# Report of Summer Internship at

# CGG GeoSoftware

**[June - August 2021]**

**Submitted by**


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*in partial fulfillment for the award of the degree of*

**Integrated Master of Science (5yr)**

*in*

**Exploration Geophysics**


**INDIAN INSTITUTE OF TECHNOLOGY KHARAGPUR**

# CERTIFICATE

**Date: 09.08.2021**

To
Ashish Himmat Meshram
IIT Kharagpur

Sub: Internship letter

This to certify that Ashish Himmat Meshram has completed his internship at CGG GeoSoftware from 1st June 2021 to 9th August 2021 with this Report of Internship being submitted herewith to the IIT Kharagpur is the bonafide work of Ashish Himmat Meshram (14EX20018) who carried out the project work under our guidance & supervision and has successfully completed the internship.

Project Title:
Uncertainty Analysis of Clay Volume, Porosity and Water Saturation on Gulf of Mexico Data using Monte Carlo Simulation.

Yours truly,

Akash Mathur

Senior Geoscientist
CGG Geosoftware, Far East

# ACKNOWLEDGEMENT

It gives me immense pleasure to acknowledge with deep sense of gratitude to all those who have extended their cooperation and support through the internship.

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I deeply express my special thanks to my Training guide/Mentor Mr. Akash Mathur (Senior Geoscientist) for his guidance, involvement and useful advice during the internship.

Date : 09.08.2021

Ashish Himmat Meshram

IIT Kharagpur (14EX20018)

# ABSTRACT

Analysis of Petrophysical properties plays a vital role in reservoir modelling. For quantitative analysis, we require well log measurements of bulk density, natural radioactivity, interval transit time, resistivity, self-potential, and hydrogen content of rock in a borehole. These logs yield clay volume, porosity, water saturation, formation water resistivity and permeability through various relationships which are derived empirically. Not all variables are directly measured by well logging tools, but are usually derived by multiple processes including acquisition, processing, interpretation and calibration. Due to this, each of the processes contribute to some error and uncertainty which affects the resultant values of the petrophysical properties of interest. Therefore, analysis and quantization of such uncertainty by a suitable method is a must for better visualization and interpretation of the data. Thus, providing a better pay summary. Monte Carlo Simulation is one such mathematical technique that can be used to estimate uncertainty by bootstrap sampling to produce petrophysical models based on certain statistical distributions. Hence, for the project, the workflow employs Monte Carlo Simulation method for uncertainty analysis of clay volume, porosity and water saturation.

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# 1. INTRODUCTION

## Overview of the Project:

- For this project, the work is aimed to perform Monte Carlo Simulation in a permeable zone of particular well log data. It is specifically intended to deploy M.C. Simulation method for different facies namely Shale, Brine sands and Hydrocarbon sands of the said permeable zone. Using the QuickLook Module in PowerLog (CGG Petrophysics and Rock Physics software), the data is obtained for clay volume, porosity and water saturation. This data is divided according to separate facies and separate models are generated using M.C. simulation. For the work different statistical distributions are tested to best fit the facies wise data for different parameters to be deployed and to bootstrap. Finally, the aim is to model each of the facies parameter's P10, P50 and P90 estimates based on Confidence Intervals of 10%, 50% and 90% of the most likely value to better define the data of each facies.

## 1.1 Background Information & GOM Data:

- The Gulf of Mexico dates from Late Triassic time, about 150 million years ago. It has a surface area of about 1.5 million square kilometers (579,000 square miles) and 20 % of its area has a depth greater than 3,000 meters (9,800 feet). The continental slope comprises 20 % of the Gulf, and the continental shelf comprises 22 %. The coastal zone out to a depth of 20 m (65.6 ft) comprises 38 % of its area. Mean water depth of the Gulf is 1,615 m (5,299 ft), and the water volume of the Gulf is approximately 2.4 million cubic km (584,000 cubic mi). The shape of the basin is basically a simple cup with thick sediment sequences. Following are the diagrams of bathymetric provinces division as well as general sedimentary distribution at Gulf of Mexico.

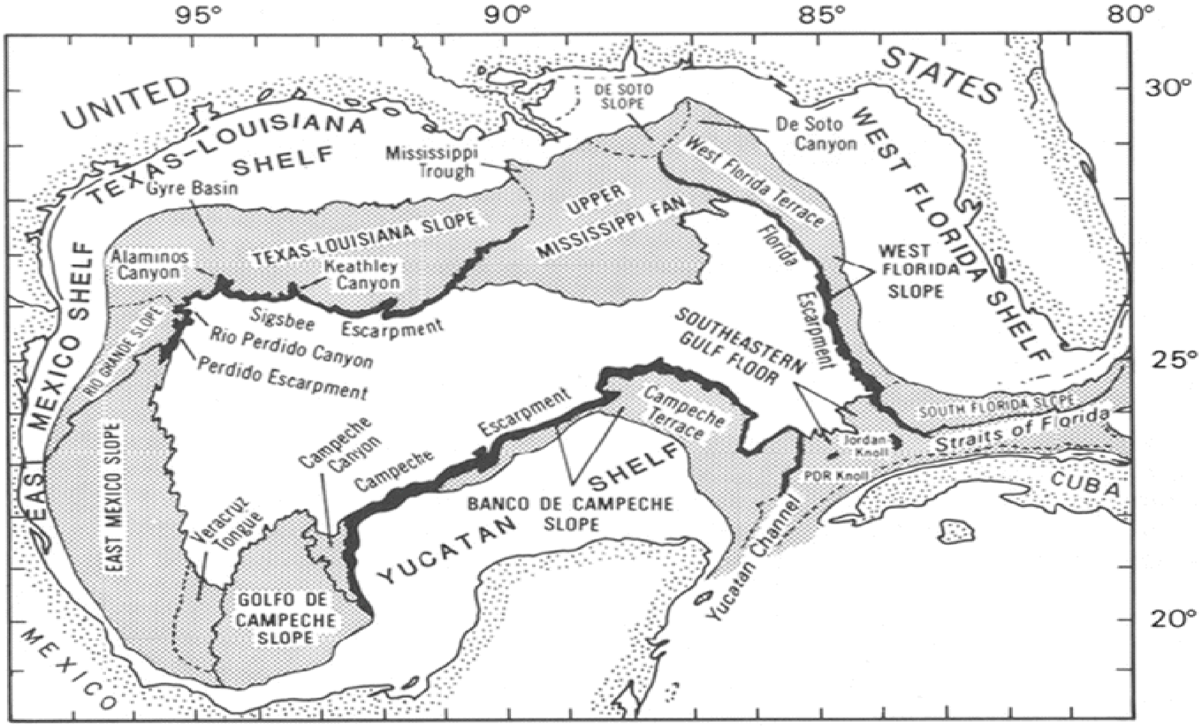


Fig 1.1.1 Bathymetric Provinces division

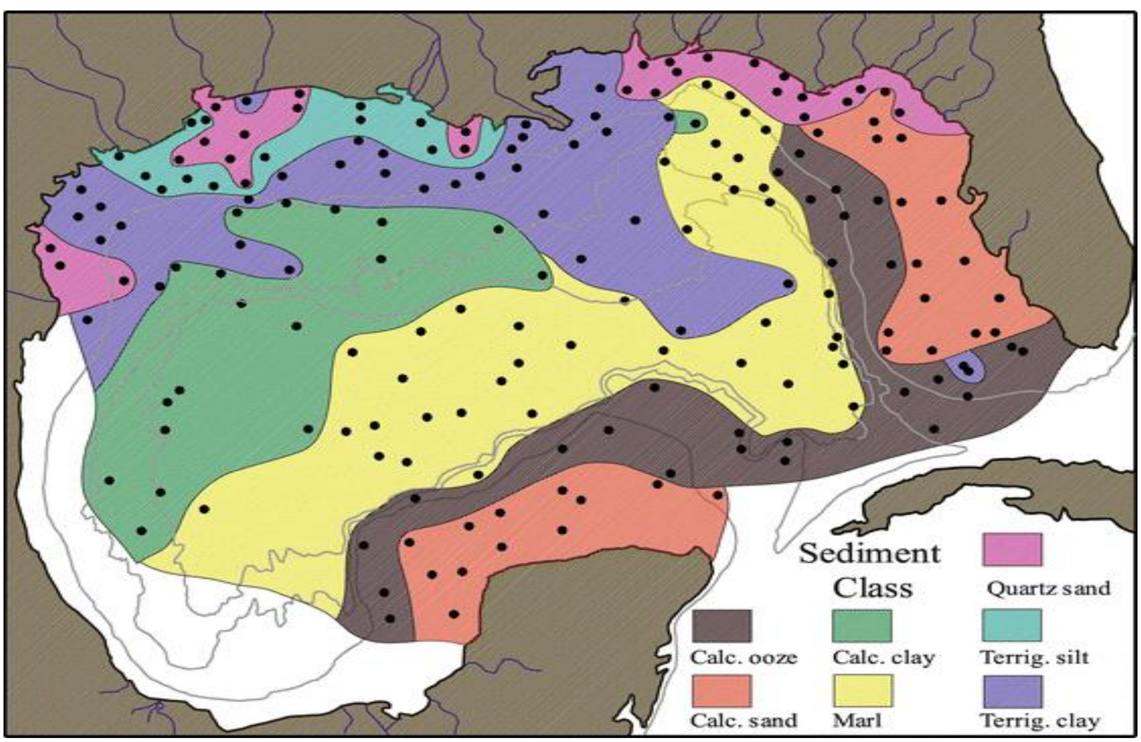


Fig 1.1.2 General Sedimentary Distribution

- The Gulf of Mexico data provided is from the GOM project. The GOM project is located offshore in the Gulf of Mexico. The wells penetrate two vertically stacked shelf edge systems. Facies in these types of deltas include the following elements:
    - Extensive upper delta-slope deformation
    - Locally ponded, slump-induced turbidites in the upper slope
    - Complex association of gravity and tractional deposits
    - Relatively thin, preserved mouth-bar deposits
    - Absence of delta-plain facies

- The GOM project data is preloaded in the software used (PowerLog). PowerLog offers tools for every phase of well log analysis. From data loading & initial evaluation to interactive editing, data conditioning as well as petrophysical interpretation. PowerLog writes data to the GeoSoftware database, allowing for integration among GeoSoftware products and across geoscience disciplines. PowerLog supports multi-well and multi-zone computations meaning several people can work in the same project at the same time, and whenever anyone edits or adds data, updates are visible to all users instantly. This project work in particular uses PowerLog for data visualization, analysis and interpretation purposes. In order to perform Monte Carlo Simulation, PowerLog pl_pydistribution_3.4.4.5 extension is used which allows to code in python 3 using Jupyter Notebook.

## 1.2 Types of Well logs & Basic Glossary:

### 1.2.1 Electrical Logs:

- **Spontaneous Potential Log:**

- SP log records electrical potential produced by interaction of formation connate water, conductive drilling fluid and certain ion selective rocks. It measures the magnitude of potential developed at the contacts between shale or clay beds and a sand aquifer where they are penetrated by a drill hole.

- SP log uses simple equipment to record yet their interpretation is quite complex especially in freshwater aquifers. This creates misinterpretation of SP logs in groundwater applications.

- SP deflection normally occurs only if permeability exists to allow ion migration between the mud and formation. When the mud is more saline than formation connate water, permeable beds give positive SP values. Else $R_{mf} > R_w$ (or) $R_{xo} > R_t$ => Negative SP value

- **Resistivity Log:**

- Resistivity logs are a record of potential variation (or apparent resistivity) with respect to depth. Resistivity is a function of measured potential difference and sending current into formation. In general, surrounding rock formations being poor conductors have a 0.2 to 1000 Ω-m resistivity range.

- Resistivity of formation depends on amount of water present, fluid type, pore structure geometry as well as formation water resistivity.

- Examples of Resistivity log: Normal Resistivity log, Lateral Resistivity log, Focused Resistivity log, Microresistivity log, Induction Resistivity log.

(i) Normal Resistivity Log:

- It is a widely used multi-electrode resistivity logging technique for groundwater hydrology but is obsolete for the oil industry.
- Log measurements are converted to apparent resistivity, which may need to be corrected for mud resistivity, bed thickness, borehole diameter, mudcake, and invasion to arrive at true resistivity.
- For normal devices the distance AM is small (1 to 6 ft) as compared with MN, MB, and BN. In practice, N or B may be placed in the hole at a large distance above A and M. The voltage measured is practically the potential of M (because of current from A), referred to an infinitely distant point. The distance AM of a normal device is its spacing. The point of measurement is midway between A and M. The most common normal spacings were 16 and 64 in.

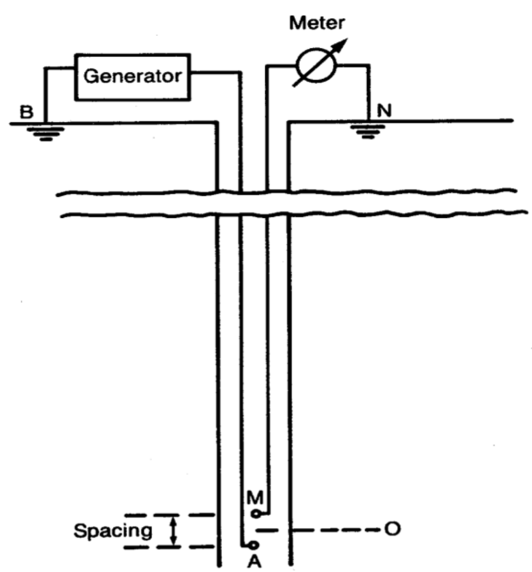


Fig 1.2.1 Normal Log Device arrangement

(ii) Lateral Resistivity Log:

- Lateral log is another multi-electrode method but it is in a different configuration. Lateral logs are designed to measure resistivity beyond the invaded zone to provide a deeper resistivity measurement, which is achieved by using a long electrode spacing.

- For lateral devices measuring electrodes M & N are close to each other and located several feet below current electrode A. Current-return electrode B is at a great distance above A or at the surface. The voltage measured is approximately equal to the potential gradient at the point of measurement 0, midway between M and N. The distance AO is the spacing of the lateral device.

