RISK AND UNCERTAINTY ANALYSIS IN RESERVOIR DEVELOPMENT

Report submitted in partial fulfilment of the requirement
For the award of the Degree of

Bachelor of Technology (Petroleum Engineering)

by

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ABSTRACT

In our Oil and Gas Industry all over cost from starting of exploration to production stage very high compare to other industry. Also during the exploration stage, we don't have more information regarding reservoir. Based on different property we found that this reservoir has oil and gas. So, next step is that we want to know how much barrel of oil is present in reservoir. For finding OOIP we use different property like Porosity, Saturation of water, Gross rock volume and Net pay thickness. But we are not directly got these properties. First we find the rock and fluid physical property then we create this to our interested property.

To find this property we are using well logging, Seismic survey, well testing. We know that reservoir is fully uncertain and this all method is giving uncertain property. So, if we are use this property to find OOIP calculation then it will give Wrong OOIP value. Also, While Simulation model making, we are using this property. So, this model is also uncertain and is we are predicting something from this then it will give wrong result. So, there is huge risk from investor side. Because investor see only OOIP value according to probability of occurrence.

From above data if we see then there is a huge risk in investor side. So, here we have use Monte Carlo simulation for the generating the expected OOIP value. Using Monte Carlo simulation, we are increasing a number of experiments to get an expected output. We have taken an input data and made a python code for depletion drive reservoir case and we generated reservoir performance data. And then we made a production profile case. And we made a worst-case scenario and best-case scenario. And then investor sees these scenarios and takes a decision that I have to invest money in this field or not.

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CHAPTER 1: INTRODUCTION

Reservoir is the porous rock body which has the Capacity to store the Fluid. Generally we found the Hydrocarbon in Sandstone or Limestone rock. Our recovery factor of the any field around the 20 to 25 % which is very less. We have to manage the Reservoir in such a way that we can produce the Maximum amount of the Hydrocarbon from the Reservoir. To get the Maximum Production from the reservoir, we have to understand the Reservoir. We can understand the reservoir from the data which we get from the Coring, Seismic, Logging etc, but our reservoir is Heterogeneous, it’s impossible for us to characterize the reservoir per every foot. Even at the initial stage of the field, we have limited amount of the data. So it’s become difficult for us to take the decision regarding the investment, Because to develop any field, we require huge amount of the Capital, even there is also the risk regarding, whether will earn the money or not. In this situation we have to develop some methods which can help us to take the decision. If we quantify the risk then it’s become easy for individual to take decision. Here we have used the Monte Carlo simulation model to quantify the risk in reserve distribution. Even we have also applied this principal in Depletion drive reservoir to get the production profile.

1.1 Overview of The Project:

So here we have divided our project into two parts. In first part we have made python program of the Monte Carlo simulation model for the reserve distribution. We don’t have the exact data of the reservoir, Moreover our reservoir properties also heterogeneous. So we can’t define whole reservoir by just in one value of the properties. So there is range in Petro-physical properties.

So the Variable which defines by the range is known as stochastic variable. We input this variable in Monte Carlo simulation model. This model gives us Number of the possible case along with probability. So It is quantify the risk, which help us to take the decision.

In Second part of the Project, we have applied this Monte Carlo in Depletion drive reservoir. Here we have made python model which give the reservoir performance data. Here we have made the python program for the reservoir model. To make this reservoir model, we have used PVT properties, Relative permeability data, material balance and Darcy equation. Base on the python model we have generated Reservoir pressure, flowing bottom hole pressure data along with the time. We have also generated the production profile data. Then we have added Monte Carlo simulation in this program. Now this model gives number of the production profiles. Among this profile, we have taken the Best and Worst case of production profile. We have also done Techno economic analysis for the ease case. We have calculated yearly production profile, NPV, Cash flow, and Net pay back time. This factor helps us to take the calculated risk and it’s become easy for us to make the decision.

1.2 Objective of The Project:

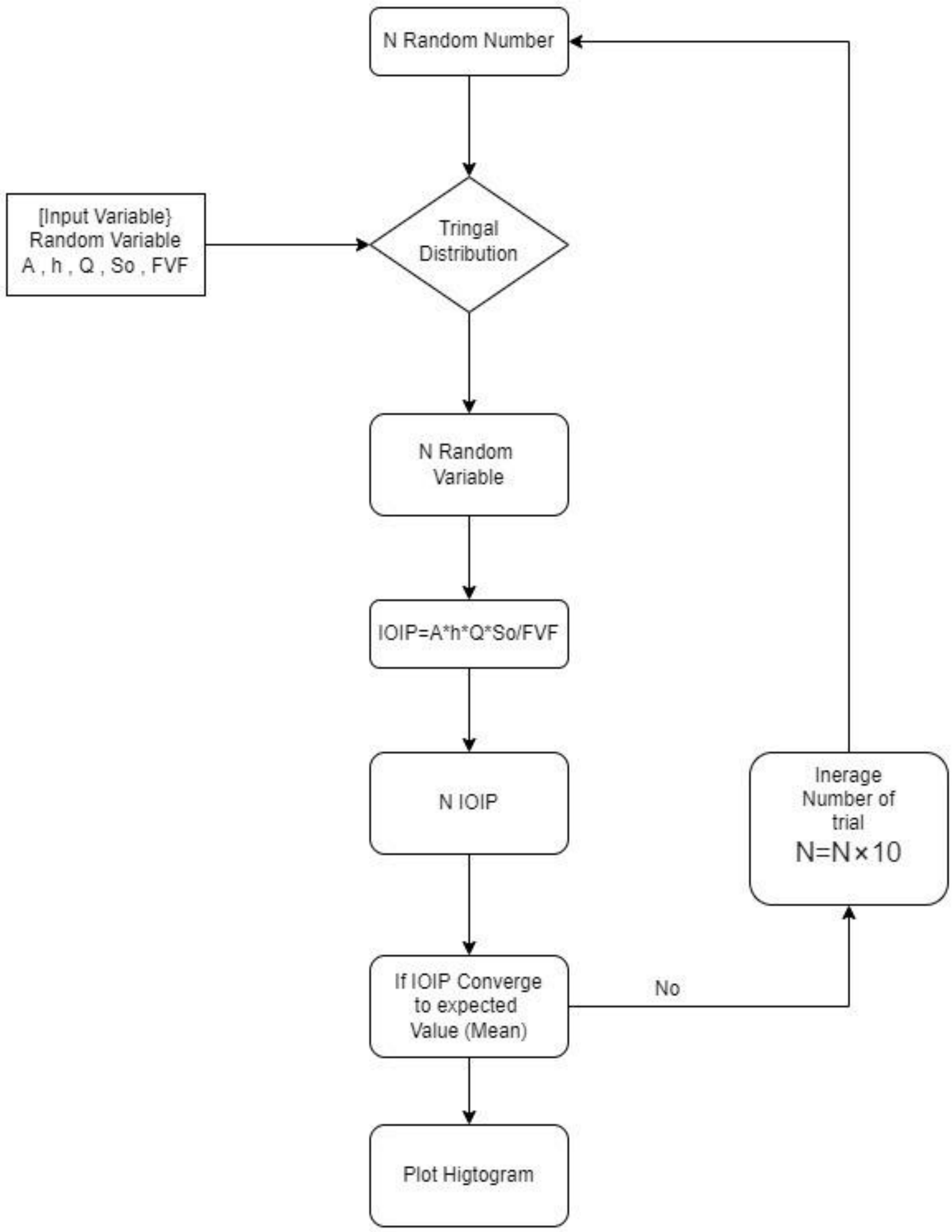
Risk Quantification by the Monte Carlo simulation Model. Generated number of possible case along with their probability. To analysis the reservoir performance. Techno economic analysis of the Reservoir Development.

1.2.1 Methodology:

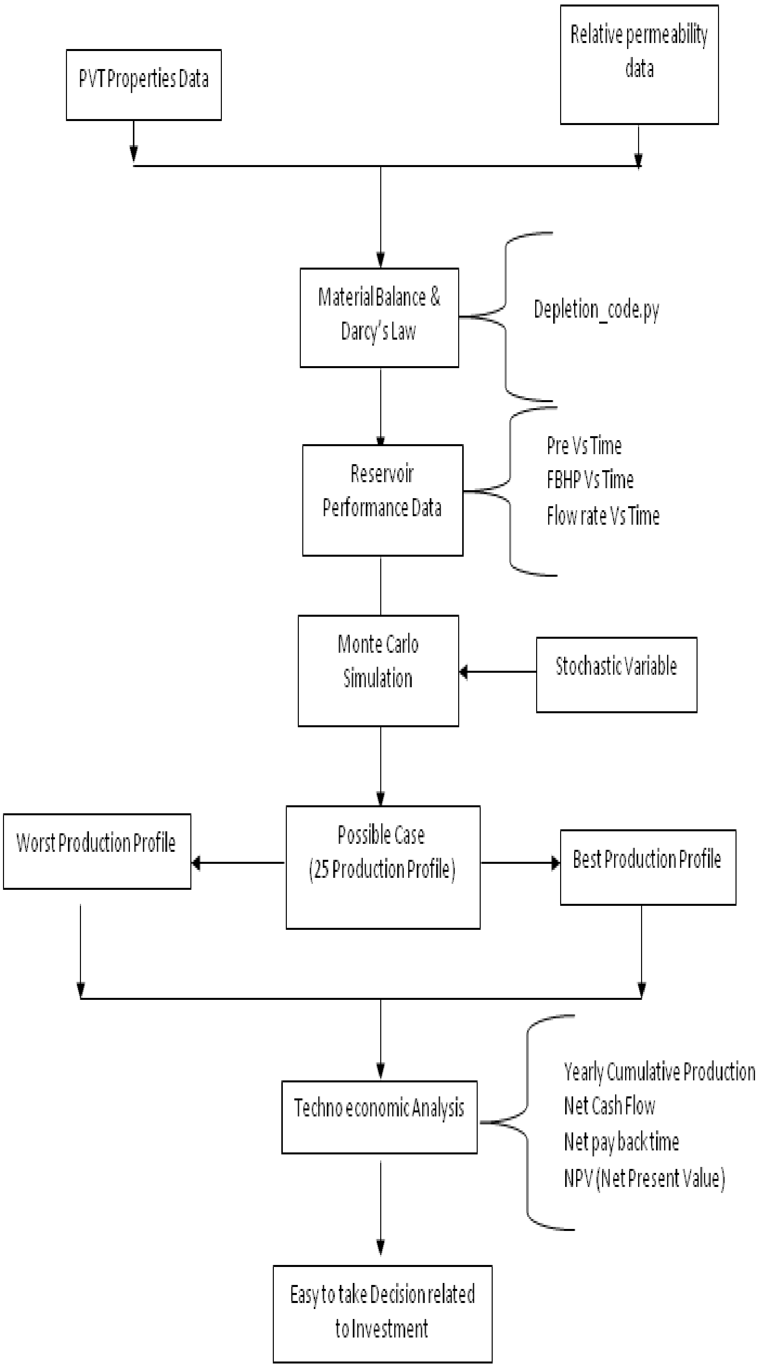
Here we have two work flow diagrams.

1. First work flow diagram is about the Reserve Distribution by the Monte Carlo Method.
2. Second work flow diagram is about the Reservoir Performance and Techno Economic analysis.

1. WORK FLOW DIAGRAM FOR IOIP.



2. WORK FLOW DIAGRAM FOR THE RESERVOIR PERFORMANCE



CHAPTER 2: RESERVOIR DEVELOPMENT

Reservoir development planning refers to strategies that begin with the exploration and appraisal well phase and end with the abandonment phase of a particular field to establish the course of action during the productive life of the asset. Figure 1.1 summarizes the phases of a reservoir development plan. The main objective of the complete cycle of a development plan is to maximize the asset value.

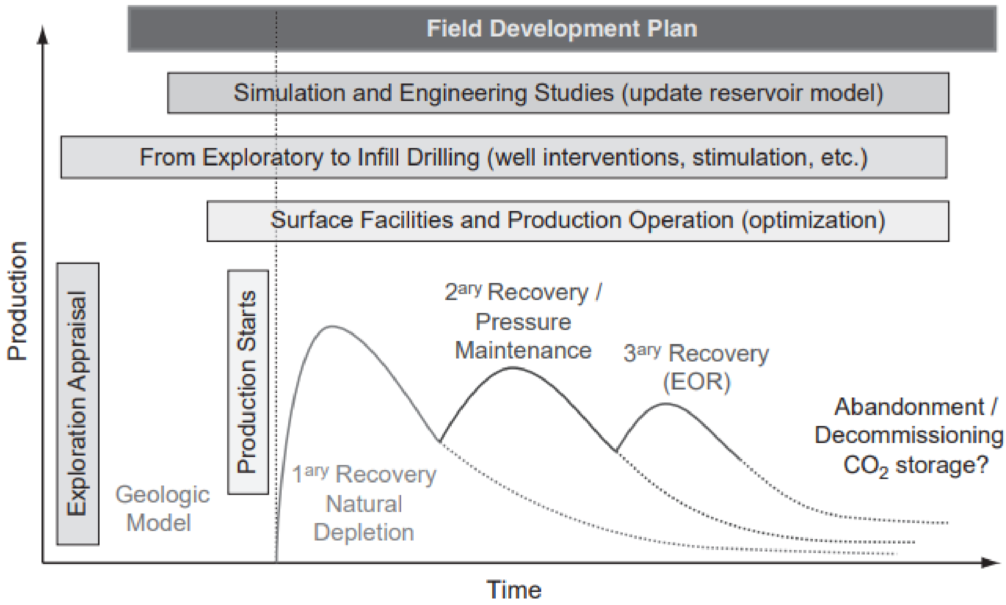


Figure 2.1 The main phases of a field development plan (Petrowiki, 2016)

Development strategies for new fields are based on data obtained from seismic surveys (which are not always acquired or readily accessible), exploratory wells, and other limited information sources such as fluid properties and reservoir analogues. Based on the information at hand, initial development plans are defined through simulation studies considering either a probabilistic or a stochastic approach to rank options using economic indicators, availability of injection fluids (i.e., water and/or gas), and oil recovery and risk, among other considerations.

Therefore, integrating the information from simulation studies helps to address the multiple and complex factors that influence oil recovery, as well as reservoir development decisions. As new information about the reservoir, its geology, and its degree of heterogeneity becomes available through drilling of new wells (i.e., development and infill wells) and production–injection history, the field can be developed in an optimal way.

There are many reason behind reservoir development plans (RDPs) change or must be adjusted or modified during the productive life of the field. Some of the reasons include the following:

• Lack of reservoir characterization and understanding of production mechanisms at the early stages of development (reduction of uncertainties with time)
• Poor production performance (e.g., production below expectations and early water breakthrough)
• Environmental constraints or drivers (e.g., CO2 storage, changes in legislation)
• Economics (e.g., low oil prices)
• New technologies (e.g., horizontal wells, multilaterals, and new recovery processes)

Managing the entire lifecycle of oil and gas fields is challenging for all E&P companies, from the early stages of asset exploration and appraisal through production activities and the eventual sale or abandonment of a field. How well are your technical teams equipped to help them understand their geological and engineering data, and the uncertainty in that data? The answer to this question is important in that it determines a company's ability to accurately estimate reserves and forecast production. Economic decisions are made based on these forecasts therefore, if asset teams fail to properly understand the reservoir, they provide inaccurate reserve estimates and poor development strategies to decision-makers.

2.1 Landmark Reservoir Development Lifecycle:

Landmark Reservoir Development Lifecycle is comprised of tools that help companies enhance their reservoir understanding and manage their asset's lifecycle. Understand your asset's potential and capture the uncertainty in that potential with earth modeling while pursuing the optimal economic outcome of developing your asset with reservoir simulation for evaluating the likely outcome of multiple development and operating plans.

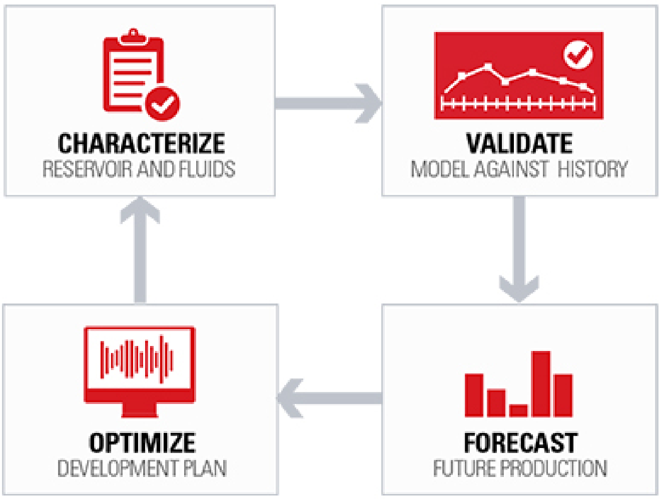


Figure 2.2 Reservoir Development lifecycle (Landmark, 2001)

2.1.1 Characterize Reservoir & Fluids:

In the exploration and appraisal lifecycle, if the asset economics are confirmed for development the process then moves to the reservoir development lifecycle where detailed analysis and asset modeling provides information needed for strategic development planning.

Asset teams gain understanding of their asset's potential and uncertainty through reservoir characterization modeling, the process of integrating subsurface G&G data to create a static 3D earth model that provides critical information for the next phase of lifecycle activities. Residing on a single collaborative platform, Earth Modeling provides companies a way to seamlessly integrate all their G&G subsurface data to create a high resolution earth model in a cross-disciplinary effort while preserving data consistency. The resulting earth model offers a clear understanding of the reservoir geometry, and rock and fluid properties along with their uncertainty.

Once you have characterized the reservoir, reservoir simulation is used to predict the potential flow of oil, gas, and water through the reservoir. The impact of proposed operating plans on recovery efficiencies can be modeled, from which an optimized plan can be devised and validated. The reservoir simulation model combines the earth model, well locations, and completion design, along with well controls imposed or proposed during the simulated time period. Predictions of future production can be made more accurate by including surface pipelines and facility behavior in the simulation model, and determining their potential effects on the performance of the wells. With Software Suite, companies can create reservoir simulation models most representative of their assets behavior for field development strategies.

2.1.2 Validate Model against History:

Due to the uncertainty in the earth model properties, predictions based upon it will also be uncertain. To reduce earth model uncertainty, any historical production data that exists for the asset can be used in reservoir simulation to determine whether the field's history is reproducible by the simulator based upon earth model properties. This calibration step, known as history matching, requires multiple simulation runs with properties chosen in accord with the distribution of properties in the earth model, and finding one or more sets of properties which lead to the observed well data being matched by the simulated wells. Companies can efficiently history match their reservoir simulation model against observed production data with Software.

2.1.3 Optimize Development Plan:

Most companies will seek an optimized development plan once the base case forecast has been completed, with the goal of increasing asset value. This process involves proposing one or more development options (e.g., water flooding or gas re-injection) which usually includes drilling additional wells. These development options are then modeled with multiple operating scenarios (different rates and pressures) which can be implemented in the field. Best practices dictate that development decisions should be made based on a comparison of forecasted behavior for various planned development options with the base case forecast. Production improvements, overall economics, field lifetime, and investment recovery time can all be considered, individually or in combination. With Software Suite companies have the ability to find the development plan which provides the greatest potential asset value.

2.1.4 Forecast Future Production:

Once the reservoir simulation model has been satisfactorily matched to production history, the process now turns to forecasting production and development planning. Forecasting is performed from the end of the field history through the expected operating life of the field, using the history-matched model to predict future behavior. The most frequent scenario is to forecast the base case in which no additional wells are drilled.

2.1.5 Uncertainty in Data:

Due to limited availability and quality of data, the complexity of the physics involved in predicting flow, and uncertainties in the modeling process, the reservoir model is always plagued by uncertainties. It is, therefore, important to analyze the input data in terms of quality, quantity, and complexities of different scales, review basic assumptions, appropriateness of the modeling workflow with reference to static and dynamic reservoir uncertainties, desired hardware and software tools to reposition the base case model with reasonable certainty for better project evaluation, risk analysis, and integrated decision making. Under these circumstances, it is necessary to achieve the right balance between short-term gains in production and optimizing long-term development. We propose a workfl ow that achieves this goal in a cost-effective way. This paper describes the workflow, and its effectiveness is demonstrated through an example.

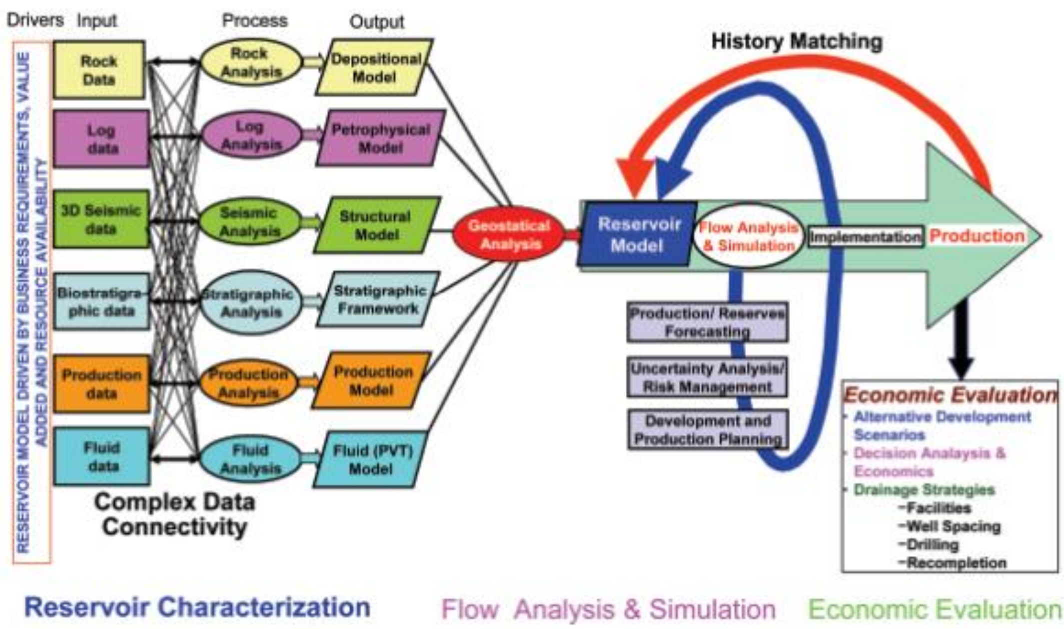


Figure 2.3 Reservoir Modeling process workflow (modology.org)

2.2 Integrated Reservoir Modeling Workflow:

The need for better decisions in field development has made it necessary to utilize multidisciplinary teams and integrate their functions/resources to maximize the economic value of the project. Figure 1 summarizes the process, shows the complex interrelation of various functions commonly implemented in a modeling effort and its iterative nature. Each process generates an output which is an input to the reservoir modeling or to other parts of the workflow. Implementation of many of these processes tends to be iterative as simple models evolve to more advanced models as additional data are collected during field development and as more understanding of a particular model is developed. The outputs from these processes are incorporated into a reservoir characterization model developed using geostatistical methods. The geologic framework forms the “static” portion of the reservoir model. Upscaling and application of flow analysis provides the “dynamic” part. Major sources of reservoir uncertainty at the early stage of development can be broadly grouped into four main categories:

- Geophysical uncertainties: Geophysical uncertainties about migration, time-to depth conversion, picking, fault positioning, and well ties.
- Geologic uncertainties: Geologic uncertainties about in-place hydrocarbon volume, sedimentary depositional environments, rock types and their heterogeneities, spatial distribution, and particle size.
- Petrophysical uncertainties: Petrophysical uncertainties about net reservoir thickness, Vshale, porosity, permeability, water saturation, and fl uid contact locations.
- Dynamic uncertainties: Dynamic uncertainties about absolute and relative permeability, fault transmissibilities, horizontal barriers, thermodynamics, injectivity, productivity indexes, and well skin.

There are no rules to systematically rank these uncertainties, but an incorrectly selected or neglected uncertainty may result in incorrect quantification of development-related risks. Therefore, all possibilities should be considered. To appropriately assess these uncertainties, we suggest a workflow that focuses on six major areas:

2.2.1 Uncertainty in OOIP Calculation:

Petrophysical interpretation identifies a consistent set of rock properties from the log and core data with the objective of developing flexible petrophysical models. Typical deliverables are net reservoir thickness, shale volume, porosity, permeability, water saturation and fluid contact locations. These data are usually provided without quantitative determination of their uncertainties.

