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Practical application of fuzzy logic and neural networks to fractured reservoir characterization

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Abstract

Until recently most fractured-reservoir modeling tools were limited to simple discrete statistical models. A new approach in fractured-reservoir characterization which uses artificial intelligence tools is described in this paper. The methodology is based on the assumption that there is a complex relationship between a large number of potential geologic drivers and fractures. Structure, bed thickness and lithology are a few of the drivers that played a role when fractures where created.

The first step in the described methodology is the ranking of all existing geologic drivers. A fuzzy neural network is used to evaluate the hierarchical effect of each geologic driver on the fractures. As a result, the geologist or reservoir engineer will be able to identify locally and globally the key geologic drivers affecting fractures.

The second step of the approach is to create a set of stochastic models using a backpropagation neural network that will try to quantify the underlying complex relationship that may exist between key geologic drivers and fracture intensity. The training and testing of the neural network is accomplished using existing data.

The third step of the approach is to perform an uncertainty analysis by examining the fracture cumulative distribution function resulting from the large number of stochastic models. Using these three steps, the 2D or 3D distribution fractures and their underlying uncertainty can be determined at undrilled locations. The methodology is illustrated with an actual tight gas fractured sandstone.

Keywords: Fractures; Reservoir modeling; Petroleum reservoirs; Neural networks; Fuzzy logic

1. Introduction

Naturally fractured reservoirs represent a significant percentage of oil and gas reservoirs throughout the world. Because of their complexity and commercial significance, naturally fractured reservoirs have been extensively studied. Many of these efforts have been devoted to understanding the various factors affecting rock fracturing. There have been numerous approaches used to estimate the spatial distribution of fractures within individual horizons, based on structural geometry (Harris et al., 1960; Murray, 1968; Lisle, 1994). Most of these approaches have been applied to small areas encompassing the scale of a gas or oil field. Although structural effects can be important, it is critical to recognize that there is a complex interplay between the fracture drivers. For example, in a slope basin carbonate oil reservoir described in Zellou et al. (1995), the increase in formation thickness and amount

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of shale negated the fracturing effect of high curvature at certain locations of the reservoir. However, in other settings, formation thickness and/or lithology can be the major factors behind natural fracturing. Since structure, pay thickness, and lithology are but three of many potential fracture drivers that can vary dramatically, especially in a regional setting, it is imperative to identify the primary geologic drivers. Only then can a comprehensive fracture prediction model be generated.

2. Factors affecting rock fracturing

Local and regional tectonic events are recognized to play a major role in many fractured reservoirs. The knowledge of the magnitude, timing, and distribution of these stresses could lead to an improved characterization of fractures. Unfortunately, the geomechanical history of the rocks is elusive and often speculative. In addition, factors such as rock thickness, heterogeneity, and lithology can also play substantial roles in natural fracture development. Due to the complexity of fracture characterization, the most frequently applied approaches rely on one or possibly two reservoir and/or structural characteristics.

Reservoir structure can be obtained easily using petrophysical logs and an interpolation mapping method. The popular use of structure is related to the fact that the paleostresses are, to some extent, revealed by present day curvature. Hence, given current structure, one can infer the magnitude of paleostresses and gain some insight into the degree of fracturing. Second derivative (curvature) techniques to approximate fracturing have been successfully employed, to various degrees, for more than three decades. However, this structural attribute approach assumes that other factors affecting rock fracturing are either relatively constant, or possibly secondary to, curvature in importance.

Although only one parameter may be needed to characterize a fractured reservoir, as has been documented on a local scale numerous times (Harris et al., 1960; Murray, 1968; Lisle, 1994; McQuillan, 1973), complex reservoirs may require a much more robust description to predict. When numerous factors are "maximized" and considered together, such as a structure with high curvatures, thin beds, and brittle lithology (e.g. dolomite, silica-cemented sandstone), it is relatively straight forward to predict a likely result — abundant natural fracturing! Conversely, minimal curvature involving thick beds and a ductile lithology (e.g. shale, limestone) could be considered, as a first approximation, relatively fracture-free. Since natural fracture drivers occur as continua in the "maximum–minimum" scale and in infinite numbers of combinations, the identification and integration of multiple, variously weighted fracture drivers (such as thickness, lithology, and curvature) would be the ideal model construction methodology. Therefore, a comprehensive analysis will result in the most robust model. From published work on fractured reservoirs, it is clear that the lack of a methodology to integrate the effects of structure, thickness, and lithology has led many researchers to focus only on the most important factor.