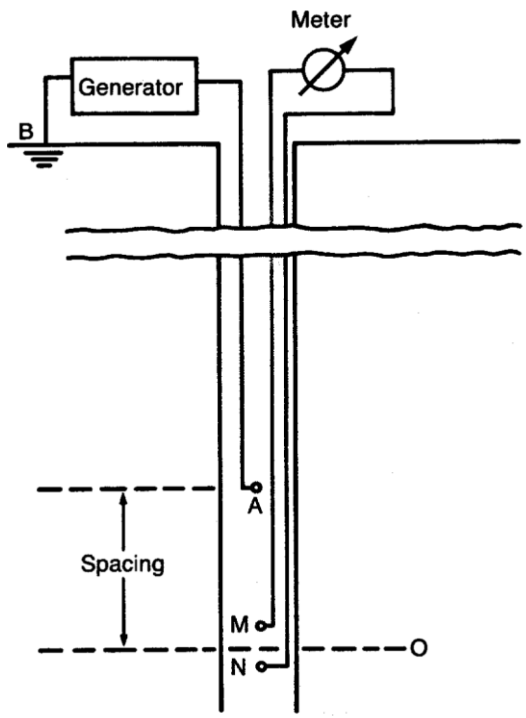


Fig 1.2.2 Lateral Log Device arrangement

(iii) Focused Resistivity Log:

- Focused resistivity logs were designed to measure thin bed resistivity or high resistivity rocks containing highly conductive fluids.
- A number of different types of focused resistivity systems are used commercially such as "guard" or "laterolog". Focused or guard logs can provide high resolution and great penetration under conditions where other resistivity systems may fail. Focused-resistivity devices use guard electrodes above and below the current electrode to force the current to flow out into the rocks surrounding the well.

(iv) Induction Logs:

- Induction logging devices are designed to make resistivity measurements in oil-based drilling muds i.e no conductive medium tool and formation.
- Simple induction probe contains one coil to transmit 20 to 40kHz AC current into the surrounding formation and the other one to receive the signal.
- AC current generates a time varying magnetic field (primary field) which induces eddy currents in conductive rock (secondary field) and therefore the magnitude in the receiving coil is proportional to the conductivity of formation.
- Induction devices provide resistivity measurements regardless of whether the fluid in the well is air, mud, or water, and excellent results are obtained through plastic casing.

### 1.2.1 Nuclear Logs:

- Nuclear logging involves techniques that either detect the presence of unstable isotopes, or that create such isotopes in the vicinity of a borehole. Since the penetrating capability of nuclear particles and photons permit detection through casing and annular materials, the method works regardless of the type of fluid in the borehole.

- Radioactivity is measured by converting the particles or photons to electronic pulses, which then can be counted and sorted as a function of their energy. The detection of radiation is based on ionization that is directly or indirectly produced in the medium through which it passes.

- Types of Nuclear logs: Gamma Ray log, Gamma-Gamma log (Density), Gamma Ray spectrometry, and several different kinds of nuclear logs.

(i) Gamma Ray Log:

- Gamma ray logs also known as natural -gamma logs are most widely used nuclear logs for most applications. Common use is for identification of lithology and stratigraphic correlation, and for this reason, gamma detectors are often included in multi-parameter logging tools.
- It measures total Gamma ray emissions from the formation in API units which is vital in clay volume (shale) calculation useful over a wide variety of borehole conditions.

(ii) Density Log (or) Gamma-Gamma Log:

- Density log is a measurement of scattered Gamma Rays reaching the detector probe at a fixed distance from the. This is translated in terms of formation density.
- The no. of Compton scattering collisions is directly related to no. of electrons in formation describing bulk resistivity of the rock.
- The density logs can be calibrated in terms of bulk density under the proper conditions and converted to porosity if grain and fluid density are known.

(iii) Neutron Log:

- Neutron log is the measurement of slowdown neutron counts.
- Neutron probes contain a source that emits high-energy neutrons. When neutrons collide with the formation, upon sufficient collisions the neutron reaches a lower energy state whereupon it is captured by the formation nuclei.
- As the nucleus captures the thermal neutron energy is dissipated and it slows down. Most of these neutron collisions are related to the amount of hydrogen present, which, in groundwater environments, is largely a function of the water content of the rocks penetrated by the drill hole.
- The most common neutron source used in porosity logging tools is americium-beryllium, in sizes that range from approximately 1 to 25 Curies. Moisture tools may use a source as small as 100 millicuries.

### 1.2.3 Acoustic Log (or) Sonic Log (or) Transit-Time Logs:

- Acoustic logs are a record of the travel time of an acoustic wave from one or more transmitters to receivers in the probe recorded with respect to depth in the formation. It includes the techniques which use piezoelectric transducers to transmit acoustic waves through the fluid in well and elastic material surrounding it.

- Based on frequencies, the way the signal is recorded and the purpose of the log different types of acoustic logs are used but it is a requirement that fluid in the well couples the signal to the surrounding rocks.

- Interval transit time for a formation depends upon lithology and porosity. Integrated transit times are also helpful in interpreting seismic records.

- Examples of Acoustic Log: Acoustic waveform log, Acoustic velocity log, Cement bond log and Acoustic Televiewer.

## 1.2.4 Basic Glossary:

### 1. Porosity (ϕ):

- Total volume of formation occupied by pores or voids denoted by (ϕ) measured as percentage.

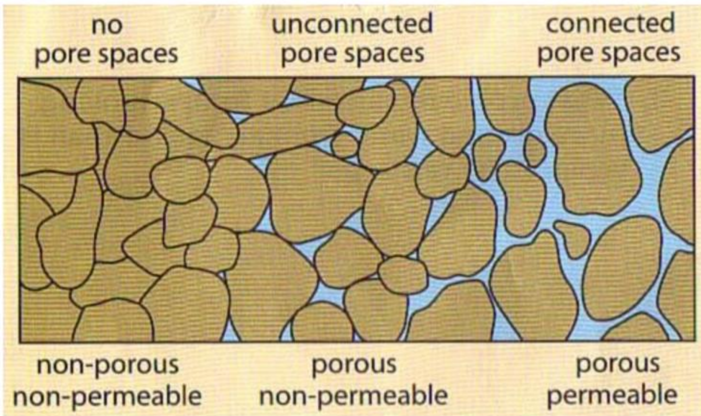


Fig 1.2.3 Porous medium v/s Non Porous medium

### 2. Volume of Shale (VSH) or Volume of Clay (VCL):

- Total volume of Shale or Clay present in the reservoir rock expressed in terms of percentage.

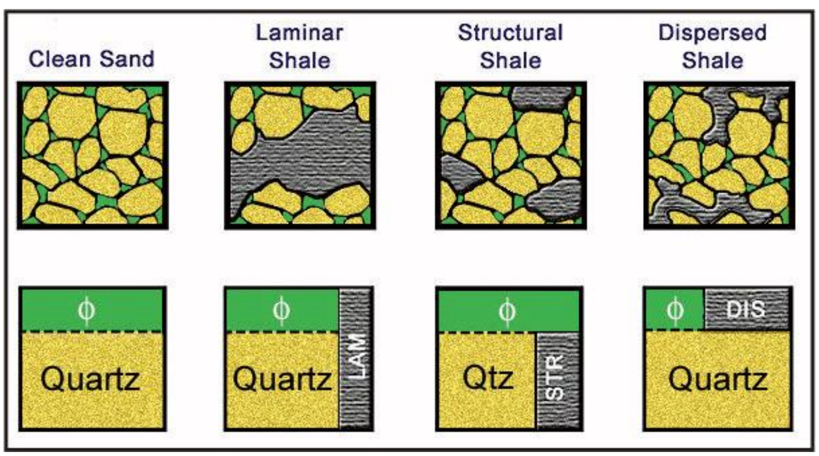


Fig 1.2.4 Shale distribution in rock pores

i) Laminar Shale: Laminated shale refers to thin lamination clay minerals of an inch to many inches in thickness interbedded with clean sand.

ii) Structural Shale: In Structural Shale, aggregates of the clay particles occur that takes place of sand grains in the framework grains of reservoir rock along with sand grains

iii) Dispersed Shale: Dispersed Shale occurs as disseminated particles in the pore spaces of the sand and replaces pore fluid.

**3. Water saturation (Sw):**

- It is the fraction of water content in a given pore volume of formation expressed in terms of percentage.

- *Sw – Fraction of pore space occupied by water.*
- *Sh – Fraction of pore space occupied by hydrocarbon.*

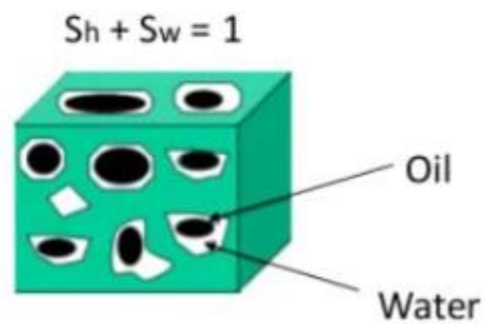


Fig 1.2.5 Water Saturation in rock pores

**4. Resistivity (R):**

- Opposition to flow of electric current offered by a material of 1 m length and 1 sq m cross sectional area measured in Ω-m.

i) True Resistivity (Rt): Resistivity of uninvaded zone beyond transaction zone.

ii) Formation water Resistivity (Rw): True resistivity of the formation water in uninvaded water bearing zone.

iii) Filtrate Resistivity (Rmf): Resistivity of the mud filtrate in the invaded zone.

iv) Invaded zone: The volume close to the borehole wall in which some or all of the moveable fluids have been displaced by mud filtrate.

# 2. PROBLEM STATEMENT

**Uncertainty Analysis of Clay Volume, Porosity and Water Saturation of Gulf of Mexico Data by Monte Carlo Simulation**

## 2.1 Uncertainty Analysis:

- Uncertainty refers to the lack of confidence in one's estimates. Simply it is the lack of certainty, a state of limited knowledge where it is impossible to exactly describe the existing state, a future outcome, or more than one possible outcome.

- Commonly, we separate uncertainty into two categories: aleatoric uncertainty (inherent uncertainty of the system) and epistemic uncertainty (uncertainty about the choice of model).

  i) Aleatoric Uncertainty:

  The uncertainty that is inherent to the system because of information that cannot be measured. In the case of aleatoric uncertainty, it cannot be eliminated even as the number of samples collected tends towards infinity.

  Eg: For a given true temperature, a thermometer may output slightly different values taking more temperature measurements will not reduce the uncertainty stemming from an imprecise thermometer.

  ii) Epistemic Uncertainty:

  Epistemic uncertainty is the uncertainty that comes from being unsure about one's model choice. It reduces with increasing no. samples for data.

  Eg: For a neural network modelling with a given finite number of samples to train on, the uncertainty of weights in the network is epistemic uncertainty. As the number of samples being trained increases, the epistemic uncertainty diminishes quicker since the correct model is approached.

- Deterministic Uncertainty analysis:

  i) Deterministic Uncertainty analysis is a method that can be used to investigate the Uncertainty from a model-based analysis using variations in a specific input parameter or set of parameters.

  ii) In a pre-specified range, one or more input (risk) parameters can be manually varied and the results are analyzed to determine how the variation has an impact on the output values.

  iii) It is usually not possible to vary more than 4 to 5 parameters at the same time in this form of analysis since we assess the impact of simultaneous variation of many input parameters. In this case, we cannot determine which particular parameter was responsible for a certain response. The results of deterministic analysis are usually expressed in some plots defining the estimates in uncertainty.

## 2.2 Monte Carlo Simulation:

- Monte Carlo Simulation is a mathematical technique that allows one to estimate uncertainty in decision making and quantitative analysis.

- For an experiment we will have a mathematical or an empirical relation involving one or multiple input parameters. The said relation is called the transfer function and the input parameters are called risk parameters in simulation. M.C. simulation method involves mathematical simulation of the experiment to determine the probability distribution of output of the transfer function. We have used M.C. Simulation with a deterministic approach.

- In implementation of the method, each risk parameter is considered a random variable which has its associated uncertainty. The probability distribution is determined on the basis of given data and the best fit statistical distribution can be used to simulate the transfer function output.

- The risk parameters themselves have their own statistical distributions like uniform, normal, beta, exponential, or lognormal distribution. We generate a large no. of random samples simulated from a statistical distribution of choice determined by some logic for the risk parameter.

- The output of the transfer function generated by the simulation upon varying an input parameter once is simulation for 1 iteration. We vary the input (risk) parameter over and over again generating different scenarios of the transfer function output, but the output's distribution type remains the same.

- The computed probability distribution is an approximation of the true probability distribution as if the process of the output variable being studied was conducted over a large number of times. This approximate distribution for a large number of iterations can hence be used for interpretation.

## General Steps for M.C. Simulation:

1. Set up the risk parameters and the transfer function for the data.

2. Specify the probability distribution used to bootstrap and range for the risk parameter to bootstrap.

3. Run iterative simulations based on statistical distribution and range.

4. Fit the output of the transfer function with a distribution and make an estimate based on it to quantify the uncertainty. Alternatively, for a given data of the transfer function output, which is to be simulated, fit this data by best fit statistical distribution to bootstrap samples and repeat this step.