A wide range of probability distribution functions (pdfs) are used and uncertainty on their mean value is introduced to fully cover the range of petrophysical uncertainties. In the case of limited well data, it is important to capture the realistic range of uncertainty for each petrophysical parameter. To avoid underestimation of uncertainty ranges, well-log petrophysical properties can be calibrated. When sufficient well data are available, Monte Carlo simulation can calculate petrophysical uncertainty. Monte Carlo modeling is flexible and quick, allowing different interpretation models to be built and quick testing of the results. However, Monte Carlo simulation requires many iterations for a stable and meaningful set of statistics. This can be time consuming and needs to be evaluated for the specific case.

This integrated petrophysical interpretation assesses the possible range of petrophysical parameters to select reasonable cut-off parameters for defining productive zones in the reservoir, to obtain probabilistic hydrocarbon initially in-place (HIIP) estimates, to understand and solve reservoir fl ow simulation problems, and to determine reservoir performance.

Quantification of the distribution of hydrocarbon-initially in place (HIIP): The hydrocarbon Volume in a reservoir can be expressed as:

$$Vhc = A*h*\varphi*(1-Sw)*B \quad \text{Or} \quad Vhc = GRV*N/G*\varphi*(1-Sw)*B \tag{2.1}$$

Where,

A = area of the reservoir filled with hydrocarbon,

h = reservoir thickness,

GRV = gross rock volume,

N/G = net to gross thickness,

φ = porosity,

Sw = water saturation,

B = hydrocarbon surface transformation factor (1/FVF),

Vhc = volume of hydrocarbon, and

FVF = formation volume factor.

After all parameters are determined, the volumetric equation can compute the distribution of HIIP. To avoid overestimates or underestimates of HIIP, it is important to include the dependency relationships between input parameters (e.g., area versus net pay, porosity versus water saturation) if any exist. The estimation of HIIP distribution combines reservoir geometrical, geologic and petrophysical uncertainties and uses reservoir geometry (structural/stratigraphic framework), facies distribution, rock types and porosity, net-to-gross, permeability and saturation). In the case of scarce data, it is necessary to define the range of uncertainties to obtain the probability distribution of HIIP.

Evaluating the impact of uncertainties on project economics and risks:

The production forecast obtained from reservoir simulation forms the basis for assessing project feasibility and business value, estimating the economic performance of various production strategies, and prioritizing them based on return on investment. The schedule of wells to be drilled, the pressure maintenance strategy, the investment schedule for the new pipelines and equipment facilities are a few of the important components of the forecasting scenario. Additionally, economic parameters, such as costs for drilling, laying new pipelines and investing in new equipment, along with pricing forecasts for oil and gas for revenue estimation, are needed for the evaluation of alternate development strategies.

The monetary value of a project can be normally determined by five factors: (1) the amount of hydrocarbon recoverable under a specific development scheme; (2) the rate at which these hydrocarbons can be produced: (3) the cost of producing hydrocarbons; (4) the price that the hydrocarbons will fetch at the market; and (5) the fiscal regime under which the hydrocarbons will be produced.

CHAPTER 3: MONTE CARLO

Monte Carlo simulation is a computerized mathematical technique that allows people to account for risk in quantitative analysis and decision making. The technique is used by professionals in such widely disparate fields as finance, project management, energy, manufacturing, engineering, research and development, insurance, oil & gas, transportation, and the environment.

Monte Carlo simulation furnishes the decision-maker with a range of possible outcomes and the probabilities they will occur for any choice of action. It shows the extreme possibilities—the outcomes of going for broke and for the most conservative decision—along with all possible consequences for middle-of-the-road decisions.

The technique was first used by scientists working on the atom bomb; it was named for Monte Carlo, the Monaco resort town renowned for its casinos. Since its introduction in World War II, Monte Carlo simulation has been used to model a variety of physical and conceptual

Monte Carlo simulation performs risk analysis by building models of possible results by substituting a range of values—a probability distribution—for any factor that has inherent uncertainty. It then calculates results over and over, each time using a different set of random values from the probability functions. Depending upon the number of uncertainties and the ranges specified for them, a Monte Carlo simulation could involve thousands or tens of thousands of recalculations before it is complete. Monte Carlo simulation produces distributions of possible outcome values.

By using probability distributions, variables can have different probabilities of different outcomes occurring. Probability distributions are a much more realistic way of describing uncertainty in variables of a risk analysis.

3.1 Monte Carlo Simulation Steps:

Step 1: Define all the variables. We must specify the measure of value of interest to us(e.g. NPV), and all the variable that affect the calculation of value.

Step 2: Define the variable relationships in the deterministic projection model. The relationship are the equation or other numerical calculation by which we make projection rated, net cash flow etc. that lead to the value calculation, e.g. NPV, of a drilling prospect. These relationships, or series of stepwise calculations, comprise the model or system we are trying to analyze.

Step 3: Sort the input variable into two groups. Those variables whose values are known with certainty or reasonable precision and can be represented as single point values. Significant unknowns will be represented as random variables for which exact values cannot be specified at the time of decision making.

Step 4: Define distributions for the random variables. Usually, the best available expert is assigned to judge each random variable.

Step 5: Perform the repetitive simulation trials so as to describe the distribution of value.

Step 6: Calculate expected value of the outcome value distribution. Usually this is EV NPV = EMV. Prepare graphical displays of the evaluation model and results.

CHAPTER 4: APPLICATION OF MONTE CARLO SIMULATION IN OOIP DISTRIBUTION

Oil in place (OIP) (not to be confused with **original oil-in-place (OOIP)**) is a specialist term in petroleum geology that refers to the total oil content of an oil reservoir. As this quantity cannot be measured directly, it has to be estimated from other parameters measured prior to drilling or after production has begun.

$$Vhc = A*h* \varphi* (1-Sw) * B \qquad (4.1)$$

Where,

A = area of the reservoir filled with hydrocarbon,

h = reservoir thickness, GRV = gross rock volume,

φ = porosity, Sw = water saturation,

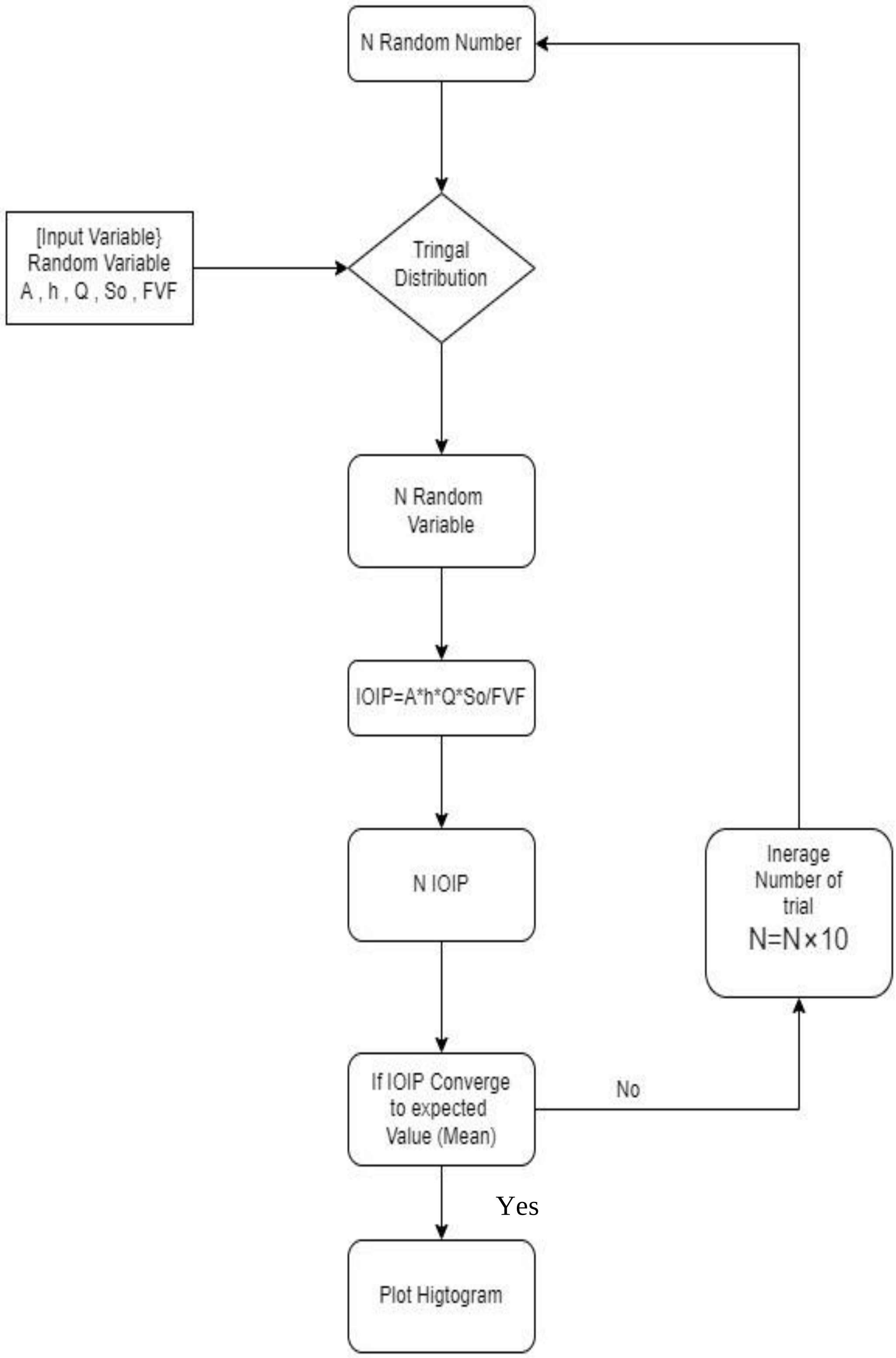
B = hydrocarbon surface transformation factor (1/FVF),

Vhc = volume of hydrocarbon, and

FVF = formation volume factor

This is the volumetric method which is used to calculate the reserve at the initial stage. Here we take the Area of the Reservoir from the Seismic data. We take the Net pay thickness, porosity, saturation from the well log data. Here we take the oil formation volume factor from the PVT analysis.

Flow Diagram:



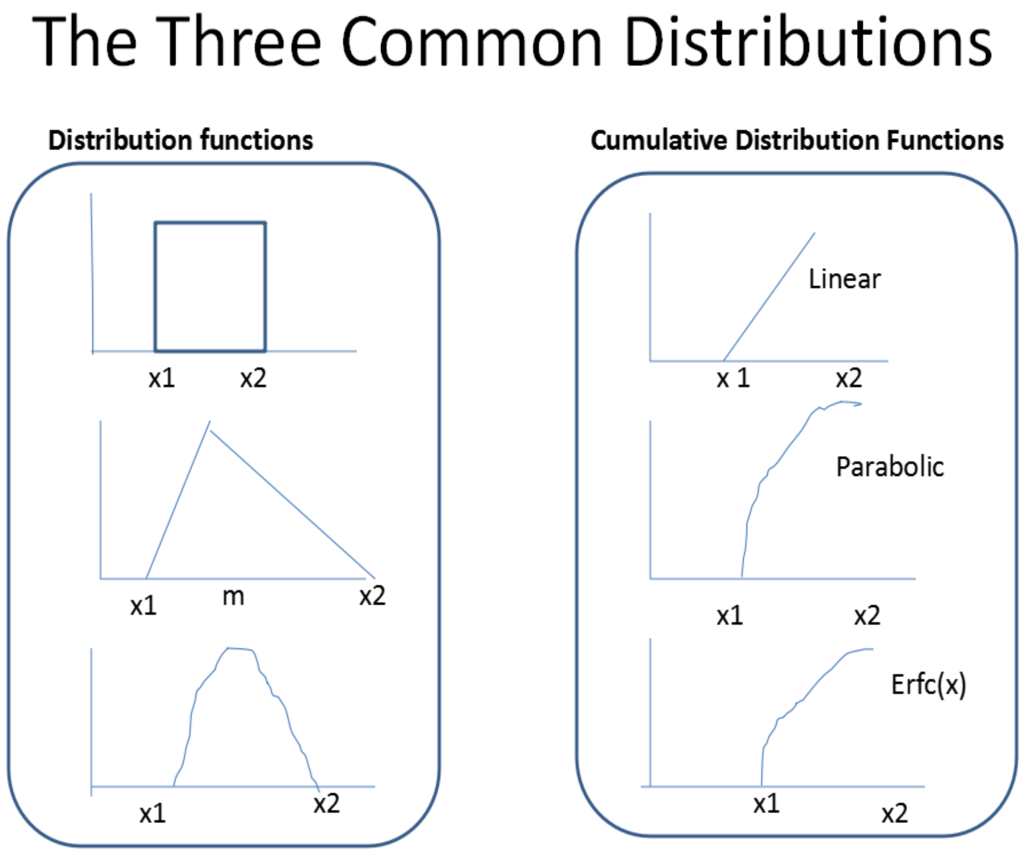


Figure 4.1 Common type of Distribution in Monte Carlo simulation (simulation, Scidirect.org)

Selection of Data Distribution depends on the surrounding nature field data. Even these things come after the Experience. Our Monte Carlo Program taking the random data which is lies between the X1 and X2.

Here X1 is minimum value

X2 is Maximum Value

X3 is Mean Value

For Triangle Distribution sampled variable is obtained as:

For $rd \leq \frac{(x3-x1)}{(x2-x1)}$

$$X = x1 + \sqrt{(rd) * (x3 - x1) * (x2 - x1)} \qquad (4.2)$$

For $rd \geq \frac{(x3-x1)}{(x2-x1)}$

$$X = x2 - \sqrt{(1 - rd) * (x2 - x3) * (x2 - x1)} \qquad (4.3)$$

Here have made Python program to generate the Reserve Distribution. For that in program we have use the Random function to generate the N Random number. Now we have used triangular distribution for each stochastic variable to generate the random variable which lies between given ranges. We have put this variable in to Volume metric equation to generate N IOIP. Now here we have to analyze, whether our Value is converge to mean value or not. If yes then we get the right data, if not then we have to increase the number of the tria

CHAPTER 5: APPLICATION OF MONTE CARLO IN DEPLETION DRIVE RESERVOIR

5.1 Reservoir Development Planning:

Here we have Depletion Drive Reservoir. Here Expansion of solution Gas and Expansion of the oil gives energy to transport crude oil from the Reservoir to the Well bore. At the Initial time we have Very Limited data to characterize the Reservoir. We have data, but it's available in range.

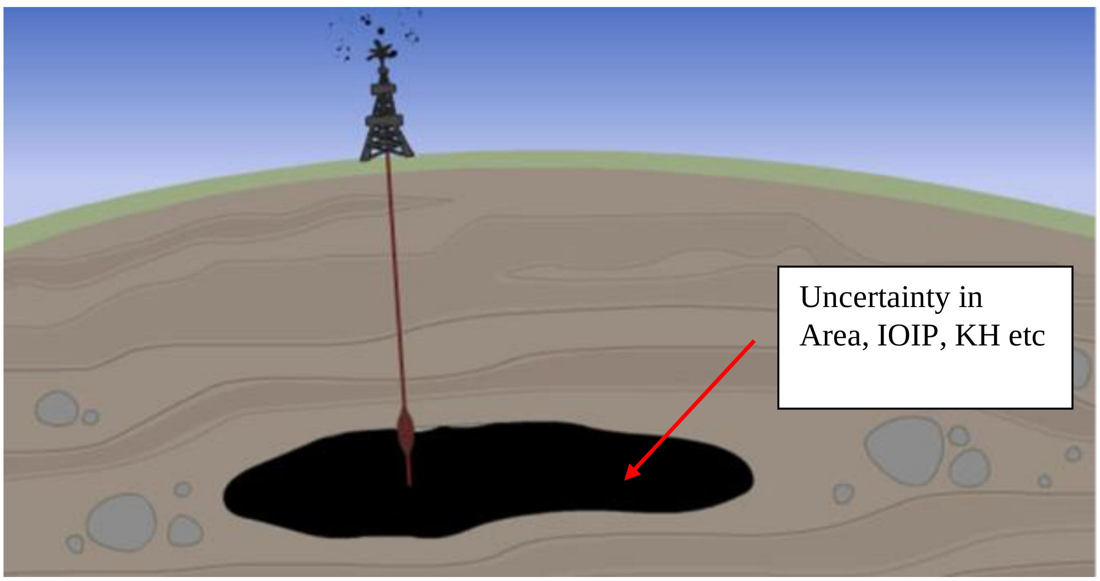


Figure 5.1 Uncertainty in Reservoir(petrowiki, 2009)

So at the initial time, there is high uncertainty in data like, Reservoir Area, IOIP, KH etc.
Input Data of Reservoir

30e+6, 15e+6, 20e+6	#Area: Max(x2), Min(x1), Mean(x3) (ft^2)
64e+6, 30e+6, 45e+6	#IOIP: Max, Min, Mean (STB)
800,300,550	#KH: Max, Min, Mean (mD-ft)
2000,1500,1750	#Q_o: Max, Min, Mean(STB/day)

It's become very difficult to decide whether we should do investment or not?

5.1.1 Other Reservoir Parameter:

API = 44.2

T = 678 R

SG of Gas = 0.781

SG of Oil =0.604

Swi = 0.2

Soi = 0.8

Sgi = 0

Pi = 2500 Psi

Rw = 0.29 ft

S = 0

KH = 647

There is huge investment require to take out the crude oil from the reservoir. So it's become the problem for us to take the decision.

There are lot of question comes like

- What will be the worst case scenario?
- What will be the Maximum Production?
- How much amount of cumulative Production will get?
- What will be Net pay time?
- What will be the NPV?
- What will be the IRR? Etc.

So,

Here we have made the Python code program which can give the all the answer of the above question, Which help us to take the Decision whether should we go for the Investment or Not?

5.2 Pvt Properties:

To understand and predict the volumetric behavior of oil and gas reservoirs as a function of pressure, knowledge of the physical properties of reservoir fluids must be gained. These fluid properties are usually determined by laboratory experiments performed on samples of actual reservoir fluids. In the absence of experimentally measured properties, it is necessary for the petroleum engineer to determine the properties from empirically derived correlations for the following reservoir fluids:

• Natural gases

• Crude oil systems

• Reservoir water systems

5.2.1 The Properties Of Natural Gas:

A gas is defined as a homogeneous fluid of low viscosity and density that has no definite volume but expands to completely fill the vessel in which it is placed. Knowledge of pressure-volume-temperature (PVT) relationships and other physical and chemical properties of gases is essential for solving problems in natural gas reservoir engineering. These properties include:

• Apparent molecular weight, Ma

• Specific gravity, gg

• Compressibility factor, z

• Density, Rhog

• Specific volume, v

• Isothermal gas compressibility coefficient, cg

• Gas formation volume factor, Bg

• Gas expansion factor, Eg

• Viscosity, mg

The above gas properties may be obtained from direct laboratory measurements or by prediction from generalized mathematical expressions. This section reviews laws that describe the volumetric behavior of gases in terms of pressure and temperature and also documents the mathematical correlations that are widely used in determining the physical properties of natural gases.

5.2.1.1 Gas Compressibility Factor:

In dealing with gases at a very low pressure, the ideal gas relationship is a convenient and generally satisfactory tool. At higher pressures, the use of the ideal gas equation-of-state may lead to errors as great as 500%, as compared to errors of 2–3% at atmospheric pressure.

Basically, the magnitude of deviations of real gases from the conditions of the ideal gas law increases with increasing pressure and temperature and varies widely with the composition of the gas. Real gases behave differently than ideal gases. The reason for this is that the perfect gas law was derived under the assumption that the volume of molecules is insignificant and that no molecular attraction or repulsion exists between them. This is not the case for real gases.

Numerous equations-of-state have been developed in the attempt to correlate the pressure-volume-temperature variables for real gases with experimental data. In order to express a more exact relationship between the variables p, V, and T, a correction factor called the *gas compressibility factor, gas deviation factor,* or simply the *z-factor,* must be introduced into Equation 2-1 to account for the departure of gases from ideality. The equation has the following form:

$$pV = znRT \tag{5.1}$$

where the gas compressibility factor z is a dimensionless quantity and is defined as the ratio of the actual volume of n-moles of gas at T and p to the ideal volume of the same number of moles at the same T and p

$$z = \frac{Vactual}{Videal} = \frac{V}{(nRT)/p} \tag{5.2}$$

Studies of the gas compressibility factors for natural gases of various compositions have shown that compressibility factors can be generalized with sufficient accuracies for most engineering purposes when they are expressed in terms of the following two dimensionless properties:

- Pseudo-reduced pressure
- Pseudo-reduced temperature

These dimensionless terms are defined by the following expressions:

$$p_{pr} = \frac{p}{p_{pc}} \qquad (5.3)$$

$$T_{pr} = \frac{T}{T_{pc}}$$

where p = system pressure, psia

ppr = pseudo-reduced pressure, dimensionless

T = system temperature, °R

Tpr = pseudo-reduced temperature, dimensionless

ppc, Tpc = pseudo-critical pressure and temperature, respectively, and defined by the following relationships:

$$p_{pc} = \sum_{i=1} y_i \, p_{ci} \qquad (5.4)$$

$$T_{pc} = \sum_{i=1} y_i \, T_{ci}$$

It should be pointed out that these pseudo-critical properties, i.e., Ppc and Tpc, do not represent the actual critical properties of the gas mixture. These pseudo properties are used as correlating parameters in generating gas properties.

Based on the concept of pseudo-reduced properties, Standing and Katz presented a generalized gas compressibility factor chart as shown in Figure. The chart represents compressibility factors of sweet natural gas as a function of ppr and Tpr. This chart is generally reliable for natural gas with minor amount of non hydrocarbons. It is one of the most widely accepted correlations in the oil and gas industry.

5.2.1.1.1 Direct Calculation of the Compressibility Factor:

After four decades of existence, the Standing-Katz z-factor chart is still widely used as a practical source of natural gas compressibility factors. As a result, there has been an apparent need for a simple mathematical description of that chart. Several empirical correlations for calculating z-factors have been developed over the years. The following three empirical correlations are described below:

- Hall-Yarborough
- Dranchuk-Abu-Kassem
- Dranchuk-Purvis-Robinson

5.2.1.1.2 The Hall-Yarborough Method:

Hall and Yarborough (1973) presented an equation-of-state that accurately represents the Standing and Katz z-factor chart. The proposed expression is based on the Starling-Carnahan equation-of-state. The coefficients of the correlation were determined by fitting them to data taken from the Standing and Katz z-factor chart. Hall and Yarborough proposed the following mathematical form

$$z = \left[\frac{0.06125\, p_{pr}\, t}{Y}\right] \exp\left[-1.2(1-t)^2\right] \qquad (5.5)$$

where P_{pr} = pseudo-reduced pressure

t = reciprocal of the pseudo-reduced temperature, i.e., T_{pc}/T

Y = the reduced density that can be obtained as the solution of the following equation:

$$F(Y) = X1 + \frac{Y + Y^2 + Y^3 + Y^4}{(1-Y)^3} - (X2)\, Y^2 + (X3)\, Y^{X4} = 0 \qquad (5.6)$$

where X1 = -0.06125*Ppr*t *exp [-1.2*(1-t)^2]

X2 = 14.76*t – 9.76*t^2 + 4.58* t^3

X3 = 90.7*t – 242.2*t^2 + 42.4 * t^3

X4 = 2.18 + 2.82*t

Equation is a nonlinear equation and can be conveniently solved for the reduced density Y by using the Newton-Raphson iteration technique. The computational procedure of solving Equation 2-37 at any specified pseudo-reduced pressure ppr and temperature Tpr is summarized in the following steps:

Step 1. Make an initial guess of the unknown parameter, Yk, where k is an iteration counter. An appropriate initial guess of Y is given by the following relationship:

$$Yk = 0.0125 * Ppr * t * \exp[-1.2 (1 - t)^2] \quad (5.7)$$

Step 2. Substitute this initial value in Equation 5.7 and evaluate the nonlinear function. Unless the correct value of Y has been initially selected,

Step 3. A new improved estimate of Y, i.e., Yk+1, is calculated from the following expression:

$$Y(k+1) = Y(k) - \frac{f(Yk)}{f'(Yk)}$$

Where f'(Y(k)) is obtained by evaluating the derivation of equation (5.7) at Y(k), or:

$$f'(Y) = \frac{1 + 4Y + 4Y^2 + 4Y^3 + Y^4}{(1-Y)^4} - 2(X2) + (X3)(X4)Y^{(X4-1)} \quad (5.8)$$

Step 4. Steps 2–3 are repeated n times, until the error, i.e., abs(Yk -Yk+1), becomes smaller than a preset tolerance,

Step 5. The correct value of Y is then used to evaluate Equation 5.8 for the compressibility factor.