3. Building a fractured geologic model

There are many different techniques to build quantitative geologic models. For example, geostatistics is frequently used in conventional reservoirs to build geologic models that account for existing spatial correlations of a given reservoir property. These techniques are inadequate when it comes to understanding complex fractured reservoirs. In such problems, the simultaneous existence of different fracture systems at different scales and their mutual interaction leads to a complex 3D flow network with little or no spatial correlations. Although each individual fracture system may present some spatial correlation, the obscure and intricate interaction between the different fracture networks often leads to an uncorrelated 3D flow network. To address such problems, computer programs such as NAPSAC (Hartley et al., 1996) and FracMan (Dershowitz et al., 1994) used Discrete Fracture Networks (DFN) representation to model fractured reservoirs. In the DFN methodology, spatial correlation such as the ones represented in geostatistics by variograms are not used and geologic models are simulated by filling randomly a 3D volume with discrete fracture planes. The filling process is constrained by first-order statistics of different observed fracture attributes and do not take advantage of the underlying relationship that may exist between fractures and geologic drivers.

The approach proposed by Ouenes et al. (1995) and implemented in ResFrac[1] for building continuous fractured geologic models, was inspired from geostatistics, where the use of variograms to account for spatial correlations is replaced by the use of a neural network. The methodology uses the assumption that any set of fractures could be related to a certain number of geologic drivers and/or to static and dynamic field measurements. Hence, constructing a fractured reservoir model becomes an integration problem, where a neural network is used to find the possible underlying relationship that exists between the input of the model (geologic drivers and field observations) and the output of the model called the Fracture Indicator FI. In this

[1] http://www.rc2.com/products/ResFrac.html

approach, the geology of the reservoir is accounted for while building geostatistical 3D models for each geologic driver. Local observations at the well, such as stress measurements, or interpreted seismic 3D cubes could be added as an input to the model and may provide in some circumstances valuable indications and constraints. The use of a neural network does provide the unique opportunity to achieve the integration of geologic drivers and field observations into continuous fractured reservoir models. The implementation of this methodology with a neural network is described below.

4. Modeling the fractures with a neural net

In a fractured reservoir, various geologic, geophysical, and engineering data may be available and used for modeling. For neural net modeling purposes the data can be viewed under two categories: (1) the inputs of the model, and (2) the Fracture Indicator, *FI*, which will be the output. The Fracture Indicator, *FI*, can be any geologic or engineering data available at the wells that could represent the fractures as accurately as possible. Fracture Indicators are not limited to static data such as FMI logs but can include dynamic data (Ouenes et al., 1995, 1998) which better represents the effects of fractures on the fluid flow.

The inputs of the model are any geologic, geophysical, or engineering data that may have a possible relationship with the fractures. The input data can be divided into the following three major areas.

1. *Rock Mechanical Properties Indicators*: These data contain indications about the brittleness of the rock and may include data such as porosity, lithology, pore pressure, and grain size.
2. *Paleostress Indicators*: These data contain possible information about the magnitude of stresses that existed when the fracturing occurred. Structure curvatures and slopes, bed thickness, and faults related information are some examples of these indicators.
3. *Stress Indicators*: Although the current state of stress could be different from the one that caused the fracturing and therefore totally misleading, seismic information and stress measurements at the wells could in many basins provide valuable information to the model.

The modeling process starts by considering N possible inputs or drivers $(D_i \mid i = 1, 2, \ldots N)$ representing the three major areas described previously. These data collected at the well locations must be mapped as accurately as possible over the entire volume of the reservoir. Geostatistical modeling is highly recommended for this step since it is the best approach to account for the spatial correlation resulting from the deposition process.

The Fracture Indicator *FI* is not mapped and is considered as point values used for the training process. We consider L training records $(FI_j \mid j = 1, 2 \ldots, L)$ for which a value of FI_j is available at a point $P_j(x, y, z)$ in the 3D reservoir volume. Since the N inputs are available in the entire reservoir volume, they are also known at the L positions $P_j(x, y, z)$. Hence, the neural net system of L training records $(D_{il}, FI_j \mid i = 1, 2, \ldots, N;\ j = 1, 2, \ldots, L)$ constitute the basis of the fractured geologic model.

