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Hybrid Modelling using Neuro Fractal for Fractured Reservoirs

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Abstract: - Due to geological reasons, fractured reservoirs are extremely heterogeneous. Modelling of these reservoirs has so far been considered complex and progress is still inadequate. This paper presents a novel and hybrid method to model discrete fracture networks in naturally fractured reservoirs. It involves investigation and systematic integration of tasks spanning cross-disciplinary areas: geological, statistical and artificial intelligence characterisation of natural fractures, rock and fracture mechanics. This paper also evaluates applications of fractal mathematics on characterising natural fracture distributions, especially discrete multifractal dimensions. A case study illustrates that discrete multifractal dimensions are greatly more suitable for such complex systems as natural fractures, compared to the commonly used single-fractal and statistical distributions.

Key-Words: - Petroleum Engineering, Naturally fractured reservoir, Discrete fracture network, Stochastic simulation, Fractal, Discrete Multifractal, Neural network.

1 Introduction

Naturally fractured reservoirs (NFR) have recently attracted intensive research attention, because the world market is increasingly under pressure to exploit energy from unconventional sources such as naturally fractured oil, gas and hot dry rock reservoirs. Overall NFR modelling involves the description of reservoir boundaries, rock heterogeneity, major faults and medium- to small-scale discrete fracture networks (DFN). Faults and fractures descriptions include both fluid flow as well as geometric properties. Comprehensive models of a NFR allow us select the best well locations, study the response of natural fractures under stimulation pressure, design optimum development plan and evaluate reservoir potential.

This paper reviews important aspects of NFR modelling, including fracture characterisation and spatial simulation. Subsequently, it presents an innovative combination of artificial neural network and discrete fractal mathematics for DFN modelling.

2 NFR Modelling: a Brief Review

Natural fractures 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 geological stresses, 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 deformational events, which eventually result in very complicated fracture systems [1]. In addition, characterization of fracture information from conventional field data represents another major problem. Different field data sources cover different scales (microscopic to regional) and are of different resolutions. No single tool can provide all information needed to fully characterize a NFR. Moreover, no single tool can provide all information needed to fully characterise a NFR. For example, seismic and outcrop are regional-scaled data sources, whose interpretation can only reveal orientation and size of major faults. Well log, core and formation micro scanner (FMS) image have high resolutions but small investigation radii. They reveal orientation, aperture and density of local fractures [2, 3]. Thus, in order to portray a complete picture, it is essential to develop a model that allows efficient integration of field fracture data. The integrated reservoir modelling should consist of computational tools and methods that utilise simultaneously, or sequentially, various data sources, representing different reservoir characteristics at different scales. This can reduce uncertainties, reproducing all observed reservoir fracture characteristics [3].

Several integrated techniques to characterize and model NFR are available in literature, for example, stochastic simulation [4-6], neural network and fuzzy logics [7] and other artificial intelligence tools [8, 9]. Although the integrated techniques could accommodate multiple data sources, cover various modelling scales, many problems remain. First, previous discrete stochastic simulations are only reliable in near wellbore regions, and the unconditioned random filling of inter-well regions limits their uses beyond the near wellbore regions. Second, interactive models [5] require very intensive manual interaction, especially for analysing data and understanding fracture behaviours. This limits their applications to typical NFR, which usually contain many fractures of various scales and heterogeneously distributed. Third, most of the previous artificial intelligent models are continuum (grid-based), whose outputs are maps of fracture intensity or similar fracture index. These models fail to take into account details of fracture properties such as orientation and size. Despite taking into account the overall effect of fracture network upon fluid flow in the reservoir, the methods did not require generation and treatment of discrete fractures. Moreover, in cases where discrete fracture properties are considered, only simple statistical measurements (e.g. histogram, variogram, normal and log-normal distributions) are used regardless of the actual fracture behaviours. These limitations are the main reasons why progress of NFR modelling has so far been inadequate.

3 Methodology

In this paper, the concept of stochastic simulation and neural networks (NN) will be further developed and used, in a hybrid manner such that the previously mentioned problems could be overcome. The aim of the first module of NN analysis is to develop statistical distributions of key fracture properties (location, orientation and size). The distributions could be either parametric or non-parametric, which are used in the second module of fractal stochastic simulation. Main features of this process are described in the following sections.

3.1 Data sources

Due to complex nature of NFR, different tools and disciplines need to be integrated to fully characterize the fracture properties. There are two main types of data sources about characteristics of fractures present in NFR.

The first group includes seismic, outcrop and other geological sources, which have been 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, thickness, lithology and curvature of various formations. These factors are directly related to several fracture characteristics, such as fracture length, spacing, orientation, density [7]. 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 [10]. Outcrops data also describe various fracture characteristics, such as orientation, size and spacing, at sub-seismic scale [4].