Hall and Yarborough pointed out that the method is not recommended for application if the pseudo-reduced temperature is less than one.

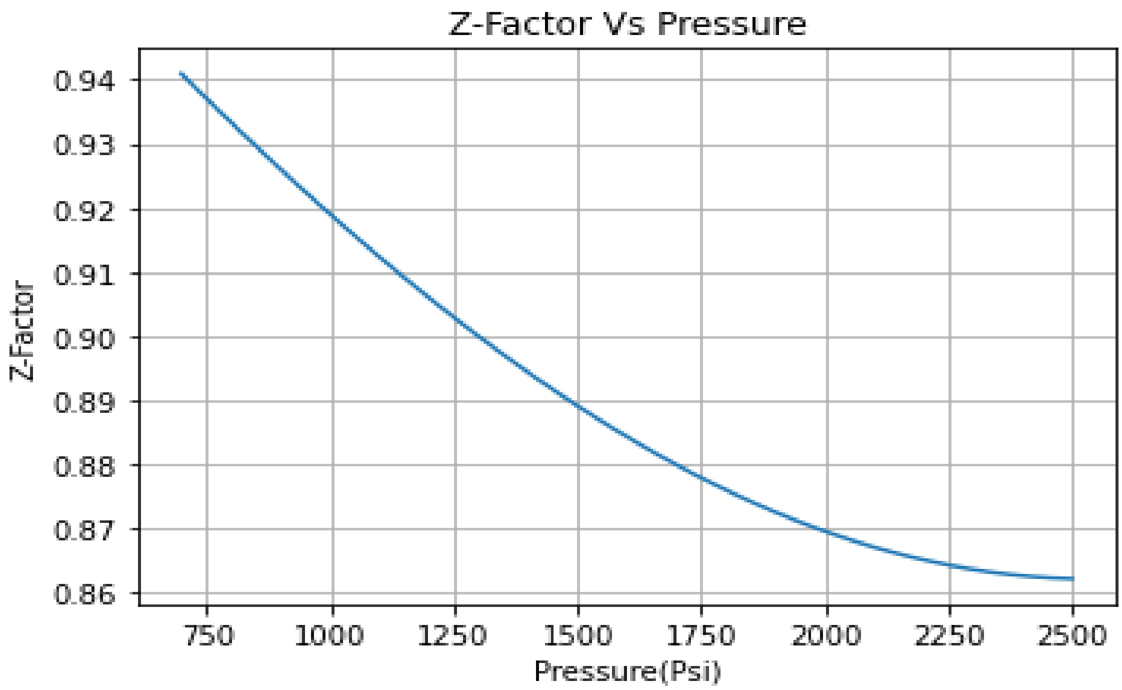


Figure 5.2 Z-factor vs Pressure

Table 5.1 Z factor data

Z-Factor	Pressure(Psi)	Z-Factor	Pressure(Psi)
0.8622125	2498	0.8634367	2318
0.8622148	2497	0.8634481	2317
0.8622172	2496	0.8634595	2316
0.8622196	2495	0.863471	2315
0.862222	2494	0.8634825	2314
0.8624499	2436	0.8658031	2163
0.8624553	2435	0.8658224	2162
0.8624607	2434	0.8658416	2161
0.8624663	2433	0.8658609	2160
0.8624718	2432	0.8658803	2159
0.8626341	2406	0.8710504	1949
0.862641	2405	0.8710802	1948
0.862648	2404	0.8711101	1947
0.862655	2403	0.87114	1946
0.8626621	2402	0.87117	1945

5.2.1.2 Gas Formation Volume Factor:

The gas formation volume factor is used to relate the volume of gas, as measured at reservoir conditions, to the volume of the gas as measured at standard conditions, i.e., 60°F and 14.7 psia. This gas property is then defined as the actual volume occupied by a certain amount of gas at a specified pressure and temperature, divided by the volume occupied by the same amount of gas at standard conditions. In an equation form, the relationship is expressed a

$$B_g = \frac{V_{p,T}}{V_{sc}}$$

where B_g = gas formation volume factor, ft^3/scf
$V_{p,T}$ = volume of gas at pressure p and temperature, T, ft^3
V_{sc} = volume of gas at standard conditions, scf

$$B_g = \frac{\dfrac{znRT}{p}}{\dfrac{z_{sc}\, n\, R\, T_{sc}}{p_{sc}}} = \frac{p_{sc}}{T_{sc}} \frac{zT}{p} \tag{5.9}$$

where z_{sc} = z-factor at standard conditions = 1.0
p_{sc}, T_{sc} = standard pressure and temperature

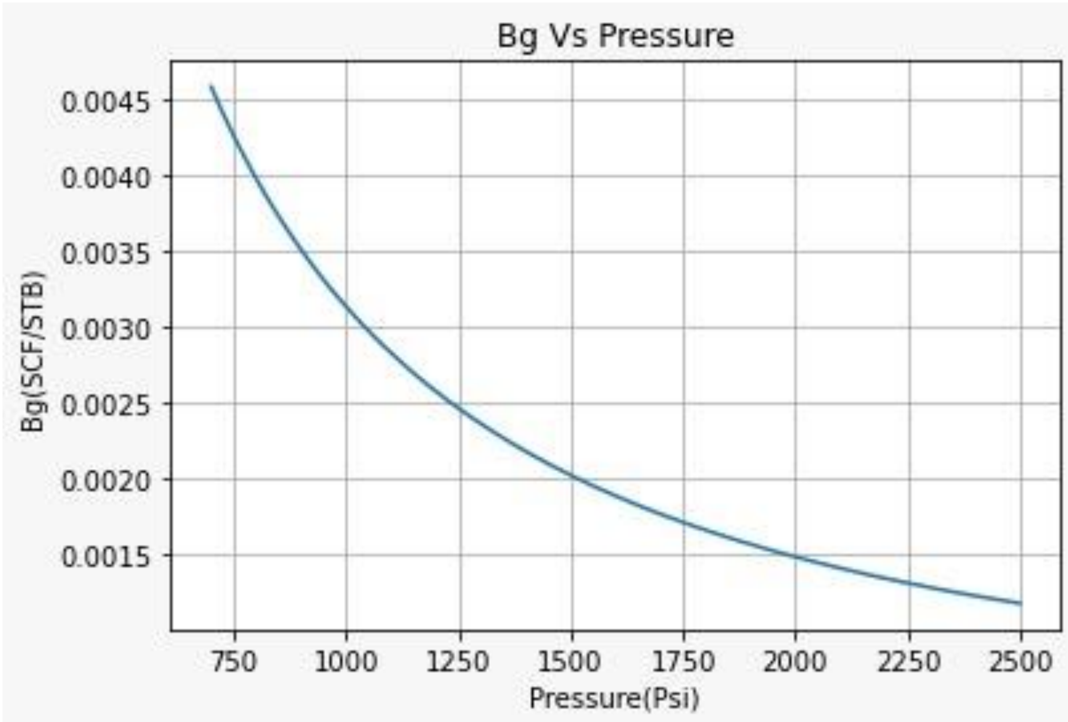


Figure 5.3 Gas formation volume factor(Bg) vs Pressure

Table 5.2 Bg factor data

Pressure(Psi)	Bg
2498	0.001178
2497	0.001179
2496	0.001179
2495	0.00118
2442	0.001206
2441	0.001206
2440	0.001207
2439	0.001207
2400	0.001227
2399	0.001228
2393	0.001231
2392	0.001231
2391	0.001232
2390	0.001232
2389	0.001233

Pressure(Psi)	Bg
2398	0.001228
2397	0.001229
2357	0.00125
2356	0.001251
2355	0.001251
2354	0.001252
2042	0.001452
2041	0.001453
2040	0.001453
2039	0.001454
1960	0.001517
1959	0.001517
1958	0.001518
1957	0.001519
1956	0.00152

5.2.1.3 Gas Viscosity:

The viscosity of a fluid is a measure of the internal fluid friction (resis-tance) to flow. If the friction between layers of the fluid is small, i.e., lowviscosity, an applied shearing force will result in a large velocity gradi- ent. As the viscosity increases, each fluid layer exerts a larger frictional drag on the adjacent layers and velocity gradient decreases.

The viscosity of a fluid is generally defined as the ratio of the shear force per unit area to the local velocity gradient. Viscosities are expressed in terms of poises, centipoise, or micropoises. One poise equals a viscosity of 1 dyne-sec/cm^2 and can be converted to other field units by the following relationships:

$$1 \text{ poise} = 100 \text{ centipoises}$$

$$= 1 * 10^{6} \text{ micropoises}$$

$$= 6.72 * 10^{-2} \text{ lb mass/ft-sec}$$

The gas viscosity is not commonly measured in the laboratory because it can be estimated precisely from empirical correlations. Like all intensive properties, viscosity of a natural gas is completely described by the following function:

$$\mu_g = (p, T, y_i) \tag{5.10}$$

where μ_g = the viscosity of the gas phase. The above relationship simply states that the viscosity is a function of pressure, temperature, and com- position. Many of the widely used gas viscosity correlations may be viewed as modifications of that expression.

5.2.1.3.1 The Lee-Gonzalez-Eakin Method

Lee, Gonzalez, and Eakin (1966) presented a semi-empirical relation- ship for calculating the viscosity of natural gases. The authors expressed the gas viscosity in terms of the reservoir temperature, gas density, and the molecular weight of the gas. Their proposed equation is given by:

$$\mu_g = 10^{-4}\, K \exp\left[X \left(\frac{\rho_g}{62.4} \right)^{Y} \right] \qquad (5.11)$$

where

$$K = \frac{(9.4 + 0.02\, M_a)\, T^{1.5}}{209 + 19\, M_a + T}$$

$$X = 3.5 + \frac{986}{T} + 0.01\, M_a$$

$$Y = 2.4 - 0.2\, X$$

ρ_g = gas density at reservoir pressure and temperature, lb/ft^3

T = reservoir temperature, °R

M_a = apparent molecular weight of the gas mixture

The proposed correlation can predict viscosity values with a standard deviation of 2.7% and a maximum deviation of 8.99%. The correlation isless accurate for gases with higher specific gravities. The authors pointedout that the method cannot be used for sour gases.

Charts And Data

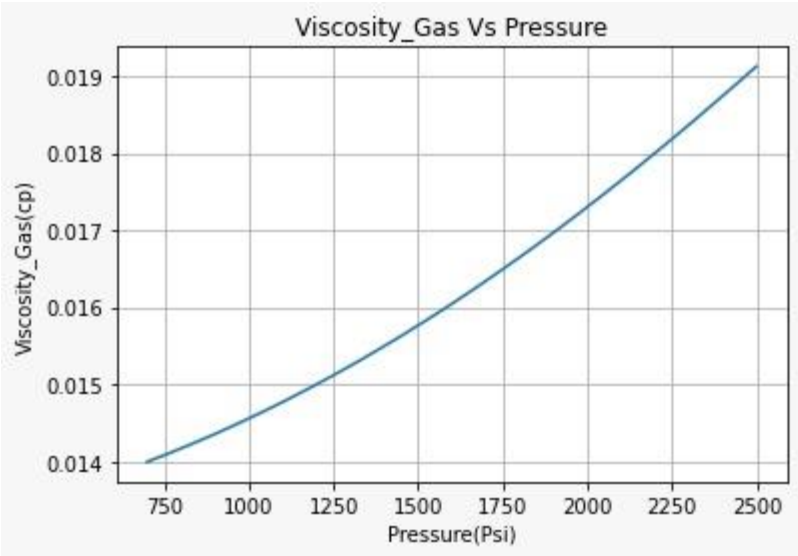


Figure 5.4 Gas viscosity vs Pressure

Table 5.3 Gas Viscosity Data

Pressure(Psi)	Mug(cP)
2230	0.018109294
2220	0.018072978
2210	0.018036765
2200	0.018000655
2190	0.017964651
2180	0.017928752
2010	0.017335195
2000	0.017301299
1990	0.01726752
1980	0.017233858
1970	0.017200313
1960	0.017166888
1720	0.016401393
1710	0.016371072
1700	0.016340879

Pressure(Psi)	Mug(cP)
1690	0.016310816
1680	0.016280882
1670	0.016251078
1660	0.016221405
1650	0.016191861
1640	0.016162449
1120	0.014816969
1110	0.014794671
1100	0.014772508
1090	0.01475048
1080	0.014728588
1070	0.01470683
1060	0.014685208
430	0.013596424
420	0.013583584

5.2.1.4 Gas Solubility:

The gas solubility R_s is defined as the number of standard cubic feet of gas which will dissolve in one stock-tank barrel of crude oil at certain pressure and temperature. The solubility of a natural gas in a crude oil is astrong function of the pressure, temperature, API gravity, and gas gravity.

For a particular gas and crude oil to exist at a constant temperature, the solubility increases with pressure until the saturation pressure is reached. At the saturation pressure (bubble-point pressure) all the available gases are dissolved in the oil and the gas solubility reaches its maximum value. Rather than measuring the amount of gas that will dissolve in a given stock-tank crude oil as the pressure is increased, it is customary to deter- mine the amount of gas that will come out of a sample of reservoir crude oil as pressure decreases.

A typical gas solubility curve, as a function of pressure for an under- saturated crude oil, is shown in Figure 2-7. As the pressure is reduced from the initial reservoir pressure p_i, to the bubble-point pressure p_b, no gas evolves from the oil and consequently the gas solubility remains con- stant at its maximum value of R_{sb}. Below the bubble-point pressure, the solution gas is liberated and the value of R_s decreases with pressure. The following five empirical correlations for estimating the gas solubility are given below:

- Standing's correlation
- The Petrosky-Farshad correlation

5.2.1.4.1 Standing's Correlation:

Standing (1947) proposed a graphical correlation for determining the gas solubility as a function of pressure, gas specific gravity, API gravity, and system temperature. The correlation was developed from a total of 105 experimentally determined data points on 22 hydrocarbon mixtures from California crude oils and natural gases. The proposed correlation hasan average error of 4.8%. Standing (1981) expressed his proposed graphi- cal correlation in the following more convenient mathematical form:

$$R_s = \gamma_g \left[\left(\frac{p}{18.2} + 1.4 \right) 10^x \right]^{1.2048} \qquad (5.12)$$

where T = temperature, °R

p = system pressure, psia

γ_g = solution gas specific gravity

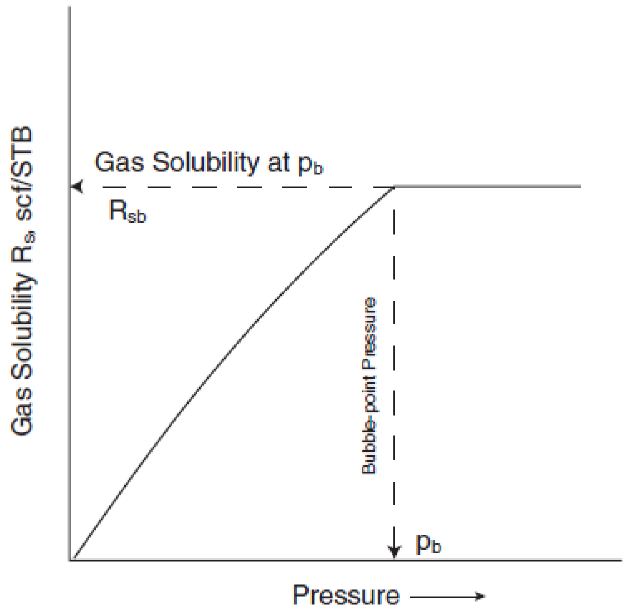


Figure 5.5 Ideal graph of Gas Solubility vs Pressure (Tarek Ahmed new edition)

It should be noted that Standing's equation is valid for applications atand below the bubble-point pressure of the crude oil.

5.2.1.4.2 The Petrosky-Farshad Correlation:

Petrosky and Farshad (1993) used a nonlinear multiple regression soft-ware to develop a gas solubility correlation. The authors constructed a PVT database from 81 laboratory analyses from the Gulf of Mexico crude oil system. Petrosky and Farshad proposed the following expression:

$$R_s = \left[\left(\frac{p}{112.727} + 12.340\right)\gamma_g^{0.8439} 10^x\right]^{1.73184} \quad (5.13)$$

with

$$x = 7.916\,(10^{-4})\,(API)^{1.5410} - 4.561(10^{-5})\,(T - 460)^{1.3911}$$

where p = pressure, psia
T = temperature, °R

Data and Chart:

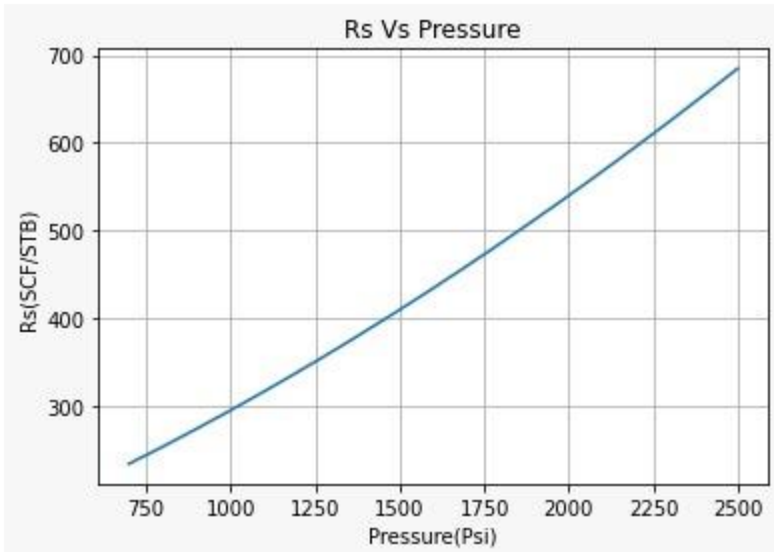


Figure 5.6 Gas Solubility vs Pressure

Table 5.4 Gas Solubility Data

Pressure(Psi)	Rs(SCF/STB)
2230	605.0121975
2220	602.1215307
2210	599.2367164
2200	596.3577589
2190	593.4846627
2180	590.6174321
2010	542.7762736
2000	540.0153918
1990	537.2604619
1980	534.5114888
1970	531.768477
1960	529.0314315
1720	465.1448704
1710	462.5585783
1700	459.9783825
1690	457.4042884
1680	454.8363013
1670	452.2744265
1660	449.7186693
1650	447.1690352
1640	444.6255294
1120	320.9502869
1110	318.7399605
1100	316.5360924
1090	314.3386894
1080	312.1477586
1070	309.9633071
1060	307.7853417
430	183.9874594
420	182.2412358

5.2.1.5 Oil Formation Volume Factor:

The oil formation volume factor, B_o, is defined as the ratio of the vol- ume of oil (plus the gas in solution) at the prevailing reservoir tempera- ture and pressure to the volume of oil at standard conditions. B_o is always greater than or equal to unity. The oil formation volume factor can be expressed mathematically as:

$$B_o = \frac{(V_o)_{p,T}}{(V_o)_{sc}} \tag{5.14}$$

where B_o = oil formation volume factor, bbl/STB

$(V_o)p,T$ = volume of oil under reservoir pressure p and temperature T,bbl

$(V_o)_{sc}$ = volume of oil is measured under standard conditions, STB

A typical oil formation factor curve, as a function of pressure for an undersaturated crude oil ($p_i > p_b$), is shown in Figure 2-8. As the pressure is reduced below the initial reservoir pressure p_i, the oil volume increases due to the oil expansion. This behavior results in an increase in the oil for-mation volume factor and will continue until the bubble-point pressure is reached. At p_b, the oil reaches its maximum expansion and consequently attains a maximum value of B_{ob} for the oil formation volume factor. As the pressure is reduced below p_b, volume of the oil and B_o are decreased as the solution gas is liberated. When the pressure is reduced to atmospheric pressure and the temperature to 60°F, the value of B_o is equal to one.

Most of the published empirical B_o correlations utilize the following generalized relationship:

$$B_o = f\ (R_s, \gamma_g, \gamma_o, T)$$

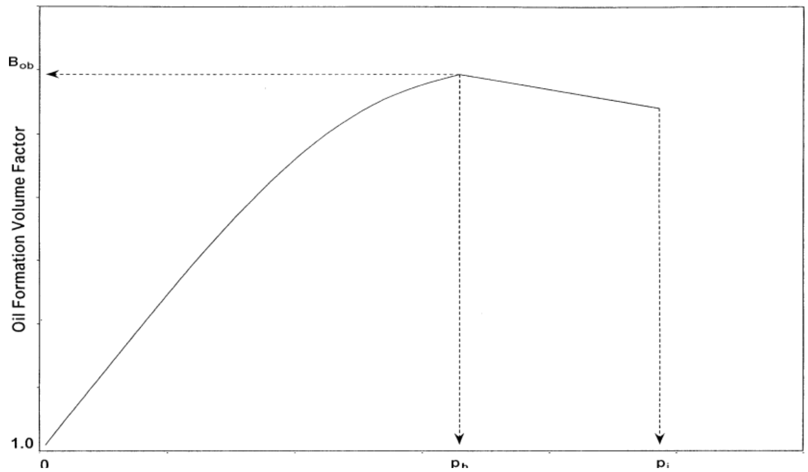


Figure 5.7 Ideal graph of oil formation volume factor vs Pressure (Tarek Ahmed new edition)

5.2.1.5.1 Standing's Correlation:

Standing (1947) presented a graphical correlation for estimating the oil formation volume factor with the gas solubility, gas gravity, oil gravity, and reservoir temperature as the correlating parameters. This graphical correlation originated from examining a total of 105 experimental data points on 22 different California hydrocarbon systems. An average error of 1.2% was reported for the correlation.

Standing (1981) showed that the oil formation volume factor can be expressed more conveniently in a mathematical form by the following equation:

$$\beta_o = 0.9759 + 0.000120\left[R_s\left(\frac{\gamma_g}{\gamma_o}\right)^{0.5} + 1.25(T-460)\right]^{1.2} \qquad (5.15)$$

where T = temperature, °R

γ_o = specific gravity of the stock-tank oil

γ_g = specific gravity of the solution gas

Chart and Data:

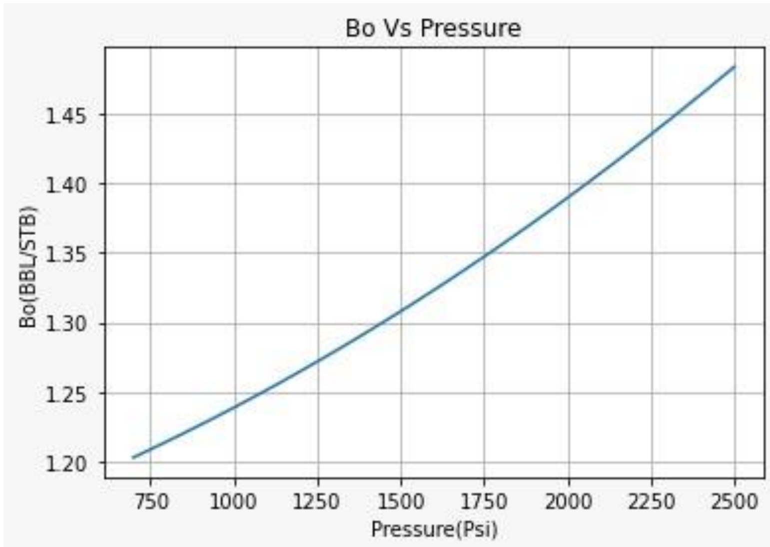


Figure 5.8 Bo vs pressure

Table 5.5 Oil Formation Volume factor

Pressure(Psi)	Bo(BBL/STB)
2230	1.370524626
2220	1.368985558
2210	1.367450606
2200	1.365919769
2190	1.364393047
2180	1.362870438
2010	1.337614251
2000	1.336165476
1990	1.334720792
1980	1.333280197
1970	1.33184369
1960	1.33041127
1720	1.297256083
1710	1.295925437
1700	1.294598846

Pressure(Psi)	Bo(BBL/STB)
1690	1.293276308
1680	1.291957823
1670	1.290643388
1660	1.289333004
1650	1.288026668
1640	1.286724379
1120	1.224551061
1110	1.223461462
1100	1.222375842
1090	1.2212942
1080	1.220216534
1070	1.219142843
1060	1.218073126
430	1.158641358
420	1.15782362

5.2.1.6 Crude Oil Viscosity:

Crude oil viscosity is an important physical property that controls and influences the flow of oil through porous media and pipes. The viscosity, in general, is defined as the internal resistance of the fluid to flow.

