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Modelling Discrete Fracture Networks using Neuro-Fractal-Stochastic Simulation

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Abstract: Modelling of discrete fracture networks in naturally fractured reservoirs is a complex process that contains large amount of uncertainty. This study presents a novel methodology that integrates various features of geological, statistical and artificial intelligence techniques in a nested loop to characterize field fractures and then to model them. Properties of natural fractures such as size, orientation and aperture are of different scales and relevancies. Their characterization is, to some extent, technique dependent. Secondary properties such as fracture density and fractal dimension are therefore defined for better description of fractures' spatial distribution. Mathematical relationships between the primary and secondary fracture properties are non-linear and have not been fully understood. A neural network is incorporated in the proposed methodology to determine these relationships, by processing field data available from logs and core analyses. Combining the characterized fracture properties, a nested stochastic technique is used to simulate different degrees of heterogeneity and model discrete fracture networks in the whole reservoir. The dual application of neural network and fractal mathematics in discrete fracture modelling is innovative in this study. The result is expected to map more closely with the actual physical distribution of fractures and their properties than that are achieved so far with simplified stochastic-fractal approaches.

Key words: Petroleum engineering, naturally fractured reservoir, discrete fracture network, stochastic simulation, fractal, discrete multifractal, neural network

INTRODUCTION

Naturally Fractured Reservoirs (NFR) refer to geological accumulation of oil, gas, water and geothermal energy that contain a network of fractures (faults, joints, cracks, cleats, etc.). It is estimated[1] that the U.S. domestic petroleum targets in NFR could be hundreds to thousands of trillions of cubic feet; a multibillion-barrel domestic and international oil resource targets also exist. Because of increasing energy needs throughout the world, recently these reservoirs have become commercially significant.

Due to geological reasons, many of the NFR possess very low permeability, which is inadequate for economic production. Therefore, some permeability enhancement techniques are required. It is proposed to activate pre-existing natural fractures by hydraulic stimulation, instead of creating a single massive fracture. We postulate that under appropriate stimulation pressure, a natural fracture will slip by shear and dilate (hence the phrase 'shear dilation') to facilitate a flow conduit for hydrocarbon. Unlike conventional hydraulic fracturing, the fracturing fluid will require no, or very little, proppants to keep the conduit open, upon the cessation of injection, as the conduit will remain open by the frictional resistance of rough natural fracture surfaces. Field experience with slowly injected and low proppant fluids has been encouraging[2,3], at least for short-term. Underlying principles of this technique, however, have not been adequately understood. To complete the design of reservoir-specific stimulation with improved efficiency, responses of natural fractures under different stimulation pressures need to be quantified. Reliable model for reservoir's Discrete Fracture Network (DFN) is essential and thus, is the subject of this study.

A BRIEF REVIEW OF FRACTURE MODELLING

Natural fractures are mechanical breaks in rocks. They occur at different scales and are highly heterogeneous. Rock fracturing is a complicated process, which is sensitive to changes in geological conditions. Under lithostatic, fluid pressure, tectonic, thermal and other geological stresses (e.g. volcanoes, uplifting and salt intrusion), fractures generally initiate and propagate when the stresses become equal or greater to the rock strength. Different geological conditions induce different fracture patterns, thus, different NFR characteristics. Most rocks have simultaneously and sequentially undergone multiple

