Hydrocarbon Resource Estimation: Application of Monte Carlo Simulation

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***Abstract*: - Hydrocarbon resource estimation is an important task for any Exploration and Production company. The economic viability of any E & P project depends on the accuracy of its resource and reserve estimation which is carried out by using several input parameters such as area, net pay thickness, porosity, hydrocarbon saturation and formation volume factors etc. These parameters are obtained from seismic, petrophysical, geochemical and well testing data. Due to uncertainties in such resource estimation, resources need to be estimated by both deterministic and stochastic methods. In case of deterministic methods, the input parameters are some specific single valued numbers and thus the output is also a single value. As the reservoir parameters are not uniform throughout the whole reservoir, the uncertainty decreases with the increase in data set. Stochastic methods are applied in such cases because through random sampling, it can generate millions of random numbers, and by proper analyzing these data set, one can solve such problems very easily. Monte Carlo Simulation is an example of such kind of stochastic tool for hydrocarbon resource estimation. It can solve nonlinear inverse problems where there is no direct relationship between data and parameters of the model or the relationship is too complex to be solved by direct mathematics. The success of stochastic hydrocarbon reserve estimation by Monte Carlo simulation depends upon the selection of the model parameters as well as the careful observation and understanding of the model parameters which are essential for satisfactory results.**

This paper deals with the application and development of an algorithm of the above method to estimate in-place resource.

Key Words: Monte Carlo Simulation, Oil-initially-in-place, Resource Estimation, Volumetric Calculation

I. Introduction

Hydrocarbon resource/reserve is estimated on the basis of some limited parameters from the sub-surface. Therefore, uncertainties always exist in such estimation and deterministic methods cannot handle such kind of uncertainties. In deterministic approach, the model parameters are some specific single values which represent the whole reservoir and the single valued result of this method is assumed to be the best. In case of stochastic reserve estimation, there exists no such industry standard in reality. In stochastic approach, all the input parameters are sampled statistically and it requires thousands of iterations to get global minima of the solution. Monte Carlo simulation is a probabilistic method based on huge number of mathematical calculation. In this method, the random variants are used to generate several sets of population with small differences in their dimensions.

Monte Carlo Simulation is used in oil and gas industry as a useful tool to estimate uncertainties in various aspects. The aim of any Exploration and Production company is to find out more oil and gas and for that hydrocarbon reserve estimation is a vital part of any Exploration and Production project. Oil and gas industry is a risk- based industry and the investments are capital-intensive. Therefore, hydrocarbon resource/reserve estimation is a vital issue in oil industry for both economical and technological point of view. Hydrocarbon reserves can be estimated in both deterministic and stochastic way. Based on some limited number of observations or data, there is always uncertainty in these estimation methods. Since, deterministic methods cannot handle uncertainties in the input data probabilistic /stochastic methods are helpful in such cases Monte Carlo simulation is a probabilistic or stochastic in nature and is widely used in oil industry. This method is based on huge number of mathematical calculations which can easily be managed with the advent of modern computation technology. Depending upon the distribution function of the input parameters (random), stochastic methods produce different results.

Using Monte Carlo methods, the affect of random variation of input parameters, insufficient data on the sensitivity and performance or reliability of the output model have been studied. The input data has been randomly generated from the probability distribution. The above simulation method gives an approximate solution through statistical sampling and thus error analysis is a major factor and needs to be considered during the interpretation of the results. Monte Carlo simulation has been used in scientific research since 1940 after its first use in nuclear fusion. Three major methods of reserve estimation such as analogy, volumetric and performance analysis have been used in oil industry. Monte Carlo simulation (Murtha, 1994 and Siemek et al., 2004) is mostly used in oil industry to quantify the uncertainties associated in hydrocarbon resource/ reserve estimation by incorporating historical data set. Monte Carlo simulation has also been used in risk and efficiency (Komlosi, 2001 and 1999) evaluation of exploration and production project (Galli et. al., 2001 and Faya et al., 2001).

Monte Carlo Simulation has been used in oil and gas industry to test the dependency between parameters and the degree of dependency by regression and correlation tools. Field data are used to populate the input for that Monte Carlo Simulation. Data are collected from 83 reservoirs to make histogram of ten classes. Twelve common distributions are to match history data and to get chi-square “goodness-of-fit”. The results have shown that original oil in-place was affected by the decision which was based on the various distributions. It has also been observed that the comparison of outputs obtained from running multiple simulations could provide satisfactory result (Murtha, 1997).

Monte Carlo Simulation has been applied for the volumetric reserve estimation of hydrocarbon reserves of Ramadan oil field by Gulf of Suez Petroleum Company. It has been observed that statistical distributions of reservoir parameters like porosity, pay zone thickness, area, water saturation recovery factor, and oil formation volume factor has influenced the Original-Oil-In-Place (OIIP) estimation. To get a satisfactory result, parameter selections are more important than the shape of parameter distribution (Macary et al., 1999).Use of multiple processors with each processor executing simultaneously, could reduce the time of simulation (Chewaroungroaj et al., 2000).

Probabilistic Reserves Estimation Package, a new computational tool has been developed using Decline Curve Analysis parameters for the determination of standard errors, confidence intervals and expectation curves (Idrobo et al., 2001).

The geological risk or probability of success (POS) in hydrocarbon resource/reserve estimation can be determined by using geostatistical approach. In Badenian clastics, the probability of success in hydrocarbon reserve estimation with stochastic methods didn’t make any difference as average porosity varied in narrow interval but in case of deeper formation porosity variation was wider and thus deterministic-stochastic approach made a difference in POS values (Malvic 2009).

Three probabilistic sampling algorithms such as Hamiltonian Monte Carlo (HMC), Neighborhood Algorithm (NA) and Particle Swarm Optimization (PSO) algorithm have been compared to minimize the uncertainties in reservoir parameters related to reservoir performance prediction. It has been observed that HMC and PSO are very effective tools to quantify those uncertainties associated in reserve estimation in petroleum industry (Mohamed et al., 2010).

Monte Carlo Simulation and Material Balance have been used for the improvement in performance prediction of a naturally fractured mature carbonate offshore field. The original oil in place (OOIP) was calculated by using reservoir parameters into Monte Carlo Simulation. Material Balance method was also used to increase the confidence level in volumetric calculation as volumetric calculation was based on static reservoir data which were more uncertain than dynamic data which were used in Material Balance (Riveros et al., 2011).

II. METHODOLOGY

In this work, a set of numbers is generated through random sampling and are analyzed by making histogram of it. Based on the analysis of that primary data set, a sampling algorithm is used to run the simulation process. Computational algorithm rely on repeated random sampling to obtain numerical results i.e., by running simulation many times over in order to calculate those same probabilities heuristically. Three factors make this difficult to solve analytically; (a) multiple integration is required (with as many dimensions as there are input variables) (b) dealing with nonlinear function (c) correlation or links between variables further complicate the integration. The simulation procedure is simply an easy way of integrating numerically in higher dimension space. The Cumulative Distribution Function (CDF) of the simulation results are plotted and if the results are satisfactory then the simulation is stopped otherwise more simulation runs are required to get the optimum result. The fig.1 shows the flow chart of the Monte Carlo simulation process.

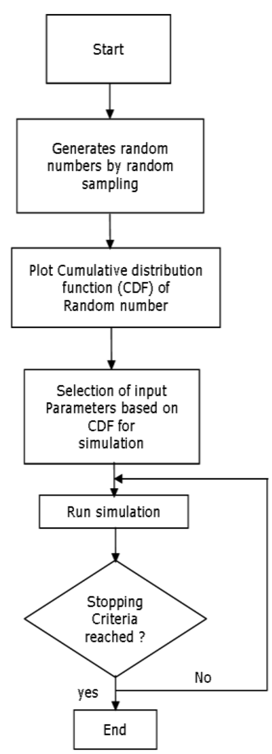

Fig. 1: Flow Chart of Monte Carlo Simulation

A. Formula for reserve estimation: The oil initially in-place equation as per the AAPG guidelines is as follows,

$$OIIP = [\, A * h * \varphi * (1 - Sw_i) / Bo \,]$$

…………………… (1)

Where,

OIIP = Oil initially in-place
A = Areal extent of the hydrocarbon pool (m^2)
h = Net pay thickness (m)
φ = Porosity (fraction)
Swi = Initial water saturation (fraction)
Bo = Formation volume factor (RB/STB)

The input parameters for volumetric calculation are areal extent of the hydrocarbon pool, net pay thickness, porosity, water saturation / hydrocarbon saturation and formation volume factor. Area is obtained from the seismic attribute map, net pay thickness is from isopach map, porosity and fluid saturation are (water/ hydrocarbon) from petrophysical data or core data and formation volume factor is from pressure-volume-temperature or drill stem test data.