## Distributions used:

1. Pearson Type III Distribution (Used for VCL and Water Saturation):
   Pearson distribution is a family of continuous probability distributions originally devised in an effort to model visibly skewed observations. It is characterized by two shape parameters, commonly referred to as β1 (skewness²) and β2 (kurtosis+3). For any distribution, skewness = 3 * (Mean – Median) / standard deviation and kurtosis = $E[((X-\mu)/\sigma)^4]$. The Pearson family of distributions is defined to be any valid solution of the partial differential equation:

$$\frac{df(x)}{dx} + \frac{a+(x-\lambda)}{d(x-\lambda)^2 + c(x-\lambda) + b} = 0$$

$$\text{with} \quad \begin{cases} b = \dfrac{4\beta_2 - 3\beta_1}{10\beta_2 - 12\beta_1 - 18}\mu_2, \\ a = c = \sqrt{\mu_2}\sqrt{\beta_1}\,\dfrac{\beta_2 + 3}{10\beta_2 - 12\beta_1 - 18} \\ d = \dfrac{2\beta_2 - 3\beta_1 - 6}{10\beta_2 - 12\beta_1 - 18} \end{cases}$$

In particular, Pearson type III distribution is a generalized gamma distribution or chi-squared distribution which follows:

$$\lambda = \mu_1 + \frac{b_0}{b_1} - (m+1)b_1$$

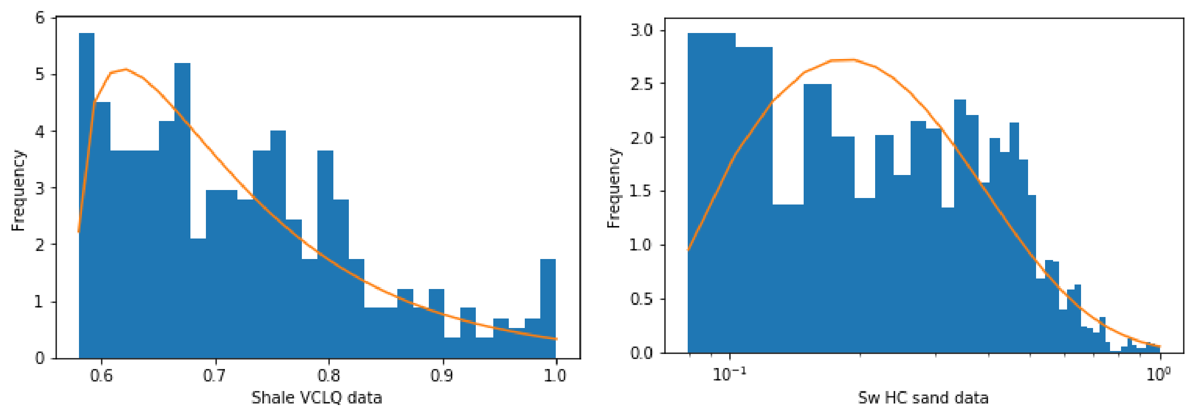


Fig. 2.2.1 Pearson type III Distribution fit for Volume of Clay from QuickLook module (VCLQ) shale & Water Saturation (SwQ) HC sands

2. Generalized Logistic Distribution (Used for Porosity):
   Generalized logistic distribution is used as the name for several different families of probability distributions which can be used for highly shape-and-bounds flexible data and can be fit by linear least squares. It can be defined by two shape parameters α and β. The most general form is the Generalized Logistic Distribution Type IV:

$$f(x;\alpha,\beta) = \left(\frac{1}{B(\alpha,\beta)}\right)\left(\frac{e^{-\beta x}}{(1+e^{-x})^{\alpha+\beta}}\right), \qquad \alpha,\beta > 0$$

$$where, \qquad B(t) = \frac{\Gamma(\beta-t)\Gamma(\alpha+t)}{\Gamma(\beta)\Gamma(\alpha)}, \qquad -\alpha < t < \beta$$

The Type III distribution can be obtained from Type IV by fixing α = β. The Type II distribution can be obtained from Type IV by fixing α =1. The Type I distribution can be obtained from Type IV by fixing β =1.

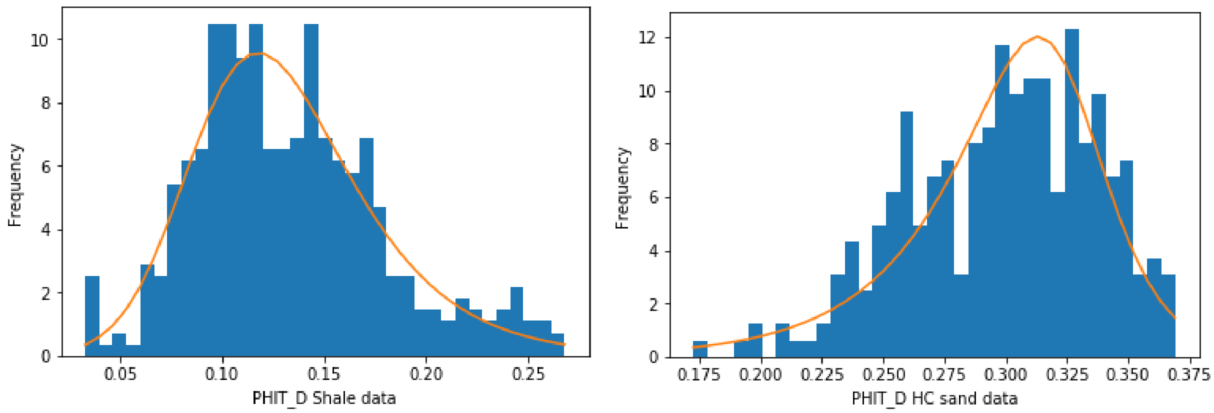


Fig. 2.2.2 Generalized Logistic Distribution fit for PHIT_D shale & HC sands data

3. Uniform Distribution:
   The continuous Uniform distribution or rectangular distribution is a family of symmetric probability distributions where there is an arbitrary outcome that lies between certain bounds defined by minimum (a) and maximum (b) values. The probability associated with this arbitrary outcome is constant such that every other point in distribution has the same probability and there are no other restrictions. Its probability density function is defined as:

$$f(x) = \begin{cases} \frac{1}{b-a} & \text{for } a \le x \le b, \\ 0 & \text{for } x < a \text{ or } x > b \end{cases}$$

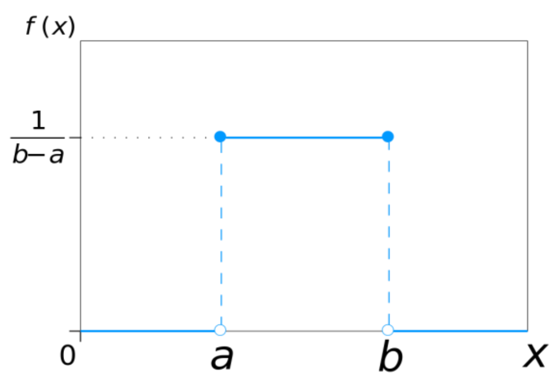


Fig. 2.2.3 Graphical Representation of Uniform Distribution

The work uses uniform distinction to vary the risk parameters GRshale, ρclay (to vary ρmatrix) and Rw for transfer functions of VCL, Porosity and Sw respectively as separate cases.

**Method used for estimates:**

i) P10, P50 and P90 estimate based on Confidence Interval:

- Confidence interval in statistics, refers to the probability that a population parameter will fall between a set of values for a certain proportion of times. Confidence interval around a particular value gives an estimated range around the measured value that is likely to include the true (population) value of the parameter.

- For a given estimation in a given sample, using a higher confidence level generates a wider (i.e. less precise) confidence interval and lower confidence level generates a narrower (i.e. more precise) confidence interval and is a representation of inherent variability of the statistical parameter.

- Here, the P10, P50, P90 are statistical confidence levels for an estimate for probabilistic Monte Carlo evaluations. P10, P50 and P90 signifies the high, best and low estimates range based on the statistical confidence level.

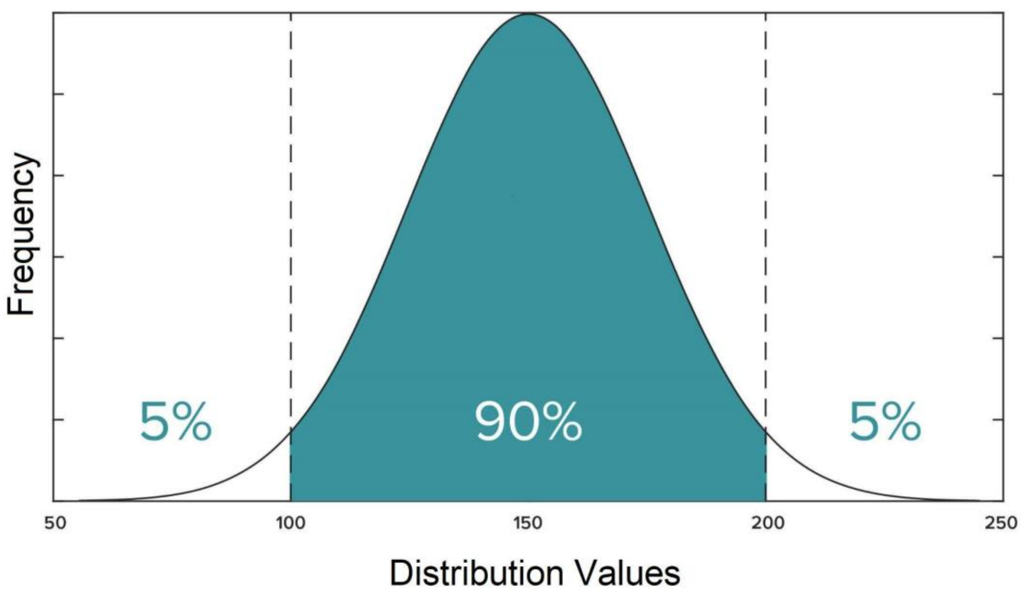


Fig 2.2.4 90% Confidence interval for mean in Normal Distribution

- In order to do confidence level based P10, P50, P90 estimates, for a particular statistical parameter, I have best fit a statistical distribution that best defines the data.

- I have used this statistical distribution's peak that is the most likely value of the data to define the confidence interval of 10%, 50% and 90%. This is done because we have skewed data and mean is not the true representation of the most likely value of the data distribution.

- Hence, I identified the peak value of the distribution and computed the proportion of values over and under the peak value. Based on this proportion I have defined how the significance interval must be in order to generate the range of 10% confidence (P10), 50% confidence (P50) and 90% confidence (P90).

- In this work, the risk parameters GRshale, ρclay and Rw values are varied using Uniform Distribution. Also, Pearson type 3 distribution is used as the best fit for VCL and Sw simulation and Generalized logistic distribution is used to best fit Density Porosity data for Monte Carlo Simulation.

# 3. WORKFLOW OF ANALYSIS

## 3.1 Observe Data Distribution

i) Create the histogram of the data to observe the distribution.

ii) Calculate basic statistical parameters such as mean, mode, variance, range etc. for the data distribution.

iii) In particular, the interest is to see distributions of Bulk Density (RHOB), Gamma Ray log (GR) and Resistivity log (ILD) whose plots are shown as Fig (3.1), Fig (3.2) and Fig (3.3) respectively.