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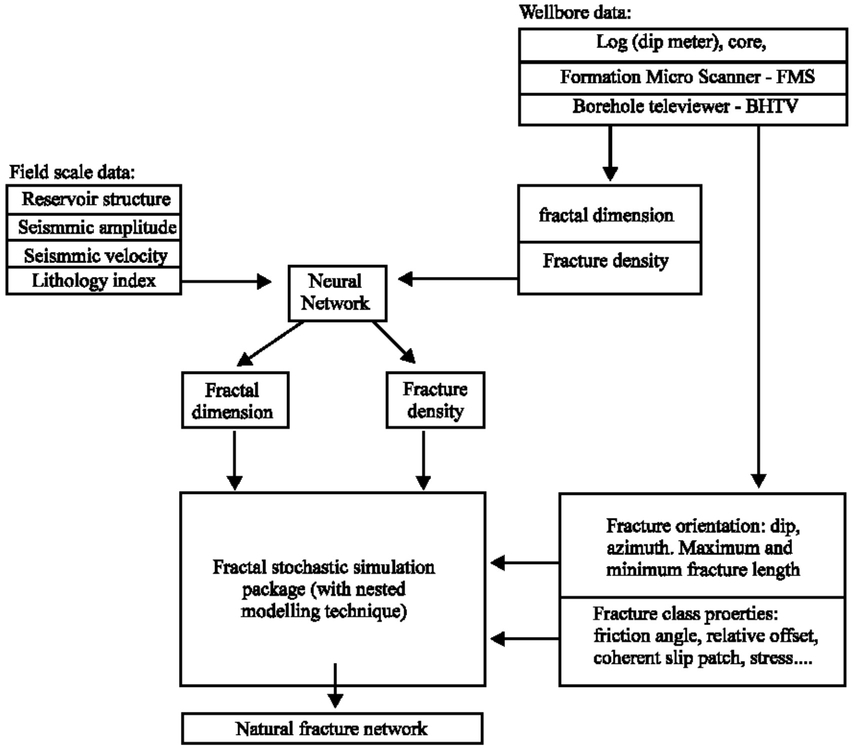

Fig. 1: Flowchart of the modelling procedure

deformational events, which eventually result in very complicated fracture systems[4].

Earlier mathematical models for fracture networks and flow through them include equivalent continuum models[5], discrete network models[6,7] and hybrid techniques[8-10]. Based on the fractal concept, equivalent discontinuum fractal models are also available[11,12]. Recently, attempts have been made to characterize natural fractures applying fuzzy logic and neural networks, where an integrated approach is adopted to encompass various information available from the field[13,14]. The data include seismic, porosity, permeability, lithology, bed thickness, state of stress, fault patterns and production data. The outcome is a network map of fracture index/intensity for each discrete block. The approach uses fuzzy logic to quantify and rank the importance of each geological parameter on fractures; and neural networks to account for complex, non-linear relationships between these geological parameters and the fracture index. Thus, it took into account the overall effect of fracture network upon fluid flow in the reservoir with a primary emphasis on predicting well performance. Their purpose, however, did not require generation and treatment of discrete fractures, as the production performance was assessed for the reservoir at its in-situ condition (i.e., without any hydraulic stimulation). Thus, the method is not directly adoptable for the proposed research work though the concept of (fuzzy) neural network will be utilized in this work as described below.

THE PROPOSED MODELLING TECHNIQUE

This study presents a systematic procedure to model DFN. Output fractures are conditioned to the available geological, geophysical and engineering data. In order to achieve this, we first review the field data sources that are typically available in a petroleum exploration and that could reveal information about key fracture properties of location, orientation and size. Statistical distributions of those properties are then determined by integrating data from the different sources at different scales. Finally, they are stochastically simulated to model the fractal-based DFN. The procedure includes two major computational modules: Back-Propagation Neural Network (BPNN) and fractal-stochastic fracture simulation. The overall process is thus named Neuro-fractal-stochastic simulation (Fig. 1). Various modules of this process are described in the following sections.

DATA SOURCES

In NFR, different field data sources cover different scales (microscopic to regional) and are of different resolutions. Moreover, no single tool can provide all information needed to fully characterise a NFR. Thus, in order to portray the multifaceted characteristics of natural fractures, an integrated approach is required, where all available field data from wide range of geological, geophysical, petrophysical, drilling and other sources are utilised[15]. There are two main types of data sources for fracture characteristics in NFR.

