Quarterly Technical Progress Report
04/01/97 - 06/30/97
15th Quarter of the Project

Increased Oil Production And Reserves From Improved Completion Techniques In The Bluebell Field, Uinta Basin, Utah

Contract DE-FC22-92BC14953

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Objectives

The objective of this project is to increase oil production and reserves in the Uinta Basin by demonstrating improved completion techniques. Low productivity of Uinta Basin wells is caused by gross production intervals of several thousand feet that contain perforated thief zones, water-bearing zones, and unperforated oil-bearing intervals. Geologic and engineering characterization and computer simulation of the Green River and Wasatch Formations in the Bluebell field will determine reservoir heterogeneities related to fractures and depositional trends. This will be followed by drilling and recompletion of several wells to demonstrate improved completion techniques based on the reservoir characterization. Transfer of the project results will be an ongoing component of the project.

SUMMARY OF TECHNICAL PROGRESS

Characterization of Fracture Property Distributions

Introduction

Fractures control flow in a reservoir to a large extent. It is important to quantify fracture property distributions, reservoir wide. Fracture frequency is one of the most important properties. Distributions of fracture frequency depends on the stress distributions and on rock types among other things. A novel approach based on geostatistical principles was used to generate fracture density distributions. Fracture density distributions were generated by using not only spatial distributions of fracture frequency but also by taking into account the dependence of frequency distributions on rock types. The fracture frequency data generated using this approach was compared to other stochastic approaches.

Fracture characterization methods

Fracture frequencies over a certain spatial domain have been generated using several different techniques. Some of the most common methods are the: (1) Monte Carlo approach, (2) geostatistical approach, (3) fractal approach, and (4) process imitating approaches. The first three approaches were based on statistical principles. The generated networks were not conditioned to observed property values. Some of the fracture networks are generated using information about stress fields. Reservoir-wide stress distributions are difficult to measure. Most of these approaches have been used to generate fracture networks in two dimensions though some have extended the application to three dimensions. In all cases, extensive fracture characterization data was available. Another feature of these methods is that the area of study was small (100 to 10,000 m^2).

In petroleum reservoir engineering, the scale of study is often larger in comparison to that used in generating networks using the first three approaches. Even after generation of fracture networks, integration of the fracture properties in reservoir models will be another practical challenge. Often times additional conditioning data are available which can be used to fracture properties distributions. Detailed analysis of the core data from the Bluebell field linked fracture frequency at different locations to rock types. This dependence of fracture frequency on rock types was used as soft conditioning data when generating frequency distributions over the entire study area. This was accomplished using the Markov-Bayes method.

Markov - Bayes method: Simulation methods based on Gaussian models provide estimates of the unknown values. On the other hand, indicator-based methods provide probability density functions of different categories at a location. These probabilistic estimates can be improved by taking into account secondary or soft data. The integration is performed through Bayes rule of conditional probability.

Bayes rule states that if a random variable y is being conditioned using the value of another random variable x, the joint probability of (x,y) is proportional to the conditional probability of y given the occurrence of x, p(y|x). From this proportionality we can write:

$$p(x,y) = p(y)p(x|y) = p(x)p(y|x) \qquad (1)$$

Equation 1 can also be written as,

$$p(y|x) = \frac{p(y)p(x|y)}{p(x)} \qquad (2)$$

Equation 2 results in,

$$p(y|x) \propto p(x)p(x|y) \qquad (3)$$

Equation 3 is one form of the Bayes Theorem of conditional probability.

The cumulative distribution function (cdf) of y is known *apriori*. In addition, n observations of a second variable x, (x_1,…..,x_n) are also available. The probability distribution of x is dependent on the unknown values of y. The conditional cdf of x based on y is a function of x for fixed y. With the likelihood principle, the conditional cdf can be considered a function of y at fixed x. Bayes' Theorem says that the posterior cdf of y, p(y | x), which takes into account all the known data, is proportional to the prior cdf of y, p(y) multiplied by the likelihood function p(x | y). In other words:

$$\text{Posterior cdf} \propto (\text{Prior cdf x likelihood function.}) \qquad (4)$$

The relationship above summarizes Bayes rule.