The oil viscosity is a strong function of the temperature, pressure, oil gravity, gas gravity, and gas solubility. Whenever possible, oil viscosity should be determined by laboratory measurements at reservoir tempera- ture and pressure. The viscosity is usually reported in standard PVT analyses. If such laboratory data are not available, engineers may refer to published correlations, which usually vary in complexity and accuracy depending upon the available data on the crude oil.

According to the pressure, the viscosity of crude oils can be classified into three categories:

Dead-Oil Viscosity: The dead-oil viscosity is defined as the viscosity of crude oil at atmospheric pressure (no gas in solution) and system temperature.

Saturated-Oil Viscosity: The saturated (bubble-point)-oil viscosity is defined as the viscosity ofthe crude oil at the bubble-point pressure and reservoir temperature

Undersaturated-Oil Viscosity: The undersaturated-oil viscosity is defined as the viscosity of the crudeoil at a pressure above the bubble-point and reservoir temperature.

5.2.1.6.1 Beal's Correlation:

From a total of 753 values for dead-oil viscosity at and above 100°F, Beal (1946) developed a graphical correlation for determining the viscos-ity of the dead oil as a function of temperature and the API gravity of the crude. Standing (1981) expressed the proposed graphical correlation in a mathematical relationship as follows:

$$\mu_{od} = \left(0.32 + \frac{1.8(10^7)}{API^{4.53}}\right)\left(\frac{360}{T-260}\right)^a \tag{5.16}$$

with

$$a = 10^{(0.43 + 8.33/API)}$$

where μ_{od} = viscosity of the dead oil as measured at 14.7 psia and reservoir temperature, cp

T = temperature, °R

Table 5.6 Oil Viscosity Data

Pressure(Psi)	Muo(cP)
2230	0.183481454
2220	0.183868903
2210	0.184258824
2200	0.184651241
2190	0.185046183
2180	0.185443676
2010	0.192620054
2000	0.193068659
1990	0.193520424
1980	0.193975385
1970	0.194433582
1960	0.194895052
1720	0.207065651
1710	0.20762372
1700	0.208186346
1690	0.208753592
1680	0.209325522
1670	0.2099022
1660	0.210483695
1650	0.211070072
1640	0.211661401
1120	0.251586189
1110	0.252592864
1100	0.253611824
1090	0.254643322
1080	0.255687619
1070	0.256744983
1060	0.257815691
430	0.375906008
420	0.379344302

5.3 Relative permeability:

Numerous laboratory studies have concluded that the effective permeability of any reservoir fluid is a function of the reservoir fluid saturation and the wetting characteristics of the formation. It becomes necessary, therefore, to specify the fluid saturation when stating the effective permability of any particular fluid in a given porous medium. Just as k is the accepted universal symbol for the absolute permeability, k_o, k_g, and $k_w$are the accepted symbols for the effective permeability to oil, gas, and water, respectively. The saturations, i.e., S_o, S_g, and S_w, must be specifiedto completely define the conditions at which a given effective permeabil-ity exists.

Effective permeability are normally measured directly in the laboratory on small core plugs. Owing to many possible combinations of saturation for a single medium, however, laboratory data are usually summarized and reported as relative permeability.

The absolute permeability is a property of the porous medium and is a measure of the capacity of the medium to transmit fluids. When two or more fluids flow at the same time, the relative permeability of each phaseat a specific saturation is the ratio of the effective permeability of the phase to the absolute permeability, or:

$$k_{ro} = \frac{ko}{K}$$

$$k_{rg} = \frac{kg}{K} \qquad (5.17)$$

$$k_{rw} = \frac{kw}{K}$$

where kro = relative permeability of oil
krg = relative permeability of oil
krw= relative permeability of oil
k= absolute permeability
ko= effective permeability to oil for a given oil saturation
kw= effective permeability to oil for a given gas saturation
kg= effective permeability to oil for a given water saturation

For example, if the absolute permeability k of a rock is 200 md and theeffective permeability k_o of the rock at an oil saturation of 80 percent is 60 md, the relative permeability k_{ro} is 0.30 at $S_o = 0.80$.

Since the effective permeabilities may range from zero to k, the rela- tive permeabilities may have any value between zero and one, or:

$$0 < k_{rw}, k_{ro}, k_{rg} < 1.0$$

It should be pointed out that when three phases are present the sum of the relative permeabilities (k_{ro}, k_{rg}, k_{rw}) is both variable and always less than or equal to unity. An appreciation of this observation and of its physical causes is a prerequisite to a more detailed discussion of two- and three-phase relative permeability relationships.,It has become a common practice to refer to the relative permeability curve for the non-wetting phase as k_{nw} and the relative permeability forthe wetting phase as k_w.

5.3.1 Two-phase Relative Permeability:

When a wetting and a nonwetting phase flow together in a reservoir rock, each phase follows separate and distinct paths. The distribution of the two phases according to their wetting characteristics results in characteristic wetting and nonwetting phase relative permeabilities. Since the wetting phase occupies the smaller pore openings at small saturations, and these pore openings do not contribute materially to flow, it follows that the presence of a small wetting phase saturation will affect the nonwetting phase permeability only to a limited extent. Since the nonwetting phase occupies the central or larger pore openings which contribute materially to fluid flow through the reservoir, however, a small nonwetting phase saturation will drastically reduce the wetting phase permeability.

Figure 5-1 presents a typical set of relative permeability curves for a water-oil system with the water being considered the wetting phase. Figure 5-1 shows the following four distinct and signific ant points:

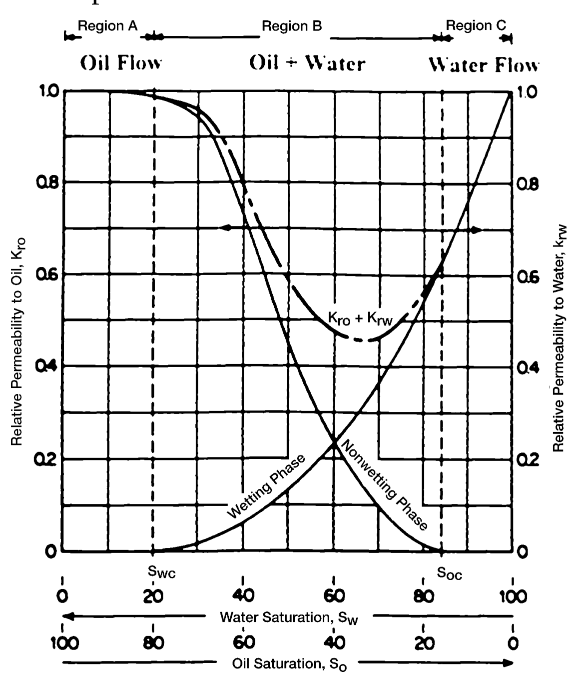


Figure 5.9 Oil & Water Relative permeability vs Saturation of water (Tarek Ahmed new edition)

- Point 1

Point 1 on the wetting phase relative permeability shows that a small saturation of the nonwetting phase will drastically reduce the relative permeability of the wetting phase. The reason for this is that the non- wetting phase occupies the larger pore spaces, and it is in these large pore spaces that flow occurs with the least difficulty.

- Point 2

Point 2 on the nonwetting phase relative permeability curve shows that the nonwetting phase begins to flow at the relatively low saturation of the nonwetting phase. The saturation of the oil at this point is called *critical oil saturation* S_{oc}.

- Point 3

Point 3 on the wetting phase relative permeability curve shows that the wetting phase will cease to flow at a relatively large saturation. This is because the wetting phase preferentially occupies the smaller pore spaces, where capillary forces are the greatest. The saturation of the water at this point is referred to as the *irreducible water saturation* S_{wir} or *connate water saturation* S_{wi}—both terms are used interchangeably.

- Point 4

Point 4 on the nonwetting phase relative permeability curve shows that, at the lower saturations of the wetting phase, changes in the wet- ting phase saturation have only a small effect on the magnitude of the nonwetting phase relative permeability curve. The reason for the phenomenon at Point 4 is that at the low saturations the wetting phase fluid occupies the small pore spaces which do not contribute materially to flow, and therefore changing the saturation in these small pore spaces has a relatively small effect on the flow of the nonwetting phase.

This process could have been visualized in reverse just as well. It should be noted that this example portrays oil as nonwetting and water as wetting. The curve shapes shown are typical for wetting and nonwetting phases and may be mentally reversed to visualize the behavior of an oil-wet system. Note also that the total permeability to both phases, k_{rw} + k_{ro}, is less than 1, in regions B and C.

The above discussion may be also applied to gas-oil relative permeability data, as can be seen for a typical set of data in Figure 5-2. Note that this might be termed gas-liquid relative permeability since it is plotted versus the liquid saturation. This is typical of gas-oil relative permeability data in the presence of connate water. Since the connate (irreducible) water normally occupies the smallest pores in the presence of oil and gas, it appears to make little difference whether water or oil that would also be immobile in these small pores occupies these pores. Consequently, in applying the gas-oil relative permeability data to a reservoir,the total liquid saturation is normally used as a basis for evaluating the relative permeability to the gas and oil.

Note that the relative permeability curve representing oil changes completely from the shape of the relative permeability curve for oil in thewater-oil system. In the water-oil system, as noted previously, oil is nor- mally the nonwetting phase, whereas in the presence of gas the oil is the wetting phase. Consequently, in the presence of water only, the oil relative permeability curve takes on an S shape whereas in the presence of gas the oil relative-permeability curve takes on the shape of the wetting phase, or is concave upward. Note further that the critical gas saturation S_{gc} is generally very small.

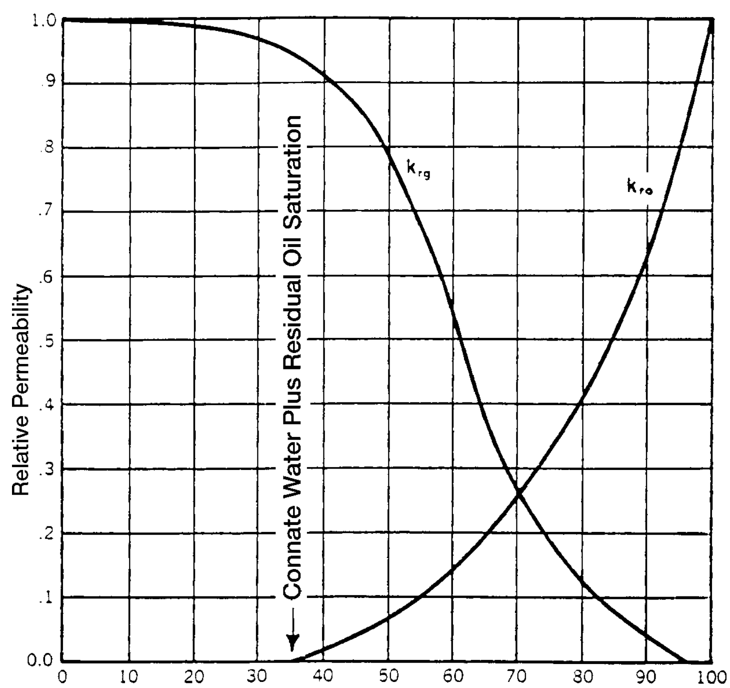


Figure 5.10 Gas-oil relative permeability curves (Tarek Ahmed new edition)

Another important phenomenon associated with fluid flow through porous media is the concept of residual saturations. As when one immiscible fluid is displacing another, it is impossible to reduce the saturation of the displaced fluid to zero. At some small saturation, which is presumed to be the saturation at which the displaced phase ceases to be continuous, flow of the displaced phase will cease. This saturation is often referred to as the *residual* saturation. This is an important concept as it determines the maximum recovery from the reservoir. Conversely, a fluid must develop a certain minimum saturation before the phase will beginto flow. This is evident from an examination of the relative permeability curves shown in Figure 5-1. The saturation at which a fluid will justbegin to flow is called the *critical* saturation.

Theoretically, the critical saturation and the residual saturation should be exactly equal for any fluid; however, they are not identical. **Critical saturation is measured in the direction of increasing saturation, whileirreducible saturation is measured in the direction of reducing saturation.** Thus, the saturation histories of the two measurements are different.

As was discussed for capillary-pressure data, there is also a saturation history effect for relative permeability. The effect of saturation history on relative permeability is illustrated in Figure 5-3. If the rock sample is initially saturated with the wetting phase (e.g., water) and relative-permeability data are obtained by decreasing the wetting-phase saturation whileflowing nonwetting fluid (e.g., oil) in the core, the process is classified as *drainage* or *desaturation.*

If the data are obtained by increasing the saturation of the wetting phase, the process is termed *imbibition* or *resaturation.* The nomenclature is consistent with that used in connection with capillary pressure. This difference in permeability when changing the saturation history is called *hysteresis.* Since relative permeability measurements are subject tohysteresis, it is important to duplicate, in the laboratory, the saturation history of the reservoir.

5.3.1.1 COREY'S METHOD:

Corey (1954) proposed a simple mathematical expression for generating the relative permeability data of the gas-oil system. The approximation is good for drainage processes, i.e., gas-displacing oil.

$$Sw^* = Sg/(1-Swc)$$

$$K_{ro} = (1- S^*_g)4 \quad (5.18)$$

$$K_{rg} = (S^*_g)(2-S^*_g)$$

where S_g^* = the effective gas saturation

Data and Chart:

Table 5.7 Relative Permeability of the Oil and gas

So	Sg	Kro	Krg
0.65	0.1	0.586182	0.003662
0.55	0.2	0.316406	0.027344
0.45	0.3	0.152588	0.085693
0.35	0.4	0.0625	0.1875
0.25	0.5	0.019775	0.335693
0.15	0.6	0.003906	0.527344

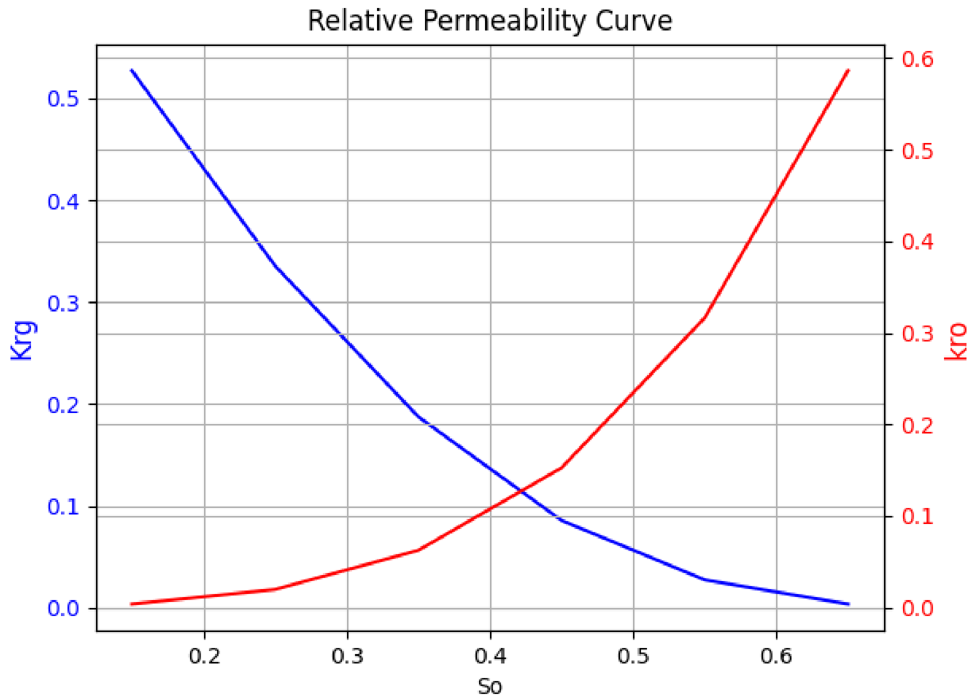


Figure 5.10 Gas-oil relative permeability curves

5.4 Primary Recovery:

For a proper understanding of reservoir behavior and predicting future performance, it is necessary to have knowledge of the driving mechanisms that control the behavior of fluids within reservoirs. The overall performance of oil reservoirs is largely determined by the nature of the energy, i.e., driving mechanism, available for moving the oil to the wellbore. There are basically six driving mechanisms that provide the natural energy necessary for oil recovery:

- Rock and liquid expansion drive
- Depletion drive
- Gas cap drive
- Water drive
- Gravity drainage drive
- Combination drive

5.4.1 The Depletion drive Mechanism:

This driving form may also be referred to by the following various terms:

- Solution gas drive
- Dissolved gas drive
- Internal gas drive

In this type of reservoir, the principal source of energy is a result of gas liberation from the crude oil and the subsequent expansion of the solution gas as the reservoir pressure is reduced. As pressure falls below the bubble-point pressure, gas bubbles are liberated within the microscopic pore spaces.

- **Reservoir Pressure**: The reservoir pressure declines rapidly and continuously. This reservoir pressure behavior is attributed to the fact that no extraneous fluids or gas caps are available to provide a replacement of the gas and oil withdrawals.

- **Water Production:** The absence of a water drive means there will be little or no water production with the oil during the entire producing life of the reservoir.

- **Gas-oil ratio:** A depletion-drive reservoir is characterized by a rapidly increasing gas-oil ratio from all wells, regardless of their structural position. After the reservoir pressure has been reduced below the bubble-point pressure, gas evolves from solution throughout the reservoir. Once the gas saturation exceeds the critical gas saturation, free gas begins to flow toward the wellbore and gas-oil ratio increases. The gas will also begin a vertical movement due to the gravitational forces, which may result in the formation of a secondary gas cap. Vertical permeability is an important factor in the formation of a secondary gas cap.

- **Ultimate Oil recovery:** Oil production by depletion drive is usually the least efficient recovery method. This is a direct result of the formation of gas saturation throughout the reservoir. Ultimate oil recovery from depletion-drive reservoirs may vary from less than 5% to about 30%. The low recovery from this type of reservoirs suggests that large quantities of oil remain in the reservoir and, therefore, depletion-drive reservoirs are considered the best candidates for secondary recovery applications.

Table 5.8 Basic Characteristics of Depletion Drive reservoir (Tarik Ahem.)

Characteristics	Trend
Reservoir Pressure	Decline rapidly and Continuously
Gas-Oil Ratio	Increase to Maximum then Decline
Water Production	None
Well behavior	Require pumping at early stage
Oil Recovery	5 to 30%

5.5 Saturated Oil Reservoirs:

If the reservoir originally exists at its bubble-point pressure, the reservoir is referred to as a saturated-oil reservoir. This is considered as the second type of the solution-gas-drive-reservoir. As the reservoir pressure declines below the bubble-point, the gas begins to evolve from solution. The general MBE may be simplified by assuming that the expansion of the gas is much greater than the expansion of rock and initial water and, therefore, can be neglected. For a volumetric and saturated-oil reservoir with no fluid injection, the MBE can be expressed by

$$N = \frac{Np*Bo+(Gp-Np*Rs)*Bg}{(Bo-Boi)+(Rsi-Rs)*Bg} \tag{5.20}$$

N = Initial Oil-in Place
Np = Cumulative Oil Production
Bo = Oil formation Volume Factor
Gp = Cumulative Gas Production
Rs = Gas Solubility

- **Initial Oil-in Place (N):** Generally, the volumetric estimate of in-place oil is used in calculating the performance. Where there is sufficient solution-gas-drive history, however, this estimate may be checked by calculating a material-balance estimate.

- **Hydrocarbon PVT data :**. Since differential gas liberation is assumed to best represent the conditions in the reservoir, differential laboratory PVT data should be used in reservoir material balance. The flash PVT data are then used to convert from reservoir conditions to stock-tank conditions. If laboratory data are not available, reasonable estimates may sometimes be obtained from published correlations. If differential data are not available, the flash data may be used instead; however, this may result in large errors for high-solubility crude oils.

- **Initial Fluid Saturation :** Initial fluid saturations obtained from a laboratory analysis of core data are preferred; however, if these are not available, estimates in some cases may be obtained from a well-log analysis or may be obtained from other reservoirs in the same or similar formations.

- **Relative Permeability data :** Generally, laboratory-determined kg/ko and kro data are averaged to obtain a single representative set for the reservoir. If laboratory data are not available, estimates in some cases may be obtained from other reservoirs in the same or similar formations.

$$S_o = (1 - S_{wi})(1 - N_p/N)(B_o/B_{oi})$$
$$k_{rg}/k_{ro} = (GOR - R_s)(\mu_g B_g/\mu_o B_o) \qquad (5.21)$$

The above results should be compared with the averaged laboratory relative permeability data. This may indicate a needed adjustment in the early data and possibly an adjustment in the overall data.

All the techniques that are used to predict the future performance of a reservoir are based on combining the appropriate MBE with the instantaneous GOR using the proper saturation equation. The calculations are repeated at a series of assumed reservoir pressure drops. These calculations are usually based on one stock-tank barrel of oil in place at the bubble-point pressure, i.e., N = 1. This avoids carrying large numbers in the calculation procedure and permits calculations to be made on the basis of the fractional recovery of initial oil in place. There are several widely used techniques that were specifically developed to predict the performance of solution-gas-drive reservoirs, including:

- Tracy's method
- Muskat's method
- Tarner's method

5.5.1 Mustak'S Method:

Muskat (1945) expressed the material balance equation for a depletion-drive reservoir in the following differential form:

$$\frac{dS_o}{dp} = \frac{\frac{S_o B_g}{B_o}\frac{dR_s}{dp} + \frac{S_o}{B_o}\frac{k_{rg}}{k_{ro}}\frac{\mu_o}{\mu_g}\frac{dB_o}{dp} + (1 - S_o - S_{wc})B_g \frac{d(1/B_g)}{dp}}{1 + \frac{\mu_o}{\mu_g}\frac{k_{rg}}{k_{ro}}} \quad (5.21)$$

with

$$\Delta S_o = S_o^* - S_o$$

$$\Delta p = p^* - p$$

where S_o^*, p^* = oil saturation and average reservoir pressure at the beginning of the pressure step
S_o, p = oil saturation and average reservoir pressure at the end of the time step
R_s = gas solubility, scf/STB
B_g = gas formation volume factor, bbl/scf

Craft, Hawkins, and Terry (1991) suggested the calculations can be greatly facilitated by computing and preparing in advance in graphical form the following pressure dependent groups :

$$X(p) = \frac{B_g}{B_o}\frac{dR_s}{dp} \quad (5.22)$$

$$Y(p) = \frac{1}{B_o}\frac{\mu_o}{\mu_g}\frac{dB_o}{dp} \quad (5.23)$$

$$Z(p) = B_g \frac{d(1/B_g)}{dp} \quad (5.24)$$

Introducing the above pressure dependent terms into Equation 5.21, gives

$$\left(\frac{\Delta S_o}{\Delta p}\right) = \frac{S_o X(p) + S_o \frac{k_{rg}}{k_{ro}} Y(p) + (1 - S_o - S_{wc}) Z(p)}{1 + \frac{\mu_o}{\mu_g} \frac{k_{rg}}{k_{ro}}} \tag{5.25}$$

Craft, Hawkins, and Terry (1991) proposed the following procedure for solving Muskat's equation for a given pressure drop Δp, i.e., (p* - p):

Step 1. Prepare a plot of krg/kro versus gas saturation.