The first group includes seismic, outcrop and other geological sources, which are used in studying reservoir geological features. This group of data is at a large (reservoir) scale, with resolution ranges from a few inches to several feet. They reveal reservoir structure, bed thickness, lithology and curvature of various formations. These factors are directly related to several fracture characteristics, such as fracture length, spacing, orientation, density[10,14]. Seismic data show orientation and size of major faults. Moreover, smaller-scale fracture orientation and density can be interpreted from classical P-wave seismic attribute maps, such as AVO and/or shear wave attributes. Outcrops data also describe various fracture characteristics, such as orientation, size and spacing, at sub-seismic scale[10] .

The other group contains the data available at the well site, such as log and core derived data, drilling and well testing[10,14]. Among the most efficient logging tools for fracture characterization are dip meter (giving fracture orientation), borehole televiewer, formation micro scanner and core. It is possible to determine fracture properties such as dip, strike, aperture, density and fractal dimension (via the box counting method). Wellbore data are of higher resolution (fraction of an inch) and more related to small-scale fractures.

NEURAL NETWORK CHARACTERIZATION

Inter-relationships between the different data sources and their relevance on fracture characterization are very complicated. The problem arises when the secondary input properties (fractal dimension, fracture density) are computed, where an integration of the data sources is required. The task of data integration is fulfilled by an artificial intelligence tool of Neural Network (NN). A NN is capable of integrating different data sources of different nature to delineate the required relationships[16].

Neural networks use a set of processing elements (or nodes) that are similar to human brain neurons. These nodes are interconnected in a network that can then identify patterns/ relationships in the input data[16,17]. In other words, NN can learn from experience. The BPNN is a supervised learning technique, which can learn almost any functions regardless of noise in the data or the complexity of their relationships. It learns through an iterative procedure: Through example. The input data are combined with a set of weighting factors (set W1 and set W2), through hidden layers, to estimate the outputs. Figure 2 shows the sketch model of a BPNN. The aim of the training process is to continually adjusting the weighting factors W1, W2 so as the error in the outputs is minimized (better fit the model).

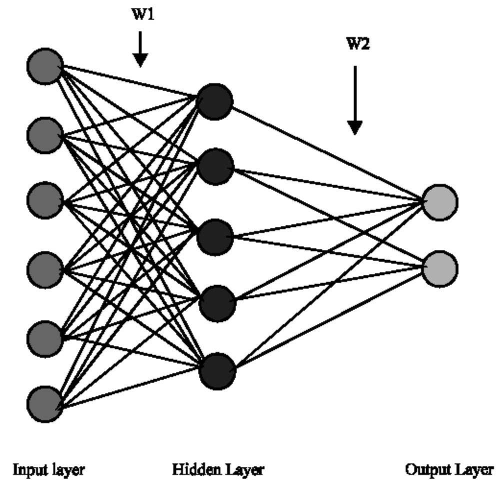

Fig. 2: Three-layer BPNN with 5 hidden neurons used in this study. W1 and W2 are the two sets of weighting factors

From available field data, fracture density (fracture area in unit volume, m^2/m^3) can be calculated directly and fractal dimension can be estimated using the box-counting method[18]. However, the calculations are cumbersome for every block of the reservoir. Moreover, the necessary data are only available at wellbores, such as borehole logs, cores, micro-seismic imaging and borehole televiewer. Thus, the NN technique is applied in computing distribution of the two key fracture properties: fracture density and fractal dimensions. Using these wellbore values for training and validation, NN estimates fracture density and fractal dimension values over the whole reservoir. This procedure is expected to make DFN modelling significantly efficient.