Soft conditioning using Bayes Theorem: Suppose sampling at a study site has resulted in m values of primary variable (u) and n values of secondary variable (v). The unknown values of u can be inferred from the posterior cdf of u. The posterior cdf is conditioned to available data.

$$\mathrm{Prob}\{U(x) \le u \mid u_1,\ldots, u_m, v_1, \ldots, v_n\} \tag{5}$$

The posterior cdf is obtained by applying Bayes Theorem as follows:

$$\mathrm{Prob}\{U(x) \le u \mid m+n\} \propto f\,\{v \mid u\} \text{ x } \mathrm{Prob}\{U(x) \le u \mid u_1,\ldots,u_m\} \tag{6}$$

The data values on u and v are used to calculate the likelihood function f {v | u}. It is assumed that u and v are independent of each other. Then the above product can be converted to a summation:

$$\Pr ob\{U(x) \le u|(m+n)\} = \lambda_0 F(u) + \sum_{j=1}^{m} \lambda_j \cdot i\left(x_j, u\right) + \sum_{k=1}^{n} \gamma_k \cdot y\left(x_k, u\right) \tag{7}$$

In the above equation $i(x_j,u)$ are the indicators defined at the m locations where the primary variable is available.

$$i(x_j,u) = 1, \text{ if } U(x_j) \le u, = 0 \text{ if not} \tag{8}$$

The first term on the right side of equation 7, F(*u*), is the global expected value for a category. The first two terms on the right side of equation 7 give the prior cdf of u based on the m primary variables. In the absence of the secondary variable, the posterior cdf will be calculated based only on the primary variable and the procedure will reduce to that of simple indicator kriging.

The third term on the right side of equation 7 gives the prior probability of ‘u’ conditioned to the secondary variable v.

$$y(x_k, u) = \mathrm{Prob}\,\{U(x_k) \le u \mid v_1, \ldots, v_n\} \tag{9}$$

The sum of the indicators conditioned to secondary variable is the likelihood function. The m primary variables and n secondary variables are independent of each others. The unbiasedness of the estimates is assured by assuming that the sum of all the weights is 1.
Procedure for Markov Bayes simulations: If data are available on a primary variable u and secondary variable v then the procedure for generating conditional cdf's using Markov-Bayes simulations is as follows.

1. The primary variable 'u' is converted into indicators defined at K different cutoffs, $i(x_i, u_k)$, k = 1,….., K; I = 1, …., m.
2. Indicator variograms are calculated from all the available primary data for each cutoff.
3. The indicator variograms are used to calculate the covariances for each cutoff.
4. The secondary variable is discretized in L different classes, v_1, ….., v_L.
5. The u and v datasets are used to calculate the secondary indicators $y(x_j, u)$. A calibration scattergram of the primary values versus the secondary values is plotted. For each class of the secondary variable, the scattergram values are used to calculate the probability distributions. An example scattergram is shown in Fig. 1.
6. The primary and secondary variable data values are also used to calculate the coefficients. These coefficients and the primary variable covariances are used to calculate the covariances and cross covariances for the secondary variables approximated by the Markov hypothesis.
7. Once all the covariances are available, the posterior cdf's are calculated using the Bayesian updating formula defined in equation 7. A schematic of the procedure is shown in Fig. 2.

The procedure described above does not depend on the distribution of the primary or secondary variable. The secondary variable could be continuous or discrete. The primary variable can be continuous like porosity values and the secondary variable can be discrete like rock types.
The data set: The Markov-Bayes simulation technique was used to generate fracture density distributions for a study area in the Uinta Basin. Analyses were performed on cores from 10 wells in the Bluebell field. The well locations are given in Fig. 3. The study area extends for 4.8 km in the east-west direction and for 1.6 km in the north-south direction. Formation names and depths from which the cores were collected are shown in Fig. 4. No information was available about the rock types. A total of 149 m of core were available from all the wells. These cores were analyzed in terms of rock type classification, porosity, permeability values, and fracture properties. Fracture orientations, relative frequencies, and nature of the fracture (open, partially closed, closed) were noted.

Petrographic analysis of thin sections from the available cores has been described by Wagner (1996). This analysis identified seven prominent rock types. The rock types were as follows: (1) shale, (2) mudstone, (3) siltstone (4) sandstone, (5) limy mudstone, (6) packstone, and (7) wackestone. Of the seven rock types, sandstone and mudstone were the most abundant.

The core samples were analyzed for fracture frequencies, which were classified qualitatively into the following categories: (1) one to two, (2) occasional, (3) few, (4) moderate, (5) frequent, and (6) very frequent.