Table 5.9 Ratio of Relative Gas to Relative permeability data

Sg	**Krg_by_Kro**
0.1	0.006247397
0.2	0.086419753
0.3	0.5616
0.4	3
0.5	16.97530864
0.6	135

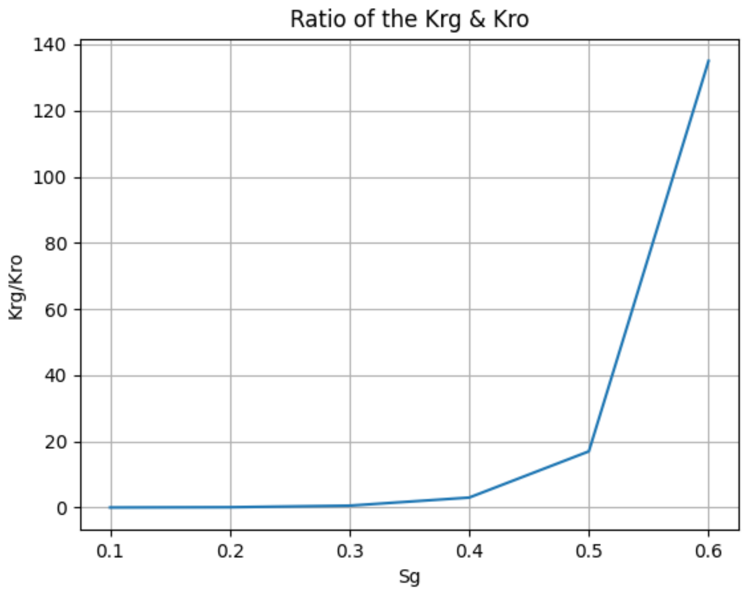


Figure 5.11 Graph between Ration of Gas relative permeability to oil relative permeability vs Gas Saturation

Step 2. Plot Rs, Bo and (1/Bg) versus pressure and determine the slope of each plot at selected pressures, i.e., dBo/dp, dRs/dp, and d(1/Bg)/dp

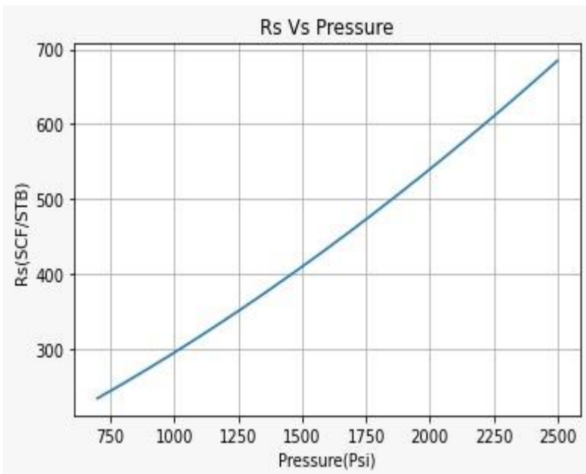


Figure 5.12 Gas Solubility vs Pressure

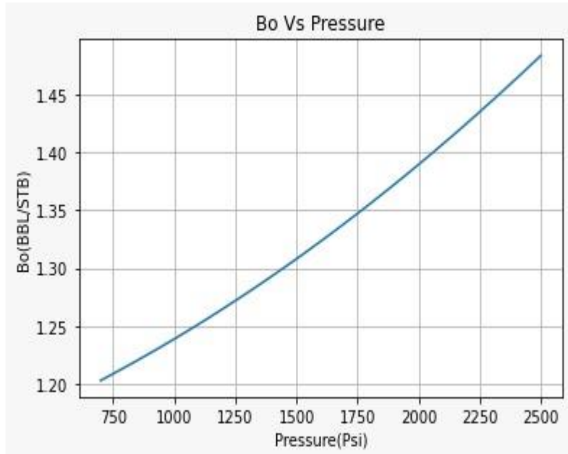


Figure 5.13 oil formation volume factor vs Pressure

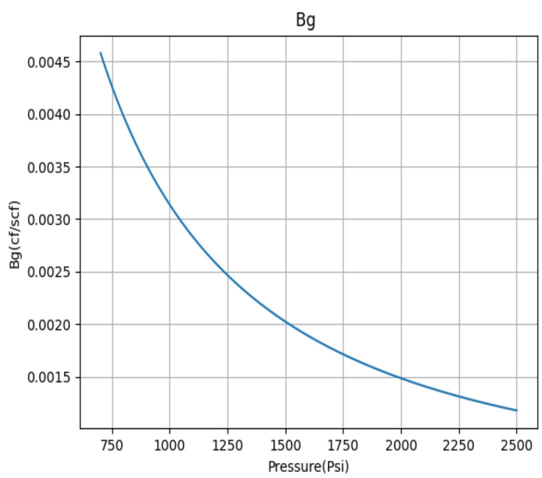


Figure 5.14 Gas formation volume factor(Bg) vs Pressure

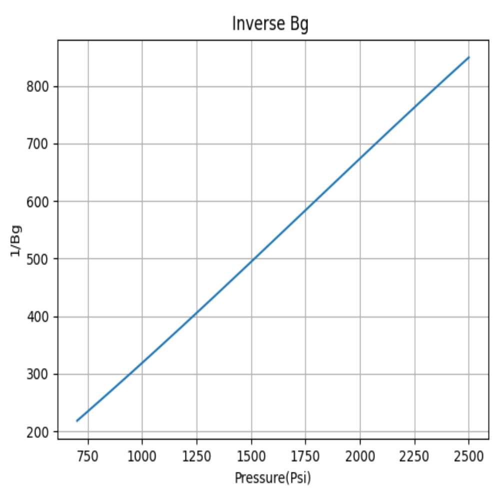


Figure 5.15 Gas expansion factor(Bg) vs Pressure

Step 3. Calculate the pressure dependent terms X(p), Y(p), and Z(p) that correspond to the selected pressures in Step 2.

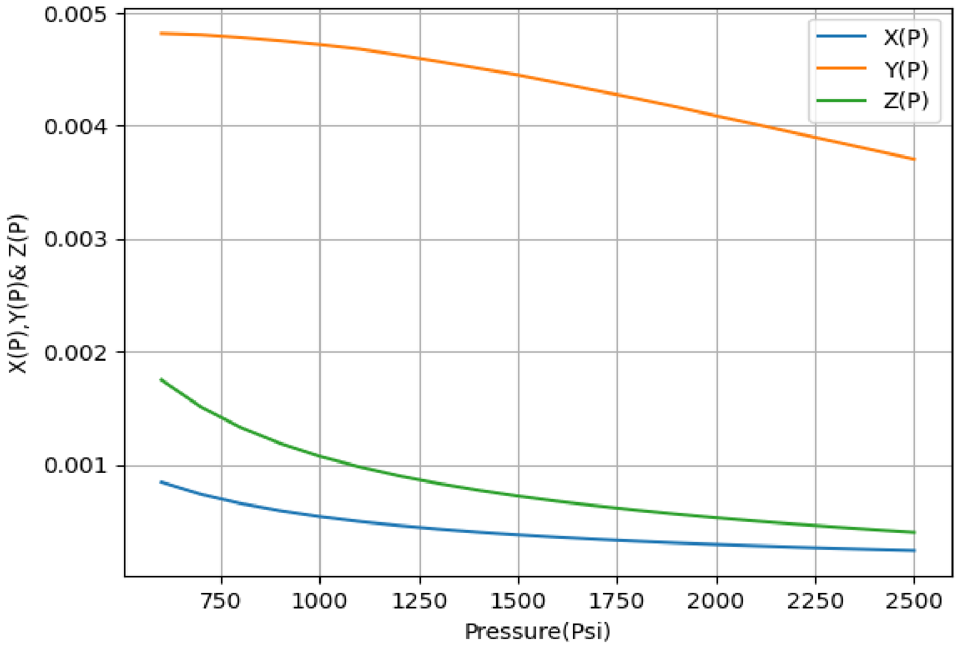


Figure 5.16 the pressure-dependent terms X(p), Y(p), and Z(p) vs pressures

Step 6. Solve Equation 5.25 for (ΔSo/Δp) by using the oil saturation So^* at the beginning of the pressure drop interval p*.

Step 7. Determine the oil saturation So at the average reservoir pressure p, from:

$$S_o = S_o^* - (p^* - p)\left(\frac{\Delta S_o}{\Delta p}\right) \tag{5.26}$$

Step 8. Using the So from Step 7 and the pressure p, recalculate (ΔSo/Δp) from Equation 5.25.

Step 9. Calculate the average value for (ΔSo/Δp) from the two values obtained in Steps 6 and 8, or:

$$\left(\frac{\Delta S_o}{\Delta p}\right)_{avg} = \frac{1}{2}\left[\left(\frac{\Delta S_o}{\Delta p}\right)_{step\,6} + \left(\frac{\Delta S_o}{\Delta p}\right)_{step\,8}\right] \quad (5.27)$$

Step 10. Using (ΔSo/Δp)avg, solve for the oil saturation So from:

$$S_o = S_o^* - (p^* - p)\left(\frac{\Delta S_o}{\Delta p}\right)_{avg} \quad (5.28)$$

Step 11. Calculate gas saturation Sg by:

$$S_g = 1 - S_{wi} - S_o \quad (5.29)$$

Step 12. Using the saturation equation, solve for the cumulative oil production.

$$N_P = N\left[1 - \left(\frac{B_{oi}}{B_o}\right)\left(\frac{S_o}{1 - S_{wi}}\right)\right] \quad (5.30)$$

Step 13. Repeat Steps 5 through 12 for all pressure drops of interest.

Input Data for the Reservoir

API = 44.2

T = 678 R

SG of Gas = 0.781

SG of Oil =0.604

Swi = 0.2

Soi = 0.8

Sgi = 0

Pi = 2500 Psi

IOIP = 53049478 (STB)

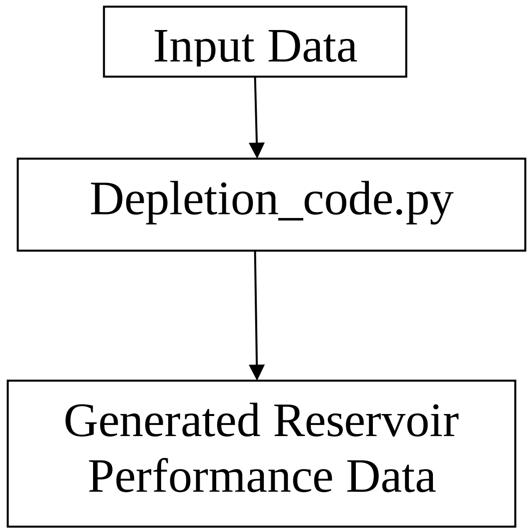
Area = 24723278 ft^2

Rw = 0.29 ft

S = 0

KH = 647

Work Flow-Diagram:



CHAPTER 6: TECHNO ECONOMICS

6.1 Basic Characteristics:

Capital Cost

- Capital costs are fixed, one-time expenses incurred on the purchase of land, buildings, construction, and equipment used in the production of goods or in the rendering of services. In other words, it is the total cost needed to bring a project to a commercially operable status.
- To make project techno economically feasible, we should try to keep capital cost of project minimum which includes drilling cost and surface facility cost in that.

Operating Cost

- Operating costs refer to the costs incurred to maintain the day-to-day operations of your business.
- In oil and gas industry, for drilling project it includes daily mud programme, contractor payment etc.
- Ultimate aim is to keep operating cost minimum to make project feasible or cost effective.

Revenue

- Revenue is the value of all sales of goods and services recognized by a company in a period. Revenue (also referred to as Sales or Income) forms the beginning of a company's income statement and is often considered the "Top Line" of a business.
- Expenses are deducted from a company's revenue to arrive at its Profit or Net Income.
- So, we can say that if revenue of company is high at the end of the time period let it be for one year, then it after deduction of cost recovery or expenses, company will be in huge profit which make project techno economical feasible.

Taxes

- Money paid to the government that is based on your income or the cost of goods or services you have bought.
- Taxes levied on available revenue for sharing should be minimum for project feasibility.

Royalty

- Royalties have historically been the most common method used by governments to gain revenue from the exploitation of the nation's mineral endowment.
- Royalties are attractive to governments because they ensure an upfront revenue stream as soon as production starts. So low royalty rate from government side may help project owner to earn more profit which makes project techno economical.

Discount rate

- It only makes sense for a company to proceed with a new project if its expected revenues are larger than its expected costs—in other words, it needs to be profitable.
- The discount rate makes it possible to estimate how much the project's future cash flows would be worth in the present.

NPV(Net Present Value)

- Net present value (NPV) is **the difference between the present value of cash inflows and the present value of cash outflows over a period of time**. NPV is used in capital budgeting and investment planning to analyze the profitability of a projected investment or project.
- Positive NPV will make project more profitable and techno economically viable.

IRR(Internal Rate of Return)

- The internal rate of return (IRR) is **a metric used in financial analysis to estimate the profitability of potential investments**. IRR is a discount rate that makes the net present value (NPV) of all cash flows equal to zero in a discounted cash flow analysis.

Abandonment costs

- Abandonment costs or Abandonment expenditure (ABEX) are **costs associated with the abandonment of a business venture**.
- Abandonment costs traditionally applied to the process of abandoning an under producing or non-producing oil or gas well. Which includes cost of recovering land, cementing cost to close the well permanently etc. Abandonment costs should be low for project feasibility.

Tangible Cost

- Tangible costs related to drilling for oil and natural gas have to be depreciated over seven years. These costs pertain to the direct cost of the drilling equipment such as drilling rigs, tractors, trailers, tandem trucks, dozers, and excavators to name a few.

Intangible Cost

- An intangible cost is an unquantifiable cost emanating from an identifiable source that can impact, usually negatively, overall company performance. Many intangible costs arise from causes that are social, legal, or political, and ignoring them can have adverse implications.

CHAPTER 7: RESULT AND DISCUSSION

Here we have run the Monte Carlo simulation model for reserve distribution. Here our input data are Porosity, Area, thickness, oil saturation. These all the data are stochastic variable. We have input this data into the Reserve_ Distribution.py file. Here We have also generated 100 stochastic variables, like porosity, area, thic First we run this code for the 100 times and generate 100 IOIP value.

7.1 Generated Random Stochastic Variables:

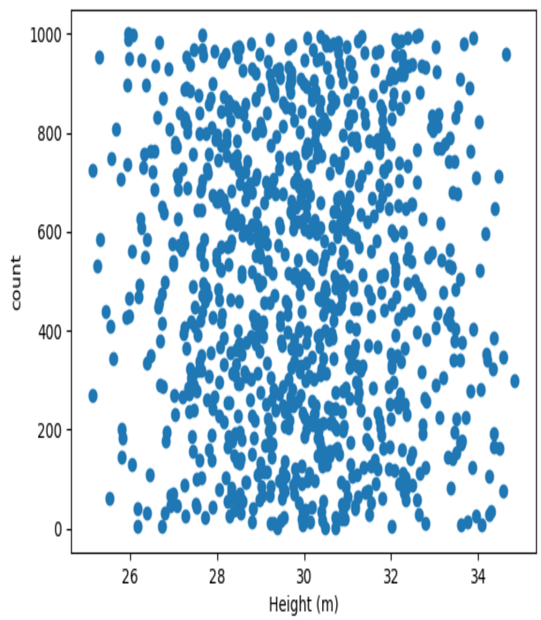


Figure 7.1 Generated 100 Random Variables

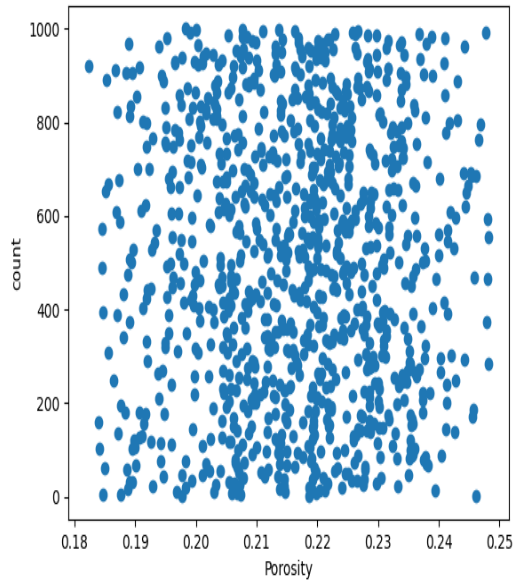


Figure7.2 Generated Random Stochastic Porosity Variables

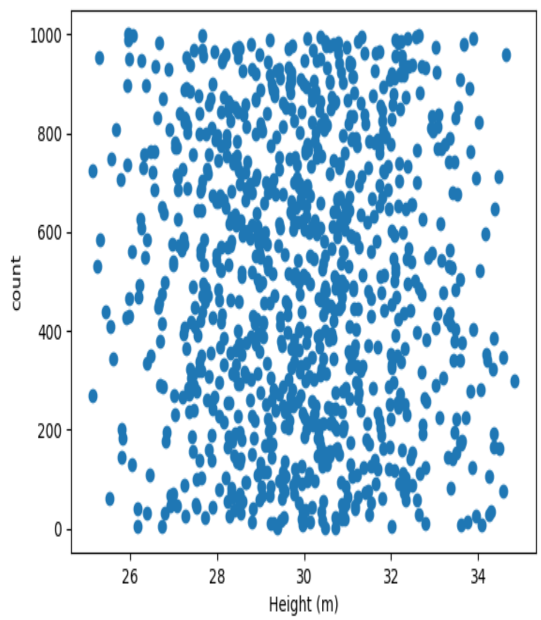


Figure7.3 Generated Random Stochastic height Variables

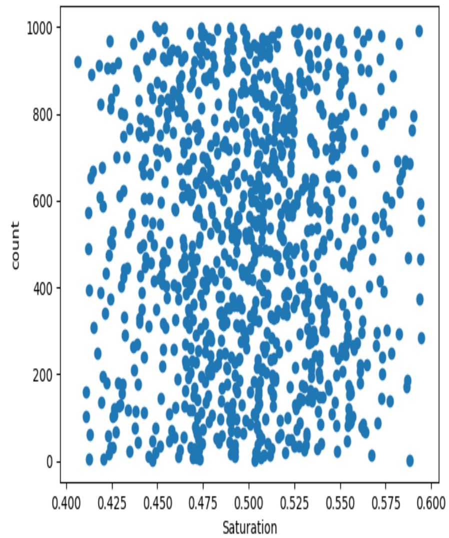


Figure 7.4 Generated Random Stochastic Saturation Variables

We have also plot the histogram and cumulative frequency data.

Here our Mean value is around 700,000 STB. So in 100 trail we have got the number of possible case along with their frequency. Base on this data we can easily determine the probability for each case.

Observation:

100 sample…

Table7.10 Probability of 100 Sample of IOIP

Range(m^3)	Frequency	Probability
3917292-4891700	16	0.16
4891701-5866109	16	0.16
5866110-6840519	11	0.11
6840520-7814928	11	0.11
7814929-8789337	18	0.18
8789338-9763746	10	0.10
9763747-10738155	8	0.08
10738156-11712564	6	0.06
11712565-12686973	1	0.01
12686974-13661382	3	0.03
	Total 100	Sum= 1.00

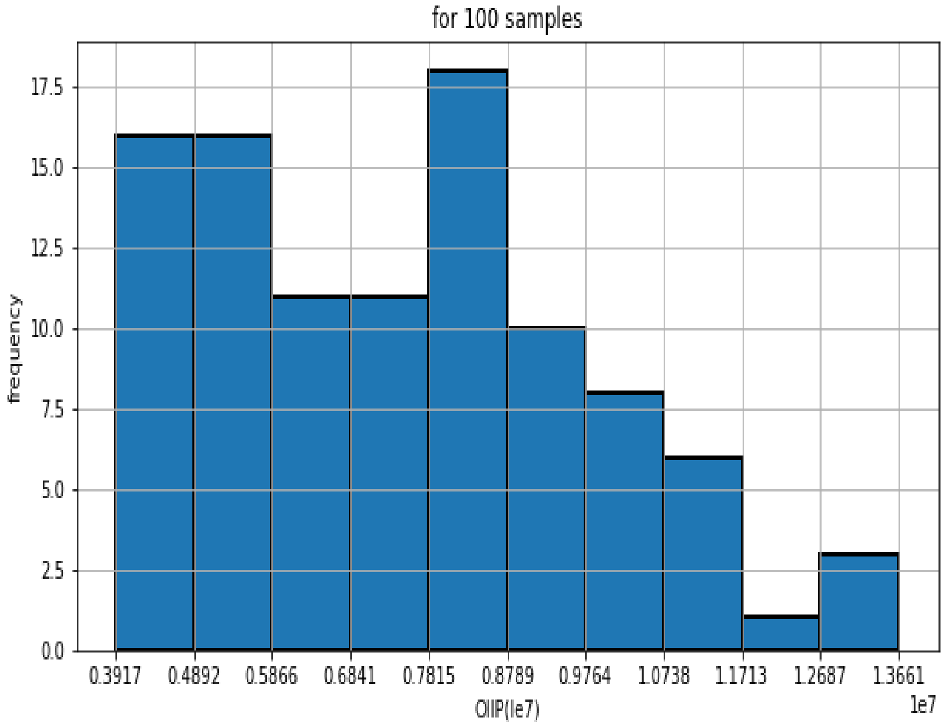


Figure 7.5 Bar chart between Frequency vs OOIP for 100 Samples

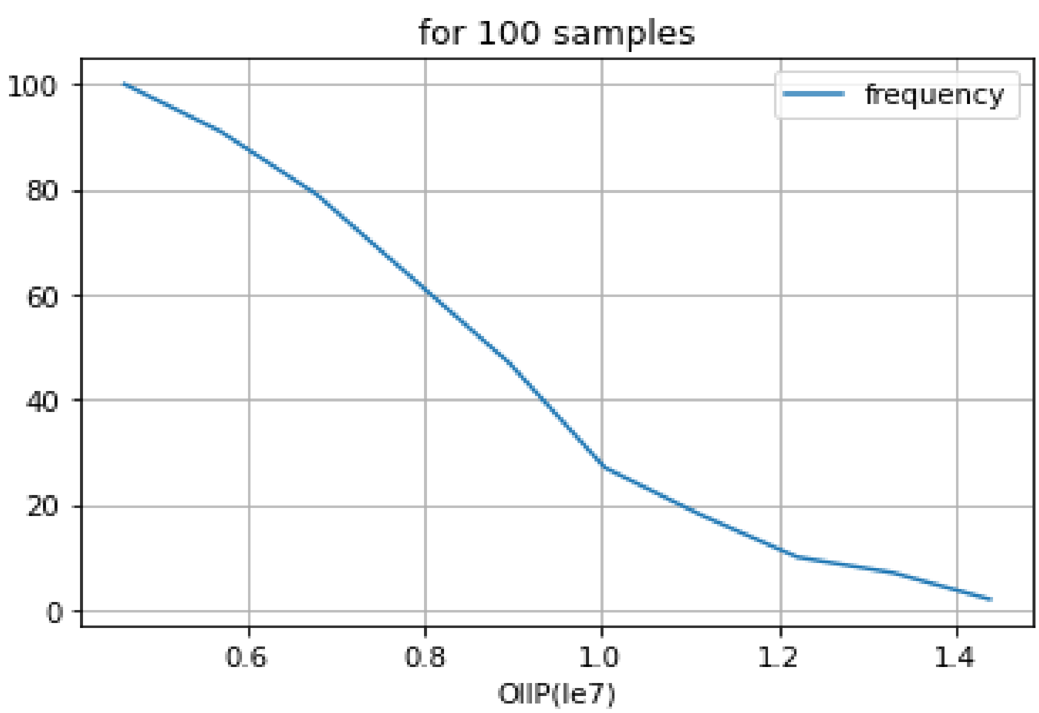


Figure 7.6 Cumulative Frequency vs OOIP for 100 Samples

Here we have generated cumulative graph for 100 trial. The X axis represents the Number of possible case and Y axis represent the frequency. Base on this graph we can interpret what is the probability for which reserve. From the data we can tell about what is P90, P50 and P10.