Each input parameter has a range of values i.e., all these values obey some statistical distribution. In every iteration of the simulation, any random value of input parameters within the range is taken as input for calculating the output. Any simulation process consists of thousands of iteration and thus the output values are graphically displayed as histogram and cumulative distribution function and are stored in computer memory.

Based on the primary data analysis; it has been decided to go for triangular distribution for the simulation. Triangular distribution is continuous probability distribution. It has minimum value *p*, mode value *q* and a maximum value *r* of each input parameter ($p < q$ and $p \le q \le r$). The probability density function for triangular distribution is as follows:

$$f(x/p,q,r) = \begin{cases} 0 & \text{for} \quad x < p \quad , \\ \dfrac{2(x-p)}{(q-p)(r-p)} & \text{for} \quad p \le x \le r \quad , \\ \dfrac{2(q-x)}{(q-p)(q-r)} & \text{for} \quad r \le x \le q \quad , \\ 0 & \text{for} \quad q < x \quad , \end{cases}$$

…………………… (2)

The shape of the distribution depends upon the minimum value, maximum value and mode value of any particular input parameter. Cumulative Distribution Function is used to know the variation of reservoir property inside the reservoir.

In Monte Carlo simulation if the inputs are multivariate then large numbers of iteration is needed to get the desired output. In this case, the data are sampled by triangular probability distribution function and from that the optimum values of the input parameters are selected for the resource estimation.

III. RESULTS AND DISCUSSIONS

To get the desired results, three runs of simulation have been performed with the help of computer. The codes for the simulation are written in Matlab platform and the results are shown in the following figures and tables.

Area Forecast:

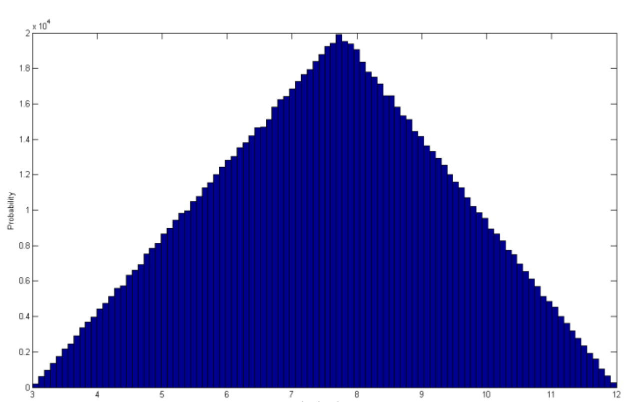

Fig. 2: Triangular distribution of Area (sq.km)

Table.1: Statistics of Area (sq.km) forecast

Statistics :	
Trials	1000000
Min	3.0030
Max	11.9912
Mean	7.5805
Median	7.6189
Mode	-
Standard Deviation	1.8379
Variance	3.3778
Skewness	-0.0534
Kurtosis	2.4000
Mean Std.Error	0.001839

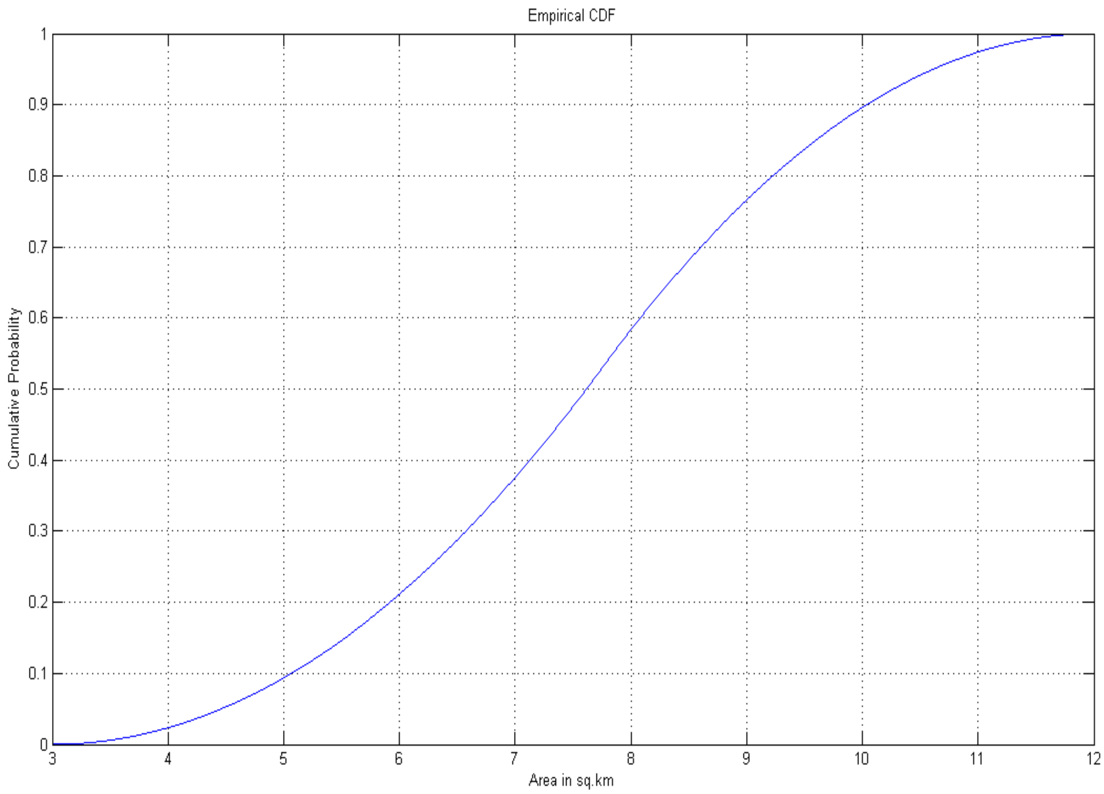

Fig. 3: Cumulative Probability of Area (sq.km)

Table.2: Percentiles: Area Forecast

Percentile	(sq.km)
0%	3.0069
10%	5.0712
20%	5.9213
30%	6.5772
40%	7.1318
50%	7.6178
60%	8.0834
70%	8.6115
80%	9.2310
90%	10.0416
100%	11.9959

Porosity Forecast:

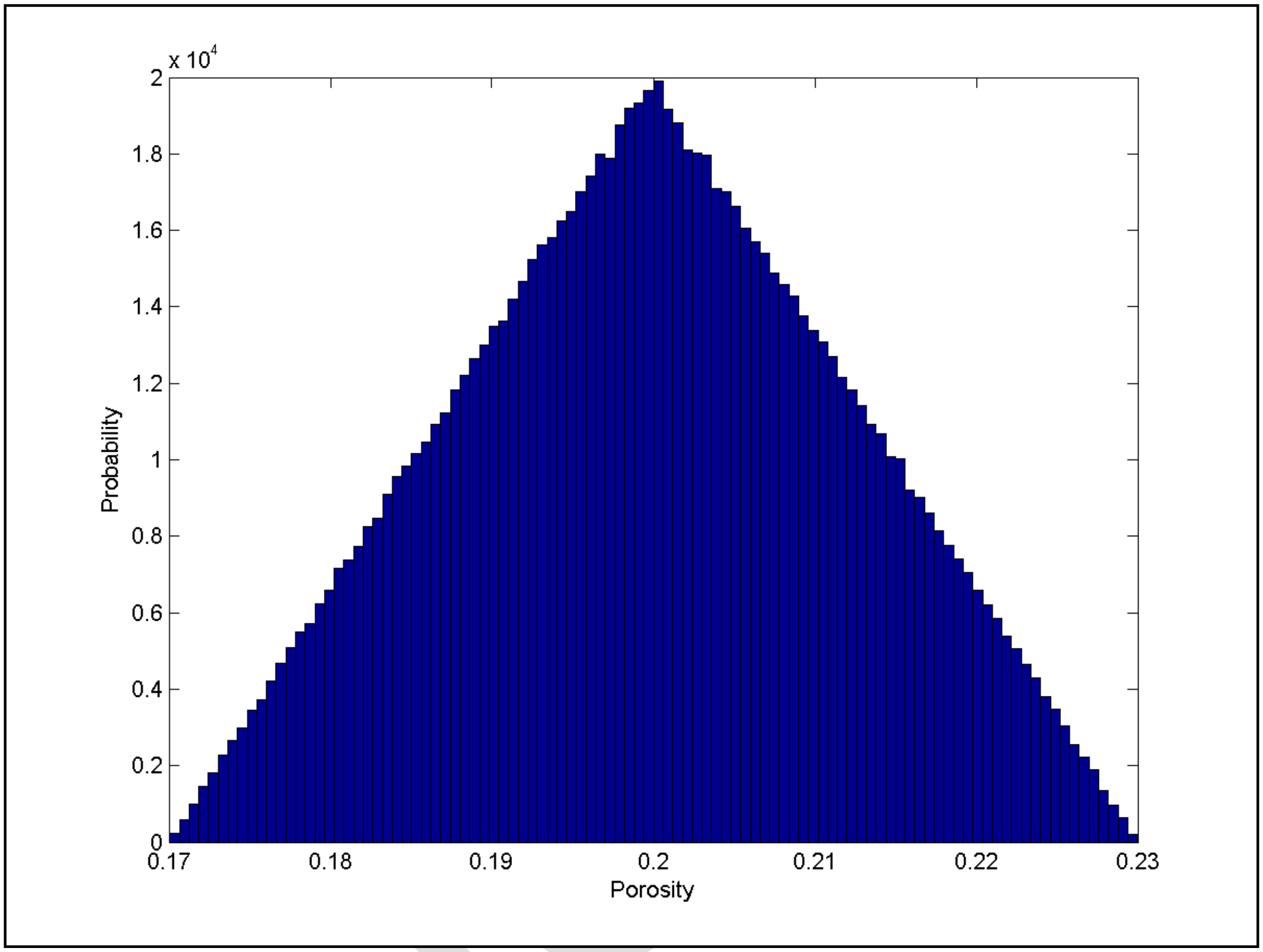

Fig. 4: Triangular distribution of Porosity (fraction)