SPATIAL NESTED MODELLING

We integrate a fractal-stochastic model with a nested geological modelling technique. There are not many data sources for fracture size (i.e. length, area and aperture). The lack of reliable field measurements makes it difficult to be analysed statistically. Fractal geometry realizes proper mathematical framework for characterizing and simulating geometry of many complex non-Euclidean shapes found in nature. It has been proved especially suitable for

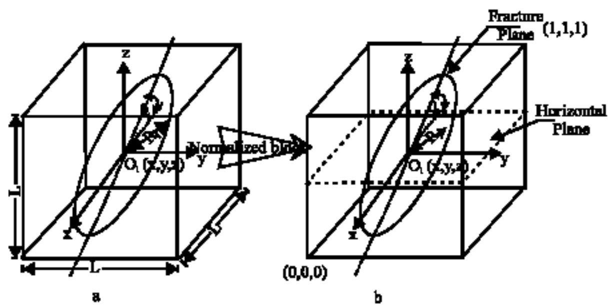

Fig. 3: Circular disc model of fracture: Characterized by centre, radius and orientation of the fracture plane- (a) in a cubic block of side length L, (b) normalized block of unit length in (x, y, z) coordinate system

natural discontinuities such as fractures[19,20]. According to this methodology, a cubic block of edge length L is considered (Fig. 3). Within this rock mass, the centres of penny-shaped (circular) fractures are generated stochastically. The radii of randomly distributed fractures are then defined as eq. 1, where, α is a randomly distributed uniform deviate between 0 and 1; r_α is the radius of a fracture for a random value of α; r_{min} and r_{max} are the minimum and the maximum radii of fractures observed in the reservoir and D is the fractal dimension. Fracture orientations of these generated fractures are conditioned statistically according to the observed dip and azimuth. Eq. 1 is executed repeatedly with different values of α until the observed fracture density is achieved by the generated fractures within r_{min} and r_{max}.

We use a nested geological modelling methodology[8] to take into account the DFN' multi-scaled characteristics and high degree of heterogeneity. The modelling is carried out in different steps, going from larger to smaller scales. In this manner, a framework is first built and details are added subsequently. The above stochastic modelling is repeated twice: the first step simulates the major faults of the whole reservoir while the second one simulates smaller-scaled fractures within each discrete block.

APPLICATIONS

We perform a case study to demonstrate capability of the proposed model. Firstly, the fracture density and fractal dimension for simulating blocks in the reservoir are estimated by a BPNN. A set of input data of seismic velocity, amplitude and lithology index is chosen (among the relevant data sources mentioned earlier), as they are widely available, reliable and of high resolution. The data are available for the whole reservoir (Fig. 4, 5 and 6).

Through training, the NN establishes the complex relationships between input data, fractal dimension and

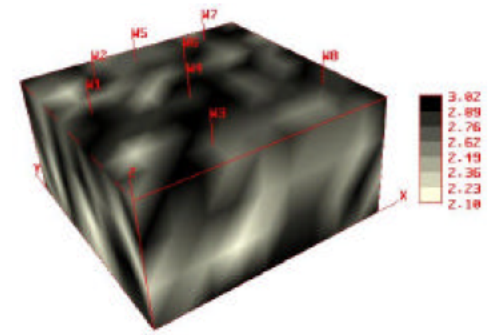

Fig. 4: Seismic velocity 3D data (m/s). W1 to W8 show the locations of existing wells

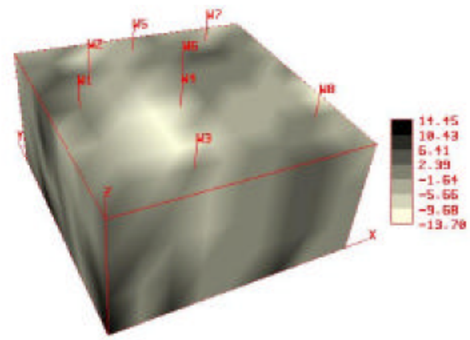

Fig. 5: Seismic amplitude 3D data (m)

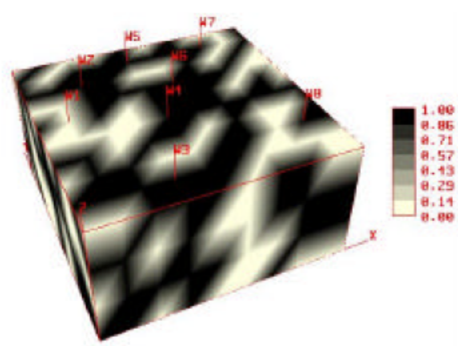

Fig. 6: Lithology index 3D data

Table 1: Difference in test set performance

Mean squared	Errors	Difference
All inputs	0.0491	
Seismic velocity	0.3355	-0.2864
Seismic amplitude	0.2292	-0.1801
Lithology index	0.3667	-0.3176

fracture density. It then generates spatial distributions of fractal dimension and fracture density in the reservoir (Fig. 7 and 8).