Fracture analysis also indicated that the distributions of fracture frequencies varied with the rock types. Figure 5 shows the fracture frequency distributions for seven different rock types as reported by Wagner (1996). The cumulative frequency distributions within each rock type for the six fracture frequency classes are compared in the figure. This information was used to generate distributions of fracture frequency using Markov-Bayes simulations. The primary variable was fracture frequency, while rock type was the secondary variable.

The rock-type distributions were first generated using principles of indicator kriging. The variation in fracture frequencies with rock type was used along with the hard frequency data when generating fracture-frequency distributions. The fracture frequencies were conditioned to hard fracture frequency data and soft rock type data. The hard and soft conditioning were performed by using Markov-Bayes principles described earlier.

For comparison purposes, two more approaches were used to generate frequency distributions. As mentioned previously, Markov-Bayes simulations reduce to simple indicator simulations in the absence of secondary data. The data on hard indicators were used to generate frequency distributions by sequential indicator simulations. These distributions were conditioned to the observed frequency indicators. The third approach used was sequential Gaussian simulations.

Comparison of fracture frequencies determined using the three approaches

The cumulative distribution functions (cdfs) of fracture frequencies for these three approaches are compared with sample data in Table 1. As shown from Table 1, the cdf's found using Markov-Bayes simulations come closest to reproducing sample data; sequential indicator simulations are next best. The cdf calculated using sequential Gaussian simulations does not reproduce the data well.

The effect of soft conditioning on the fracture frequency distributions was also examined. Analysis of sample data had showed that the fracture-frequency distribution varied with rock type. As a result, the cdf's of frequency varied with rock type. Soft indicators were calculated for fracture-frequency distributions generated using the three methods. These indicators are compared with the soft indicators for the sample data for sandstone and shale in Figs. 6 and 7. As can be seen from the figures, the cdf's for the sequential Gaussian and sequential indicator simulations do not change with the rock type. The cdf of each category is the same as the global cdf. The results for Markov-Bayes simulations capture the trends of fracture frequency distributions for various rock types. The trends in the frequency distributions are well captured through soft conditioning.

Effects of using fracture frequency distributions generated using the different approaches on flow simulations will be discussed in the next quarterly report.

Table 1- Comparison of proportions of fracture frequency categories with sample data for three approaches.

	Sample Data	Markov - Bayes Simulations	Seq. Gaussian Simulations	Seq. Indicator Simulations
Category 1	0.1576	0.1636	0.2163	0.1465
Category 2	0.2153	0.2163	0.2682	0.2036
Category 3	0.5333	0.5688	0.5242	0.5153
Category 4	0.7567	0.7277	0.7008	0.7771
Category 5	0.8270	0.8056	0.7571	0.8398
Category 6	1.0000	1.0000	1.0000	1.0000

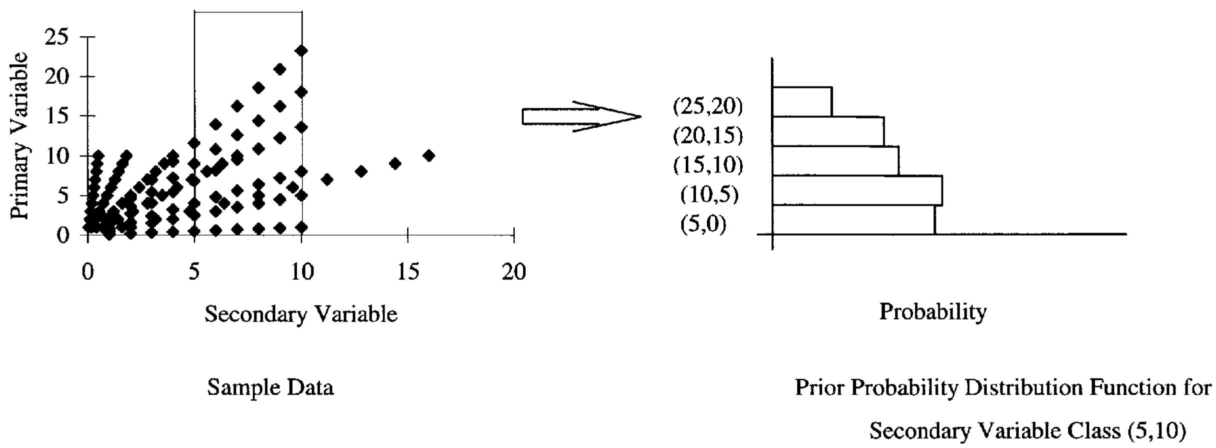

Figure 1. A scattergram and corresponding prior probability distribution function.