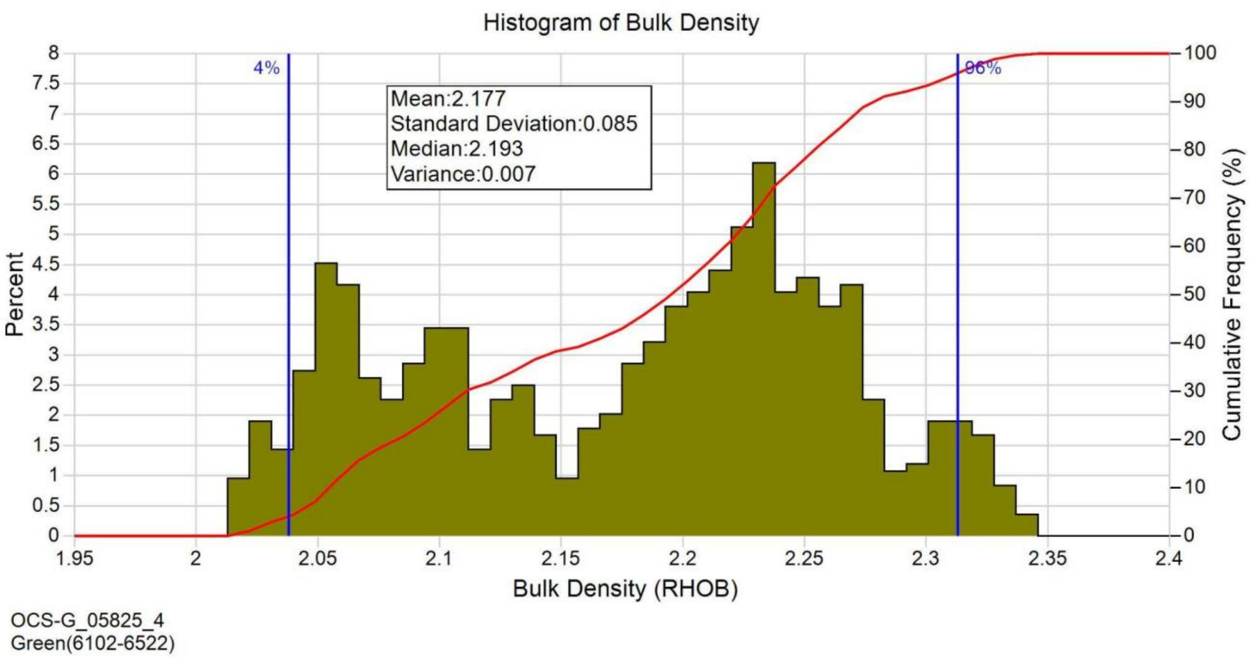


Fig 3.1 RHOB log Data
(*in Well OCS-G_05825_4 for Green Zone)*

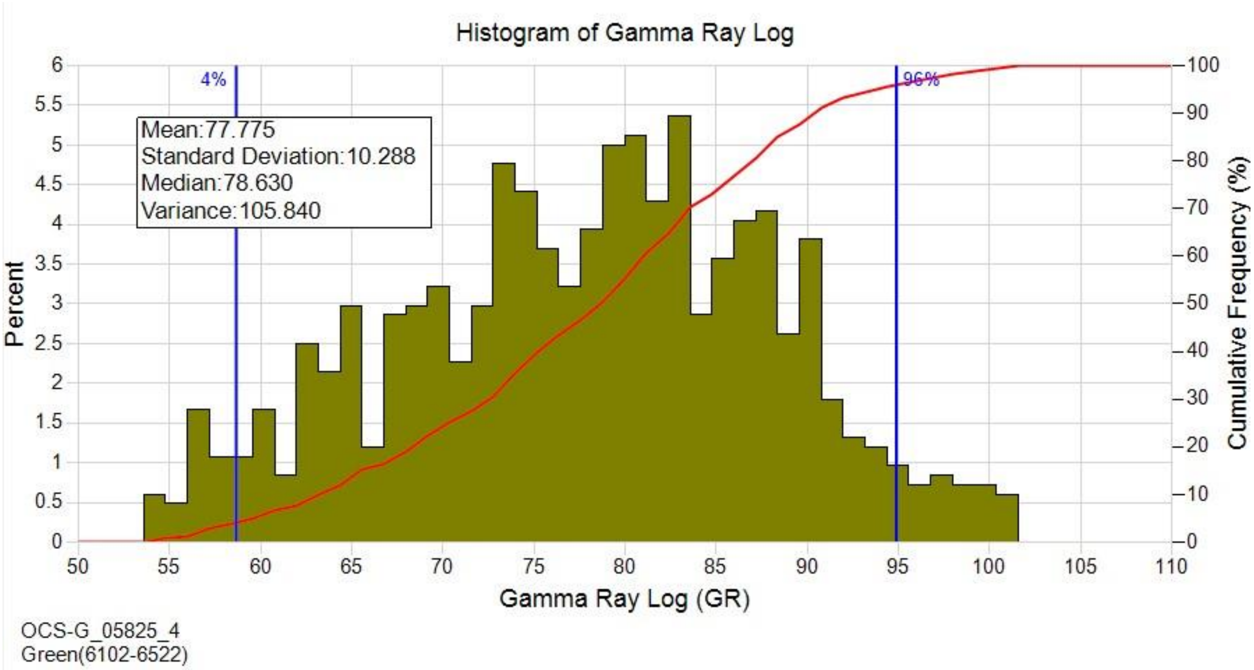


Fig 3.2 GR log Data

*(in Well OCS-G_05825_4 for Green Zone)*

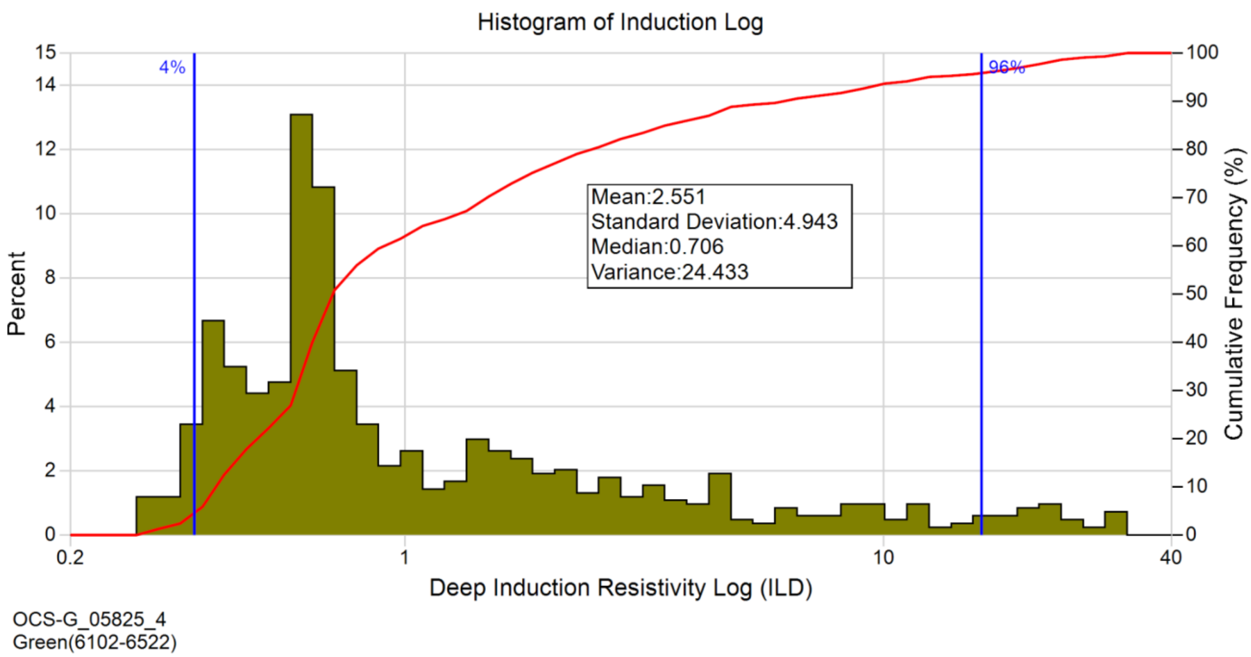


Fig 3.3 ILD log Data

*(in Well OCS-G_05825_4 for Green Zone)*

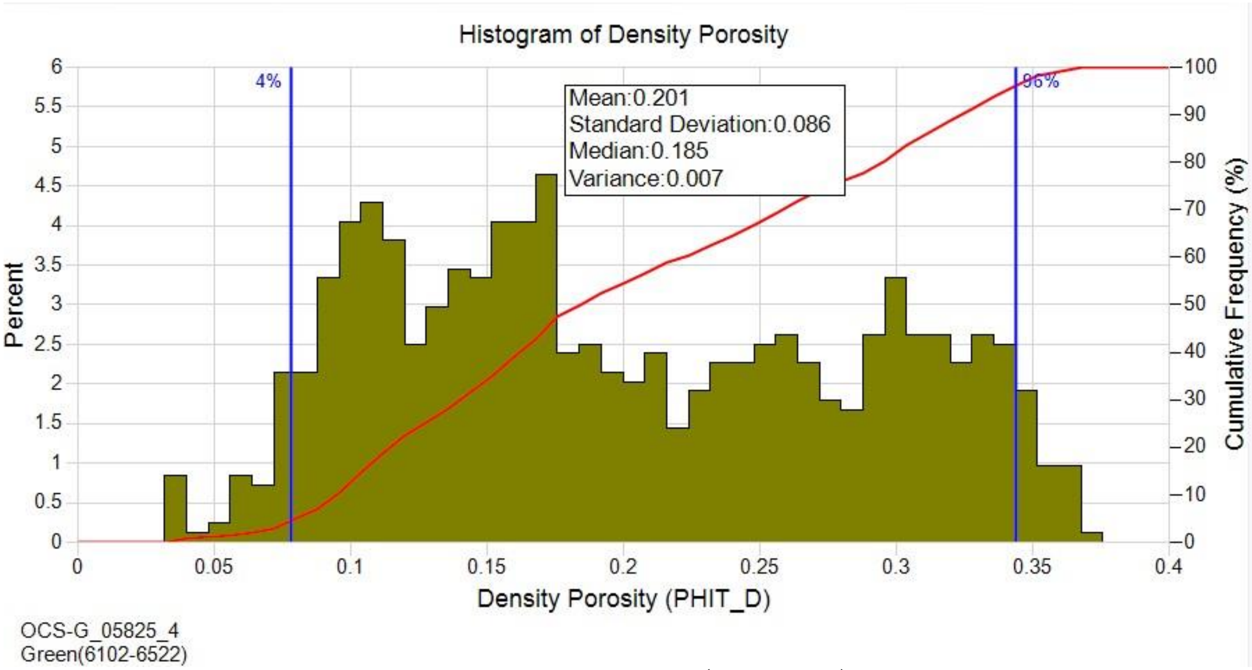


Fig 3.4 Density Porosity (PHIT_D) Data
*(in Well OCS-G_05825_4 for Green Zone)*

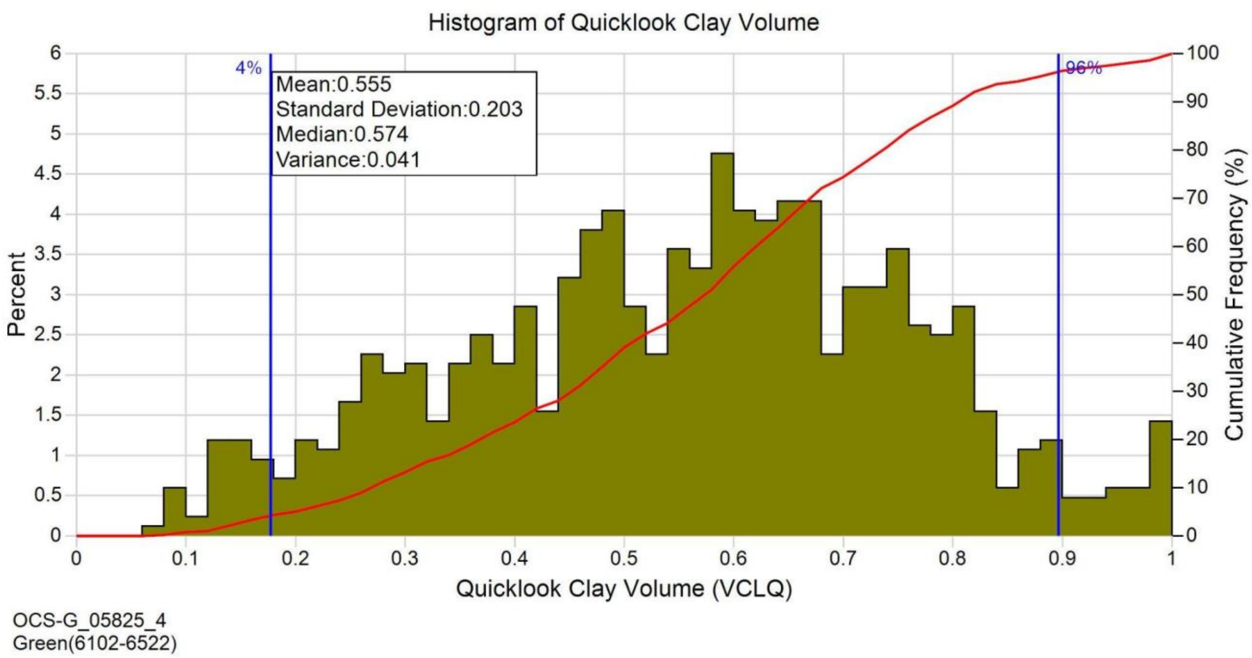


Fig 3.5 QuickLook VCL (VCLQ) Data
*(in Well OCS-G_05825_4 for Green Zone)*

## 3.2 Generate Facies Curve

i) From the QuickLook Module in PowerLog, porosity and water saturation data are to be obtained.

ii) Based on this data, in a particular zone, divide the facies into shale facies (f1), brine sands facies (f2) and Hydrocarbon sands (f3).

iii) At a particular depth:

- To discriminate between shale facies and sand facies, if clay volume is greater than 0.6 then call it a shale facies and otherwise it is a sand facies.
- In sand facies, we can have brine sands and hydrocarbon sands. To discriminate between them, if the water saturation is less than 0.6 then it is a hydrocarbon facies and otherwise it is brine sands.

iv) Generate the Facies curve based on (iii) which is below:

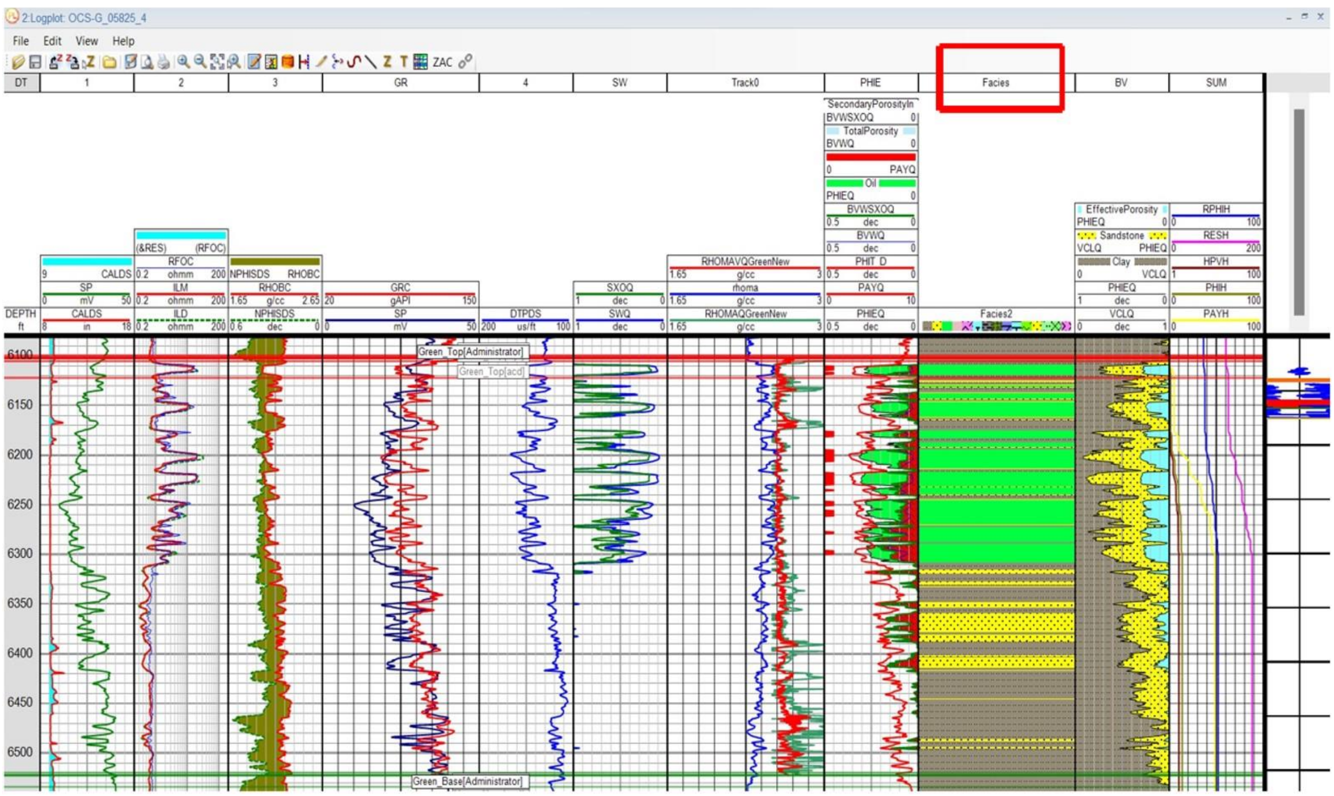

Fig 3.6 Well OCS-G_05825_4 for Green Zone Logplot

Note: Here in Facies track, Facies2 curve indicates the Facies curve where [green] indicates Hydrocarbon sands, [yellow dotted] indicates Brine sands and [grey] indicates Shale in the Green Zone for Well OCS-G_05825_4.

## 3.3 Monte Carlo Simulation of Volume of Clay (VCLQ):

**Overview**:

i) Obtain VCLQ from the QuickLook Module in PowerLog and split the data facies wise. Best fit the Pearson type 3 distribution to bootstrap VCLQ and obtain M.C. simulated VCL.

ii) The ρmatrix is also "simulated" since the M.C. simulated VCL is one of the input parameters to the ρmatrix equation. We use this ρmatrix to compute Porosity.

iii) To compute Sw, we keep Formation Water Resistivity (Rw), Tortuosity (a), Cementation exponent (m) and Saturation exponent (n) as is.

iv) It is done since a, m, n & Rw are constants which are obtained from Pickett plot and the Formation factor values are determined by using VCL varied Porosity that we have just simulated.

iv) Finally, compute Sw using a, m, n, F & Rw (for n iterations) in Archie's Equation.