Comparing the computed outputs with the input data (Fig. 9) we can test accuracy of the BPNN. Both graphs give close correlations, with R-squared being very close to 1. Moreover, by analysing the weighting factor sets

Table 2: Input data for the model: data are available for 4 different regions of different fracture characteristics

Rock and fracture class	Class 1	Class 2	Class 3	Class 4	Overall (nested modelling)
Rock properties Young's modulus (GPa)	60	60	60	60	60
Poisson's ratio	0.25	0.25	0.25	0.25	0.25
Density (Kg/m3)	2700	2700	2700	2700	2700
Fracture basic friction angle (Degree)	40	40	40	40	40
Shear dilation angle (Degree)	3	3	3	4	4
90% closure stress (MPa)	20	20	30	30	30
Fractures properties					
Fractal dimension, D	2.57	2.54	2.50	2.47	2.52
Fracture density (m2/m3)	0.357	0.364	0.300	0.141	0.052
Fracture sets[19]					
Weighting (%)	60	60	50	40	All sets
Dip range (Degree)	25-30	60-70	40	80	
Strike range (Degree)	165-175	20-25	40	230	
Weighting (%)		50	25		
Dip range (Degree)		25-35	60		
Strike range (Degree)		340-350	90-130		
Smallest fractures radius (m)	10	10	10	10	100
Largest fractures radius (m)	100	100	100	100	500
Stress					
Vertical stress, σ_v (MPa)	50	50	50	50	50
Maximum horizontal stress, σ_H (MPa)	60	60	60	60	60
Minimum horizontal stress, σ_h (MPa)	35	35	35	35	35
Stress gradient					
Vertical stress (Mpa m^{-1})	0.0333	0.0333	0.0333	0.0333	0.0333
Maximum horizontal stress (Mpa m^{-1})	0.0682	0.0682	0.0682	0.0682	0.0682
Minimum horizontal stress (Mpa m^{-1})	0.0426	0.0426	0.0426	0.0426	0.0426
Direction of maximum horizontal *in-situ* stress, σ_H (Degree)	100	100	100	100	100
Fluid properties					
Density (kg/m^3)	1000	1001	1002	1003	1004
Viscosity (Pa.s)	3x10-4	3x10-5	3x10-6	3x10-7	3x10-8
Hydrostatic fluid pressure (MPa)	19	19	19	19	19
Well and reservoir data					
Well radius (m)	0.2	0.2	0.2	0.2	0.2
Number of wells	8				
Reservoir depth (m)	2000				
Model size (3D: m*m*m)	1000*1000*500				

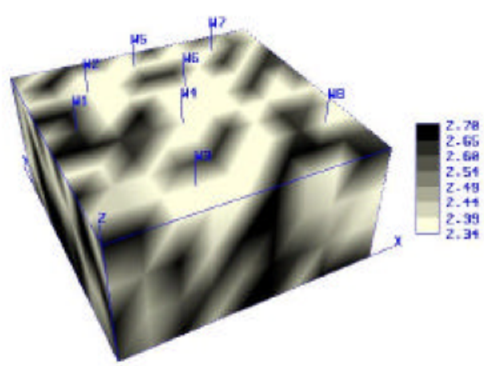

Fig. 7: Characterized 3D Fractal dimension

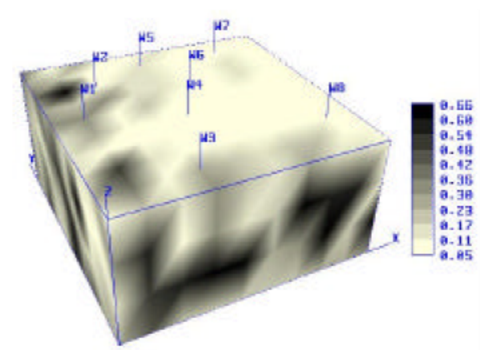

Fig. 8: Characterised 3D fracture density (m2/m3)