Table.3 : Statistics of Porosity (fraction) forecast

Statistics :	
Trials	1000000
Min	0.17
Max	0.23
Mean	0.20
Median	0.20
Mode	-
Standard Deviation	0.0122
Variance	1.50×10^{-4}
Skewness	4.306×10^{-4}
Kurtosis	2.3994
Mean Std.Error	0.00001

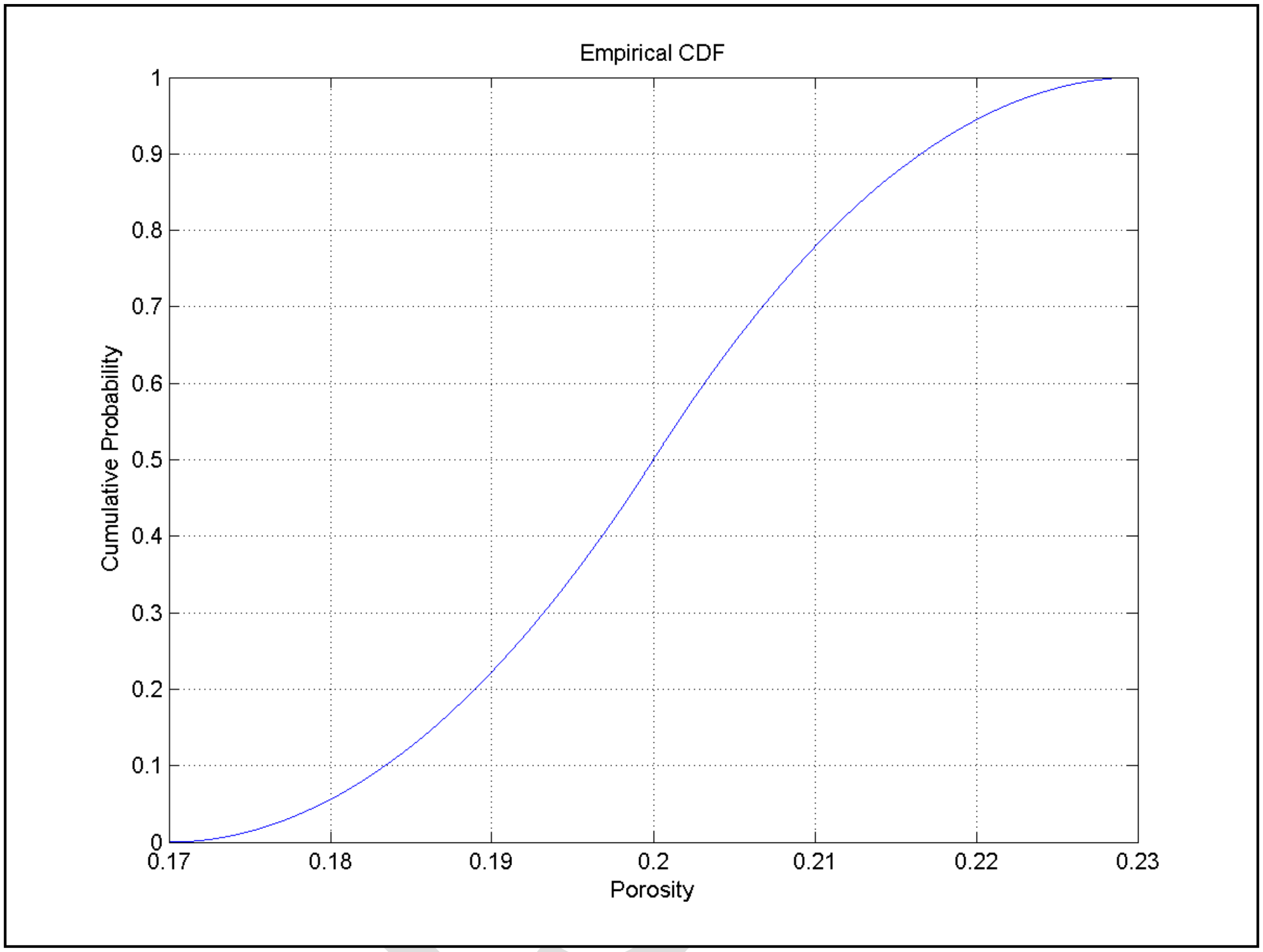

Fig. 5: Cumulative Probability of Porosity (fraction)

Table.4: Percentiles: Porosity (fraction) Forecast

Percentile	fraction
0%	0.17
10%	0.18
20%	0.19
30%	0.19
40%	0.20
50%	0.20
60%	0.20
70%	0.21
80%	0.21
90%	0.22
100%	0.23

Oil Saturation Forecast:

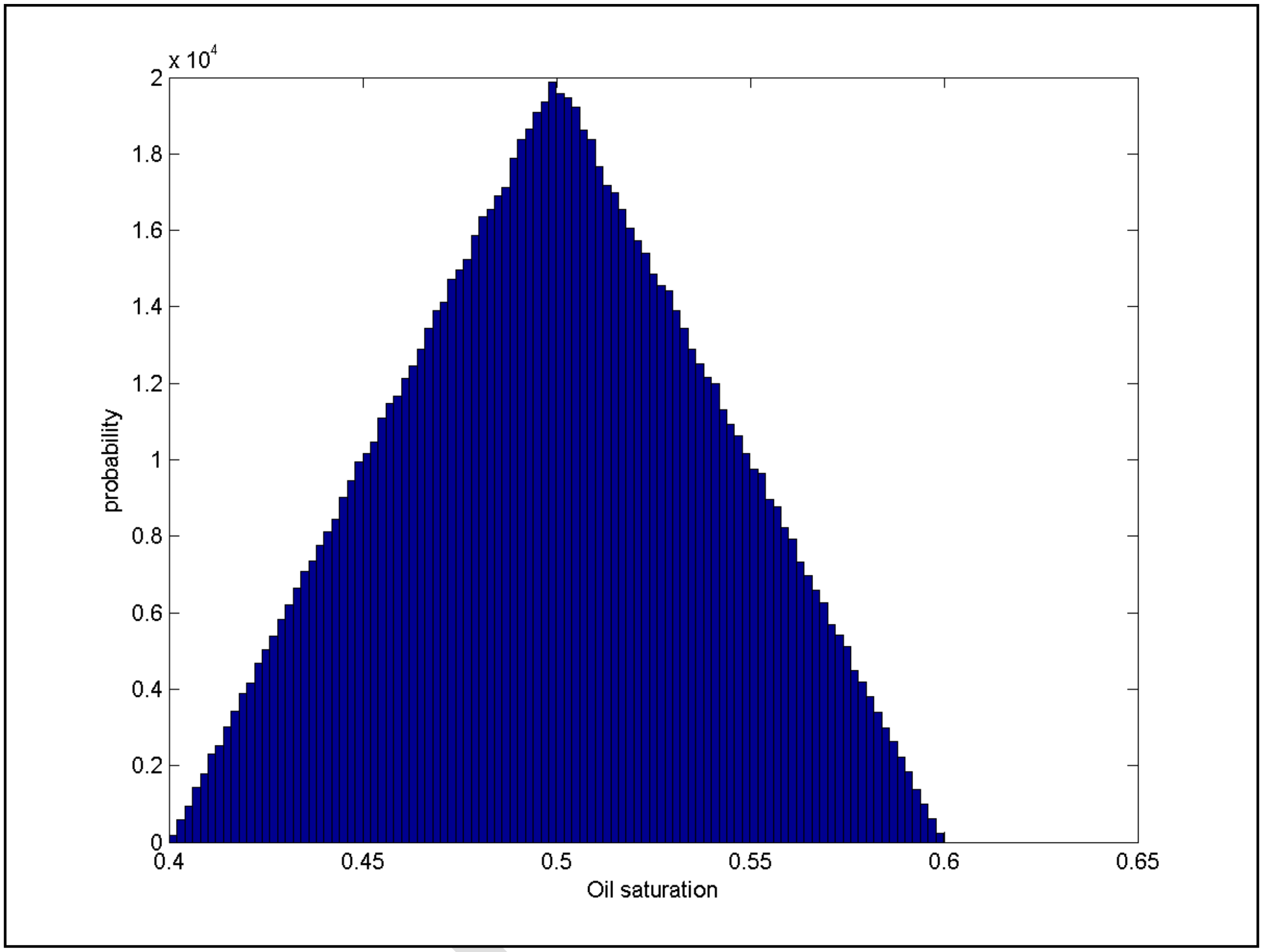

Fig .6: Triangular Distribution of Oil Saturation (fraction)