## Flowchart:

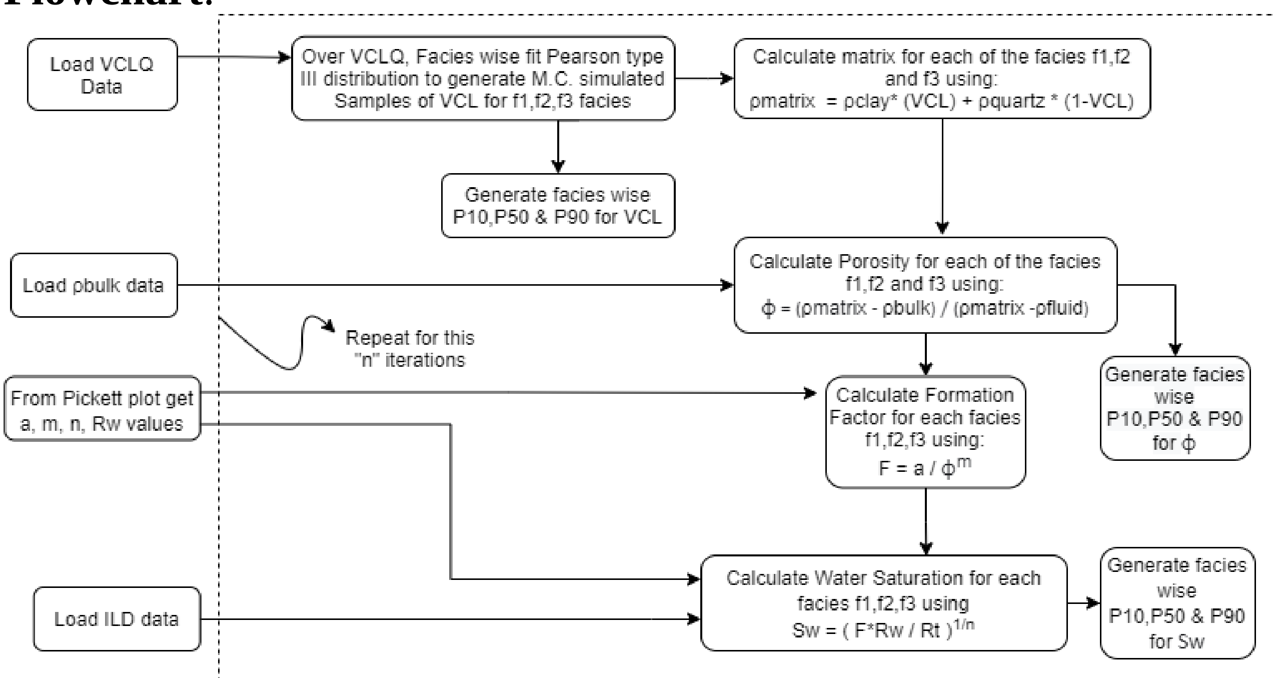


Fig 3.7 Workflow for VCLQ M.C. Simulation

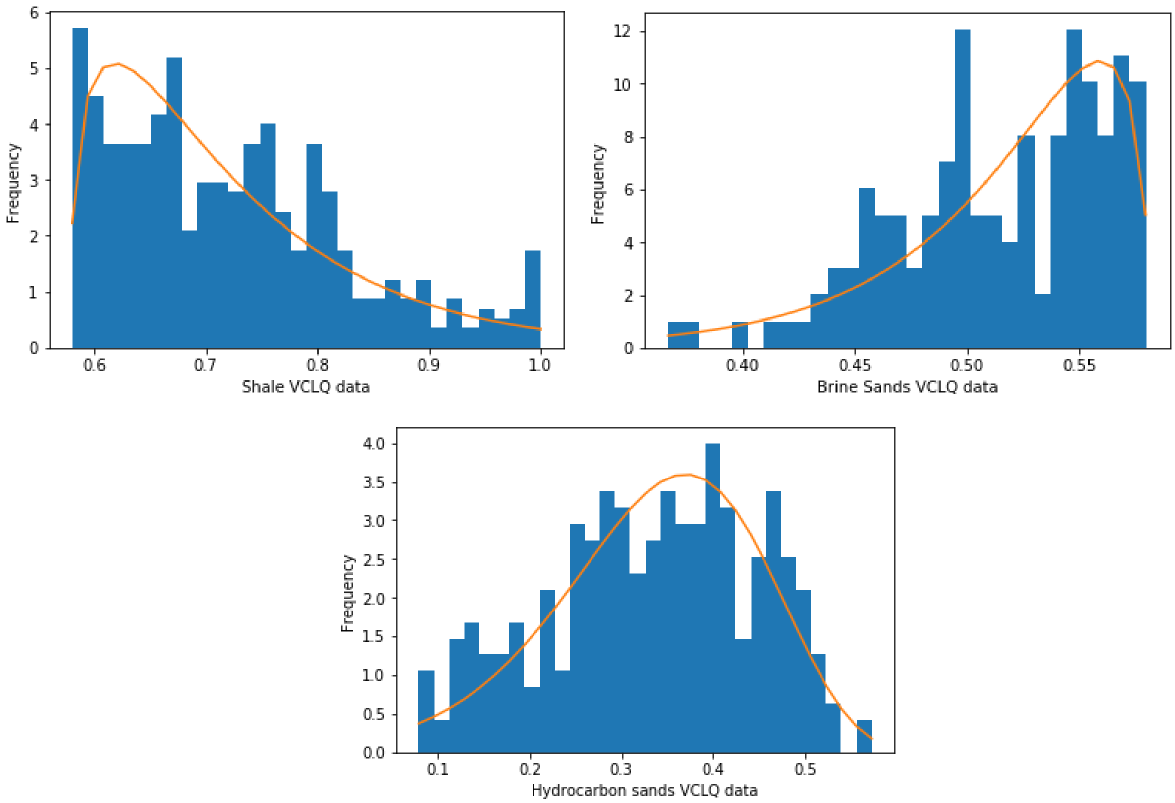


Fig 3.7.1 Facies wise Pearson type III Distribution fit for VCLQ

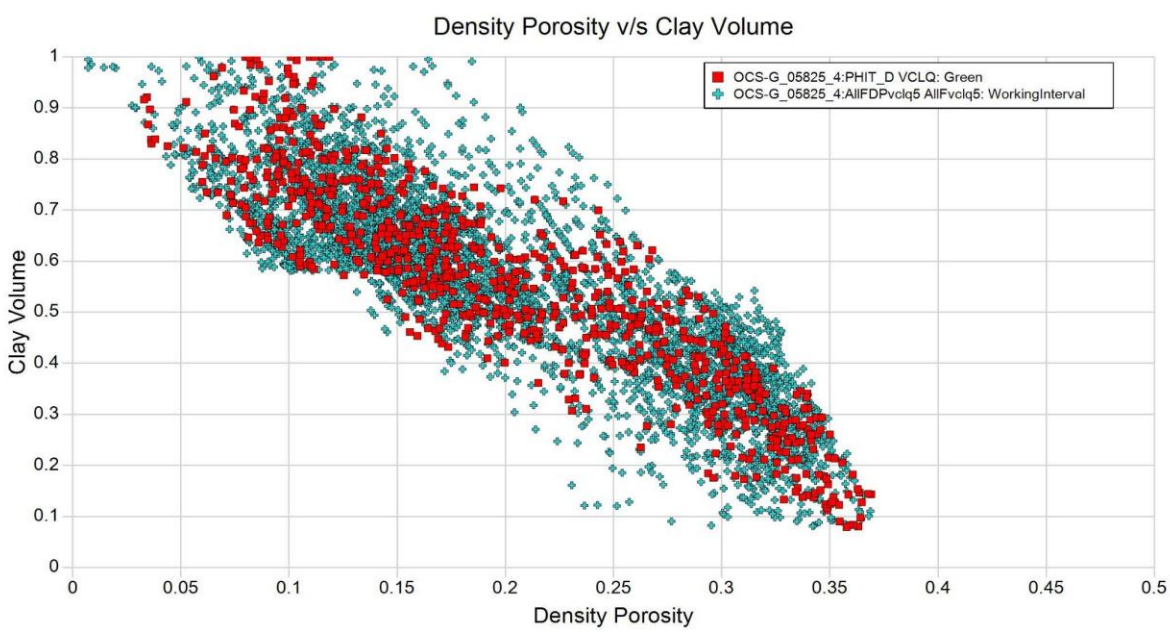


Fig 3.7.2 Density porosity vs. Clay Volume plot for 5 iterations

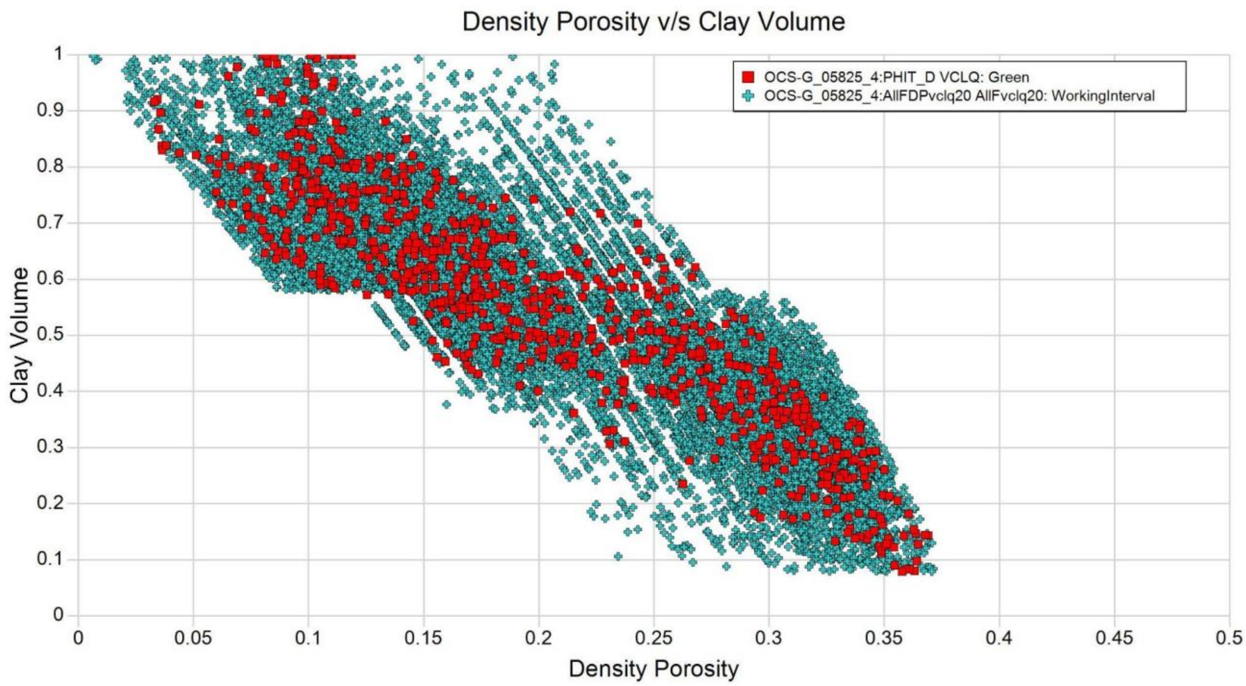


Fig 3.7.3 Density porosity vs. Clay Volume plot for 20 iterations

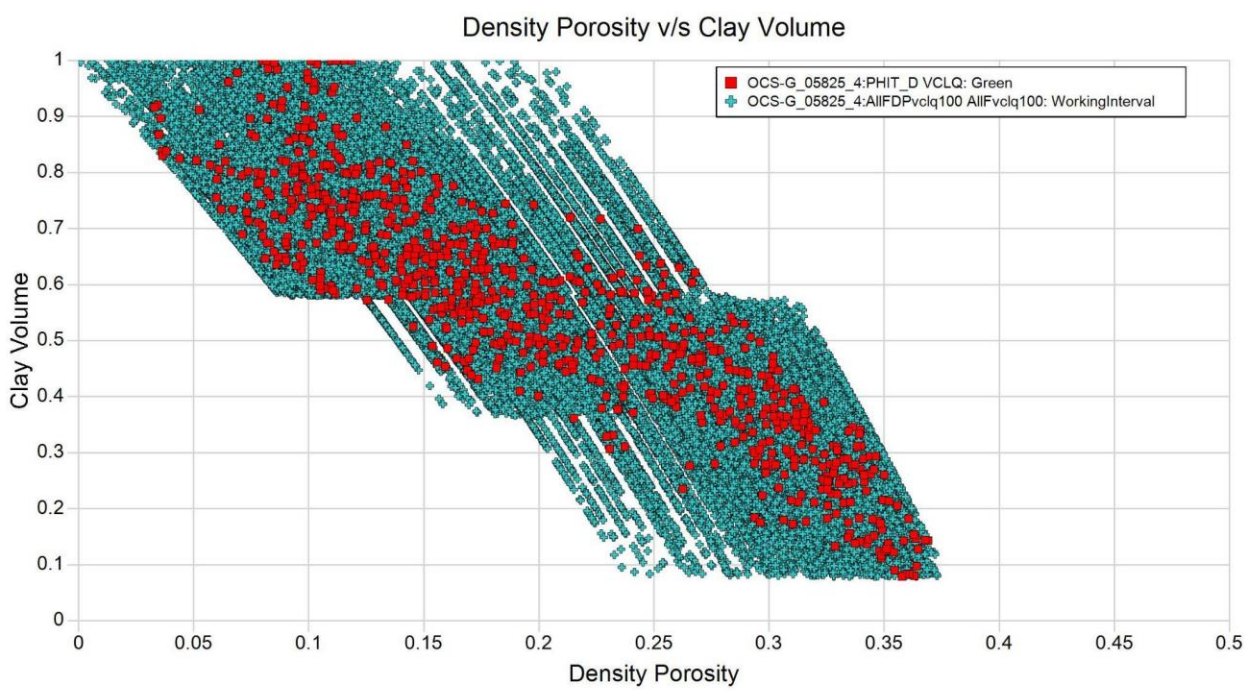


Fig 3.7.4 Density porosity vs. Clay Volume plot for 100 iterations

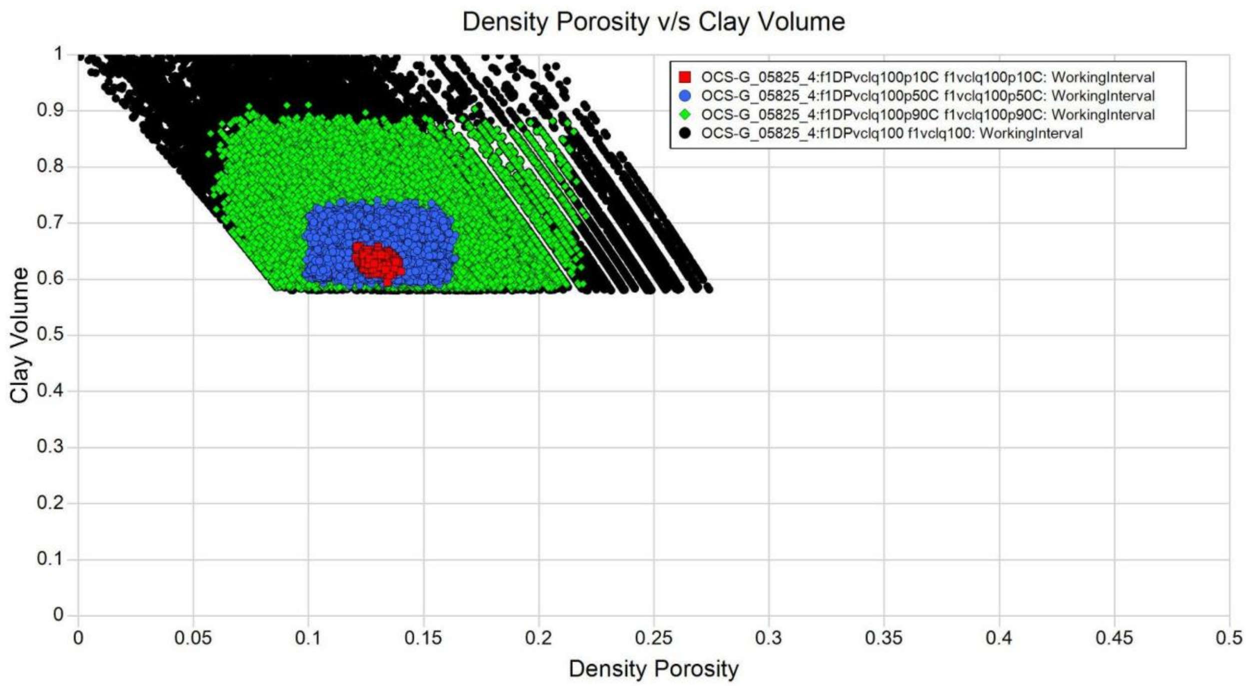


Fig 3.7.5 Density porosity vs. Clay Volume plot for 100 iterations of shale facies

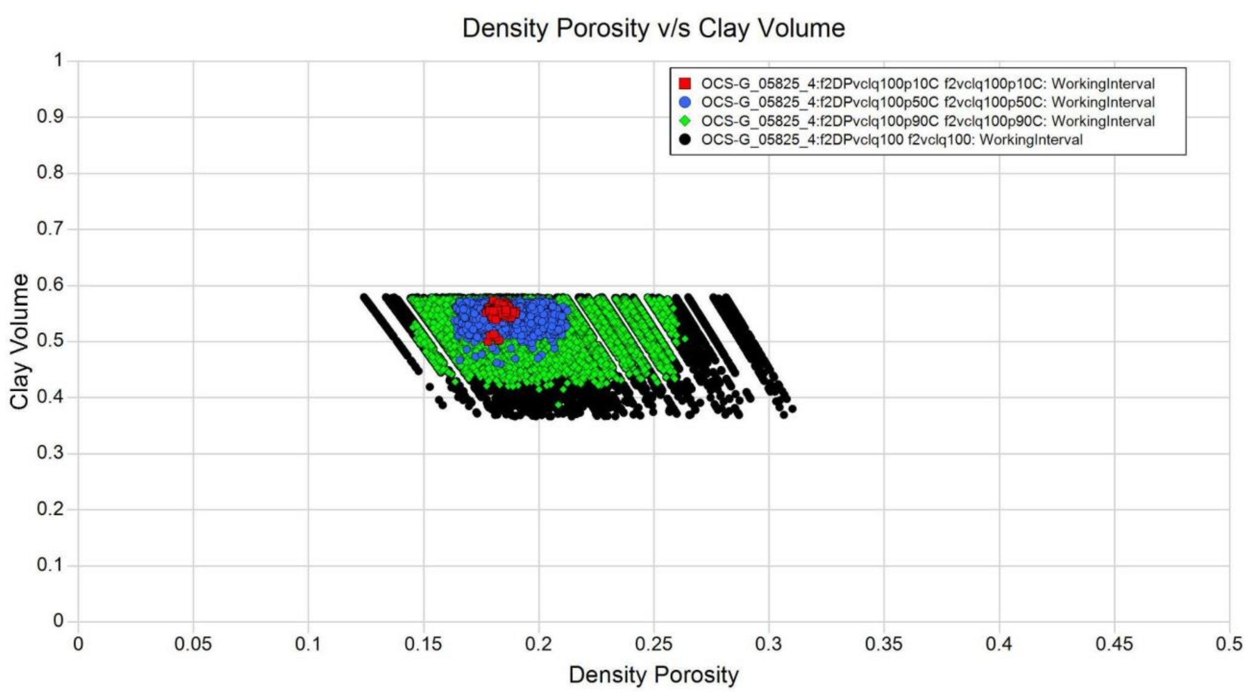


Fig 3.7.6 Density porosity vs. Clay Volume plot for 100 iterations of brine sands