The neural network can be used to find a mathematical model that relates the N inputs, D, to the Fracture Indicator *FI*. In other words, the neural network becomes a multivariate regression tool. However, the advantage of the neural network model over conventional multivariate regression methods is its ability to mimic complex non-linear models without a priori knowledge of the underlying model. The process of determining these mathematical models is described as training. The basic idea is to provide to the neural net L_1 training records (patterns) that will direct the adjustment of the neural net parameters represented by a weight matrix $W_{n_i n_j}$. The reader is referred to neural nets literature (e.g. Lippman, 1987; Wasserman, 1989) for a complete description of these artificial intelligence tools. The following paragraph gives a brief description necessary for understanding the fracture modeling problem. Furthermore, we will address only backpropagation (or "backprop') neural networks used in this application.

The backprop neural net uses a subset L_1 of the L training patterns to adjust the weight matrix, $W_{n_i n_j}$ through training. For the lth training pattern, the N inputs D_{il} are fed-forward from the input layer, through all the hidden layers, and finally the neural net provides its output $FI_l^{nn}(W)$ which is different from the known target output FI_l measured in the field. The training process consists of estimating the weights $W_{n_i n_j}$ that minimize the quadratic error:

$$E(W) = \sum_{l=1}^{L_1} [FI_i - FI_l^{nn}(W)]^2.$$

The error E backpropagates from the output layer to the input layer and is used to adjust the matrix weight $W_{n_i n_j}$. In practice, the training process is monitored using a linear correlation coefficient between the actual and the predicted Fracture Indicator computed on the L_1 values. After successful training, the neural network can be used for testing the subset L_2, of L that were not used for training. $(L_2 = L - L_1)$. The neural network architecture consists of the usual input and output layers and two additional hidden layers. An example of this architecture can be found in Ouenes et al. (1995). For a specific application such as the one considered, the need to change the neural network architecture by adding multiple hidden layers defies the purpose of finding a geologic model. When building a geologic model, the purpose is to find the potential relationship that may exist between the considered drivers, D, and the Fracture Indicator, FI. If such a relationship exists, it will be captured by the neural net architecture composed of two hidden layers. On the other hand, if successful training and testing is not achieved, it is probably better to question the validity of the inputs considered rather than the neural network architecture. In other words, successful use of a neural network requires a careful analysis of the considered inputs prior to neural net modeling.

5. Ranking the model inputs with a fuzzy neural net

When considering N possible drivers, the relative importance of each parameter and the impact on the Fracture Indicator, FI, is critical. Given the L training records, many different techniques could be used to rank the N parameters. The most popular techniques are statistical methods based on principal components analysis. In our methodology, we employ a fuzzy logic approach (Lin, 1994) that has proven efficient and fast in ranking our geologic parameters.

Zadeh's (1965) original idea for fuzzy logic is based on a simple fact: when dealing with a complex system, it is simpler to find a model of the parameters which drive and control the system rather than finding a model for the system itself. The knowledge of these parameters can be expressed by a set of fuzzy rules such as: "if X is A and Y is B, then Z is C", where X and Y are variable outputs of the system, and Z is a command variable that controls the system. A, B, and C are linguistical rules such as *high, normal*, and *low*. For example, if we consider the statement "X is A" to be "the temperature is high", then the usual way of thinking (boolean) would be either the statement is true (1) or false (0). However, in fuzzy logic the statement can be characterized by a "range of truth" from 0 (false) to 1 (true) described by a membership fuzzy function. For a complete discussion on the new mathematical theory of fuzzy sets, the reader is referred to Dubois and Prade (1980). An important feature of fuzzy logic is the ability to use deterministic tools (using fuzzy membership functions) to quantify uncertainty. With this simple and brief introduction of fuzzy logic, we notice that the key point in fuzzy logic is to find the appropriate fuzzy rules. Various approaches were used to obtain the fuzzy rules, and we limit ourselves to the neural net approach (Kosko, 1992; Zadeh, 1992). In this approach, a neural net is trained to represent the fuzzy rules. Notice that the fuzzy neural net described in this section is different from the neural net used for building the geologic model and is specifically designed for ranking the drivers. This promising approach had an important drawback: the training of a backprop neural net was too slow for fuzzy logic applications. Lin (1994) developed a new approach that overcomes all the previous limitations and that is well adapted to ranking problems.