Table.5 : Statistics of Oil Saturation (fraction) Forecast

Statistics	
Trials	1000000
Min	0.40
Max	0.60
Mean	0.50
Median	0.50
Mode	-
Standard Deviation	0.04
Variance	0.0017
Skewness	-0.000412
Kurtosis	2.40
Mean Std.Error	0.00004

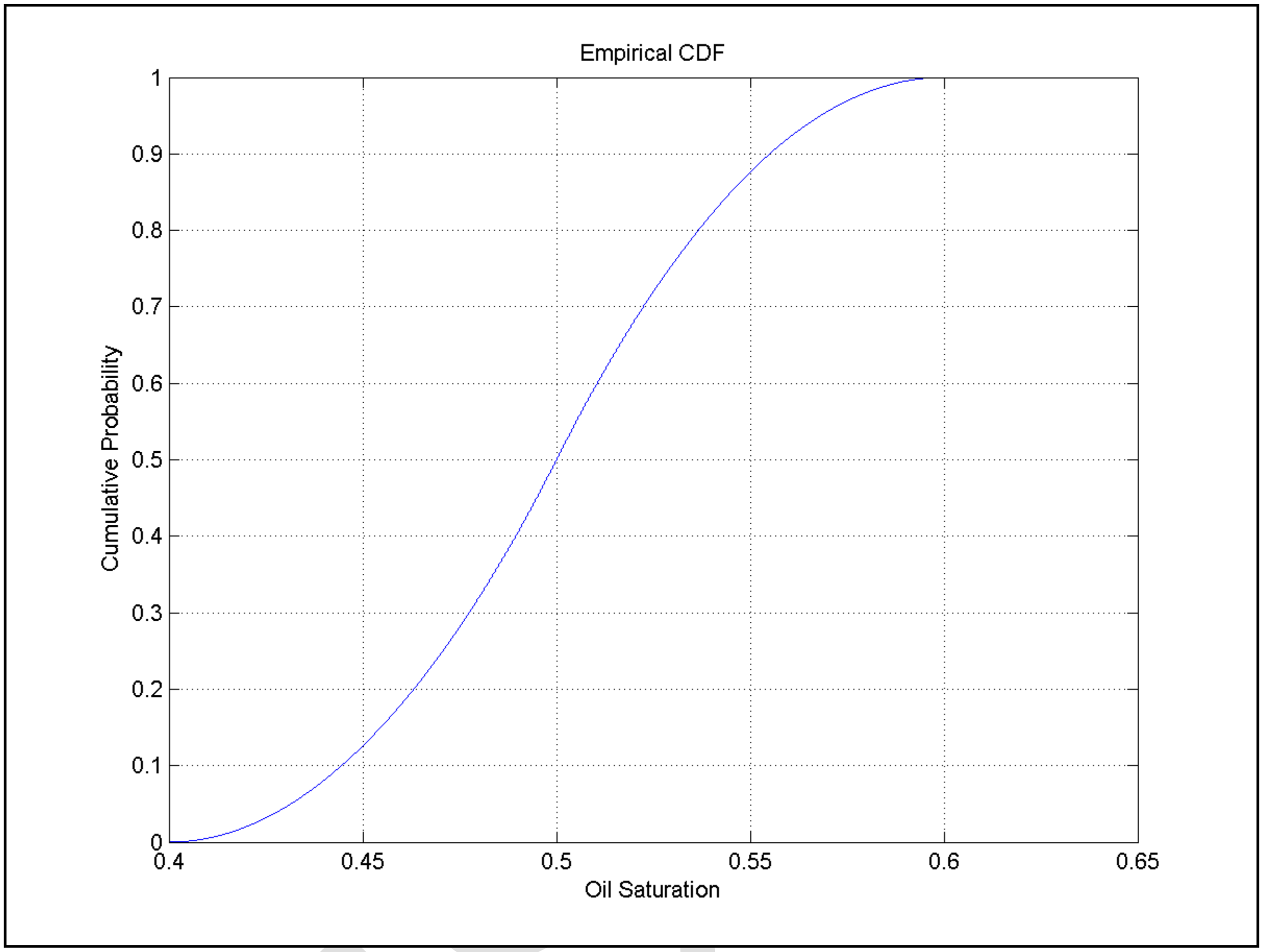

Fig. 7: Cumulative Probability of Oil Saturation (fraction)

Table.6: Percentiles: Oil Saturation (fraction) Forecast

Percentile	fraction
0%	0.40
10%	0.44
20%	0.46
30%	0.48
40%	0.49
50%	0.50
60%	0.51
70%	0.52
80%	0.54
90%	0.55
100%	0.60

Net Pay Thickness Forecast:

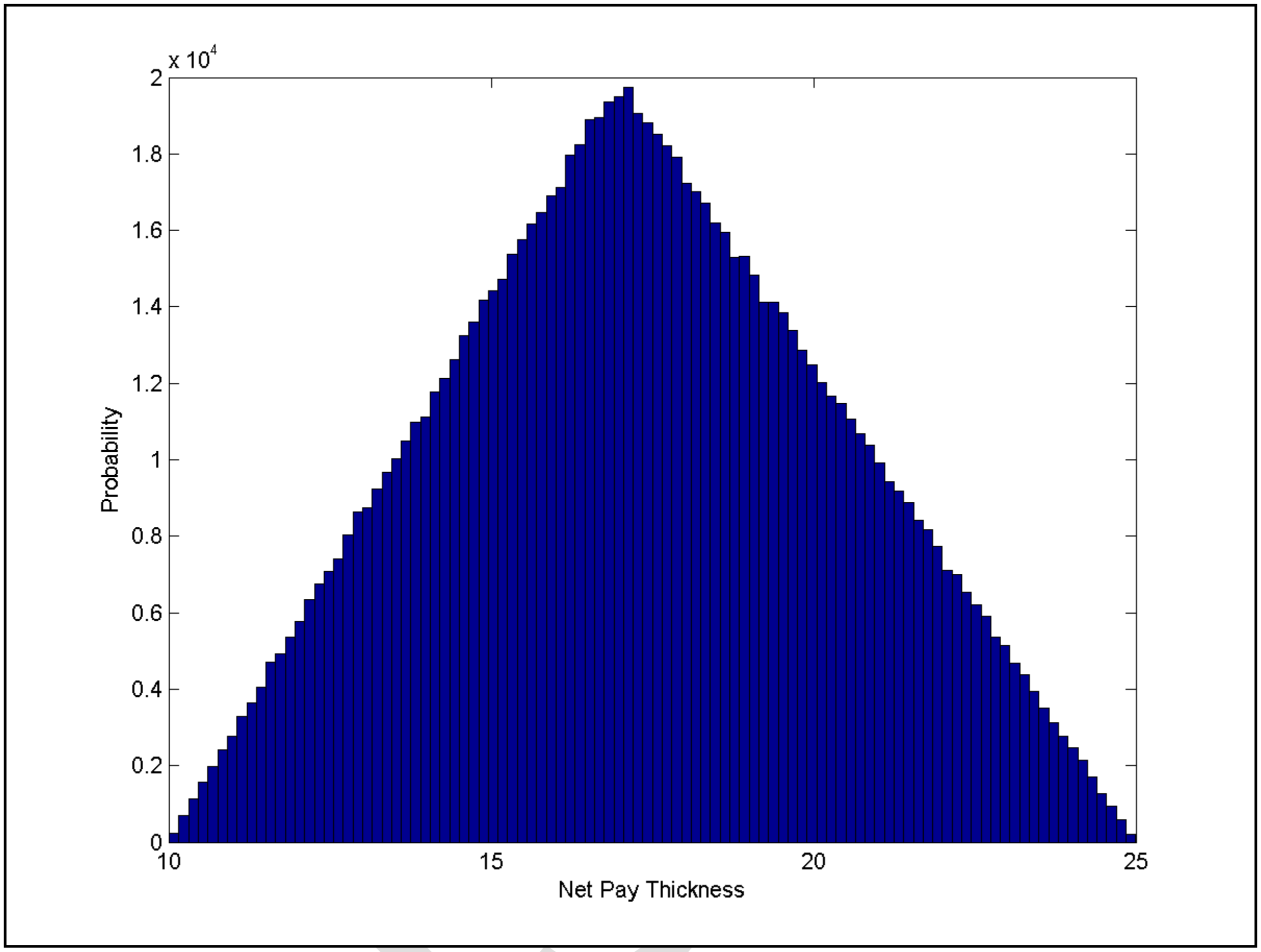

Fig. 8: Triangular Distribution of Net Pay Thickness (m)