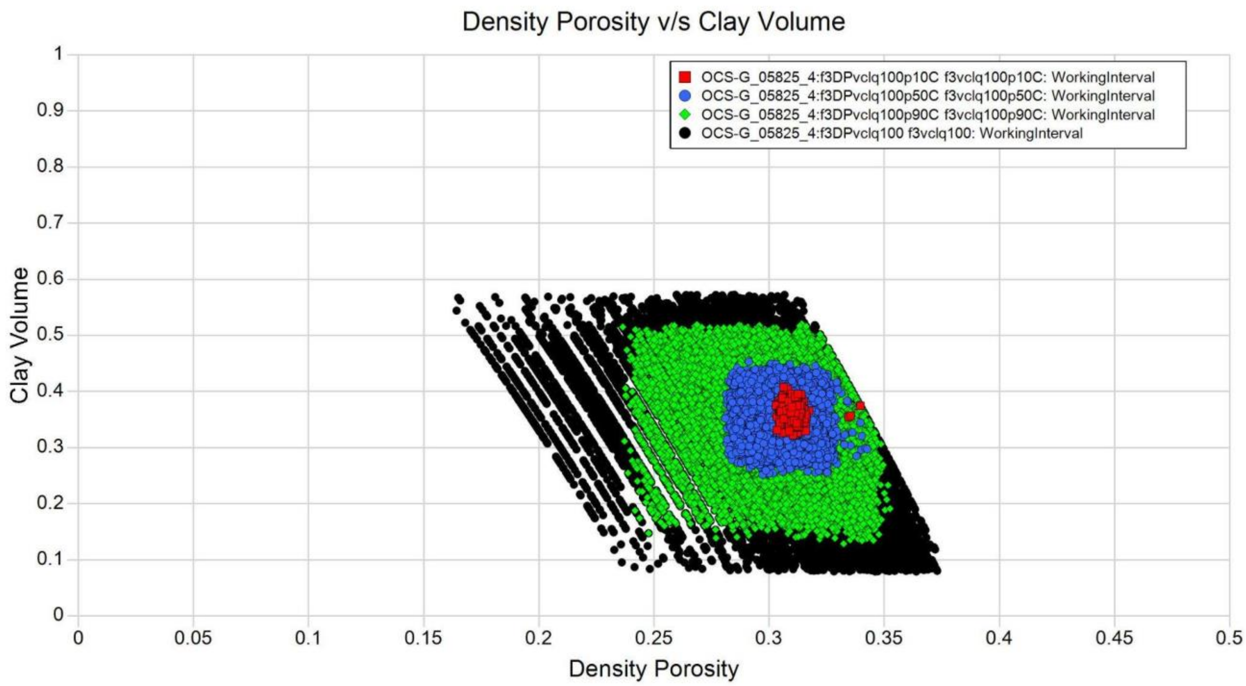


Fig 3.7.7 Density porosity vs. Clay Volume plot for 100 iterations of HC sands

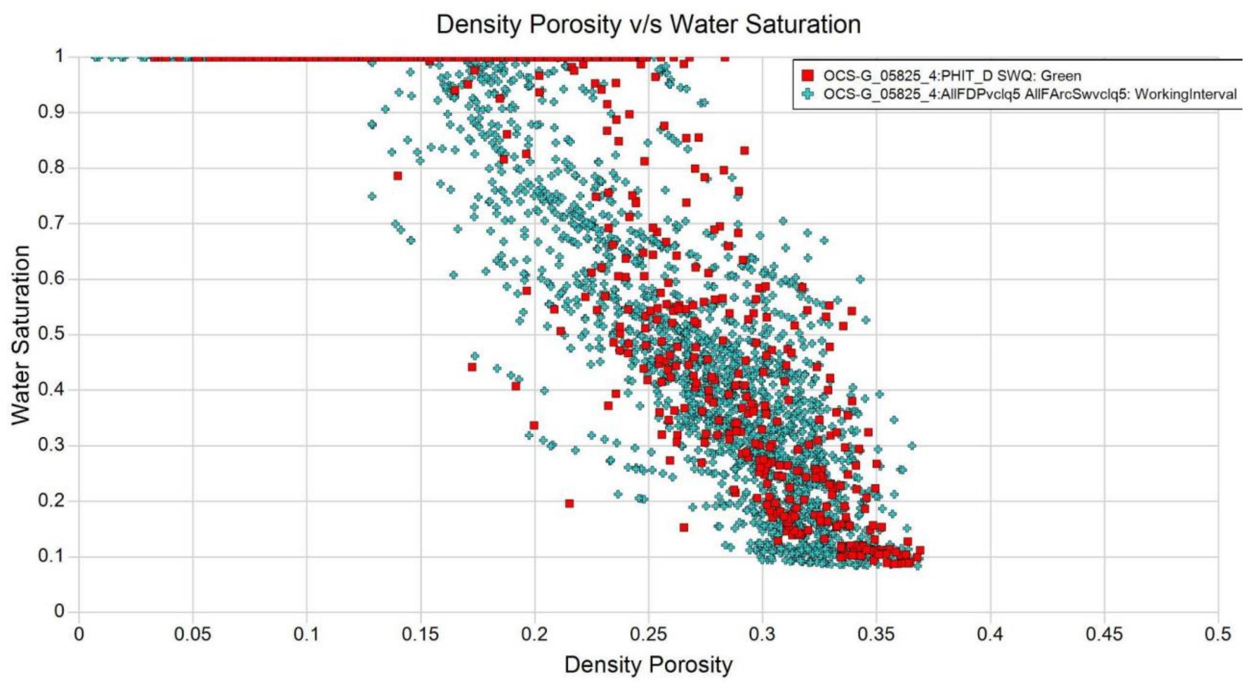


Fig 3.7.8 Density porosity vs. Water Saturation plot for 5 iterations

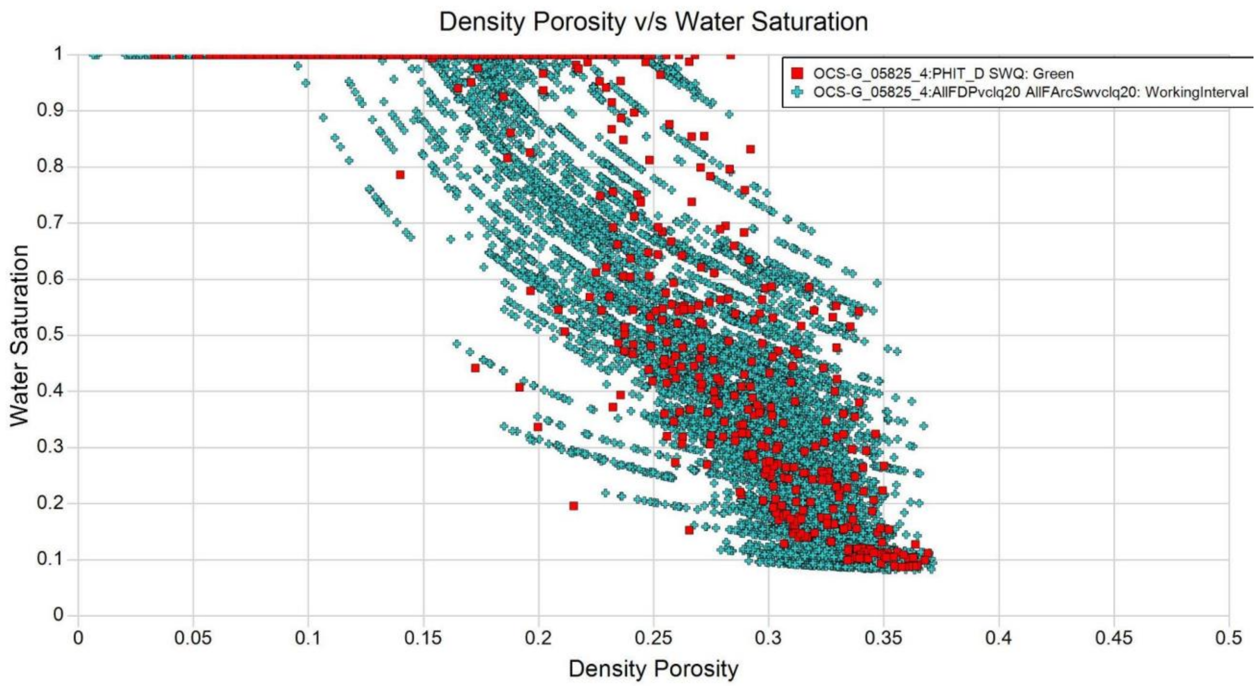


Fig 3.7.9 Density porosity vs. Water Saturation plot for 20 iterations

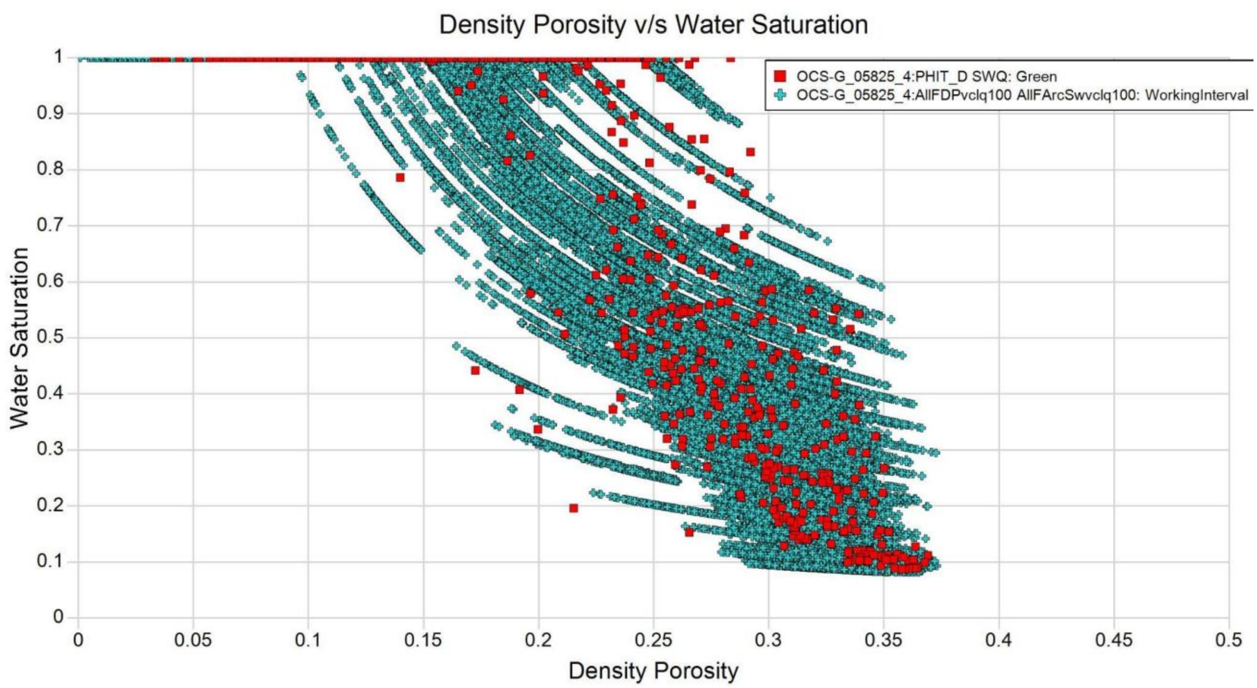


Fig 3.7.10 Density porosity vs. Water Saturation plot for 100 iterations

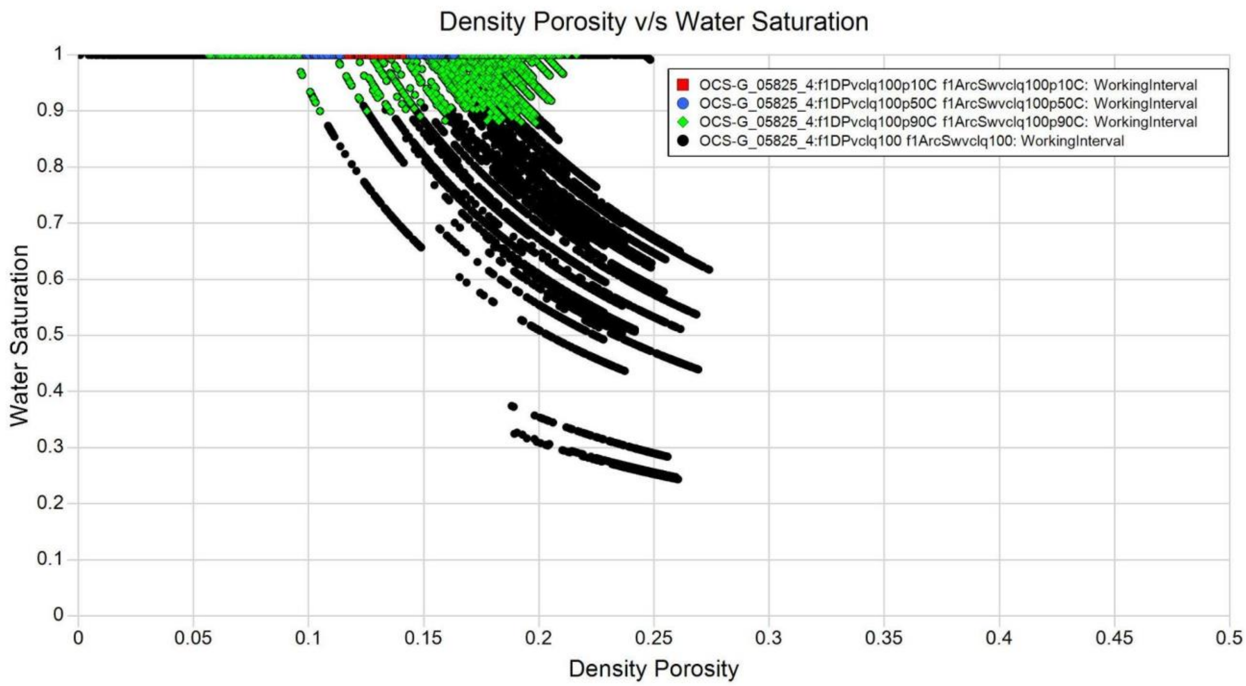


Fig 3.7.11 Density porosity vs. Water Saturation plot of 100 iterations of shale

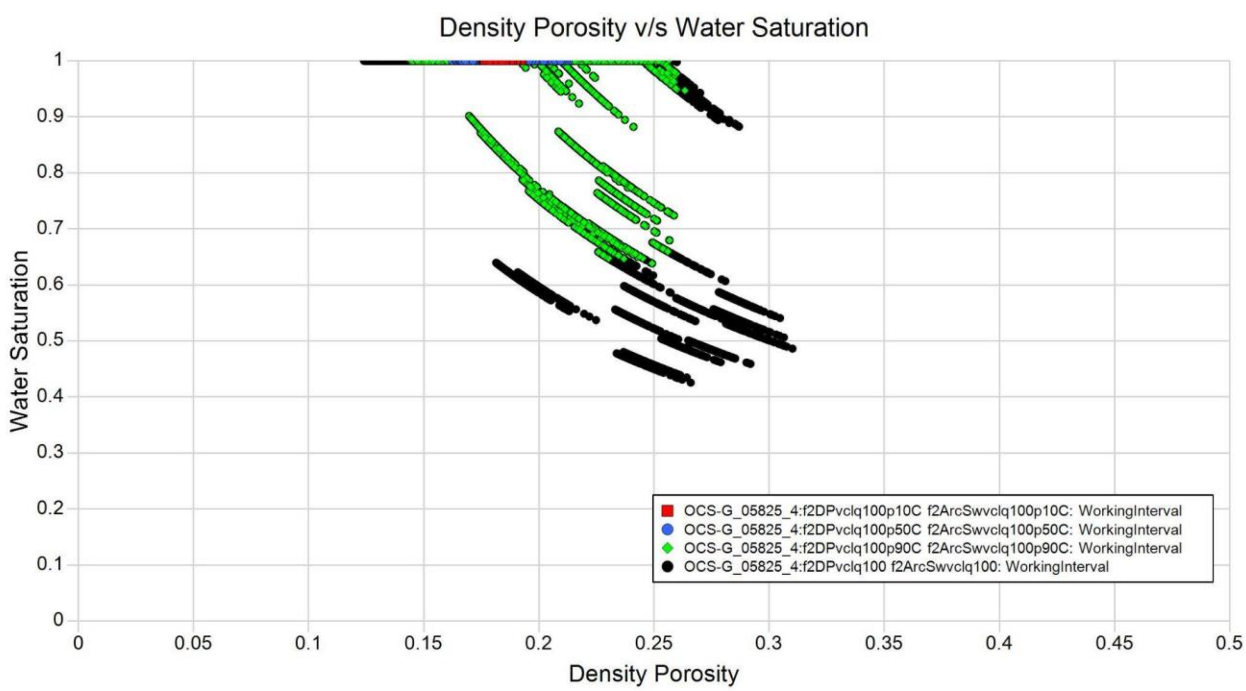


Fig 3.7.12 Density porosity vs. Water Saturation plot of 100 iterations of brine sands

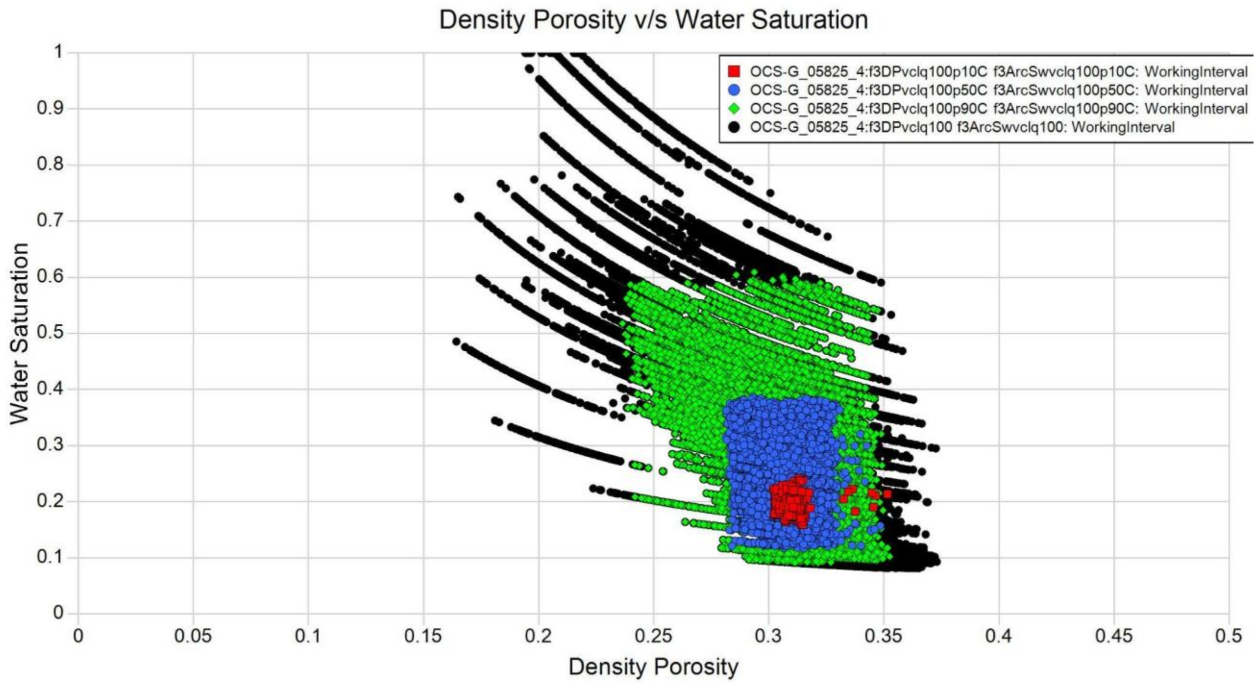


Fig 3.7.13 Density porosity vs. Water Saturation plot of 100 iterations of HC sands

Note:
In Non facies wise plots:

- Represents recorded data and Represents simulated data

In facies wise Confidence level plots:

- Represents 10% confidence of the most likely value
- Represents 50% confidence of the most likely value
- Represents 90% confidence of the most likely value
- Represents entire facies data

### 3.4 Monte Carlo Simulation of Density Porosity (PHIT_D):

**Overview**:

i) Obtain Density Porosity curve (PHIT_D) using basic log functions from PowerLog.

ii) Take VCL data (VCLQ) generated from the QuickLook Module in PowerLog as is since we are simulating for PHIT_D only.

iii) Split the PHIT_D data depth wise based on the Facies curve and fit Generalized Logistic distribution over each facies data to bootstrap samples iteratively. We use these simulated porosity values to calculate the Formation Factor.

iv) Finally, to calculate Water Saturation use Archie's equation where a, m, n and Rw are constants which are obtained from Pickett plot.