From the data we can analyze that our distribution of the data is vast. We are not sure about whatever data or probability of each case we have generated is right or wrong.

Simulation For 1000 Samples

Table 7.11 Probability of 1000 Sample of IOIP

Range(m^3)	Frequency	Probability
3,721,687-4,851,523	74	0.074
4,851,524-5,981,360	126	0.126
5,981,361-7,111,197	192	0.192
7,111,198-8,241,034	171	0.171
8,241,035-9,370,871	164	0.164
9,370,872-10,500,708	107	0.107
10,500,709-11,630,546	75	0.075
11,630,547-12,760,383	50	0.05
12,760,384-13,890,220	33	0.033
13,890,221-15,020,058	8	0.008
	Total = 1000	Sum = 1

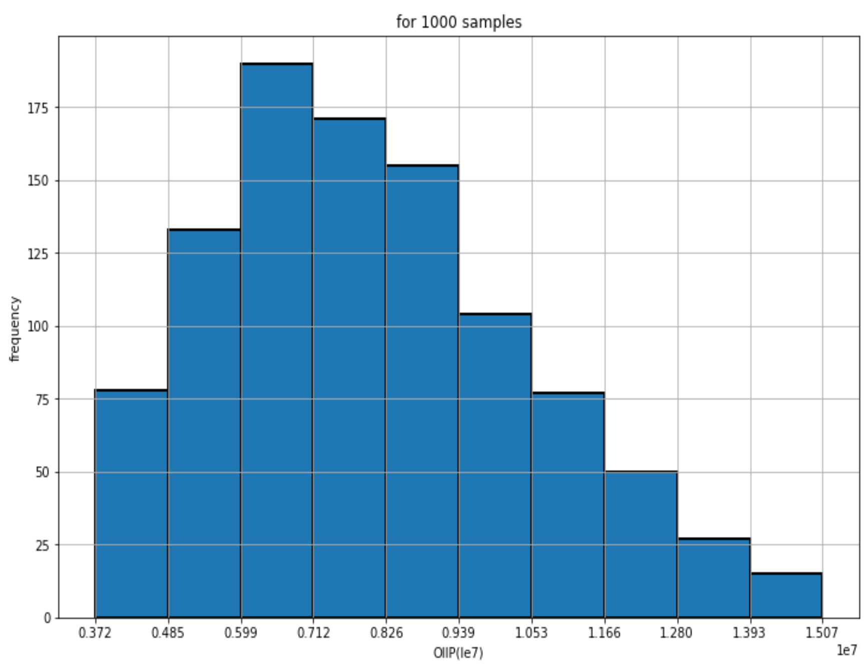


Figure 7.7 Bar chart between Frequency vs OOIP for 1000 Samples

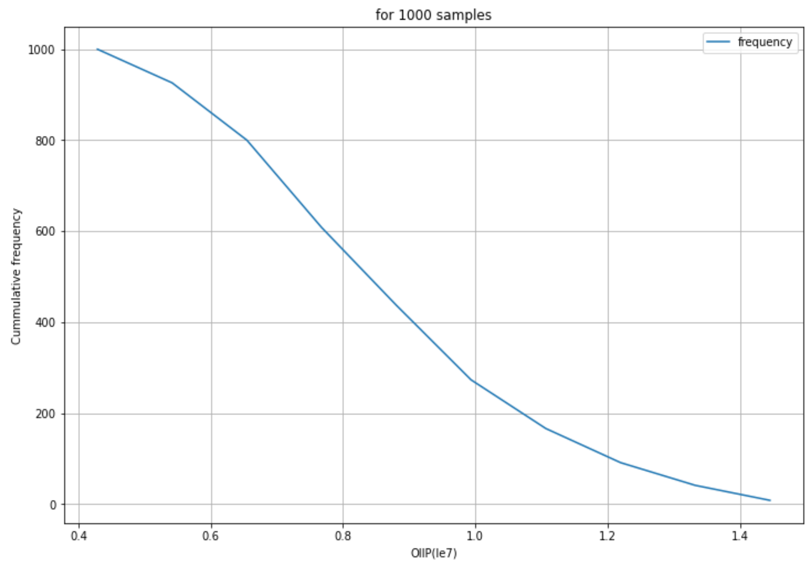


Figure 7.8 Cumulative Frequency vs OOIP for 1000 Samples

Monte carlo simulation for 1 million samples:

Here we have increased the number of the trial to get the accurate distribution. Here we have run the simulation for 1 Million times, We have also plot the histogram base on this data, From each case of data we analyze that as we increase the number of trials our data is converge to mean value.

Observation:

1 Million sample…

Table 7.12 Probability of 1 Million Sample of IOIP

Range(m^3)	Frequency	Probability
3537003-4726634	66683	0.06668
4726634 -5916265	154787	0.154787
5916265 -7105896	194903	0.194903
7105896-8295528	188746	0.188746
8295528-9485159	142905	0.142905
9485159-10674790	102966	0.102966
10674790-11864421	70920	0.070920
11864421-13054052	45423	0.045423
13054052-14243683	24847	0.024847
14243683-15433314	7820	0.07820
	Total= 1,000,000	Sum= 1.0000

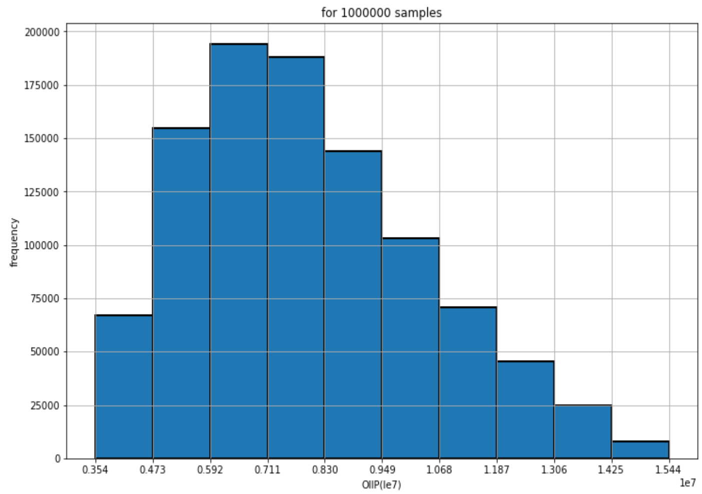


Figure 7.9 Bar chart between Frequency vs OOIP for 1 million Samples

And last two case is give moreover same distribution. The Law of large number tells that when we increase the number of trial our data is converge to mean value. Same thing here we have found from the data. From this we can say that data distribution which we have got from the 1 million sample is more accurate than distribution of the 100 samples.

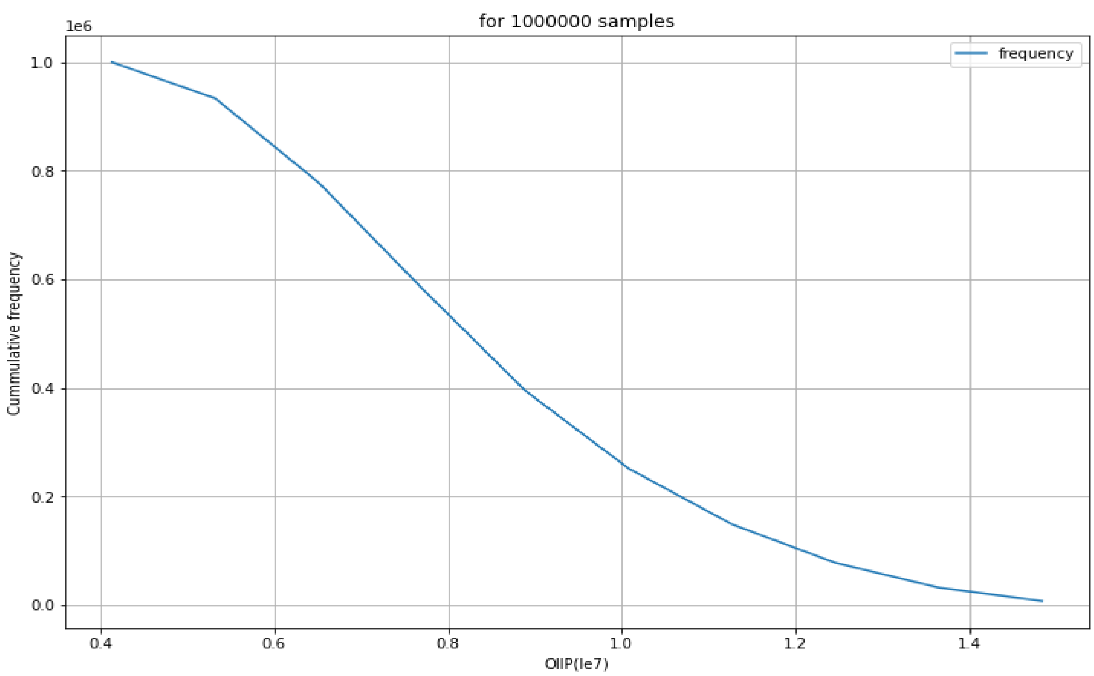


Figure 7.10 Cumulative Frequency vs OOIP for 1 million Samples

Here we have also generated cumulative frequency graph for the 1 Million sample. From this graph we can find the P90, P50, and P10.

Here P90 = 4 Ma

P50 = 8 Ma

P10 = 10 Ma

There is 90% chance that our reserve is more than 4 Ma barrel crude oil.

There is 50% chance that our reserve is more than 8 Ma barrel Oil.

There is 10% chance that our reserve is more than 10 Ma barrel Oil.

So now it's become easy to quantify what is minimum amount of hydrocarbon will get after investing the money. So, for the investor, it's become easy for them to take the decision, whether should we do investment or not.

In this way Monte Carlo help us to quantify the risk, so we can take the calculated risk.

Generated Reservoir Performance Data (Pressure Vs Np)

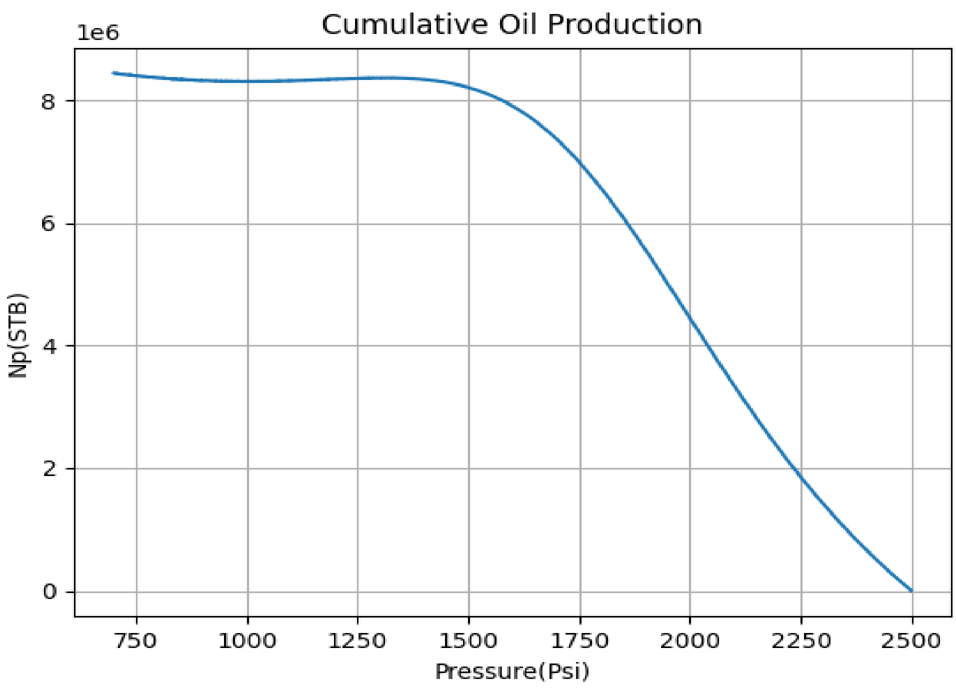


Figure 7.11 Cumulative oil production (Np) vs pressure

Table 7.13 Cumulative Production w.r.t Pressure

Pressure(Psi)	Np(STB)
2499	5978.982276
2498	11968.9713
2497	17969.21985
2496	23977.97073
2495	29996.24786
2494	36033.17907
2493	42072.08719
2492	48124.64485
2491	54183.27732
2490	60269.16152
2489	66340.357
2488	72450.08488
2487	78540.01853
2486	84659.47413
2485	90782.5364
2484	96927.99924
2483	103076.2522
2482	109240.0597
2481	115410.4592
2480	121591.5157
2479	127783.3236
2478	133974.4859
2477	140187.6635
2476	146398.9913
2475	152645.8155
2474	158878.2716
2473	165161.4893
2472	171400.3542
2471	177722.2138
2470	183967.0101
2469	190297.6973
2468	196592.9208
2467	202914.5031
2466	209229.9183
2465	215600.3997
2464	221927.4548
2463	228321.4306

Pressure(Psi)	Np(STB)
2226	2076011.294
2225	2085340.075
2224	2094837.791
2223	2104123.408
2222	2113570.449
2221	2122919.846
2220	2132060.659
2219	2141705.267
2218	2150723.803
2217	2160348.777
2216	2169726.968
2215	2179269.769
2214	2188566.413
2213	2198247.784
2212	2207744.429
2211	2217118.194
2210	2226624.25
2209	2236132.155
2208	2245468.861
2207	2255113.257
2206	2264667.126
2205	2274179.956
2204	2283892.597
2203	2293512.148
2202	2303041.061
2201	2312462.553
2200	2322194.728
2199	2331867.946
2198	2341525.277
2197	2351224.4
2196	2360768.974
2195	2370714.308
2194	2380213.849

Here we have made depletion_code.py file to generate the reservoir performance data. In the code we have used the Mustak's method to solve the material balance equation. After solving the equation we have got the Cumulative production data with respect to Depletion of pressure.

From the graph we analyze that, as the pressure decreases our cumulative production increases. At the initial time, oil is accumulated in reservoir at high pressure. Now, when we create the drawdown so fluid transport from the reservoir to the well bore.
Due to continuous production reservoir pressure decline with respect to time.

Generated Reservoir Pressure Data

Table 7.14 Reservoir Pressure, FBHP, Flow rate data w.r.t Time

Days	Q(STB/days)	Np(STB)	Pr(Psi)	FBHP
365	1847.674178	674401.0748	2392	932.4500427
730	1847.674178	1348802.15	2300	815.2033168
1095	1847.674178	2023203.224	2220	714.4910558
1460	1739.548561	2658138.449	2151	719.5241604
1825	1654.293373	3261955.53	2091	717.2464946
2190	1573.216537	3836179.566	2036	721.5372382
2555	1511.225528	4387776.884	1984	714.9592224
2920	1437.160441	4912340.445	1934	722.4830627
3285	1380.530585	5416234.108	1885	717.1535311
3650	1326.132172	5900272.351	1835	711.1555373
4015	1261.1385	6360587.903	1783	713.682219
4380	1199.330165	6798343.414	1726	711.4763625
4745	1129.145543	7210481.537	1660	711.6127041
5110	1041.913059	7590779.803	1573	717.7271773
5475	942.2874943	7934714.739	795	712.9050519

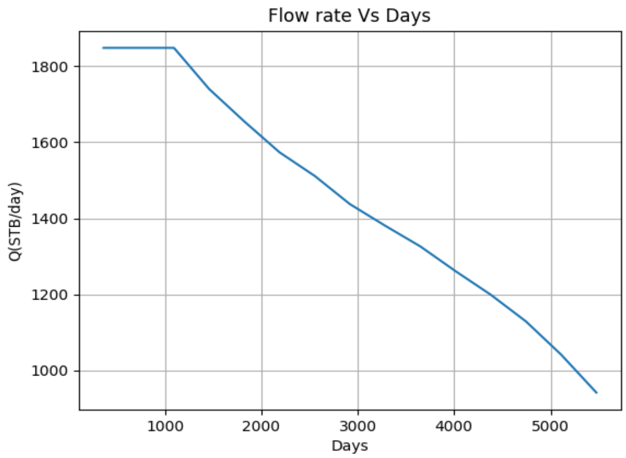


Figure 7.12 Flow rate (Q) vs Days

Here we have combined the Darcy equation with MBE to get the production profile w.r.t to time.

In production profile graph x axis represent time and Y axis represent the flow rate.

In the production profile at the initial time, our flow rate remains constant. After few years our flow rate start to decline and it's continuous decrease with respect to time. This thing happens due to reduction of the reservoir pressure.

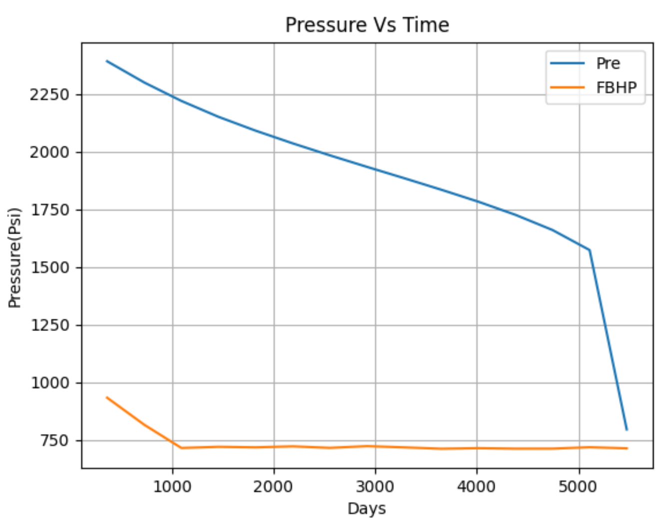


Figure 7.13 Pressure(pre, FBHP) vs Time

From the model we have also got the pressure trend of the reservoir. Here we have got pressure profile from the python code.

From the graph we analyze that there is continuous reduction of profile . Flowing bottom hole pressure also follow the same trend. Here we are producing the very high flow rate that's why there is more drawdown.

7.1.1 Applying Monte Carlo in Depletion Drive Reservoir

Input Data (Stochastic Variable)

```
30e+6,15e+6,20e+6          #Area: Max(x2),Mi.n(x1),Mean(x3) (ft^2)
64e+6,30e+6,45e+6          #IOIP: Max,Min,Mean (STB)
800,300,550                #KH: Max,Min,Mean(mD-ft)
2000,1500,1750             #Qo: Max,Min,Mean(STB/day)
```

Depletion_code.py

Generated Reservoir Performance Data

Now we have applied the Monte Carlo in Depletion drive reservoir to get the multiple production profile. Here we have used Area, IOIP, KH (Permeability and thickness) and flow rate as stochastic variable. We input this variable into Depletion_code.py file to get the multiple production profile. We run this program 25 time to generate 25 production profile. Among this profile Q23 is best case scenario, where we maintain the plateau period for more time as compare to other profile. So in Q23 condition there is high cumulative production compare to other profile.

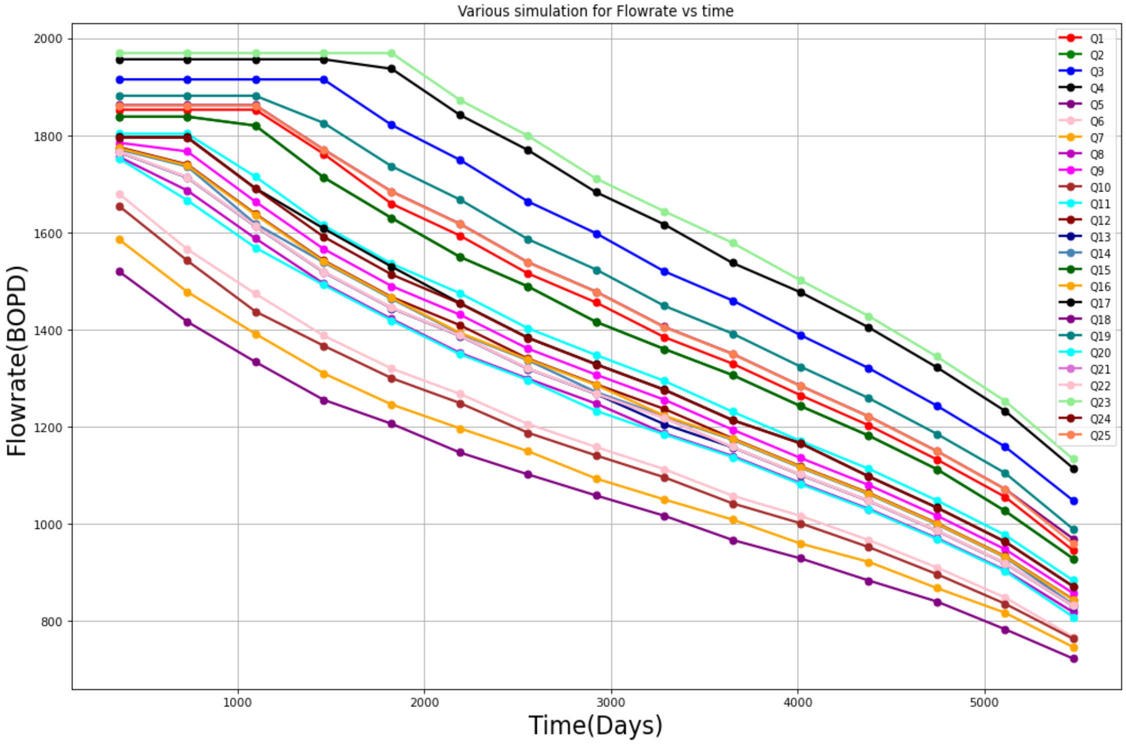


Figure 7.14 Various Simulation flow rate (Q BOPD) vs time (Days)

7.2 Technoeconomic Analysis of Depletion Drive Reservoir:

From the Monte-carol Simulation Model, We have got the Production profile of the Reservoir. Here we have run the Code around 25 times, by using the Stochastic Variable (Area, IOIP, KH, Flow rate). After running the simulation 25 times we have got the 25 Production Profiles.

Here we have compared the Worst and the Best Production Profile Scenario out of 25 Production Profiles.

7.2.1 Worst Case Scenario

Among this profile Q25 is worst case scenario. Here we directly get the depletion period, where our flow rate is continuous decreases.