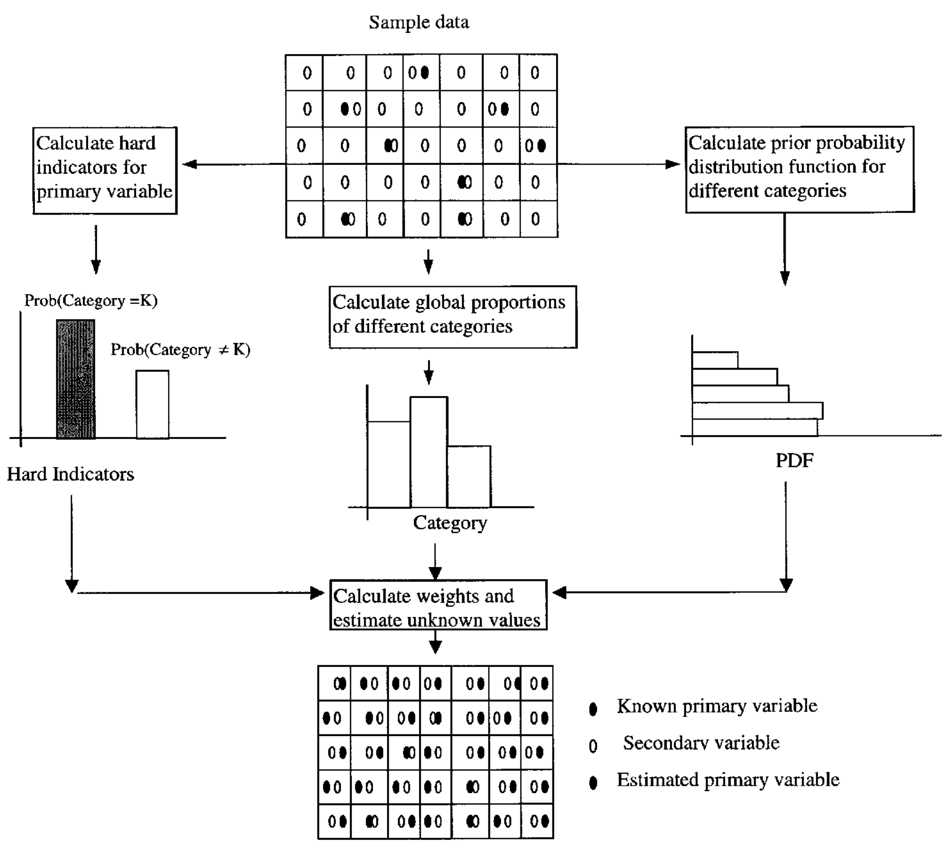

Figure 2. A schematic diagram showing the steps involved during Markov-Bayes simulation procedure.