We consider the same problem where the system has N possible inputs ($D_i \mid i = 1, 2 \ldots, N$) and L records of the output, FI ($FI_j \mid j = 1, 2, \ldots, L$). The question to be asked is: what are the significant input variables D_i that have a real impact on the output FI?

The method proposed by Lin (1994) provides a robust way to address this problem. It uses "fuzzy curves" to find a relationship between each of the input variables and an output variable. For each output we built N fuzzy curves that were related to the N inputs, respectively. To build a fuzzy curve for input i with respect to the output FI, the L pairs (D_{il}, $FI_j \mid= 1, 2, \ldots, L$) of the training data were used. We first put all L data points in the ($D_i - FI_j$) space. We applied a fuzzy rule to each point in the space, and we had L fuzzy rules for the L points. Each of these fuzzy rules was represented as "if (D_i is μ_{il}) then (FI_j is FI_{jl})" where (μ_{il}) is the lth fuzzy membership function of input D_i, and calculated as:

$$\mu_{il}(D_i) = \exp\left[-\left(\frac{D_i - D_{ij}}{b}\right)^2\right]$$

where b is a constant of about 1/10 of the input interval of D_i . Then the fuzzy curve of D_i with respect to FI_j noted as ($D_i - C_{ij}$), was obtained by defuzzifying the L fuzzy rules using centroid defuzzification:

$$C_{ij}(D_i) = \frac{\sum_{l=1}^{L} FI_{jl} \times \mu_{il}(D_i)}{\sum_{l=1}^{L} \mu_{il}(D_i)}.$$

We decided on the significance of the input D_i with respect to the output, FI in the following way. If the fuzzy curve for the given input was flat, then this input had little influence in the output data and was not a significant input. If the range of a fuzzy curve $C_{ij}(D_i)$ was about the range of the output data FI, then the input candidate D_i was important to the output variable FI. We ranked the importance of the input variables D_i with respect to FI according to the range covered by their fuzzy curves $C_{ij}(D_i)$. This fuzzy logic approach provided the hierarchical order of the inputs D_i based on their significance.

In practice, the ranking of the inputs must be accomplished prior to any neural net modeling. Two major benefits can be derived from this task. The first benefit is the gained geologic understanding of the impact each model input or driver has on the fractures. The second one is purely computational and it consists of identifying possible geologic drivers or field measurements that may not have a strong correlation with fractures. Including these input into the neural net model will only reduce the reliability of the generated models.

Although this ranking is a necessary step in creating reliable geologic models with reasonable prediction capabilities, one must remember that the neural net approach is data driven. Therefore, the modeling effort must be considered in a stochastic framework where multiple realizations of the geologic model are generated. The use of a neural network is suitable for stochastic modeling where each realization could be obtained by using a limited subset of the available Fracture Indicator data for training. From the multiple realizations, probability maps may be drawn and used for further modeling and for decision making. The entire methodology is illustrated with a tight gas sandstone reservoir.

6. Dakota production and geology

The San Juan Basin of northwestern New Mexico contains some of the largest gas fields in the United States. Gas is produced from three Upper Cretaceous sandstone formations: the Dakota, Mesaverde, and Pictured Cliffs as well as from the Fruitland coal. Fassett (1991) suggested that the gas produced from the Dakota, Mesaverde, and Pictured Cliffs reservoirs are structurally enhanced by natural fracturing. Unfortunately, little has been published on the subsurface pattern of these fractures.

In excess of 4.8 trillion cubic feet (TCF) of gas (135.9 billion m^3), as well as substantial volumes of condensate, have been produced from three primary sandstone complexes that comprise the upper Dakota formation. This production is largely from the Basin Dakota field located in the south-central part of the San Juan Basin. The productive upper Dakota sandstones are a complex of marine and fluvial-marine sandstone reservoirs. The upper Dakota is a tight gas reservoir with porosity generally between 5 and 10% and permeability ranging from less than 0.1 to 0.25 millidarcies. Consequently, these Dakota reservoirs generally cannot produce commercial flow rates without natural or induced fracturing.

The key for optimal exploration and exploitation of upper Dakota reservoirs resides in the ability to predict the spatial distribution of fracture intensity. However, when considering a productive interval in excess of 200 feet (60 m) covering over 120 townships (4300 square miles — 11,128 km^2) the use of simple analysis tools focused on one or two fracture parameters, such as second derivative structural curvature, will not result in a comprehensive understanding of the spatial distribution of fracture intensity. Hence, numerous fracture drivers must be characterized and integrated into the analysis.