The other group contains the data available at the well sites, such as logs, core, drilling and well testing. Among the most efficient logging tools for fracture characterization are dip meter (giving fracture orientation), borehole televiewer, formation micro scanner and core. They allow determination of fracture properties such as dip, strike, aperture, density and fractal dimension (via the box counting method) [7]. Wellbore data are of higher resolution (fraction of an inch) and more related to small scale fractures than the seismic and outcrop data.

3.2 Neural network characterization

Different data sources reveal different aspects of the fracture system and are of different scales. The inter-relationships between different data types and their relevance on fracture characterization are very complicated. Problem arises when secondary parameters (fractal measurement, fracture density) are computed, where an integration of several data sources is required. NN is hence used to incorporate the available data to characterize the complex relationships that might exist between them and the fracture parameters. A NN is capable of integrating different data sources of different nature to delineate the required relationships [11].

Back-propagation NN uses 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 [11]. In other words, NN can learn from experience. The NN is a supervised learning technique, which can learn almost any functions regardless of noise in the data or the complexity of their relationships. The NN 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. Fig.1 shows the sketch model of a NN. 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). The NN technique is applied in computing distribution of the two key fracture properties: fracture density and fractal dimensions.

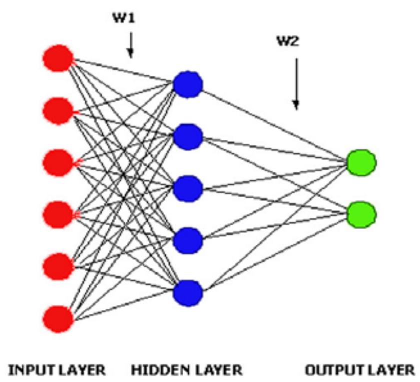

Fig. 1- Three-layer NN with 5 hidden neurons used in this study. W1 and W2 are the two sets of weighting factors.

3.3 Fracture density distribution

Density is defined as mean fracture area per unit volume. It is one of the most important fracture characteristics, being directly proportional to the total number of fractures, their relative size and distribution. It is an improved version of intensity, which refers to mean number of fractures per unit volume. Density takes into account the different roles that big and small fractures have. Fracture density map quantifies degree of fracture clustering and represents true measurement on spatial point pattern (random, regular, clustered or mixed).

Due to its importance, both characterisation and simulation of fracture density are desired in NFR modelling. Nevertheless, previous works did not present these steps satisfactorily. Firstly, most works involved only fracture intensity, whose map can reveals just certain patterns of centre points [6, 12]. Secondly, the characterisations employed simple methods such as least squared errors, kernel and kriging. The predictions of density or intensity values from well data over the field were made by pure mathematical estimations [13]. They could be greatly improved by incorporating variations in physical conditions such as rock strength and lithological contents. Finally, grid-based models stopped at output fracture intensity maps. On the other hand, due to mathematical intricacy, most of discrete models neglected density or intensity distribution data.

In this work, fracture density values are first calculated directly from fracture data at wellbores (e.g. wellbore images and core). They are then used as NN training data. Density distribution map is subsequently determined from the NN outputs. The resulting density map is expected to be more reliable compared to results of previous methods.

3.4 Discrete multifractal

There are not many data sources for characterisation of 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 geometrical study of many complex non-Euclidean shapes found in nature. It has been proved especially suitable for natural discontinuities such as fractures [14]. Fractal is a fundamental concept in the field of theoretical geometry. It describes features that appear self-similar under varying degrees of magnification. The invariant self-similarity can be portrayed by a single quantity of fractal dimension (D) [15]. The fractal dimension is a function of strength, tectonic history and lithology of the fractured rock mass. It is related to number of fractures (N_r), whose radii greater than a radius value (r):

$$N_r = \frac{C}{r^D} \tag{1}$$

where C is a proportional constant. Value of fractal dimension can be easily evaluated by the graphical box-counting analysis on core, wellbore images, outcrop and seismic data [14].

Although a large number of investigations validated fractal characteristics of a DFN, many others disagreed [16]. It has been argued that several self-similarity ranges exist in complicated networks of micro scaled and regional scaled fractures. Several investigators used the box-counting method to realise that fractal property of a DFN is scale-variant. Thus, single fractal dimension is not always sufficient to explain natural fractures over a significant range of scales. Due to the irregularities, multifractal analysis is more suitable.

In broad terms, objects with more than one fractal dimensions are multifractal. In other words, multifractal objects contain a union of subsets, with separate scaling exponents. There are two approaches for extension from single fractal to multifractal. One is to introduce new parameters to account for spatial intertwines of fractal dimensions. Fractal dimension is generalised by continuous fractal spectrum. Most of existing multifractal models employ this approach [17]. The other approach uses discrete multifractal, where a set of different fractal dimensions (i.e. array of limited values, instead of continuous spectrum) account for all ranges of self-similarity.