Table.7: Statistics of Net Pay Thickness (m) Forecast

Statistics	
Trials	1000000
Min	10
Max	25
Mean	17.3345
Median	17.2519
Mode	-
Standard Deviation	3.0649
Variance	9.3936
Skewness	0.0638
Kurtosis	2.3970
Mean Std.Error	0.003

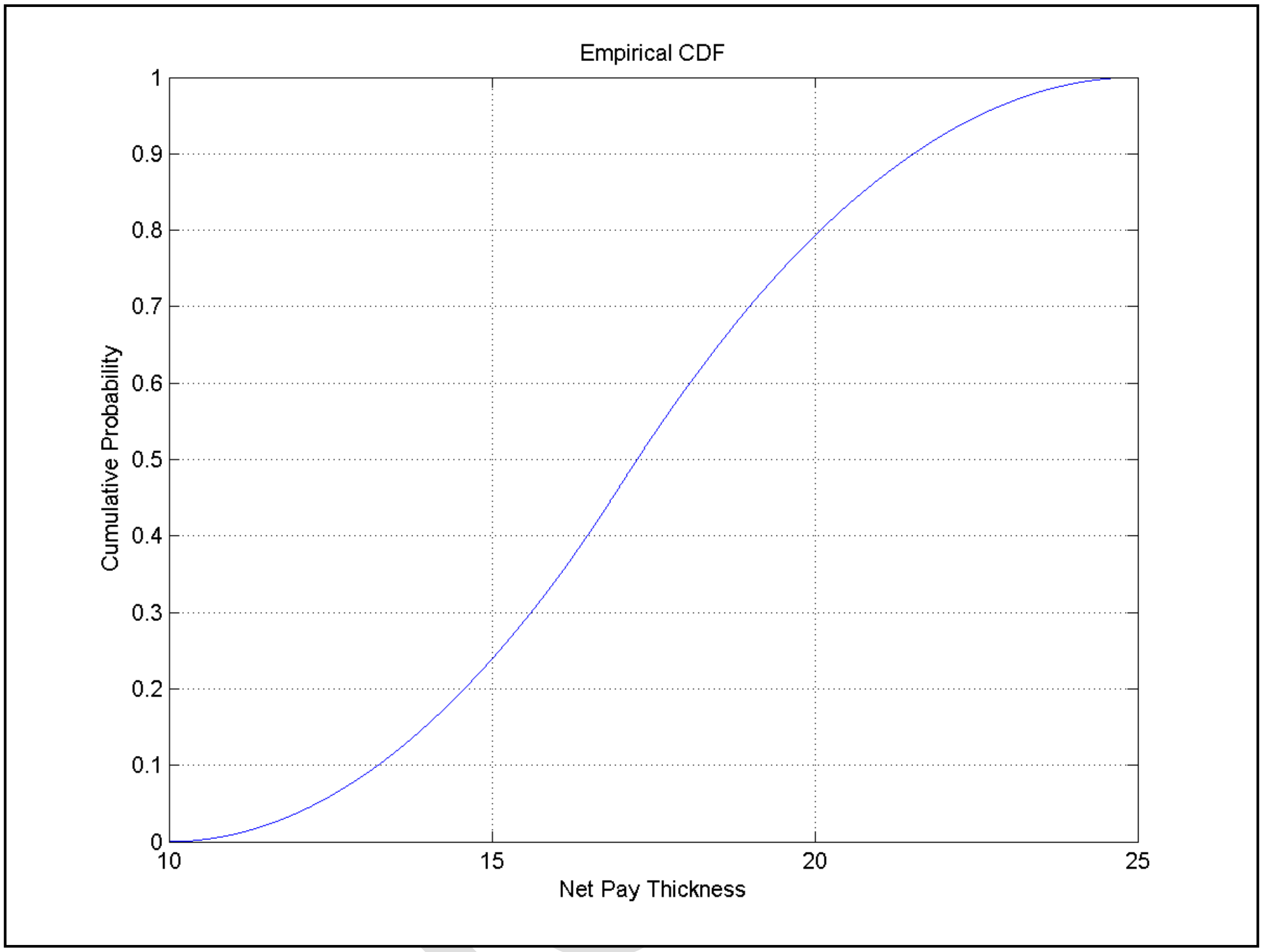

Fig. 9: Cumulative Probability of Net Pay Thickness (m)

Table.8: Percentiles: Net Pay Thickness (m) Forecast

Percentile	(m)
0%	10.0061
10%	13.2388
20%	14.5819
30%	15.6167
40%	16.4837
50%	17.2547
60%	18.0703
70%	18.9989
80%	20.0976
90%	21.5331
100%	24.9867

Formation Volume Factor Forecast:

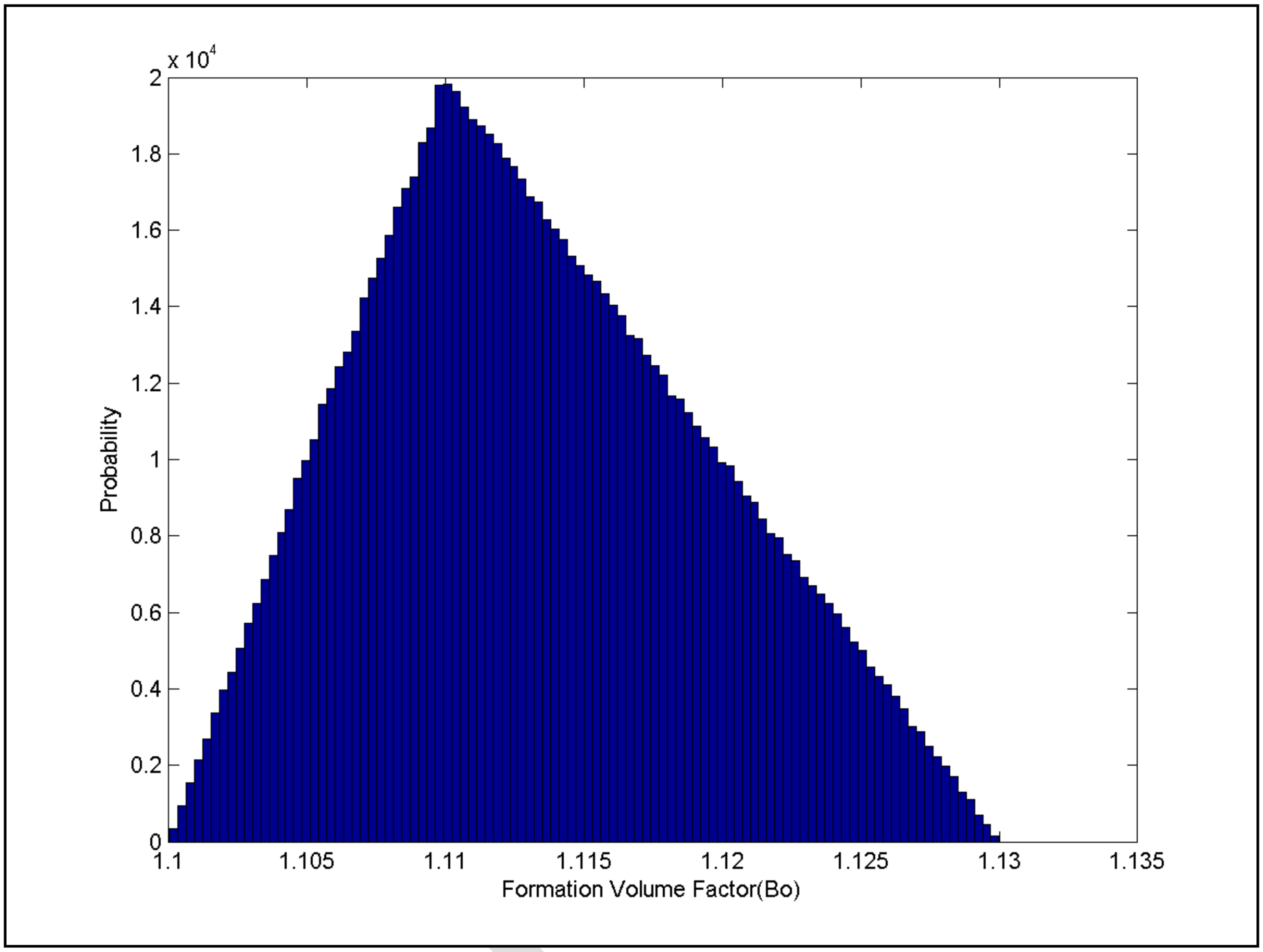

Fig.10: Triangular Distribution of Formation Volume Factor for Oil

Table.9: Statistics of Formation Volume Factor Forecast for Oil

Statistics	
Trials	1000000
Min	1.10
Max	1.13
Mean	1.1133
Median	1.111
Mode	-
Standard Deviation	0.0062
Variance	3.8891×10^{-5}
Skewness	0.3059
Kurtosis	2.4042
Mean Std.Error	0.00