7. Factors affecting fracturing in the Dakota

The study area representing the 24 townships (869.5 square miles — 2251 km^2), has been divided in grid blocks which are 0.5×0.5 miles (0.8×0.8 km). A total number of 3478 grid blocks are used across the area. For each fracturing factor, a two dimensional map is drawn over the entire grid.

The structure of the Dakota is computed using Graneros log top in 2108 wells and the Laplacian interpolation method (Ouenes et al., 1995). The same interpolation method is used to draw the estimated ultimate recovery (EUR) map using 1304 "parent" wells drilled on 320 acres, spacing. The EURs vary from 0.1 to 14.7 BCF (2.83–416.1 million m^3) and four major, highly productive "sweetspots" are present in the eastern as well as in western parts of the study area. Extensive geological and engineering analysis of the Dakota formation by Burlington Resources has established that the primary driver to reservoir performance is the degree of natural fracturing. The EUR is considered to be a measure of fracture density. The gas is produced from three major sands (horizons) that make the upper Dakota.

In many previous studies, structural effects were accounted for using curvatures taken in one or two directions. Ouenes et al. (1995) introduced the use of curvatures (second derivatives) and first derivatives of the structure in multiple directions, which better reflect stress states which can be described by a tensor that has directional properties. Another reason for the use of multiple directions is that structural effects could have different directions over the study area. Therefore, in each gridblock, structural effects are represented by a set of four curvatures and slopes computed in four directions, north-south, east-west, northeast-southwest, northwest-southeast. In addition to these structural effects, this study considered the thickness and degree of "shaliness" as parameters driving Dakota natural fracturing.

The upper Dakota is composed of three major productive sandstone units which, in ascending order, will be referenced as Sands A, B, and C respectively. The three gross pay isopach maps of these sands show significant pay thickness variation across the 24-township area. This thickness variation dramatically impacts the intensity of natural fracture development and is considered in the analysis.

As previously discussed, EUR from these three sand complexes is used as a fracture intensity indicator. This analysis was prompted by the results of a previous fracture prediction study in the San Juan Basin Mesaverde formation (Basinski et al., 1997). In addition to pay thickness, facies maps are needed to delineate the third fracturing factor, lithology.

Whole core analysis indicates a very strong correlation between resistivity and fractures. In the study area, resistivity, as a rule, is a function of facies and not hydrocarbon saturation. A detailed explanation of this correlation can be found in Lorenz et al. (1999). Highly resistive intervals represent a facies with minimal clay content that were subsequently diagenetically silicified and rendered brittle. Consequently, where resistivity is high, abundant natural fractures are developed in the core. Although resistivity may not be the ideal lithology indicator, in this study area, it contains valuable information about the facies changes and degree of fracturing in Sands A and B. In this study, the average pay thickness and resistivity for Sands A, B, and C over the entire net pay is used. These data are mapped using information from fewer than 200 wells in the 24-township study area.

At each gridblock, 13 possible parameters, which may have played a role in rock fracturing are used as inputs for the neural network analysis: four first derivatives (slopes); four second derivatives (curvatures); three thicknesses; and two resistivities. These reservoir properties are easy to derive and are adequate to characterize the reservoir fracture intensity. For any set of chosen reservoir properties, the objective is to design a geological model that can explain the observed production data. In exploration areas, the structural properties and thicknesses could be estimated from 3-D seismic travel time data, as illustrated by Zellou et al. (1995) for the Spraberry.

8. Ranking the Dakota fracturing factors

When considering the entire study area, the fuzzy logic ranking reveals that the six most important factors are: (1) the thickness of Sand B; (2) the inverse thickness of Sand A; (3) the thickness of Sand C; (4) the resistivity of Sand B; (5) the first derivative in the northwest-southeast direction; and (6) the Sand A resistivity.