Yearly production data is given, Overall cumulative production is 5.91 MMSTB, Here our recovery factor is 11.81%

Yearly Production data

Table 7.15 Yearly Production data (Worst Case)

Days	Yearly production(MMSTB)
365	0.554449824
730	0.516783468
1095	0.486541377
1460	0.458069048
1825	0.4400193
2190	0.418453976
2555	0.40196522
2920	0.386126186
3285	0.370911274
3650	0.352732931
4015	0.338833846
4380	0.322227616
4745	0.306435257
5110	0.285617684
5475	0.263552203

Cash flow Data of Worst Case

Table 7.16 Cash flow data (Worst Case)

Year	($ in millions)
Year 1	-167
Year 2	-119
Year 3	178.8394234
Year 4	179.6364609
Year 5	169.0994813
Year 6	159.1972594
Year 7	152.9766328
Year 8	164.8846894
Year 9	158.4101597
Year 10	152.0795084
Year 11	146.1804925
Year 12	138.9865706
Year 13	133.51919
Year 14	126.9007819
Year 15	120.7140091
Year 16	112.5129381
Year17	103.8802319

NPV Data of Worst Case

Table 7.17 NPV data (Worst Case)

Year	($ in millions)
Year 1	-167
Year 2	-112.2641509
Year 3	159.1664502
Year 4	150.8262365
Year 5	133.9426276
Year 6	118.9614532
Year 7	107.8424897
Year 8	109.6577356
Year 9	99.38849393
Year 10	90.01562738
Year 11	81.6264235
Year 12	73.2163916
Year 13	66.35494688
Year 14	59.4960385
Year 15	53.39192262
Year 16	46.94771796
Year17	40.89206723

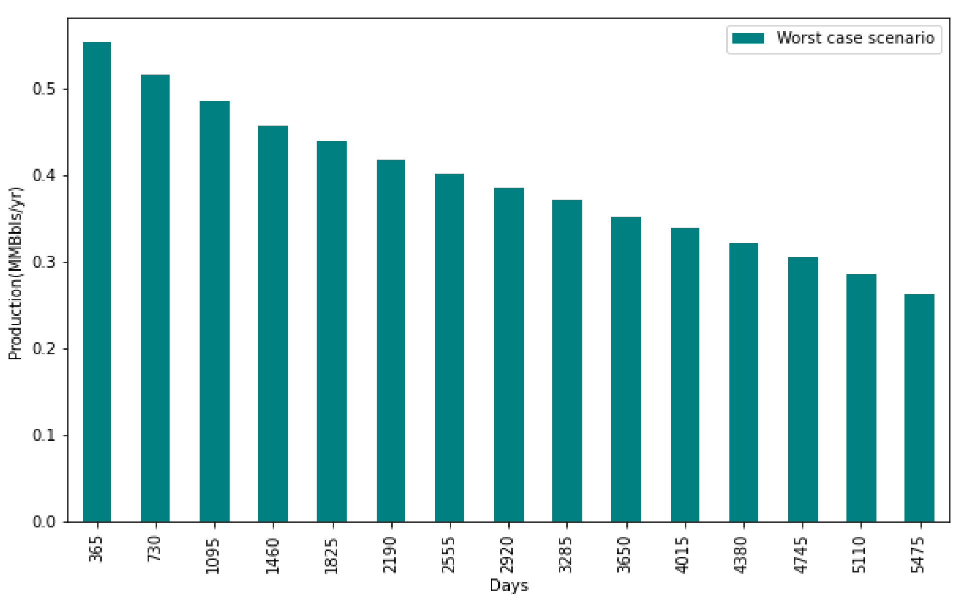


Figure 7.15 Production profile of worst-case scenario

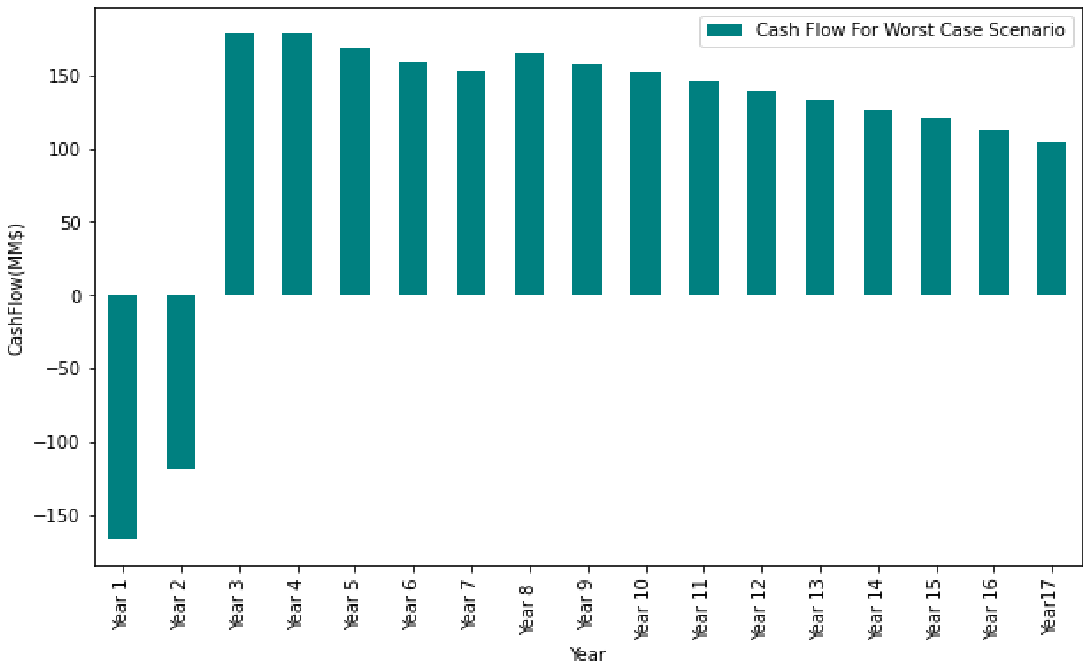


Figure 7.16 Cash flow for worst case scenario

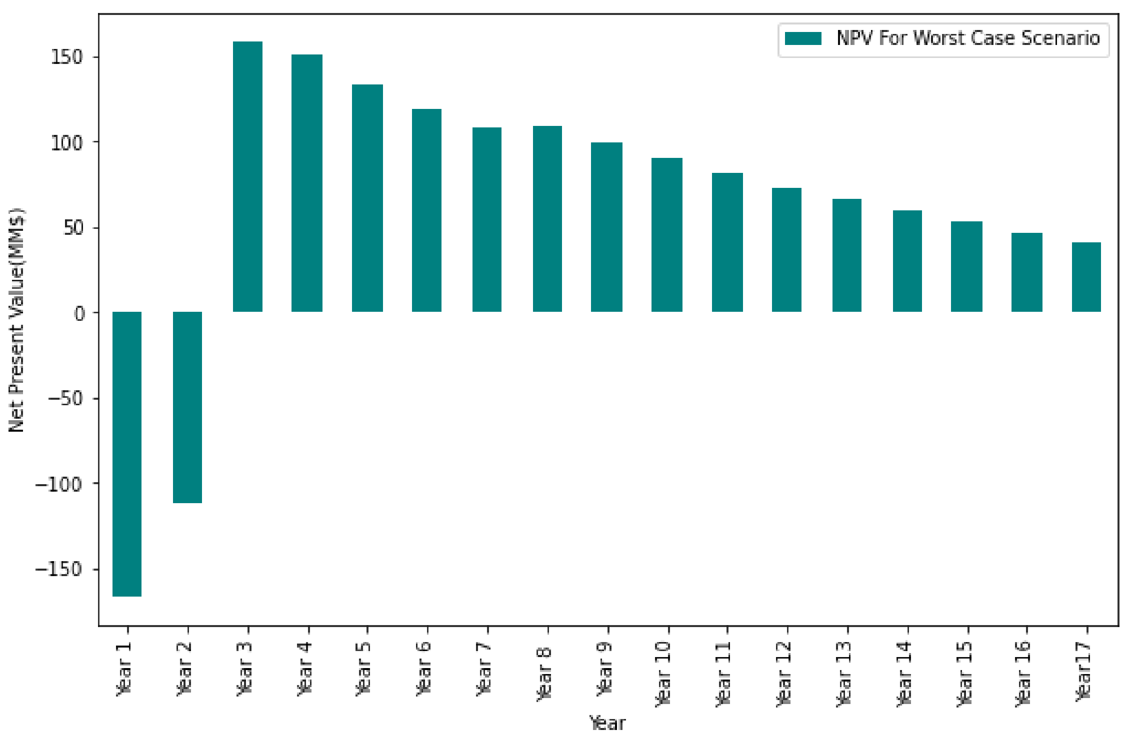


Figure 7.17 NPV for worst case scenario

7.2.2 Best Case Scenario

Yearly Production data

Table 7.18 Yearly Production data (Best Case)

Days	Yearly Production (MMSTB)
365	0.718646976
730	0.718646976
1095	0.718646976
1460	0.718646976
1825	0.718646976
2190	0.683426123
2555	0.656496407
2920	0.624321551
3285	0.599720791
3650	0.576089399
4015	0.547855286
4380	0.521004926
4745	0.490515796
5110	0.457192776
5475	0.413476951

Cash flow Data of Best Case

Table 7.19 Cash flow data (Best Case)

Year	($ in millions)
Year 1	-167
Year 2	-119
Year 3	235.840675
Year 4	249.840675
Year 5	249.840675
Year 6	249.840675
Year 7	249.840675
Year 8	269.340435
Year 9	258.6934306
Year 10	246.0321281
Year 11	236.3922728
Year 12	227.0401744
Year 13	215.8176563
Year 14	205.3145303
Year 15	193.2287416
Year 16	180.1358038
Year17	162.8703913

NPV Data of Best Case

Table 17.20 NPV data (Best Case)

Year	($ in millions)
Year 1	-167
Year 2	-112.264150
Year 3	209.8973612
Year 4	209.7710484
Year 5	197.8972155
Year 6	186.6954863
Year 7	176.1278173
Year 8	179.1267723
Year 9	162.3074588
Year 10	145.6260386
Year 11	132.0002104
Year 12	119.6019316
Year 13	107.2547633
Year 14	96.25946364
Year 15	85.46525874
Year 16	75.16437709
Year17	64.11332424

Here our total cumulative production is 9.16 MMSTB

Here our Recovery factor is 18.32%.

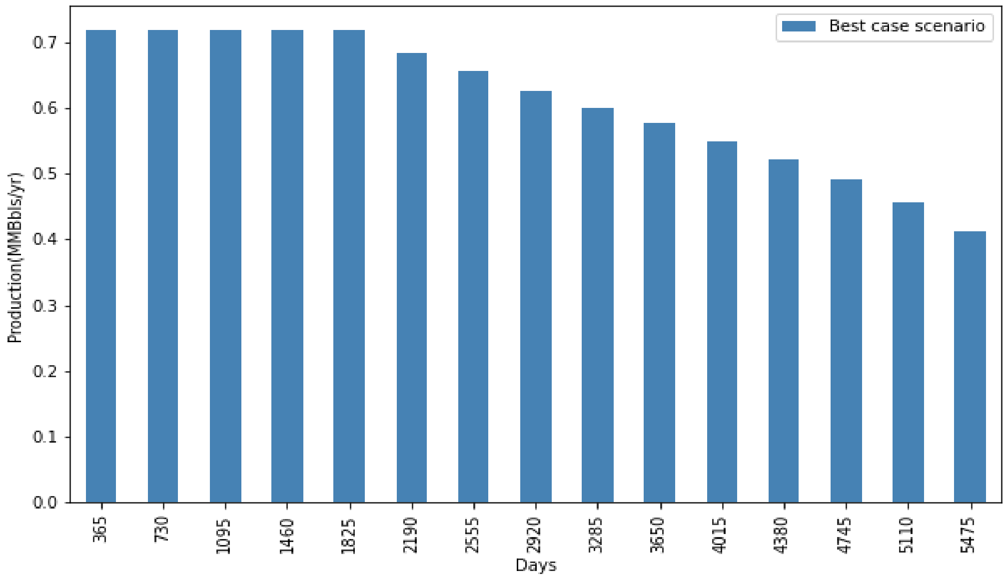


Figure 7.18 Production profile of Best case scenario

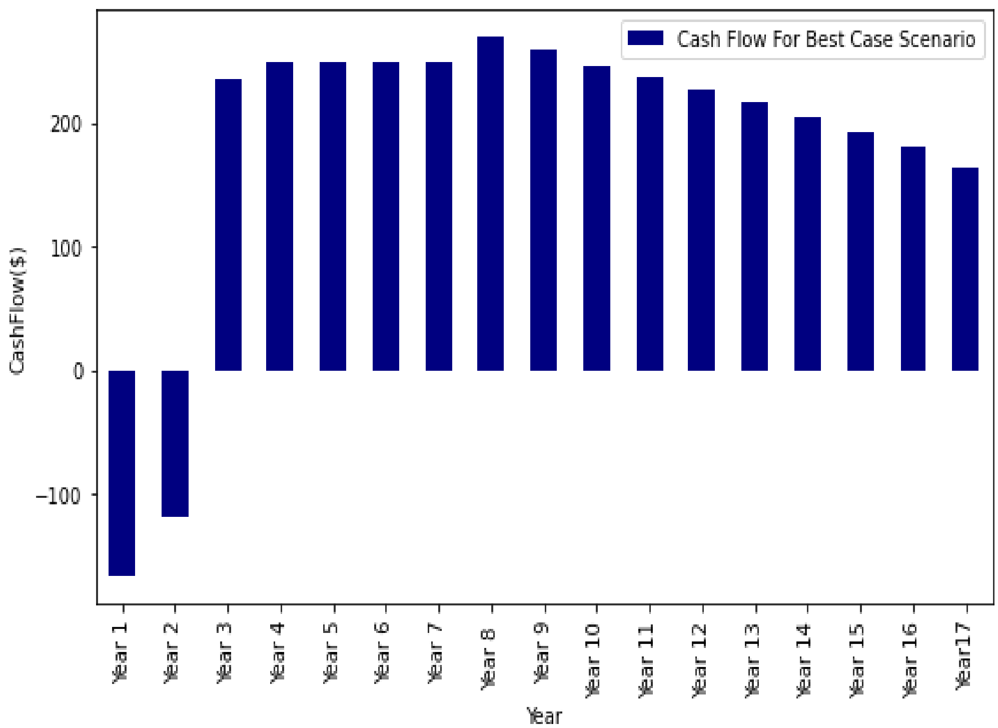


Figure 7.19 Cash flow for Best case scenario

Here we have also generated net cash flow data and graph for each case. Here we have also calculated NPV data for each case.

So from the graph we see that at the initial time our NPV is negative. After two year when we start the production we have got the positive value of NPV.

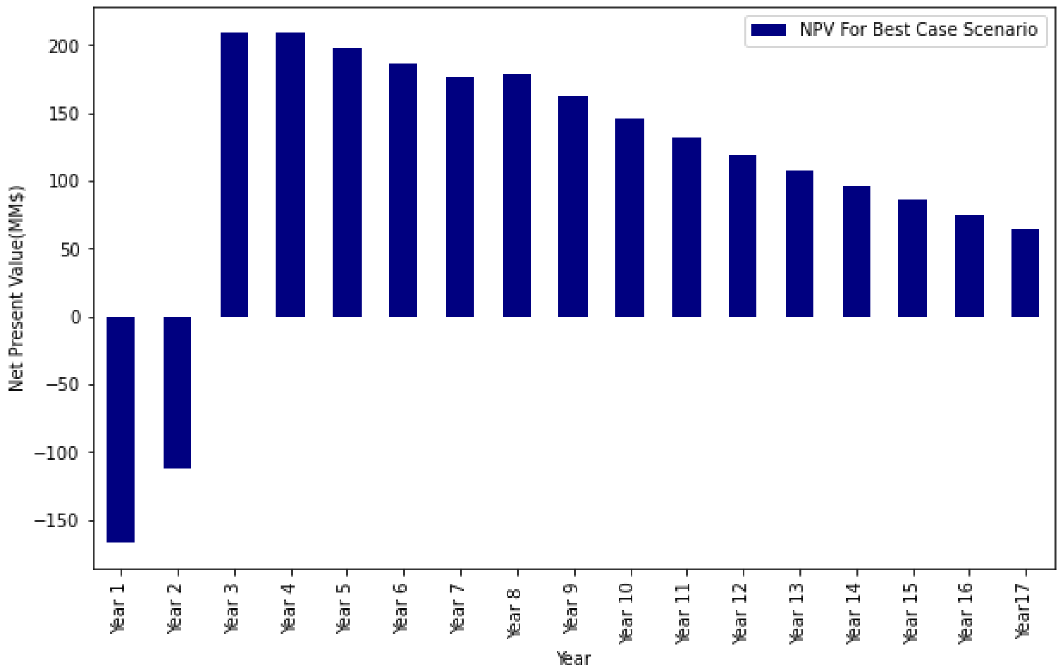


Figure 7.20 NPV for Best case scenario

Overall Economic Analysis for the Worst case

Table 7.21 Economic analysis of Worst Case

				Worst case scenario													
Royalty	12.50%															Denominator f	1.06
Income-Tax	30%																
Operating expense rate	25%																
Discount Factor	6%																
	Year 1	Year 2	Year 3	Year 4	Year 5	Year 6	Year 7	Year 8	Year 9	Year 10	Year 11	Year 12	Year 13	Year 14	Year 15	Year 16	Year17
Oil Price($ PER BARREL)	$ 75.00	$ 75.00	$ 75.00	$ 75.00	$ 75.00	$ 75.00	$ 75.00	$ 85.00	$ 85.00	$ 85.00	$ 85.00	$ 85.00	$ 85.00	$ 85.00	$ 85.00	$ 85.00	$ 85.00
Oil Production(BOPD)	0	0	1519.00	1415.00	1332.00	1254.00	1205.00	1146.00	1101.00	1057.00	1016.00	966.00	928.00	882.00	839.00	782.00	722.00
Oil Production(MBBLS/yr)	0	0	5.54435	5.16475	4.8618	4.5771	4.39825	4.1829	4.01865	3.85805	3.7084	3.5259	3.3872	3.2193	3.06235	2.8543	2.6353
Gross Revenue($M)	$ -	$ -	$ 415.83	$ 387.36	$ 364.64	$ 343.28	$ 329.87	$ 355.55	$ 341.59	$ 327.93	$ 315.21	$ 299.70	$ 287.91	$ 273.64	$ 260.30	$ 242.62	$ 224.00
Royalty($M)	$ -	$ -	$ 51.98	$ 48.42	$ 45.58	$ 42.91	$ 41.23	$ 44.44	$ 42.70	$ 40.99	$ 39.40	$ 37.46	$ 35.99	$ 34.21	$ 32.54	$ 30.33	$ 28.00
Net revenue($M)	$ -	$ -	$ 363.85	$ 338.94	$ 319.06	$ 300.37	$ 288.64	$ 311.10	$ 298.89	$ 286.94	$ 275.81	$ 262.24	$ 251.92	$ 239.44	$ 227.76	$ 212.29	$ 196.00
Intengible Capital Exp.($M)	$ 47.00	$ 47.00	$ 36.38	$ 33.89	$ 31.91	$ 30.04	$ 28.86	$ 31.11	$ 29.89	$ 28.69	$ 27.58	$ 26.22	$ 25.19	$ 23.94	$ 22.78	$ 21.23	$ 19.60
Tangible Capital Exp.($M)	$ 100.00	$ 60.00	$ 20.00	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -				$ -
Operating Expense($M)	$ 20.00	$ 12.00	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -
Taxable Income($M)	$ (167.00)	$ (119.00)	$ 255.48	$ 256.62	$ 241.57	$ 227.42	$ 218.54	$ 235.55	$ 226.30	$ 217.26	$ 208.83	$ 198.55	$ 190.74	$ 181.29	$ 172.45	$ 160.73	$ 148.40
Income Tax($M)	$ -	$ -	$ 76.65	$ 76.99	$ 72.47	$ 68.23	$ 65.56	$ 70.66	$ 67.89	$ 65.18	$ 62.65	$ 59.57	$ 57.22	$ 54.39	$ 51.73	$ 48.22	$ 44.52
Net cash flow($M)	$ -167.00	$ -119.00	$ 178.84	$ 179.64	$ 169.10	$ 159.20	$ 152.98	$ 164.88	$ 158.41	$ 152.08	$ 146.18	$ 138.99	$ 133.52	$ 126.90	$ 120.71	$ 112.51	$ 103.88
Net cash flow Accumulated($M)	$ 1,911.82																
Discounted Cash Flows	$ (167.00)	$ (112.26)	$ 159.17	$ 150.83	$ 133.94	$ 118.96	$ 107.84	$ 109.66	$ 99.39	$ 90.02	$ 81.63	$ 73.22	$ 66.35	$ 59.50	$ 53.39	$ 46.95	$ 40.89
NPV(Net Present Value)	$ 1,112.46																
IRR(Internal Rate Of Return)	47%																

Overall Economic Analysis of Best Case

Table 7.21 Economic analysis of Best Case

Best case scenario

Royalty	12.50%	Denominator f	1.06
Income-Tax	30%		
Operating expense rate	25%		
Discount Factor	6%		

	Year 1	Year 2	Year 3	Year 4	Year 5	Year 6	Year 7	Year 8	Year 9	Year 10	Year 11	Year 12	Year 13	Year 14	Year 15	Year 16	Year17
Oil Price($ PER BARREL)	$ 75.00	$ 75.00	$ 75.00	$ 75.00	$ 75.00	$ 75.00	$ 75.00	$ 85.00	$ 85.00	$ 85.00	$ 85.00	$ 85.00	$ 85.00	$ 85.00	$ 85.00	$ 85.00	$ 85.00
Oil Production(BOPD)	0	0	1968.00	1968.00	1968.00	1968.00	1968.00	1872.00	1798.00	1710.00	1643.00	1578.00	1500.00	1427.00	1343.00	1252.00	1132.00
Oil Production(MBBLS/yr)	0	0	7.1832	7.1832	7.1832	7.1832	7.1832	6.8328	6.5627	6.2415	5.99695	5.7597	5.475	5.20855	4.90195	4.5698	4.1318
Gross Revenue($M)	$ -	$ -	$ 538.74	$ 538.74	$ 538.74	$ 538.74	$ 538.74	$ 580.79	$ 557.83	$ 530.53	$ 509.74	$ 489.57	$ 465.38	$ 442.73	$ 416.67	$ 388.43	$ 351.20
Royalty($M)	$ -	$ -	$ 67.34	$ 67.34	$ 67.34	$ 67.34	$ 67.34	$ 72.60	$ 69.73	$ 66.32	$ 63.72	$ 61.20	$ 58.17	$ 55.34	$ 52.08	$ 48.55	$ 43.90
Net revenue($M)	$ -	$ -	$ 471.40	$ 471.40	$ 471.40	$ 471.40	$ 471.40	$ 508.19	$ 488.10	$ 464.21	$ 446.02	$ 428.38	$ 407.20	$ 387.39	$ 364.58	$ 339.88	$ 307.30
Intengible Capital Exp.($M)	$ 47.00	$ 47.00	$ 47.14	$ 47.14	$ 47.14	$ 47.14	$ 47.14	$ 50.82	$ 48.81	$ 46.42	$ 44.60	$ 42.84	$ 40.72	$ 38.74	$ 36.46	$ 33.99	$ 30.73
Tangible Capital Exp.($M)	$ 100.00	$ 60.00	$ 20.00	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -				$ -
Operating Expense($M)	$ 20.00	$ 12.00	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -
Taxable Income($M)	$ (167.00)	$ (119.00)	$ 336.92	$ 356.92	$ 356.92	$ 356.92	$ 356.92	$ 384.77	$ 369.56	$ 351.47	$ 337.70	$ 324.34	$ 308.31	$ 293.31	$ 276.04	$ 257.34	$ 232.67
Income Tax($M)	$ -	$ -	$ 101.07	$ 107.07	$ 107.07	$ 107.07	$ 107.07	$ 115.43	$ 110.87	$ 105.44	$ 101.31	$ 97.30	$ 92.49	$ 87.99	$ 82.81	$ 77.20	$ 69.80
Net cash flow($M)	$ -167.00	$ -119.00	$ 235.84	$ 249.84	$ 249.84	$ 249.84	$ 249.84	$ 269.34	$ 258.69	$ 246.03	$ 236.39	$ 227.04	$ 215.82	$ 205.31	$ 193.23	$ 180.14	$ 162.87
Net cash flow Accumulated($M)	$ 3,144.07																
Discounted Cash Flows	$ (167.00)	$ (112.26)	$ 209.90	$ 209.77	$ 197.90	$ 186.70	$ 176.13	$ 179.13	$ 162.31	$ 145.63	$ 132.00	$ 119.60	$ 107.25	$ 96.26	$ 85.47	$ 75.16	$ 64.11
NPV(Net Present Value)	$ 1,868.04																
IRR(Internal Rate Of Return)	63%																

We have also done overall economic analysis for each case. Here we have calculated NPV value for each year. We are able to minimum flow rate up to the 17 years. So upto the 17 year our project is able to generate the money.

For the worst case our NPV is 1.112 $ Billion and IRR is 47%.

For the Best case our NPV is 1.868 $ Billion and IRR is 63%.

So here we have taken the best and worst case scenario. So our NPV value and IRR values lies between this range 1.112 to 1.868 $ Billion and 47 to 63 % respectively.

CHAPTER 8: CONCLUSION

In oil and Gas Industry we have to deal with uncertain data. Even this oil and gas industry requires huge investment. So, there is high risk for the investor side to take the decision regarding the investment. In first part of our project we have generated number of Possible IOIP case along with the Probability. While increasing the number of trial our data converge to the mean value. For the 1 Million data sample, our data distribution is more accurate than 100 samples.