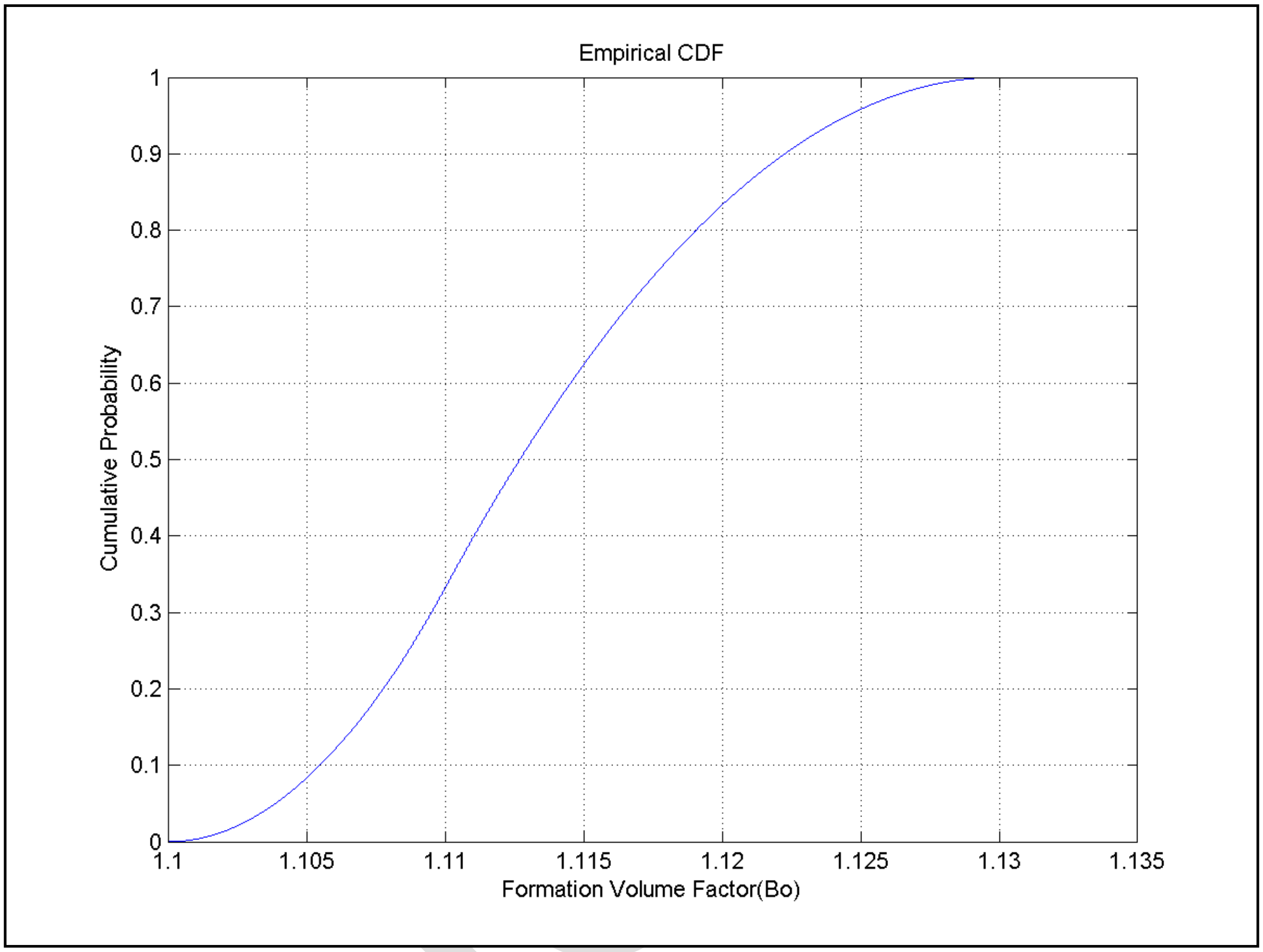

Fig.11: Cumulative Probability of Formation Volume Factor for Oil

Table.10: Percentiles: Formation Volume Factor Forecast for Oil

Percentile	FVF (Bo)
0%	1.1000
10%	1.1055
20%	1.1077
30%	1.1095
40%	1.1110
50%	1.1127
60%	1.1145
70%	1.1166
80%	1.1190
90%	1.1222
100%	1.1300

Table. 11: Parameters for In-place Resource Estimation:

Parameters	Min	Most Likely Value	Max	Average
Area (m^2)	3.0 x 10^6	7.74 x 10^6	12 x 10^6	7.67 x 10^6
Pay Thickness(m)	10	17.25	25	17.33
Porosity (fraction)	0.17	0.20	0.23	0.20
Oil Saturation (fraction)	0.40	0.50	0.60	0.50
Formation Volume Factor(B_o)	1.100	1.110	1.130	1.113
Formation Volume Factor(B_g)	0.00640	0.00642	0.00645	0.006425

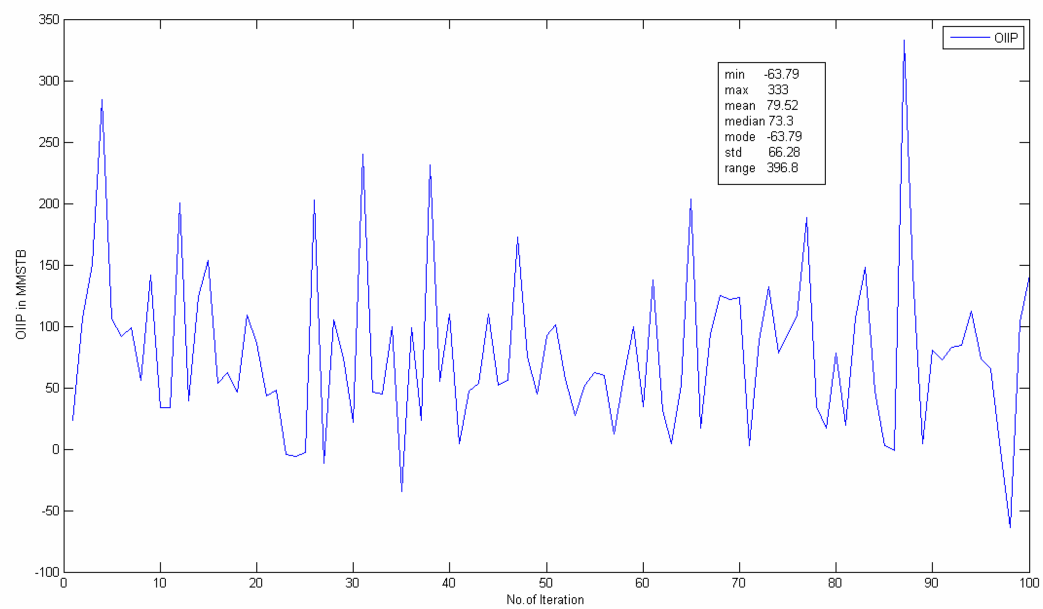

Fig.14: Monte Carlo Simulation for OIIP in MMSTB (100 Iterations)