The most important factor, thickness of Sand B, suggests that a large portion of gas produced is from the Sand B and thicker reservoir equates to higher EUR. Consequently, Sand B behaves more like a conventional gas reservoir in this ranking where the production is mostly controlled by original gas-in-place. The inverse thickness of Sand A implies a typical fractured sand behavior where the thinner intervals contain the highest fracture intensity. Thickness of Sand C, the third most important parameter, indicates an analogous relationship to Sand B. Very significantly, the first bit of structural information, the northwest–southeast orientation of the first derivative, or slope of the structure, is ranked fifth and illustrates that structural changes are not the main fracturing factors for the entire study area. However, this orientation is consistent with the long axis of the basin and parallel with

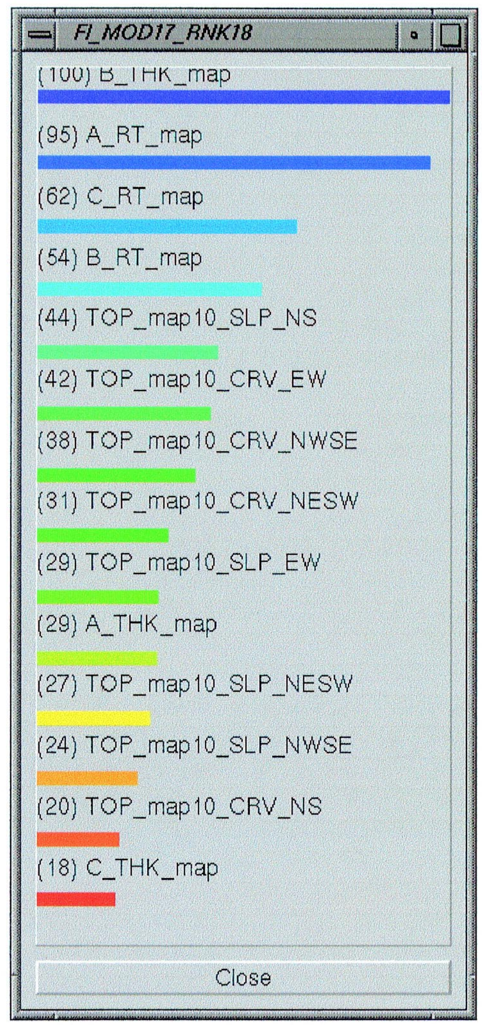

Fig. 1. Ranking geologic drivers. Ranking scale is from 0 to 100. In this example thickness of sand B is highest ranked driver, followed by resistivities of Sand A, B, and C. First structural driver is slope in north–south direction.

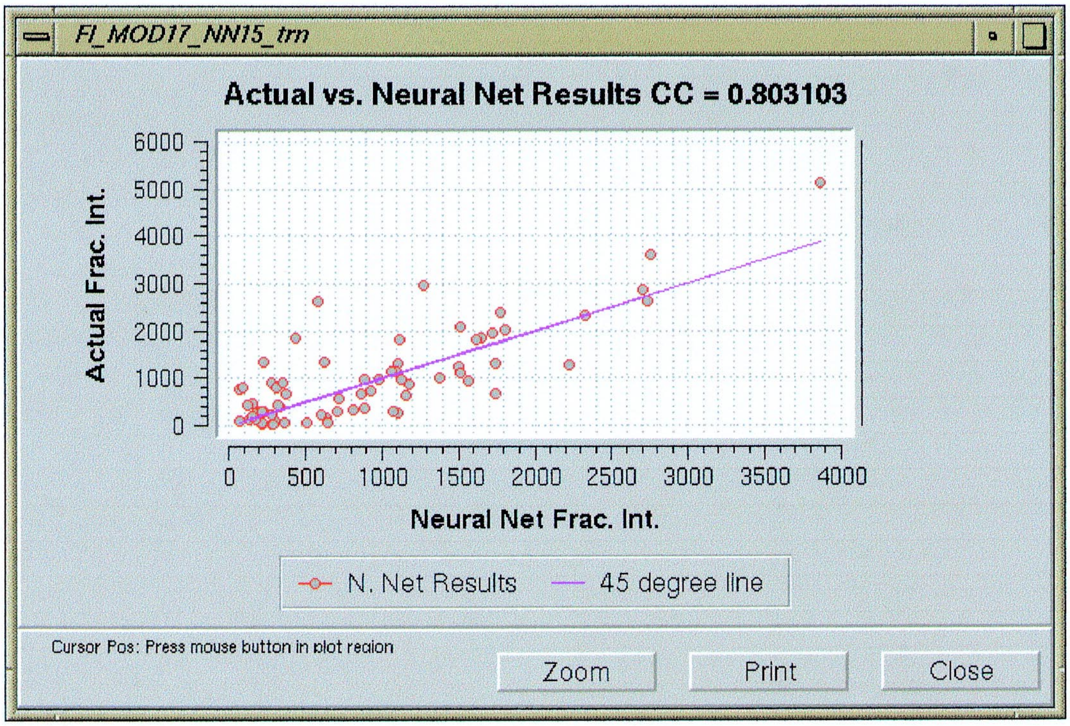

Fig. 2. Training on 30% of available data.