W1 and W2, we can also understand the effects of different inputs on the two outputs. Table 1 confirms the importance of three chosen inputs, with lithology index is the most dominant factor while seismic amplitude is the least.

The result fractal dimension and fracture density are important data for the next step: fractal-stochastic fracture generation. There are also other data, such as rock properties, fracture orientation, class properties, approximate length and stress data.

The fracture orientation distribution contains dip, azimuth and probability that occurs (weighting). It is obtained from seismic profiles, outcrops, measurements on cores and borehole images. The DFN is divided into four different classes, based on distinction in their geological, lithological and physical (including fractal)

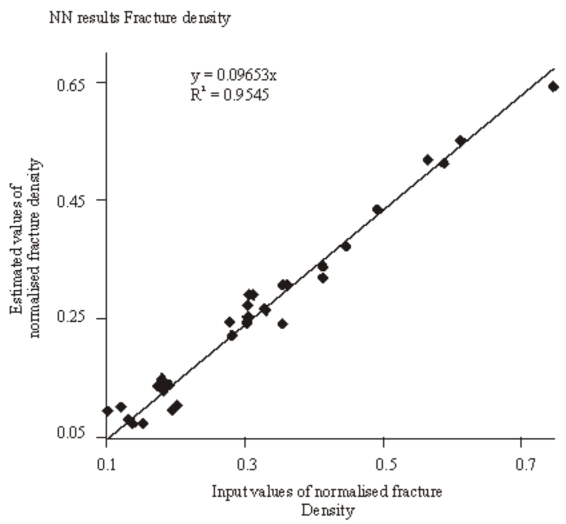

Fig. 9: NN results: Plot of estimated fracture density and the input data. R-squared is 0.955

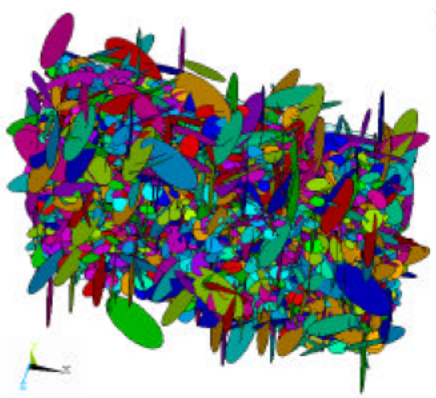

Fig. 10: Result DFN (Small, medium fractures)

properties. Class details are basic friction angle, shear dilation angle at zero normal stress, initial relative offset, largest fracture and smallest fracture to simulate, largest coherent slip patch, fractal dimension, 90% normal closure reference stress and cohesion. Those are also computed directly from the same data sources as fracture orientation (Table 2).

In a nested procedure, major faults (bigger-radius fractures) are firstly generated. Fractures from 100 m to 500 m in radii are generated in the entire reservoir. In the second run, we simulate fractures whose radii are smaller than 100 m, in each smaller region within the reservoir. Different regions have different geological and fracture properties. The final output is the reservoir's detailed and realistic DFN (Fig. 10).

CONCLUSIONS

In this study, an intelligent efficient method is developed to extrapolate well data throughout the whole reservoir and to derive important properties (fractal dimension, fracture density) required for fracture modelling. Moreover, through integration of data from different sources, NN, fractal analysis and stochastic analysis techniques, a hybrid neuro-fractal-stochastic model is derived. The design of an artificial intelligent NN, together with fractal mathematics, for DFN application is innovative in this study. In addition, incorporation of nested simulation concept has enhanced the model's versatility. The DFN modelling process can be repeated and improved throughout the development of a field. The more data available, the more accurate it expected to be.