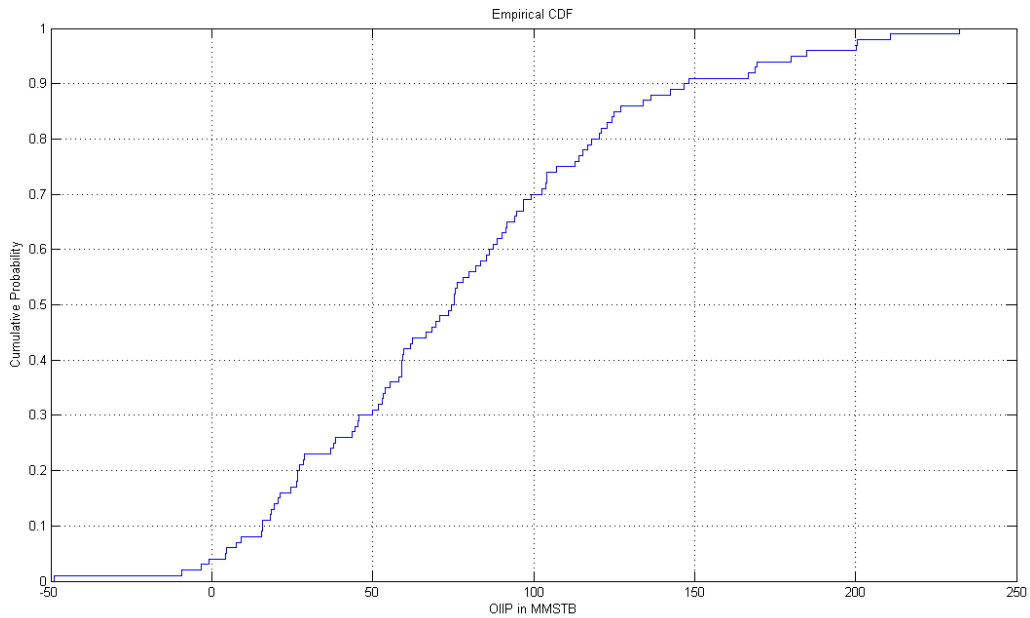

Fig.15: Cumulative Probability of Monte Carlo Simulation for OIIP in MMSTB (100 Iterations)

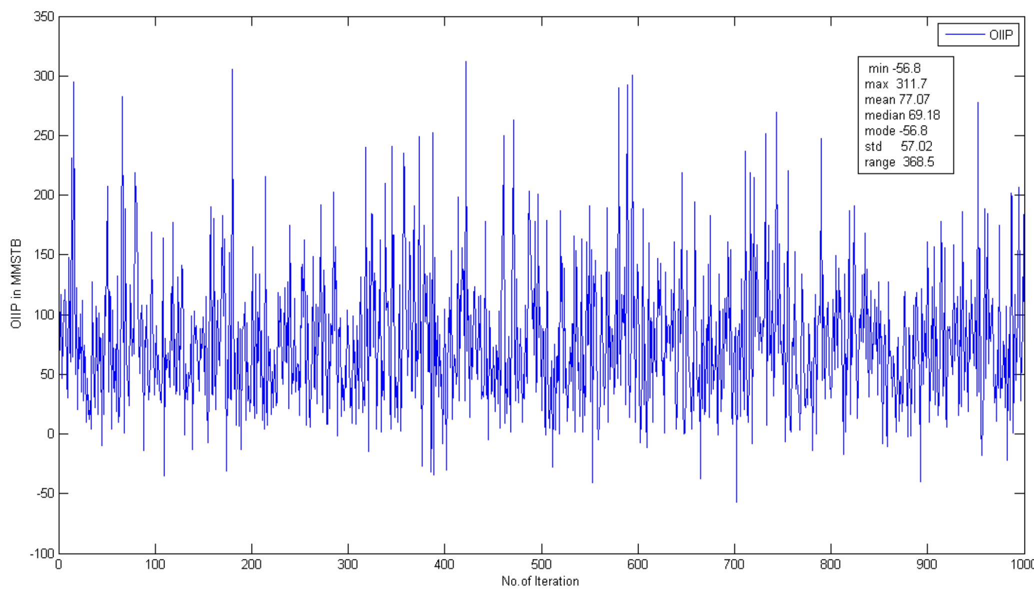

Fig.16: Monte Carlo Simulation for OIIP in MMSTB (1000 Iterations)

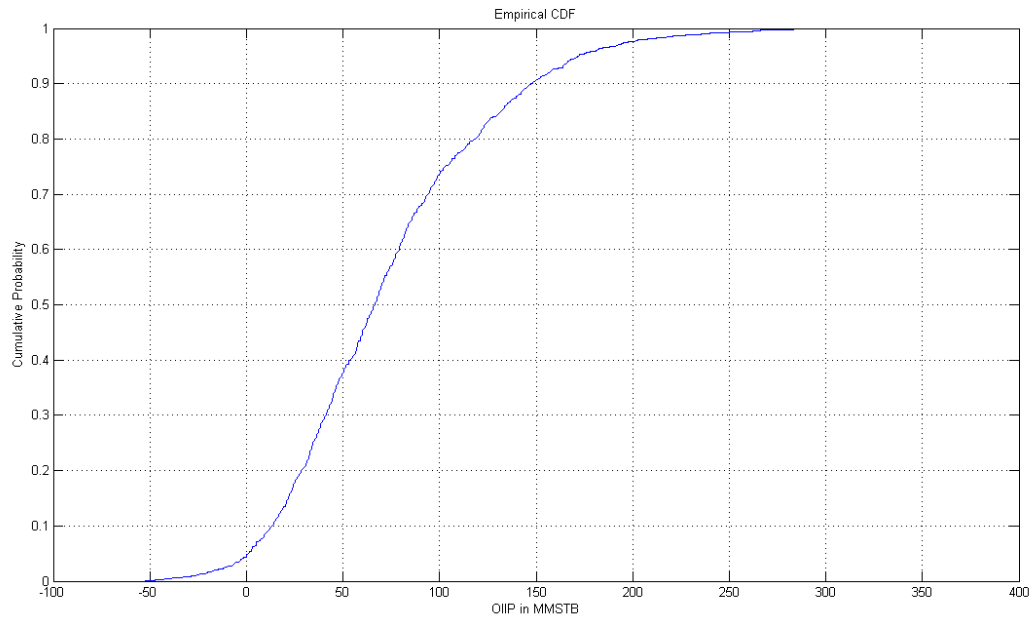

Fig.17: Cumulative Probability of Monte Carlo Simulation for OIIP in MMSTB (1000 Iterations)

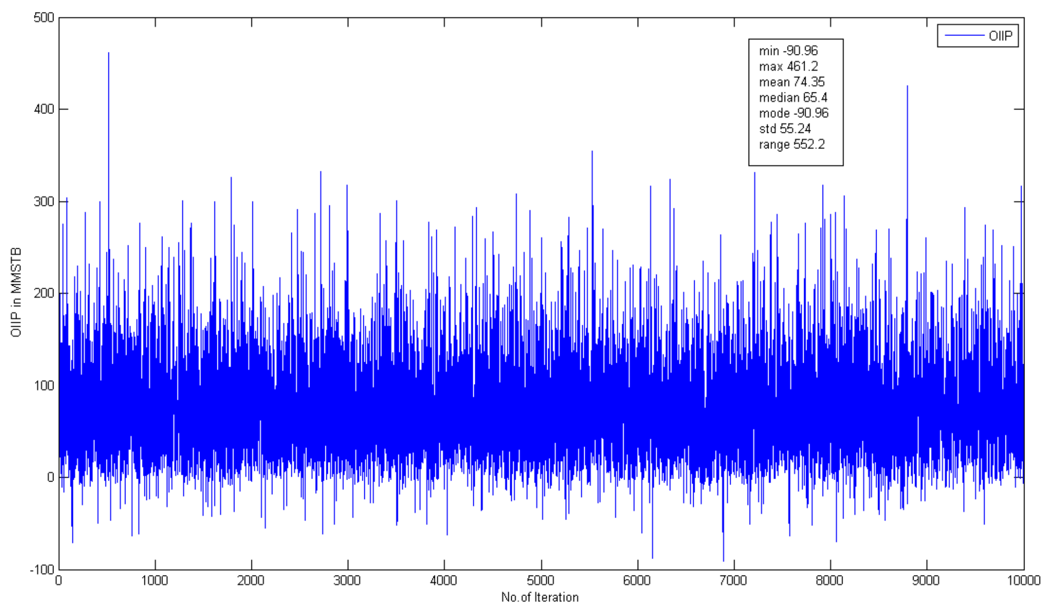

Fig.18: Monte Carlo Simulation for OIIP in BBL (10,000 Iterations)