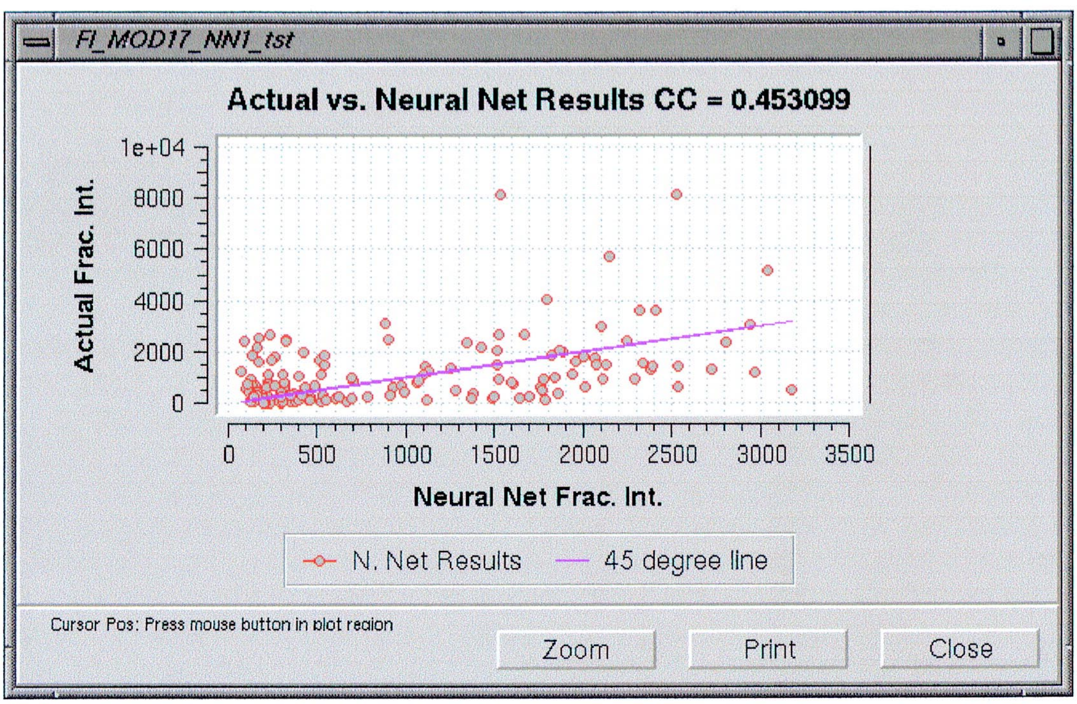

Fig. 3. Testing remaining 70% of data with derived neural network model.

many Dakota producing trends, demonstrates that structural changes cannot be neglected in fracture analysis. The same approach can be used on a portion of the study area to identify the local geologic drivers. Depending on the location of the sub-area considered, the ranking can change (Fig. 1) indicating a change of geologic conditions that cause rock fracturing.

The first, second derivative parameter, or curvature, in the ranking is seventh in overall importance and illustrates that structural changes can sometimes be better represented by slopes rather than curvatures. Armed with this knowledge, a geologic model is built to relate all the 13 factors to EUR. Indeed, this ranking was confirmed for the various productive sands after the parameters were empirically tied back to core analysis, petrophysics, and production.

9. Neural network models

The neural network is an "*equation maker*" or a "*complex regression analysis*" that combines several reservoir properties (the inputs), the curvatures in multiple directions, the thicknesses, and resistivities, in this case, to correlate with the Fracture Indicator (the output *FI*), being EUR in this study. The neural network is trained using a set of wells where both the inputs and the output are known to find the relation, or the "*equation*", between the inputs and the output. Once this relation is found, the neural network uses only the inputs, in this instance the structural information, thicknesses of each sand, and the resistivities of Sands A and B, to predict the production performance, EUR.