Continuous multifractal spectrum

Application of multifractal analysis is examined on a 2D DFN (Fig.2). The network is divided into boxes with linear size (l) and $N(l)$ is the number of boxes that intersect or contain fractures. Values of fractal dimensions, as derived from eq. 1:

$$\alpha = D(l) = -\frac{\log N(l)}{\log l} \qquad (2)$$

where α is called the coarse Holder exponent [18].

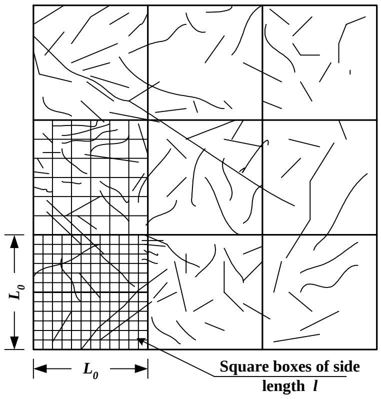

Fig. 2- Box-counting method for a DFN

Define $N(l,\alpha)$ as the number of boxes of size (l) having coarse Holder exponent (α). The probability of a cell corresponding to value α is:

$$P(l,\alpha) = C \cdot N(l,\alpha) \cdot l^2 \qquad (3)$$

where C is a constant. By considering the limit $l \rightarrow 0$, the continuous fractal dimension ($f(\alpha)$) [18] and co-dimension ($c(\alpha)$) spectra [17] are defined as:

$$f(\alpha) = \lim_{l \to 0}\left[-\frac{\log N(l,\alpha)}{\log l}\right] \qquad (4)$$

$$c(\alpha) = \lim_{l \to 0}\left[\frac{\log P(l,\alpha)}{\log l}\right] \qquad (5)$$

Multifractal can be represented by either of the two. In case of mono fractal, the limit $f(\alpha)$ converges to the single fractal dimension value. The continuous multifractal can be evaluated using the box-counting procedure and eqs. 4 and 5.

Discrete multifractal

Alternatively, the discrete multifractal model is used. Discrete values of the coarse Holder exponent (α_k) (k = 1,…, m) corresponds to m discrete values of $f(\alpha_k)$:

$$f(\alpha_k) = \lim_{l \to 0}\left[-\frac{\log N(l,\alpha_k)}{\log l}\right], \qquad k = 1,...,m \qquad (6)$$

Discrete multifractal values can be calculated based on the moment method as in Cheng [19]. According to the author, discrete multifractal exists and can be used in many fields of science.

It could be observed that multifractal analysis is desired for DFN characterisation. When there are sufficient representative data, both continuous multifractal dimension function and discrete multifractal values can be accurately determined, based on methods described above. However, it is usually not the case. Limited data include a few major faults from seismic maps, local 2D network map from outcrops and small-scaled fractures from cores and wellbore images. Thus, even though it is likely that multifractal exists, its characterisation is difficult. This is the reason for the popularity of single fractal in fracture literature, although it is unrealistic. In this work introduces the combination of a NN and multifractal dimension mathematics to effectively study natural fracture spatial distribution. First, discrete fractal dimensions are calculated at different ranges of available data. Graphical box-counting method is routinely applied. Then, a NN integrates other data sources to predict values of fractal dimensions at all scales and locations. This procedure is not analogous to conventional interpolation and extrapolation method as kriging. When predicting dimension value for a point (region) in the field, the result depends on not only geographical locations but also geological, lithological, seismic and/or well log responses. Due to the lack of representative data, a great deal of predictive modelling is involved. As a result, despite popularity of continuous multifractal, discrete multifractal is believed to be more suitable for fracture characterisation and modelling.

3.5 Spatial simulation of fracture network

Having reservoir distributions of fracture density and discrete multifractal dimensions, we simulate the NFR using a geological stochastic modelling technique. The reservoir is divided into grids, each grid a cubic block of edge length L. Within this rock mass, the centres of penny-shaped (circular) fractures are generated stochastically. The radii of randomly distributed fractures are then defined as:

$$r_\alpha = \left\{(1-\alpha) r_{\min}^{-D} + \alpha r_{\max}^{-D}\right\}^{-1/D} \qquad (7)$$

in which, 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 value at the grid's centre. Eq. 7 is executed repeatedly with different values of α until the target fracture density distribution is achieved.

4 Case Study

A case study is used to demonstrate capability of the proposed model. First, the fracture density and discrete multifractal dimension for simulating blocks in the reservoir are estimated by a NN. Input data are seismic velocity, amplitude and lithology index. They are chose among the previously mentioned data sources, as they are widely available, reliable and of high resolution. The data are available for the whole reservoir (e.g. Fig.3).