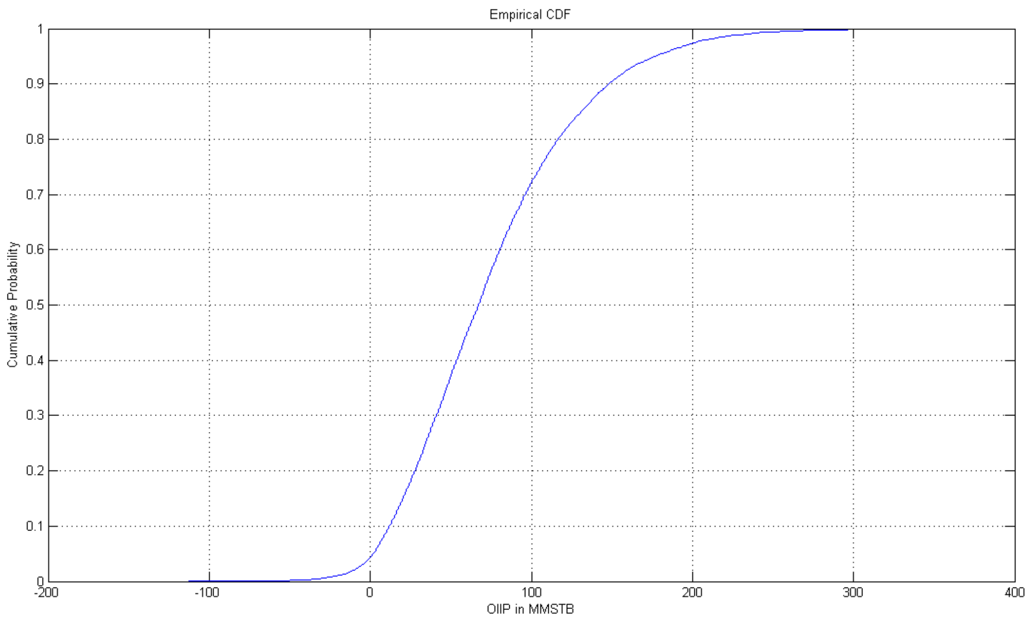

Fig.19: Cumulative Probability of Monte Carlo Simulation for OIIP in BBL (10,000 Iterations)

Table. 12: Percentiles of Monte Carlo Simulation Results for OIIP (BBL)

Percentile	100 Itr	1000 Itr	10000 Itr
0%	4.1639	0.0752	0.0344
10%	19.4820	20.6711	18.3998
20%	34.4120	33.2330	32.5843
30%	53.0395	44.7328	45.0568
40%	61.5840	57.6845	57.1070
50%	75.5386	68.7122	69.9788
60%	88.7131	81.0326	82.8188
70%	103.4097	95.9761	98.3539
80%	120.4973	120.7793	118.8001
90%	147.9586	149.9334	150.5120
100%	232.2536	399.2686	383.7562

Table.13: 1P, 2P and 3P Estimation for OIIP

Oil initial in-place		MMBbl
OIIP	**1P (P90)**	18.40
	2P(P50)	69.98
	3P(P10)	150.51

Table. 14: Statistics of Monte Carlo Simulation Results

Statistics	OIIP (MMSTB)		
	100 Itr	1000 Itr	10,000 Itr
min	-63.79	-56.8	-90.96
max	333	311.7	461.2
mean	79.52	77.07	74.35
median	73.3	69.18	65.4
mode	-63.79	-56.8	-90.96
std	66.28	57.02	55.24
range	396.8	368.5	552.2
Skewness	0.8110	1.0334	0.8520
Kurtosis	3.3509	4.2779	4.1925
Mean standard error	6.628	1.803	1.747

The figure numbers 2, 4, 6, 8 and 10 show the triangular distribution of the input parameters such as area, porosity, oil saturation, net pay thickness and formation volume factor for oil respectively. The figure numbers 3, 5, 7, 9 and 11 show the Cumulative Distribution Function of area, porosity, oil saturation, net pay thickness and formation volume factor for oil and gas respectively. Similarly the table numbers 1, 3, 5, 7 and 9 show the statistics of the forecasting of area, porosity, oil saturation, net pay thickness and formation volume factor for oil and gas respectively. Table numbers 2, 4, 6, 8 and 10 show the percentiles of the forecasting of area, porosity, oil saturation, net pay thickness and formation volume factors for oil and gas respectively. Monte Carlo simulations for 100, 1000 and 10,000 iterations are shown in the figure numbers 14, 16 and 18 whereas figure numbers 15, 17 and 19 show the Cumulative Distribution of the Monte Carlo simulation for OIIP for the above mentioned simulation runs respectively. The table number 12 shows the percentiles of Monte Carlo simulation results for OIIP. The table number 13 represents the 1P, 2P and 3P of the estimated OIIP. The statistics of the Monte Carlo simulation results have been presented in the table number 14.

The mean standard errors in calculation of OIIP for 100, 1000 and 10,000 iterations are 6.628, 1.803 and 1.747 respectively which gives unbiased standard deviation estimation. The accuracy with which a sample represents a population is measured by mean standard error. To have good representation of the sample, the mean standard error should be minimum.

The expected values of the OIIP are the mean value of the estimation. As the variable is normally distributed so the median value should be very close to mean value. The differences between mean and median values of OIIP for 100, 1000 and 10,000 iterations are 0.06%, 0.08% and 0.09% respectively.

The relative measure of the shape of the output curve with the normal distribution curve is measured by kurtosis. The normal distribution curve has a kurtosis value of zero and the kurtosis values of OIIP for 100, 1000 and 10,000 iteration are 3.3, 4.3 and 4.2 respectively. Thus the output curve is flatter with respect to the normal distribution curve.

The measure of asymmetry of the output curve is known by skewness. A normal distribution curve has a skewness of zero. The skewness of OIIP for 100, 1000 and 10,000 iterations are 0.81, 1.03 and 0.85 respectively. This shows that the tail of the distribution curve extends to the right.

CONCLUSION:

Monte Carlo simulation is a useful tool for resource/reserve estimation. The Cumulative Distribution Function of the Monte Carlo simulation gives a range of resource values with associated probability of occurrence. It is found that with 10,000 iterations the solution space reaches global minima. The efficacy of the algorithm is demonstrated using data set taken from literature. In the current example the estimated value of 1P, 2P and 3P for OIIP are 18.40 MMSTB, 69.98 MMSTB and 150.51 MMSTB respectively. The robustness of the developed algorithm will help the industry to estimate resource in stochastic sense where a global minimum is reached by completely avoiding local minima which is a case in most of the algorithms.

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REFERENCES

I. Chewaroungroaj, J., Varela, O. J. and Lake, L.W. (2000) "An Evaluation of Procedures to Estimate Uncertainty in Hydrocarbon Recovery Predictions," Paper SPE 59449 Presented at the SPE Asia Pacific Conference on Integrated Modelling for Asset Management, April 25-26, Yokohama, Japan.

II. Faya, L. C., and Companc, P. (2001) "Probabilistic Model to Develop Multilayer Gas and Oil Prospects," Paper SPE 69614 Presented at the SPE Latin American and Caribbean Petroleum Engineering Conference, March 25-28,Buenos Aires, Argentina.

III. Galli, A., Jung, T., Armstrong, M. and Lhote, O. (2001) "Real Option Evaluation of a Satellite Field in the North Sea," Paper SPE 71410 Presented at the SPE Annual Technical Conference and Exhibition, Sept. 30-Oct. 3, New Orleans, Louisiana.

IV. Idrobo, E.A., Jimenez, E.A. and Bernal, M.C. (2001) "A New Tool to Make Quick Estimates of Probabilistic Reserves from Production Trends," Paper SPE 68597 Presented at the SPE Hydrocarbon Economics and Evaluation Symposium, April 2-3, Dallas, Texas.

V. Komlosi, Z. (1999) "How to Measure Exploration-Production Efficiency," Paper SPE 56458 Presented at the SPE Annual Technical Conference and Exhibition, Oct 3-6, Houston, Texas.

VI. Komlosi, Z. P. (2001) "Application: Monte Carlo Simulation in Risk Evaluation of E & P Projects," Paper SPE 68578 Presented at the SPE Hydrocarbon Economics and Evaluation Symposium, April 2-3, Dallas, Texas.

VII. Macary, S.M., Hassan, A. and Ragaee, E. (1999) "Better Understanding of Reservoir Statistics is the Key for Reliable Monte Carlo Simulation," Paper SPE 53264 Presented at the SPE Middle East Oil Show and Conference, Feb 20-23, Bahrain.

VIII. Malvic.T. (2009) "Stochastical Approach in Deterministic Calculation of Geological Risk-Theory and Example", NAFTA, Vol 60 (12), pp.651-657.

IX. Mohamed, L., Christie, M. and Demyanov, V. (2010) "Comparison of Stochastic Sampling Algorithms for Uncertainty Quantification," SPE Journal, Vol 15 (1), pp. 31-38.

X. Murtha, J.A. (1994) "Incorporating Historical Data into Monte Carlo Simulation," SPE Computer Applications, Vol 6 (2), pp.11-17.

XI. Murtha, J.A. (1997) "Monte Carlo Simulation: Its Status and Future," Journal of Petroleum Technology, Vol 49 (4), pp. 361-373.

XII. Riveros, G.V., Saputelli, L., Patino, J., Chacon, A. and Solis, R. (2011) "Reserves Estimation Uncertainty in a Mature Naturally-Fractured Carbonate Field Located in Latin America," Paper OTC 22517 Presented at the Offshore Technology Conference, Oct.4-6, Rio de Janeiro, Brazil.

XIII. Siemek, J., and Nagy, S. (2004) "Estimation of Uncertainles in Gas-Condensate Systems Reserves by Monte Carlo Simulation," Acta Montanistica Slovaca, Rocnik 9, Cislo 3, pp 289-292.