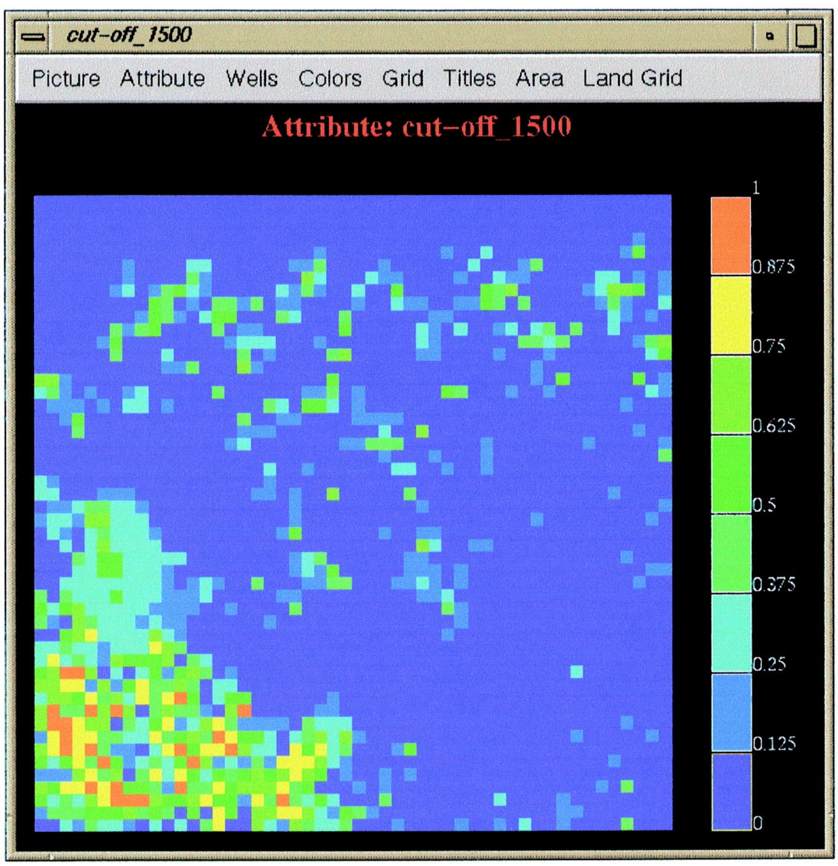

Fig. 4. Color map showing probability to have Fracture Indicator higher than 1500 MMCF. Map was generated using 10 neural network realizations with testing correlation coefficient higher than 0.45.

The neural network inputs for this study are the first and second structural derivatives in four directions, the thickness of sand B and C, the inverse thickness of sand, and the resistivity of Sands A and B; the network output was the EUR of the "parent" wells. The 24 township area encompasses 1304 "parent" wells and the intensity of the fracturing is represented by the EUR of these wells. The level of confidence in these EURs is high: most of the "parent" wells have over 40 years of production history. Only the "parent" well EUR was used to represent reservoir fracture intensity because "infill" wells are somewhat depleted in highly fractured areas.

Many geologic models are constructed using a limited number of training wells representing no more than 30% of the available training set. All the models have been trained with a correlation coefficient equal to or higher than 0.8 (Fig. 2). Using the derived weight matrix, 70% of the data could be tested and a correlation coefficient derived. Most of the derived models have a testing correlation coefficient exceeding 0.45 (Fig. 3). This indicates that despite the complexity of the problem, the neural net was able to capture the underlying relationship that exists between the considered drivers and the Fracture Indicator. Using all the generated realizations, a probability map (Fig. 4) quantifying the chance of drilling a well with an EUR higher than a certain economic limit was drawn and used for selecting potential drilling locations. The actual drilling of many wells using this technique has proven reliable and able to locate accurately the fractures which guarantee successful wells.

10. Conclusions

The extensive application of neural networks and fuzzy logic to fractured reservoir modeling indicates that:

1. A neural network can be successfully used to integrate various geologic, geophysical, and reservoir engineering data into continuous fractured reservoir models.
2. The careful use of robust ranking techniques such as the fuzzy logic method and the use of a stochastic framework can minimize the common pitfalls of data driven approaches and assist the process interpretation.
3. Complex fractured reservoirs with multiple sets of fractures, such as the ones found in the Dakota formation, were modeled accurately with the described artificial intelligence tools.

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