The training data for the NN are composed of the above set of input data, fractal dimension and fracture density at the wellbore. Through the training, the NN establishes complex relationships between these parameters. Using these relationships, the model generates the distribution of fractal dimension and fracture density in the whole reservoir (Figs.4 and 5). The NN analysis has very high reliability, with the matching (between output and input values) correlation being very close to 1. Moreover, by analysing the weighting factor sets W1 and W2, one can also understand the effects of different inputs on the two outputs. Table 1 confirms the relevance of three chosen inputs, with lithology index is the most dominant factor while seismic amplitude is the least.

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

The fracture orientation distribution contains dip, azimuth and the probability that occurs (weighting). It is obtained from fracture outcrops, measurements on core or borehole images logging and seismic profile. The reservoir fractures are divided into four different classes, based on the distinction in their geological, lithological and physical (including fractal) properties. The 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 data are also computed directly from the same sources as fracture orientation. Output of simulation is the reservoir's detailed and realistic DFN (Fig.6).

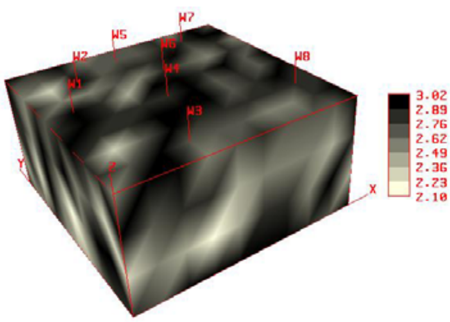

Fig.3- Seismic velocity 3D data (m/s). W1 to W8 show the locations of existing wells.

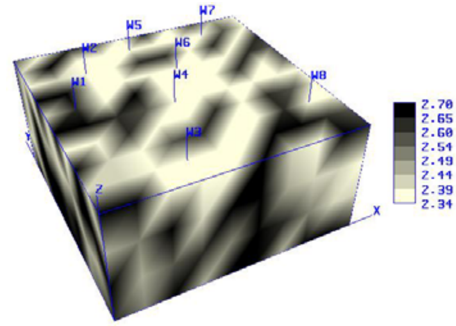

Fig.4- Characterized 3D Fractal dimension.

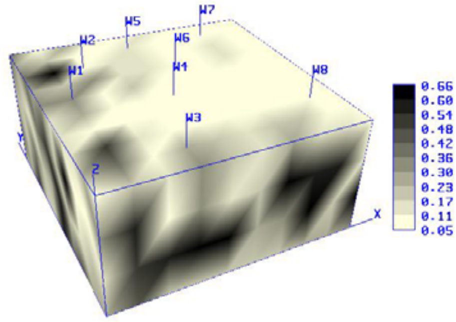

Fig.5- Characterised 3D fracture density (m2/m3).

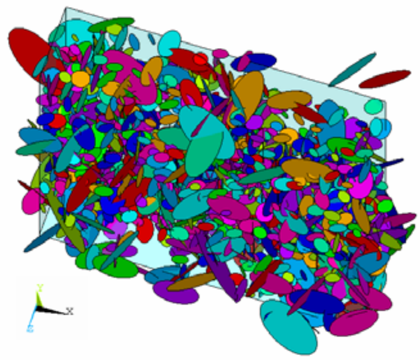

Fig.6- Result DFN (Medium scaled fractures).

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

5 Discussion

The introduction of discrete multifractal and NN to NFR characterisation and modelling denotes a number of important advantages. First, multifractal is a powerful tool that has been used in various fields of science for self-similarity characterisation. It can distinguish patterns in the spatial distribution of geological features [19]. Multifractal is especially suitable for natural fractures. By using multifractal to represent the fracture length distribution, inconsistent and inaccurate probability density functions can be avoided. Thus, characterisation of fracture size becomes a great deal more informative, flexible and representative. Besides, together with fracture density, multifractal signifies relationships between the number of fractures, their size and spatial distribution. Second, NN allows consistent computation of discrete multifractal dimensions over the whole reservoir. Consequently, unlike its continuous form, discrete multifractal can now be applied into the modelling process.

6 Conclusion

In conclusion, an intelligent efficient method has been developed to extrapolate well data throughout the whole reservoir and to derive important parameters (discrete multifractal, fracture density) for DFN modelling. This paper has shown how data from different sources can be processed by combination of different techniques to derive more realistic natural fracture characteristics. The integration of data from different sources and NN, fractal analysis and stochastic analysis techniques has yielded a hybrid neuro-fractal-stochastic model for NFR modelling. It could also be noted that the modelling process can be repeated throughout the field life, as more and more data become available.

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