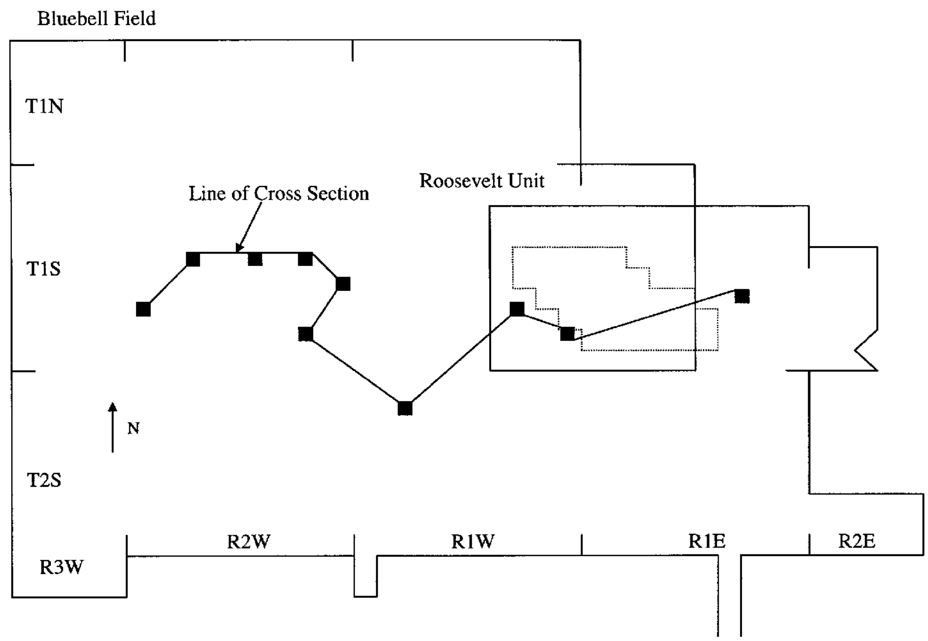

Figure 3. A map of the Bluebell Field showing the locations of core samples.

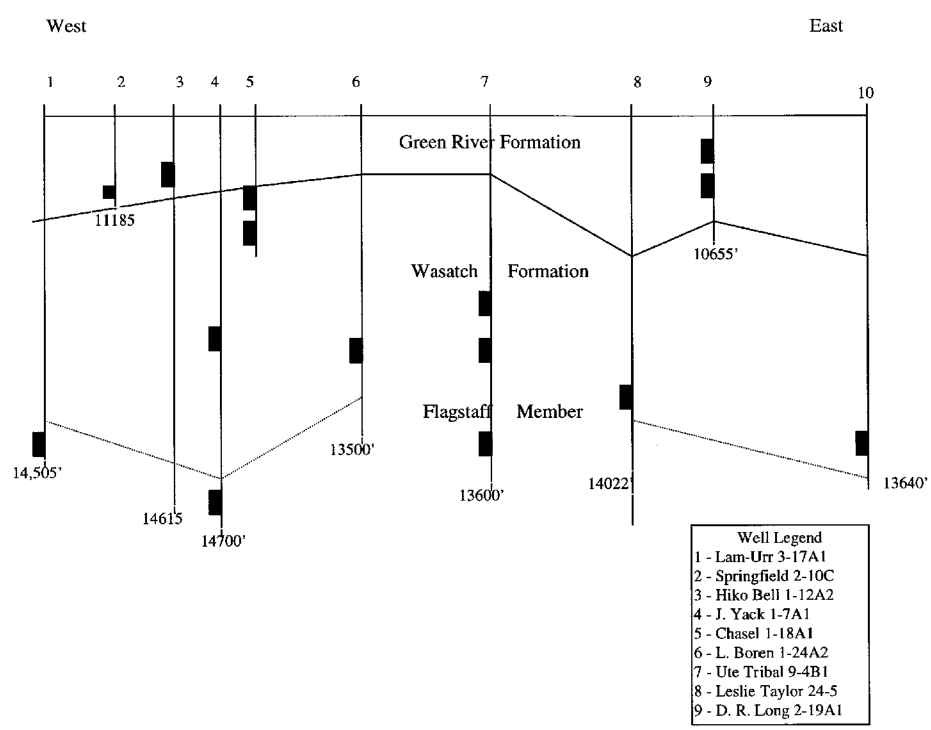

Figure 4. Cross section showing the formation and depth of sampled cores.

