirs, Marine and Petroleum Geology 40:115–134 ·

Jeffreys, P. (2005). Geological Analysis Of Formation Micro Imager (FMI). Schlumberger. Field Gachsaran, Well No.245, Well Services of Iran (Schlumberger Methods).

Jafari, A. and Babadagli, A. (2012). Estimation of equivalent fracture network permeability using fractal and statistical network properties, Journal of Petroleum Science and Engineering 92-93:110-123 · August 2012, DOI: 10.1016/ j.petrol.2012.06.007.

Jenkins, C., Quenes, A., Zellou,A., Wingard, J. (2009).Quantifying and predicting naturally fractured reservoir behavior with continuous fracture models. AAPG Bulletin 93(11):1597-1608 · November 2009.

Ouahed, A.K., Tiab, D., Mazouzi, A. (2005). Application of artificial intelligence to characterize naturally fractured zones in the Hassi Messaoud Oil Field, Algeria, Journal of Petroleum Science and Engineering 49 (3) : 122-141 , DOI: 10.1016/ j.petrol.2005.05.003.

Russo, J. and Juandi, D., Chittick, S., Battawy, A. (2010).Integration of Borehole Image Log and Formation Pressure Sampling to Determine Reservoir Barrier in a Tight carbonate, KazGeo 2010 – 1st International Geosciences Conference for Kazakhstan Where Geoscience Meets the Silk Road Almaty, Kazakhstan , ISBN: 978-1-63266-995-7.

Kingston, G. B., M. F. Lambert, H. R. Maier (2005), Bayesian training of artificial neural. Campbell, 2001; Thiemann et al., 2001; Vrugt et al., 2003.

Lamb, M., Largeau, D., Mathieu, G., Laronga, R., Montaggioni, P., Faivre, O., Vessereau, P., Garber, M., Kovacs, J., Kusama, A., Lindsay, H., Silinsky-Kephart, L. (2001). Looking Through the Borehole, Muddily.

Ma, T. A. (1993). Natural and Induced fracture, classification using image analysis. Viewed 8 of February 2012, www.onepetro.org.

Malallah, A., Sami Nashawi, I. (2005). Estimating the fracture gradient coefficient using neural networks for a field in the Middle East, Article (PDF Available) in Journal of Petroleum Science and Engineering 49 (3-4): 193-211 · December 2005, DOI: 10.1016/j.petrol.2005.05.006.

McCulloch, W. , Pitts, W. (1943). A logical calculus of the ideas immanent in nervous activity. Bulletin of Mathematical Biophysics, 7:115–133.

Michael, A. (2005). The Metaphorical Brain 2: Neural Networks and Beyond, John Wiley & Sons, Inc. New York, NY, USA ©1989 ISBN:0471098531.

Mitra, S. (2002). Fold Accommodation Faults. AAPG Bulletin, v. 86, no. 4, pp. 671-693.

Motiei, H. (1993). Stratigraphy of Zagros in Hushmandzadeh. Treatise on the Geology of Iran: Tehran, Geological Survey of Iran, 536 p.

Motiei, H. (1995). Petroleum Geology of Zagros. Geological Survey of Iran with cooperation of Deputy Ministry of project and planning, no. 25.

Movahed, Z. (2004). Evaluation of Oil-Base-Mud Imaging, Field Gachsaran, Well No.325, Well Services of Iran (Schlumberger Methods).

Movahed, Z. (2005). Evaluation of Oil-Base-Mud Imaging, Field Marun, Well No.322, Well Services of Iran (Schlumberger Methods).

Movahed, Z., Junin, R., Safarkhanlou, Z., Akbar, M. (2014). Formation Evaluation in Dezful Embayment of Iran using oil-based-mud Imaging Techniques, Journal of Petroleum Science and Engineering, 121 (2014)23–37 37.

Movahed, Z., Junin, R., Jeffreys, P. (2014). Evaluate the Borehole Condition to Reduce Drilling Risk and Avoid Potential Well bore Damages by using Image Logs, Journal of Petroleum Science and Engineering122 (2014)318-330.

Nelson, R. A. (2001). Geologic Analysis of Naturally Fractured Reservoirs. Houston, Texas: Gulf publishing company. Pp. 322.

Ranalli, G. , Gale, A.D. (1976). Lectures on the rheology of the earth. 1. Basic concepts, Part1Volume 76, Issue 1 of Geological papers / Carleton University. Dept of Geology.

Rumelhart, D. E. , McClelland, J. L. (1986).“Distributed memory and the representation of general and specific information,” J. Exper. Psychol.—General, vol. 114, pp. 158–188, 1988.

Safarkhanlou, Z. (2004). Evaluation of Oil-Base-Mud Imaging, Field Gachsaran, Well No.264, Well Services of Iran (Schlumberger Methods).

Schlumberger (1994). Borehole Image Measurements. Schlumberger documents.

Schlumberger (2002). UBI- Advanced borehole imaging independent of mud type, SMP-5871.

Schlumberger (2005). Stratigraphy and Geology of Iran, Reservoir Symposium.

Sematech, N. (2012). Handbook of Statistical Methods, http://www.itl.nist.gov/div898/handbook/, date.

Sepehr, M. (2004). The Structural Framework of the Zagros Fold–Thrust Belt, Iran, DOI: 10.1016/ j. marpetgeo.

Sirat, M. (2013). Fracture System in the Carbonate Reservoirs of Abu Dhabi: Implications for Field Development, SPE-166013-MS

Soliman, M., Osama M., Saad Aba, A., Bader, A. (2010). Tectonic and Climatic Controls of Post Glacial Terminal Fluvial Systems, Permian Unayzah Reservoir.

Stocklin, J. (1968). Structural History and Tectonics of Iran. AAPG, Bull.52, pp. 509-526.

Szabo, F. , Kheradpir, A. (1978). Permian and Triassic stratigraphy, Zagros Basin, South West Iran. Journal of Petroleum Geology, 1,2, pp. 57-82.

Tatar, M., Hatzfeld, D., Ghafory-Ashtiany, M. (2004). Tectonics of the Central Zagros (Iran) deduced from micro-earthquake seismicity, Geophysical Journal International, v. 156, pp. 255-266.

Wang, Y. (2003). Neural Network Forecasting of the Production Level of Chinese Construction Industry. Volume 6, No. 2 .

World Energy Outlook, (2006).International Energy Agency,English ,ISBN:
9789264109902 (PDF) ;9789264109896(print) ,http://dx.doi.org/10.1787/weo-2006-en

Xue, Y., Cheng, L., Mou, J., Jao, W. (2014). A new fracture prediction method by Combining genetic algorithm with neural network in low-permeability reservoirs, Journal of Petroleum Science and Engineering, DOI: 10.1016/ j.petrol.2014.06.033.

Yang, J., Gou, X., Hilmi, N., Xia, R. (2008). Identify Fracture Features and to Classify Fracture Types. Fractured carbonate reservoirs.

Yanfang, W., Salehi, S. (2014). Refracture Candidate Selection Using Hybrid Simulation with Neural Network and Data Analysis Techniques, Journal of Petroleum Science and Engineering ,DOI: 10.1016/j.petrol.2014.07.036.

Zerrouki, A.A. ,Aifa,T. , Baddari, K. (2014). Prediction of natural fracture porosity from well log data by means of fuzzy ranking and an artificial neural network in the Hassi Messaoud oil field, Algeria, Journal of Petroleum Science and Engineering ,DOI: 10.1016/j.petrol.2014.01.011.