REFERENCES

1. Laubach, S., R. Marrett and J. Olson, 2000. New directions in fracture characterization, The Leading Edge, pp: 704-711.
2. Mahoney, J.V., P.B. Stubbs, F.C. Schwerer and F.X. Dobscha, 1981. Effects of A No-proppant foam stimulation treatment on a coal seam degasification borehole, J. Petroleum Technol., pp: 2227.
3. Palmer, I.D., R.T. Fryar, K.A. Tumino and R. Puri, 1991. Water fracs outperform gel fracs In coal-bed pilot, Oil and Gas J., 12: 71.
4. National Research Council, Rock Fractures and Fluid Flow-Contemporary Understanding and Applications, National Academy Press: Washington D.C.
5. Hsieh, P.A. and S.P. Neuman, 1985. Field Determination of The Three-dimensional Hydraulic Conductivity Tensor Of Anistropic Media, Water Resour. Res., 21: 1655-1666.
6. Long, J.C.S., C. Doughty, K. Hestir and S. Martel, 1992. Modelling Heterogeneous and Fractured Reservoirs With Inverse Methods Based On Iterated Function System, Reservoir Characterization III, Linville, B. (Eds.), Penwell Books, Tulsa.
7. Sudicky, E.A. and R.G. McLaren, 1992. The laplace transform galerkin technique for large scale simulation of mass transport In discretely fractured porous formations, Water Resour. Res., 28: 499-514.
8. Cacas, M.C., J.M. Daniel and J. Letouzey, 2001. Geological modelling of naturally fractured reservoirs, Petroleum Geoscience, 7: 43-52.
9. Oda, M., Y. Hatsuyama and Y. Ohnishi, 1987. Numerical experiments on permeability tensor and its application to jointed granite at stripa mine, Sweden, J. Geophysical Res., 92: 8037-8048.
10. Tran, N.H., Z. Chen and S.S. Rahman, 2005. Practical Application of Hybrid Modelling to Naturally Fractured Reservoirs, J. Petroleum Sci. Engin., (In Press).
11. Chang, J. and Y.C. Yortsos, 1990. Pressure transient analysis of fractal reservoirs, SPE Formation Evaluation, 631.

12. Watanabe, K. and H. Takahashi, 1995. Fractal geometry characterization of geothermal reservoir fracture networks, J. Geophysical Res., 100: 521-528.
13. Ouenes, A., 2000. Practical application of fuzzy logic and neural networks to fractured reservoir characterization, Computers and Geosci., 26: 953-962.
14. Quintero, E.J., L.P. Martinez and A., Gupta, 2001. Characterization of naturally fractured reservoirs using artificial intelligence, SPE Paper Number 67286.
15. Tran, N.H., Z. Chen and S.S. Rahman, 2005. Integrated conditional global optimisation for discrete fracture network modelling, J. Computers Geosci., 32: 17-27.
16. Kosko, B., 1992. Neural networks and fuzzy systems: A dynamical systems approach to machine intelligence, Prentice Hall, New Jersey.
17. Gallant, S.I., 1994. Neural network learning and expert systems, The MIT Press, Massachusetts.
18. Sahimi, M., 2000. Fractal-wavelet neural-network approach to characterization and upscaling of fractured reservoirs, Computers and Geosci., 26: 877-905.
19. Willis-Richards, J., 1996. Progress toward a stochastic rock mechanics model of engineered geothermal systems. J. Geophysical Res., 101: 17481-17496.
20. Clark, R.M, S.J.D. Cox, G.M. Laslett, 1999. Generalizations of power-law distributions applicable to sampled fault-trace lengths: Model Choice, Parameter Estimation and Caveats, Geophysics J. Intl. 136: 357-372.