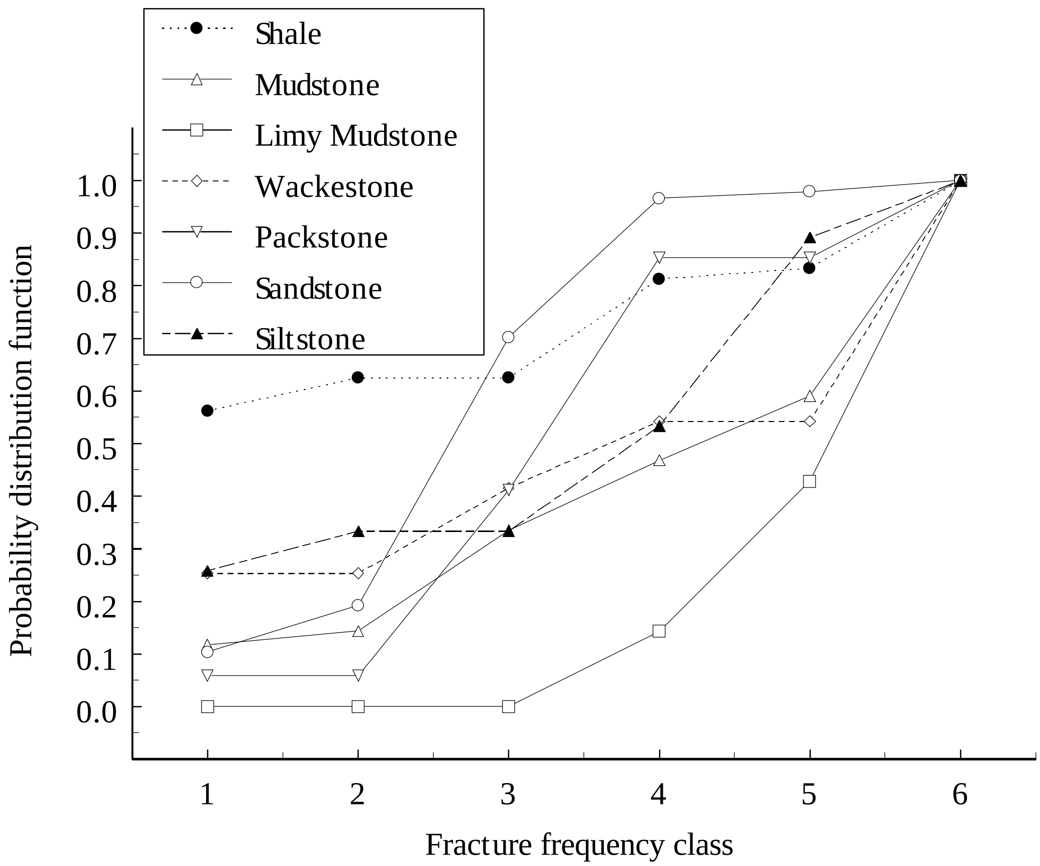

Figure 5. Fracture frequency distribution in different rock types.

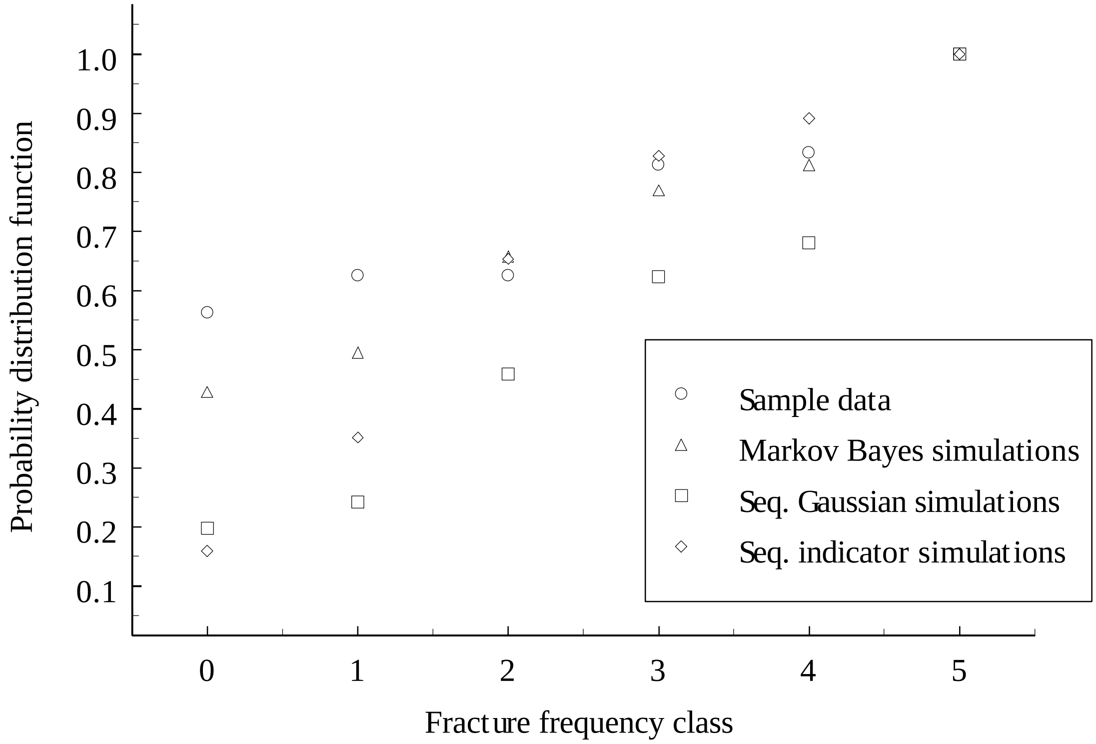

Figure 6. Comparisons of probability distribution functions for different fracture frequency categories for shale.