In second part of our project, by running the Depletion_code.py (python program) we have generated 25 production profiles. From the production profile we have taken worst case scenarios and Best case scenarios. From the both scenarios we got the range. For the Cumulative production worst case scenarios is 5.91 MMSTB and best case scenarios is 9.16 MMSTB. So, we get the range of cumulative production from 5.91 to 9.16 MMSTB. For the Recovery factor worst case scenarios is 11.81% and best case scenarios is 18.32%. So, we get the range of cumulative production from 11.81% to 18.32%. For the NPV worst case scenarios is $1.112 billion and best case scenarios is $1.868 billion So, we get the range of cumulative production from $1.112 billion to $1.868 billion. . For the IRR worst case scenarios is 47% and best case scenarios is 63%. So, we get the range of IRR is from 47% to 63%. Now we have all the range of the economic data. So if we see the NPV and IRR for both cases, then it's gives good value for each case. So here Our Project has capacity to generate good amount of the profit after calculating the uncertain parameter. But here our recovery factor is very low. A very large amount of the crude oil is still remaining inside the reservoir. So we have to find some other alternative techniques to increase the Recovery factor.

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APPENDIX

Appendix I: Python code for monte carlo simulation for IOIP

```
import math as m
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
"""
Here Data is imported from data.txt file and converted
this data into array form
"""
Data = np.genfromtxt("Reserve_Data.txt",delimiter=',')
FVF = Data[0,0]

Porosity = []
Saturation = []
Height = []
Area = []
IOIP_L = []

def IOIP(A, h, So, Phi, FVF):
    """
    :param A: Area(m^2)
    :param h: Thickness (m)
    :param Sw: Saturation of oil
    :param Phi: Porosity
    :param FVF: Formation Volume factor
    :return: Initial Oil in place (m^3)
    """

    Oil_in_place = (A*h*So*Phi)/FVF
    return Oil_in_place

# Sampling the Data (Random Variable)
for i in range(100):
    rd = np.random.random()  # Random Number

    # Random Variable 1 : Porosity
    """
    To generate 100 Random Variable For Porosity
    Triangle Distribution
    """
    if rd <= ((Data[3,2] -Data[3,1])/(Data[3,0]-Data[3,1])):
        X = Data[3,1] + m.sqrt(rd*(Data[3,2] -Data[3,1])*(Data[3,0]
-Data[3,1]))
    elif rd >= ((Data[3,2] -Data[3,1])/Data[3,0]-Data[3,1]):
        X = Data[3,0] - m.sqrt((1-rd)*(Data[3,0]-Data[3,2] )*(Data[
3,0]-Data[3,1]))
    Porosity.append(X)
```

```
    # Random Variable 2 : Saturation
    """
    To generate 100 Random Variable for the Saturation
    Triangle Distribution
    """
    if rd <= ((Data[4,2] -Data[4,1])/(Data[4,0]-Data[4,1])):
        X1 = Data[4,1] + m.sqrt(rd*(Data[4,2] -Data[4,1])*(Data[4,0
]-Data[4,1]))
    elif rd >= ((Data[4,2] -Data[4,1])/Data[4,0]-Data[4,1]):
        X1 = Data[4,0] - m.sqrt((1-rd)*(Data[4,0]-Data[4,2] )*(Data
[4,0]-Data[4,1]))
    Saturation.append(X1)

    # Random Variable 3: Height (meter)
    """
    To generate 100 Random Variable for the Height
    Triangle Distribution
    """

    if rd <= ((Data[5,2] -Data[5,1])/(Data[5,0]-Data[5,1])):
        X2 = Data[5,1] + m.sqrt(rd*(Data[5,2] -Data[5,1])*(Data[5,0
]-Data[5,1]))
    elif rd >= ((Data[5,2] -Data[5,1])/Data[5,0]-Data[5,1]):
        X2 = Data[5,0] - m.sqrt((1-rd)*(Data[5,0]-Data[5,2] )*(Data
[5,0]-Data[5,1]))
    Height.append(X2)

    # Random Variable 4 : Area (m^2)
    """
    To generate 100 Random Variable for the area
    Triangle Distribution
    """

    if rd <= ((Data[2,2] -Data[2,1])/(Data[2,0]-Data[2,1])):
        X3 = Data[2,1] + m.sqrt(rd*(Data[2,2] -Data[2,1])*(Data[2,0
]-Data[2,1]))
    elif rd >= ((Data[2,2] -Data[2,1])/Data[2,0]-Data[2,1]):
        X3 = Data[2,0] - m.sqrt((1-rd)*(Data[2,0]-Data[2,2] )*(Data
[2,0]-Data[2,1]))
    Area.append(X3)

    """
    Find oil initial in place
    """
    Oil_in_place = IOIP(X3,X2,X1,X,FVF)
    IOIP_L.append(Oil_in_place)

dict1 = {"porosity":Porosity,
         "Saturation":Saturation,
         "Height(m)":Height,
         "Area(m^2)":Area,
         "Oil in Place(m^3)":IOIP_L}
print("Dict1",dict1)
df = pd.DataFrame(dict1)
```

```
print(df)
#df.to_excel("Reserve_Calculation.xlsx")

x = IOIP_L
plt.hist(x,10,ec="red")
plt.xlabel("OIIP (m^3)")
plt.ylabel("count")
plt.show()
```

Appendix II: Python code Application of monte carlo in depletion drive reservoir

```
import math as m
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from scipy.optimize import curve_fit

"""
Here Data is imported from data.txt file and converted
this data into array form
"""
Data1 = np.genfromtxt("Depletion_Data.txt",delimiter=',')

"""
Here Data is imported from data.txt file and converted
this data into array form
"""
Data2 = np.genfromtxt("Application_Data.txt",delimiter=',')


"""
Using the Corelation to find the PVT properties
Making all the Co-relation as the Function of the Pressure
"""


def Rs_GOR(P):
    """
    This function gives value of Solution GOR
    :param P: Pressure (Psi)
    :return: solution GOR (SCF/STB)
    """
    x = (7.916*(0.0001)*Data1[0][0]**1.541) - 4.561*(0.00001)*(Data
1[0][1]-460)**1.3911

    Rs = (((P/112.727)+ 12.340)*((Data1[0][2])**0.8439)*(10**x))**1
.73184

    return Rs



def OIL_FVF(P):
    """
```

```
    Standing Corelation
    This function gives value of oil formation volume factor
    :param Rs: Solution GOR (Scf/STB)
    :return: Oil formation volume factor (bbl/STB)
    """
    Rs = Rs_GOR(P)
    Bo = 0.9759 + 0.000120*(Rs*((Data1[0][2]/Data1[0][3])**0.5)+1.2
5*(Data1[0][1]-460))**1.2
    return Bo

def Muo_Oil(P):
    """
    This function gives value of the oil at  pressure
    :param Rs: Gas solubiolity (SCF/STB)
    :return: Saturated  oil viscosity (cp)
    """
    Rs = Rs_GOR(P)
    Z = 3.0324 - 0.020238*Data1[0][0]
    Y = 10**Z
    X = Y*(Data1[0][1]-460)**(-1.163)
    Muo_d = 10**X - 1     #Dead oil viscosity (P = 14.7 psi)

    a = 10.715 * (Rs + 100) ** (-0.515)
    b = 5.44 * (Rs + 150) ** (-0.338)
    Mu_ob = a * ((Muo_d) ** b)    #Viscosity at Bubble point Pressur
e
    return Mu_ob



def viscosity_gas(P):
    """
    This Function gives the value of the Viscosity of gas
    :param P: Reservoir Pressure (Psi)
    :return: Viscosity (cP)
    """
    Mw = Data1[0][2]*28.96                              # Molecular of
weight of gas
    Z = Z_factor(P)
    Rho_G = (1.4935*1e-3*P*Mw)/(Z*Data1[0][1])          # Density of
gas(in gm/cc)
    K = ((9.4+0.02*Mw)*(Data1[0][1]**1.5))/(209+19*Mw+Data1[0][1])
    X = 3.5+(986/Data1[0][1])+0.01*Mw
    Y = 2.4-0.2*X
    Mug = 1e-4*K*m.exp(X*(Rho_G)**Y)         # Visocity (In cP)
    return Mug

def Z_factor(P):
    """
    This function Gas compresibility factor
    :param P: Pressure (Psi)
    :return:  z (Compresiblity Factor)
    """
```

```
    if Data1[0][2] < 0.75:
        # Here gas consider as dry gas
        Tc = 168 + 325 * Data1[0][2] - 12.5 * (Data1[0][2]) ** 2  #
In degree Renkine unit
        Pc = 677 + 15 * Data1[0][2] - 37.5 * (Data1[0][2]) ** 2  #
In psia unit
    else:
        # Here gas consider as wet gas
        # Here specific gravity is more than the 0.75
        Tc = 187 + 330 * Data1[0][2] - 71.5 * (Data1[0][2]) ** 2  #
In degree Renkine unit
        Pc = 706 + 51.7 * Data1[0][2] - 11.1 * (Data1[0][2]) ** 2
# In psia unit


    Tr = Data1[0][1] / Tc            # Reduce Temperature
    Pr = P / Pc            # Reduce Pressure

    """
    The Hall-Yarboprough Metho to find the Z-Factor
    """


    tr = Tr
    pr = Pr
    t = 1 / tr
    X1 = -0.06125 * t * pr * (m.exp((-1.2) * (1 - t) ** 2))
    X2 = 14.76 * t - 9.76 * (t ** 2) + 4.58 * (t ** 3)
    X3 = 90.7 * t - 242.2 * (t ** 2) + 42.4 * (t ** 3)
    X4 = 2.18 + 2.82 * t

    y = 0.0125 * pr * t * (m.exp(-1.2 * (1 - t) ** 2))

    """
    Newton Rapson Method Use to solve the Non-linear
    equation
    """

    for i in range(10000):
        fny = X1 + (y + y ** 2 + y ** 3 + y ** 4) / ((1 - y) ** 3)
- X2 * (y ** 2) + X3 * (y ** X4)
        dfny = ((1+4*y+4*(y**2)-4*(y**3)+y**4)/((1-y)**4)) - (2*X2*
y) + X3*X4*(y**(X4-1))
        y_new = y - (fny / dfny)
        if abs(y_new - y) < 1e-12:
            break
        y = y_new

    y1 = y_new

    z = (0.06125 * pr * t * m.exp(-1.2 * (1 - t) ** 2)) / y1

    return z
```

```python
def Inverse_FVF_gas(P):
    """
    This function guives value of Gas formation volume factor
    :param P: Pressure (Psi)
    :return: Gas Formation volume factor(bbl/scf)
    """

    Z_fac = Z_factor(P)
    Bg = (0.005035*Z_fac*Data1[0][1])/P
    return 1/Bg

def FVF_gas(P):
    """
    This function guives value of Gas formation volume factor
    :param P: Pressure (Psi)
    :return: Gas Formation volume factore (cf/scf)
    """

    Z_fac = Z_factor(P)
    Bg = (0.005035*Z_fac*Data1[0][1])/P
    return Bg

def Rel_K(Sg):
    """
    Using Corile's Corelation to Get Relative Permeability
    :param Sg: Saturation of Gas
    :return: Kro
    """
    Sg_star = Sg / (1 - Data1[1][0])
    Kro = (1 - Sg_star) ** 4
    Krg = (Sg_star ** 3) * (2 - Sg_star)
    return Kro


def Rel_Kg(Sg):
    Sg_star = Sg / (1 - Data1[1][0])
    Kro = (1-Sg_star)**4
    Krg = (Sg_star**3)*(2-Sg_star)
    return Krg


def Ratio_Rel_K(Sg):
    Sg_star = Sg/(1-Data1[1][0])
    Kro = (1-Sg_star)**4
    Krg = (Sg_star**3)*(2-Sg_star)
    return Krg/Kro


def dRs_by_dP(P):
    """
    This Function gives derivative of the Gas solubility
    :param P: Pressuer(Psi)
    :return: derivative
    """
```

```
    h = 0.00000001
    return (Rs_GOR(P+h) - Rs_GOR(P))/h

def dBo_by_dP(P):
    """
    This function gives the derivative of the oil formation volume
factor
    :param P: Pressure(Psi)
    :return: Derivative of the Bo
    """
    h = 0.00000001
    Rs_1 = Rs_GOR(P)
    Rs_2 = Rs_GOR(P+h)
    return (OIL_FVF(Rs_2) - OIL_FVF(Rs_1))/h

def dP_by_dBg(P):
    """
    This Function give the Derivative of the Inverse the Bg
    :param P: Pressure(Psi)
    :return: Gives d(1/Bg)/dP
    """
    h = 0.00000001
    return (Inverse_FVF_gas(P+h)-Inverse_FVF_gas(P))/h

def X_of_P(P):
    return (FVF_gas(P) / OIL_FVF(P)) * dRs_by_dP(P)

def Y_of_P(P):
    return (1/OIL_FVF(P))*(Muo_Oil(P)/viscosity_gas(P))*dBo_by_dP(P
)*10

def Z_of_P(P):
    return FVF_gas(P) * dP_by_dBg(P)


"""
Following the Stepes which are written in the Tarik-Ahemad
Book
"""

# Step: 3 Prepare the Graph between the X_of_P,Y_of_P and Z_of_P an
d P

X = []
Pr = []
Y = []
Z = []
for i in range(2500,500,-100):
    P = i
    X_of_P1 = X_of_P(P)
    Y_of_P1 = Y_of_P(P)
    Z_of_P1 = Z_of_P(P)
    Pr.append(i)
    X.append(X_of_P1)
```

```
    Y.append(Y_of_P1)
    Z.append(Z_of_P1)


dict1 = {"Pressure":Pr,
         "X_of_P":X,
         "Y_of_P":Y,
         "Z_of_P":Z}

df = pd.DataFrame(dict1)
print(df)

plt.plot(df["Pressure"],df["X_of_P"],label = 'X(P)')

plt.plot(df["Pressure"],df["Y_of_P"],label="Y(P)")
plt.plot(df["Pressure"],df["Z_of_P"],label = "Z(P)")
plt.legend()
plt.xlabel("Pressure(Psi)")
plt.ylabel("X(P),Y(P)& Z(P)")
plt.grid()
plt.show()

#Step_6: solve the Mustak Equation
P_i = Data1[1][3]
Sgi = Data1[1][2]
Sg = Sgi
Soi = Data1[1][1]
So = Soi

def del_So_by_del_P(P,So,Sg):
    return ((So*X_of_P(P)) + (So*Ratio_Rel_K(Sg)*Y_of_P(P)) + (1-So
-Data1[1][0])*Z_of_P(P))/(1+(Muo_Oil(P)/viscosity_gas(P))*Ratio_Rel
_K(Sg))

Pre_Psi = []
Np_STB = []
Gp_SCF = []
Saturation_Oil = []
Saturation_Gas = []
Bo = []
Relative_K = []
I_GOR = []
Krg = []
So_by_Bo = []

"""
    Random Variable 2 : IOIP(STB)
    Generating 100 Variable of the IOIP
    """
rd = np.random.random()

if rd<=((Data2[1][2]-Data2[1][1])/(Data2[1][0]-Data2[1][1])):
    IOIP1 = Data2[1][1] + m.sqrt(rd*(Data2[1][2]-Data2[1][1])*(Data
2[1][0]-Data2[1][1]))
```

```
elif rd>= ((Data2[1][2]-Data2[1][1])/(Data2[1][0]-Data2[1][1])):
    IOIP1 = Data2[1][0]- m.sqrt((1-rd)*(Data2[1][0]-Data2[1][2])*(D
ata2[1][0]-Data2[1][1]))

# Cumulative Oil Production
P = 2500
for i in range(2500,700,-1):

    P_new = i-1
    dSo_by_dP_1 = del_So_by_del_P(P, So, Sg)  #This term Constant F
or Every Iteration
    So_new = Soi - (P - P_new) * del_So_by_del_P(P, So, Sg)
    Sg_1 = 1 - Data1[1][0] - So_new
    dSo_by_dP_2 = del_So_by_del_P(P_new, So_new, Sg_1)

    dSo_by_dP_avg = (dSo_by_dP_1 + dSo_by_dP_2) / 2

    So_2 = Soi - (P - P_new) * dSo_by_dP_avg

    Sg_f = 1 - Data1[1][0] - So_2
    K = Rel_K(Sg_f)
    Rel_Krg = Rel_Kg(Sg_f)
    Np = IOIP1 * (1 - ((OIL_FVF(P) / OIL_FVF(P_new)) * (So_2 / (1 -
Data1[1][0]))))

    #GOR_1 = Rs_GOR(P) + Ratio_Rel_K(Sg) * (Muo_Oil(P) / viscosity_
gas(P))
    GOR_2 = Rs_GOR(P_new) + (Ratio_Rel_K(Sg_f) * (Muo_Oil(P_new) /
viscosity_gas(P_new)))

    #Gp = ((GOR_1 + GOR_2) / 2) * Np
    Pre_Psi.append(P_new)
    Np_STB.append(Np)
    #Gp_SCF.append(Gp)
    Saturation_Oil.append(So_2)
    Saturation_Gas.append(Sg_f)
    Bo.append(OIL_FVF(P_new))
    So_by_Bo.append(So_2/OIL_FVF(P_new))
    Relative_K.append(K)
    Krg.append(Rel_Krg)
    I_GOR.append(GOR_2)

    #So = So_2
    #Sg = Sg_f



dict2 = {"Pressure(Psi)":Pre_Psi,
         "Np(STB)":Np_STB,
         "So":Saturation_Oil,
         "Sg":Saturation_Gas,
         "Bo":Bo,
         "Relative":Relative_K,
         "Krg":Krg,
```

```
          "So/Bo":So_by_Bo,
          "I_GOR1(SCF/STB)":I_GOR}

df2 = pd.DataFrame(dict2)
#df2.to_excel("Np_&_data_r1100.xlsx")
print(df2)

"""
plt.plot(Saturation_Gas,Krg)
plt.title("Krg Vs Sg")
plt.xlabel("Sg")
plt.ylabel("Krg")
plt.grid()
plt.show()

plt.plot(Pre_Psi,Krg)
plt.title("Krg Vs P")
plt.xlabel("Pressure(Psi)")
plt.ylabel("Krg")
plt.grid()
plt.show()

plt.plot(Pre_Psi,Np_STB)
plt.title("Cumulative Oil Production")
plt.xlabel("Pressure(Psi)")
plt.ylabel("Np(STB)")
plt.grid()
plt.show()

plt.plot(Pre_Psi,Saturation_Oil)
plt.title("Saturation")
plt.xlabel("Pressure(Psi)")
plt.ylabel("So")
plt.grid()
plt.show()

plt.plot(Pre_Psi,I_GOR)
plt.title("I_GOR")
plt.xlabel("Pressure(Psi)")
plt.ylabel("I_GOR(SCF/STB)")
plt.grid()
plt.show()

"""

"""
Calculation of the Reservoir Pressure
"""

def R_H_S(Np):
    return ((1-Data1[1][0])/OIL_FVF(Data1[1][3]))*(1-(Np/Data1[0][0
]))

def Reservoir_P(Np):
```

```
    RHS = Np
    i = 0
    while True:
        LHS = df2["Np(STB)"][i]
        if abs(LHS-RHS)<6000:
            #print(LHS-RHS)
            P = df2["Pressure(Psi)"][i]
            #print("P Np",P,Np)
            break
        i = i+1
    return P


# Combination of Darcy and MBE

def Re(A):
    """
    This function gives the value of Draniage radius
    :param A: Area
    :return: Radius (in ft)
    """
    return m.sqrt(A/m.pi)

def Qmax():
    """
    This Function Gives Maximum Flow Rate
    :return: Qmax (STB/day)
    """
    return (0.00708*Data1[2][2]*Rel_K(Data1[1][2])*Data1[1][3])/(Mu
o_Oil(Data1[1][3])*OIL_FVF(Data1[1][3])*(deno))


def FBHP(Qo,P,A,KH):
    """
    Gives the Flowing bottom hole Pressure
    :param Qo: Oil flow Rate (STB/day)
    :param P: Pressure(Psi)
    :return: Flowing Bottom Hole Pressure(psi)
    """
    deno = m.log(Re(A) / Data1[2][3], m.e) - 0.75 + Data1[3][0]
    Pwf = P - ((141.2*Qo*Muo_Oil(P)*OIL_FVF(P)*deno)/KH)
    return Pwf

FBHP_L = []
Pre_Reservoir_L = []
Q_L = []
Np_L = []
Days_L = []
P = 2500


for i in range(1):
```

```
    """
       Random VAriable 1: Qo (STB/day)
       Generating 100 VAriable of the Qo
       """

    if rd <= ((Data2[3][2] - Data2[3][1]) / (Data2[3][0] - Data2[3]
[1])):
        Qo1 = Data2[3][1] + m.sqrt(rd * (Data2[3][2] - Data2[3][1])
* (Data2[3][0] - Data2[3][1]))
    elif rd >= ((Data2[3][2] - Data2[3][1]) / (Data2[3][0] - Data2[
3][1])):
        Qo1 = Data2[3][0] - m.sqrt((1 - rd) * (Data2[3][0] - Data2[
3][2]) * (Data2[3][0] - Data2[3][1]))


    """
    Random Variable 2: Area(ft^2)
    Generating 100 rnadom variable of the Area
    """

    if rd<=((Data2[0][2]-Data2[0][1])/(Data2[0][0]-Data2[0][1])):
        A1 = Data2[0][1] + m.sqrt(rd*(Data2[0][2]-Data2[0][1])*(Dat
a2[0][0]-Data2[0][1]))
    elif rd>= ((Data2[0][2]-Data2[0][1])/(Data2[0][0]-Data2[0][1]))
:
        A1 = Data2[0][0]- m.sqrt((1-rd)*(Data2[0][0]-Data2[0][2])*(
Data2[0][0]-Data2[0][1]))

    """
    Random Variable 3: KH(mD-ft)
    Generating 100 Variable of the KH
    """
    if rd <= ((Data2[2][2] - Data2[2][1]) / (Data2[2][0] - Data2[2]
[1])):
        KH1 = Data2[2][1] + m.sqrt(rd * (Data2[2][2] - Data2[2][1])
* (Data2[2][0] - Data2[2][1]))
    elif rd >= ((Data2[2][2] - Data2[2][1]) / (Data2[2][0] - Data2[
2][1])):
        KH1 = Data2[2][0] - m.sqrt((1 - rd) * (Data2[2][0] - Data2[
2][2]) * (Data2[2][0] - Data2[2][1]))

    Q = Qo1
    i = 1

    while True:
        FBHP_Pwf1 = FBHP(Q,P,A1,KH1)
        if FBHP_Pwf1<711:

            while True:
                Q = Q*0.99
                FBHP_Pwf1 = FBHP(Q, P,A1,KH1)
                if FBHP_Pwf1>711:
                    break
        FBHP_L.append(FBHP_Pwf1)
```

```
    #Q_L.append(Q)
    if i == 1:
        Np = 0
    Np = Np + Q*365
    #print("Np",Np)
    #print("Q", Q)


    if Np>IOIP1*0.15:
        break

    Np_L.append(Np)
    Pr = Reservoir_P(Np)
    Pre_Reservoir_L.append(Pr)
    P = Pr
    Q_L.append(Q)
    Days_L.append(i*365)
    i = i+1
    if P<800:
        break



dict_d = {"Days":Days_L,
          "Q(STB/days)":Q_L,
          "Np":Np_L,
          "Pr(Psi)":Pre_Reservoir_L,
          "FBHP":FBHP_L
          }
df_frame = pd.DataFrame(dict_d)
df_frame.to_excel("Data_PP.xlsx")
print("IOIP", IOIP1)
print("Q", "A", "KH", Qo1, A1, KH1)

plt.plot(Days_L,Q_L)
plt.title("Flow rate Vs Days")
plt.xlabel("Days")
plt.ylabel("Q(STB/day)")
plt.grid()
plt.show()

plt.plot(Days_L,Pre_Reservoir_L,label="Pre")
plt.plot(Days_L,FBHP_L,label="FBHP")
plt.title("Pressure Vs Time")
plt.xlabel("Days")
plt.ylabel("Pressure(Psi)")
plt.grid()
plt.legend()
plt.show()
```