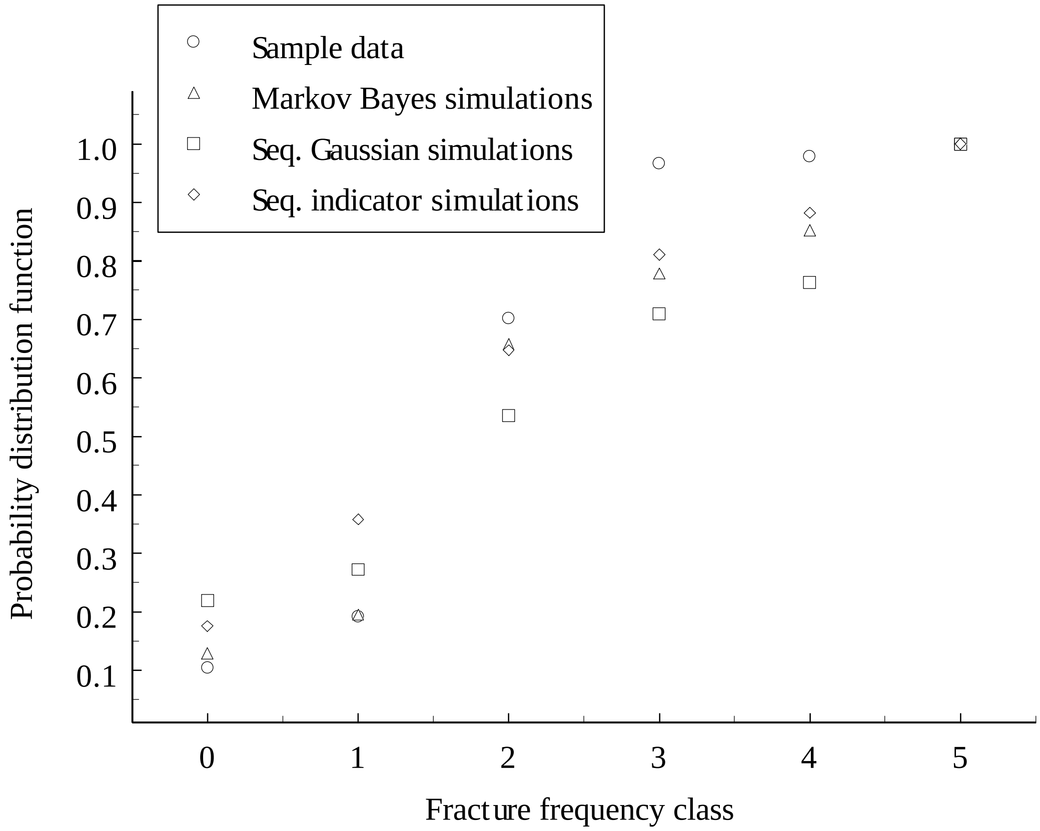

Figure 7. Comparisons of probability distribution functions for different fracture frequency categories for sandstone.

Technology Transfer

A poster was presented at the AAPG National Convention in Dallas Texas highlighting the results of the first demonstration, the recompletion of the Michelle Ute well (Morgan, 1997).

The Utah Geological Survey maintains a Bluebell home page on its web site containing the following information: (1) a description of the project, (2) a list of project participants, (3) each of the Quarterly Technical Progress Reports, (4) a description of planned field demonstration work, (5) portions of the First and Second Annual Technical Reports with information on where to obtain complete reports, (6) a reference list of all publications that are a direct result of the project, (7) an extensive selected reference list for the Uinta Basin and lacustrine deposits worldwide, and (8) daily activity reports of the Michelle Ute 7-1 demonstration work. The home page address is ***http://www.ugs.state.ut.us/bluebell.htm***

References

Morgan, C.D., 1997, Improving primary oil recovery from a (DOE Class I) fluvial-dominated deltaic lacustrine reservoir Uinta Basin, Utah: AAPG Annual Convention Program with Abstracts p. A85.

Wagner, M., 1996, Core analysis and description as an aid to hydrocarbon production enhancement - Lower Green River and Wasatch Formations, Bluebell field, Uinta Basin, Utah: Provo, Brigham Young University, M.S. Thesis, 233p.