## Flowchart:

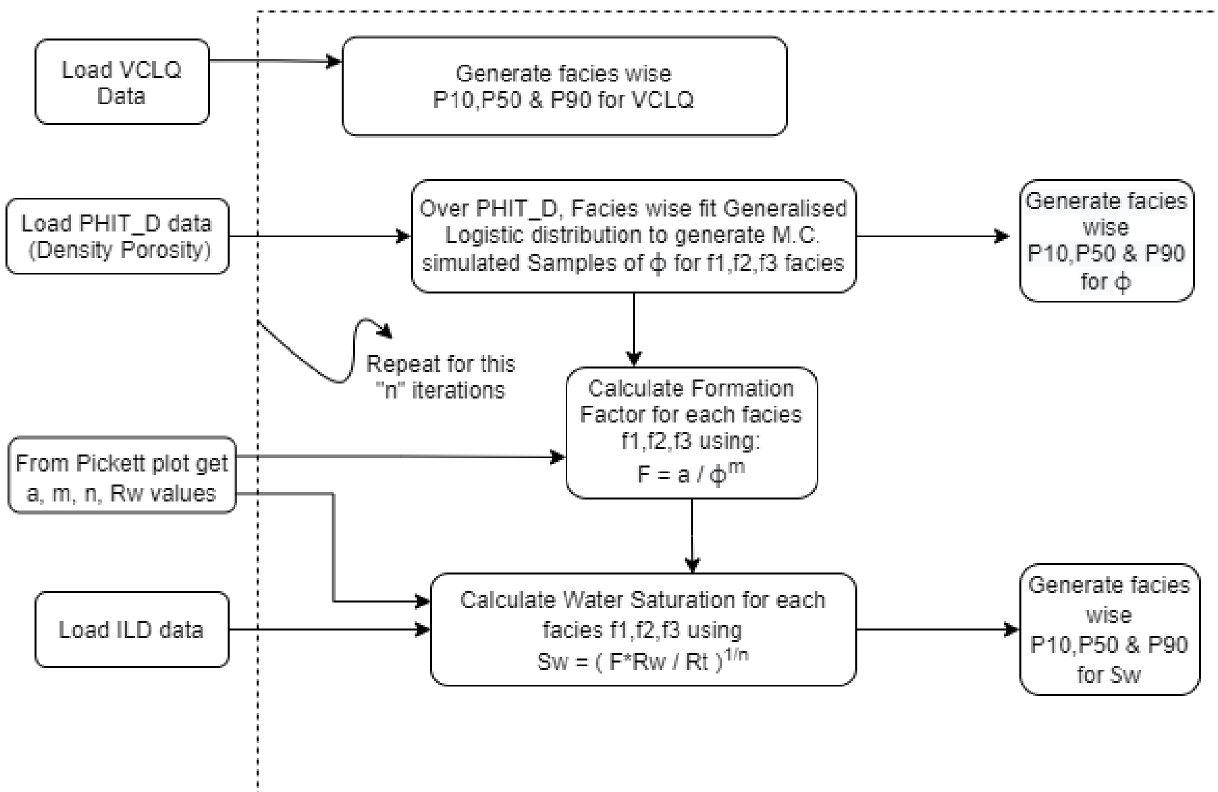


Fig 3.8 Workflow for PHIT_D M.C. Simulation

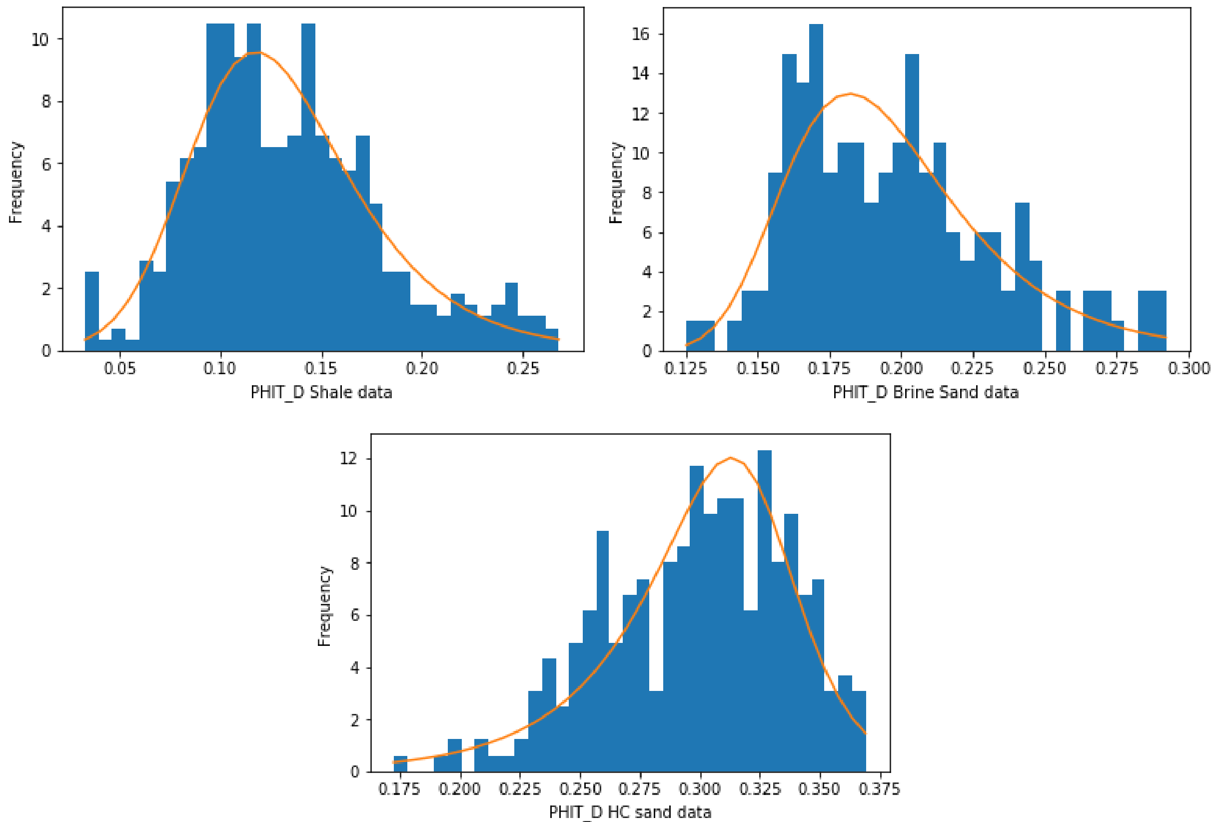


Fig 3.8.1 Facies wise Generalized Logistic Distribution fit for PHIT_D

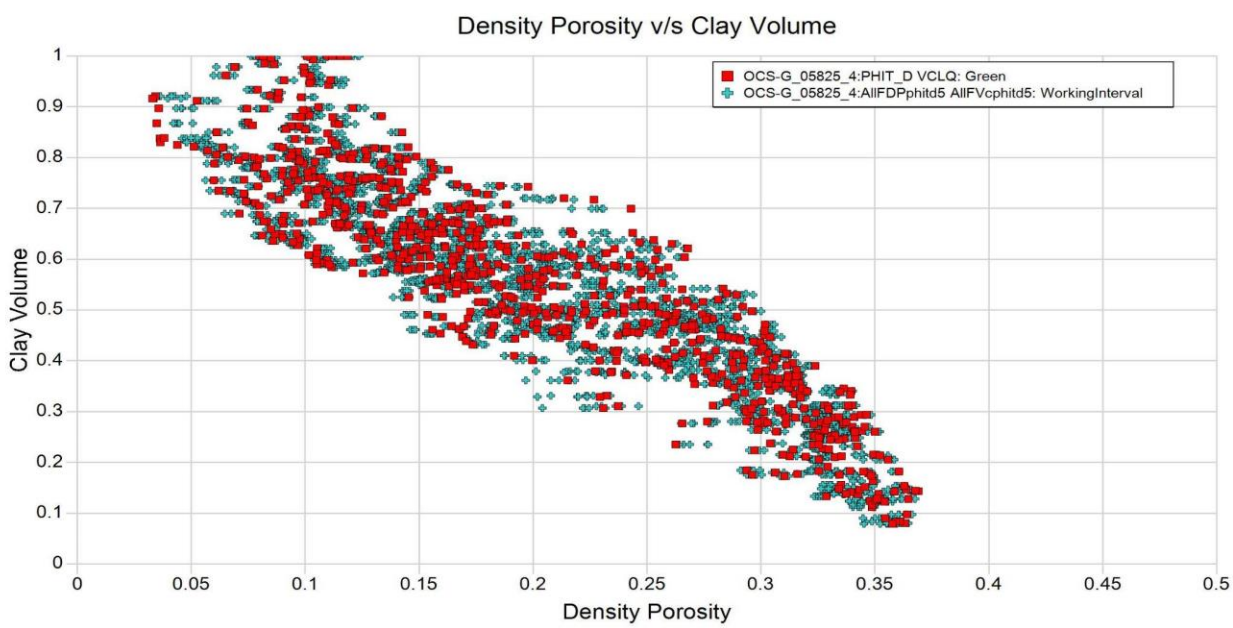


Fig 3.8.2 Density porosity vs. Clay Volume plot for 5 iterations

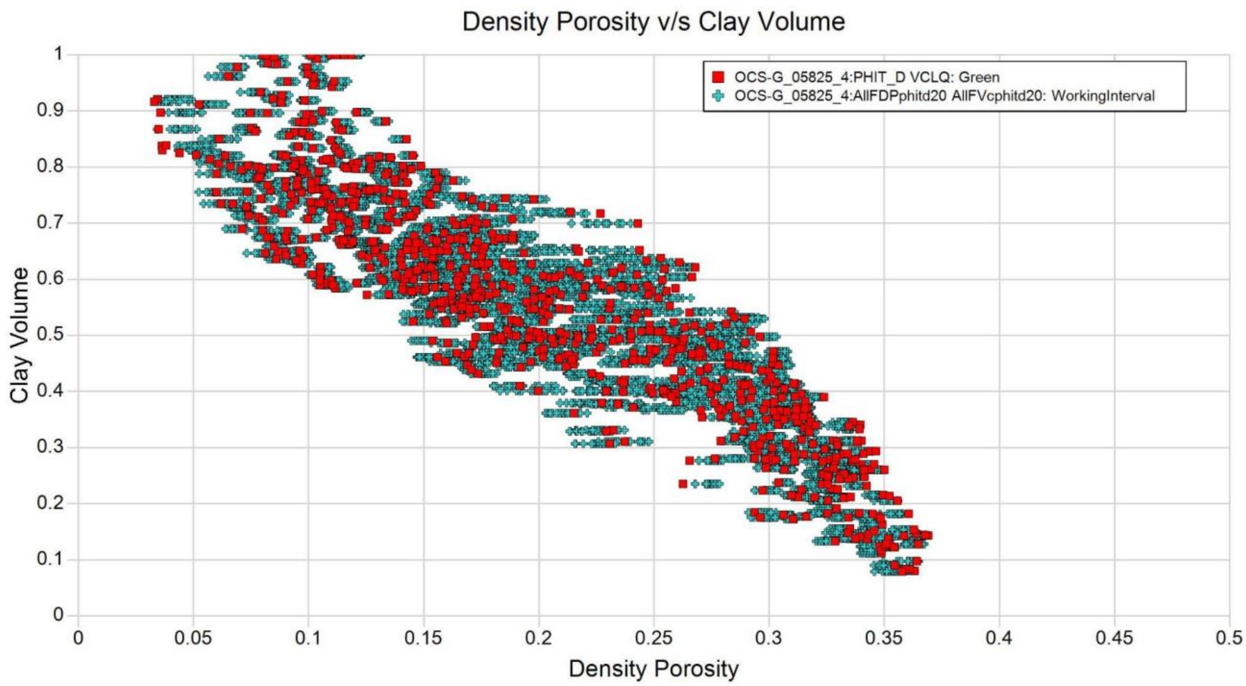


Fig 3.8.3 Density porosity vs. Clay Volume plot for 20 iterations

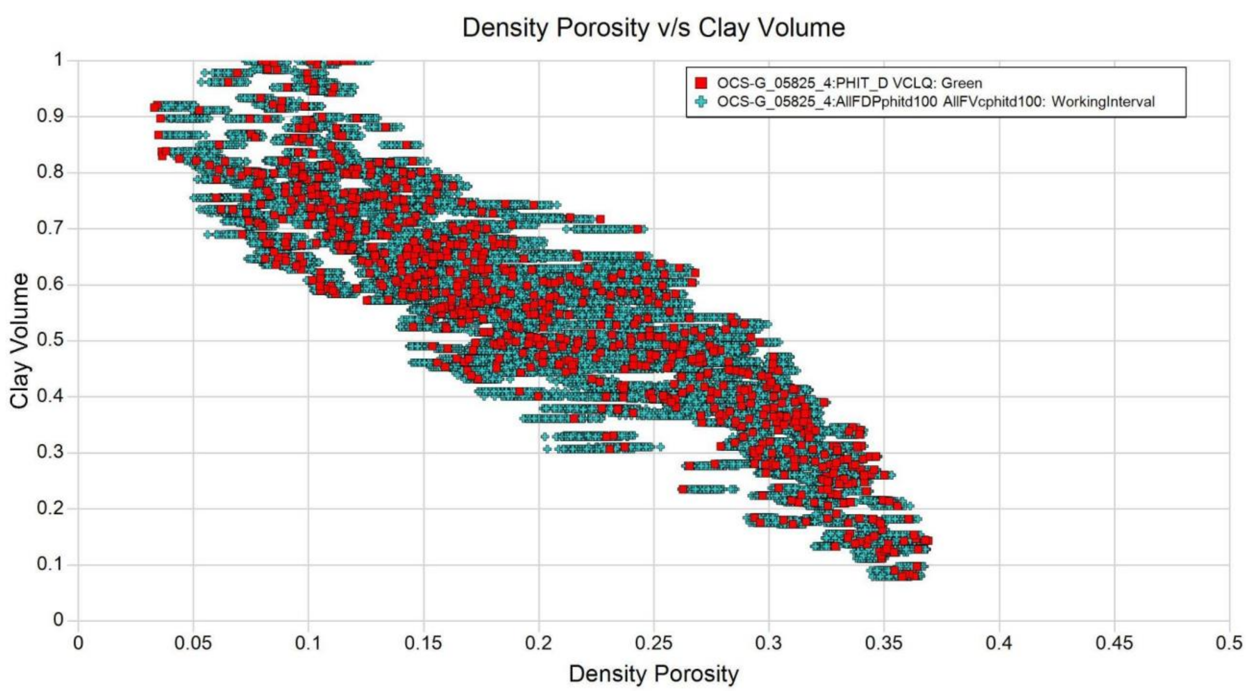


Fig 3.8.4 Density porosity vs. Clay Volume plot for 100 iterations

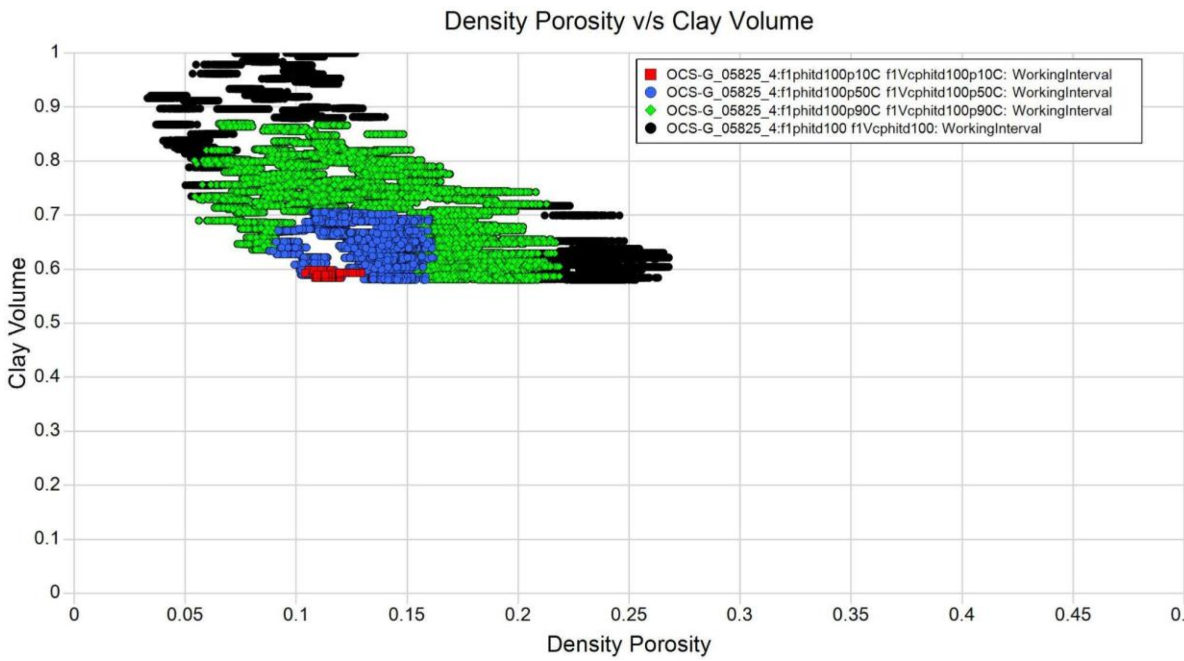


Fig 3.8.5 Density porosity vs. Clay Volume plot for 100 iterations of shale facies

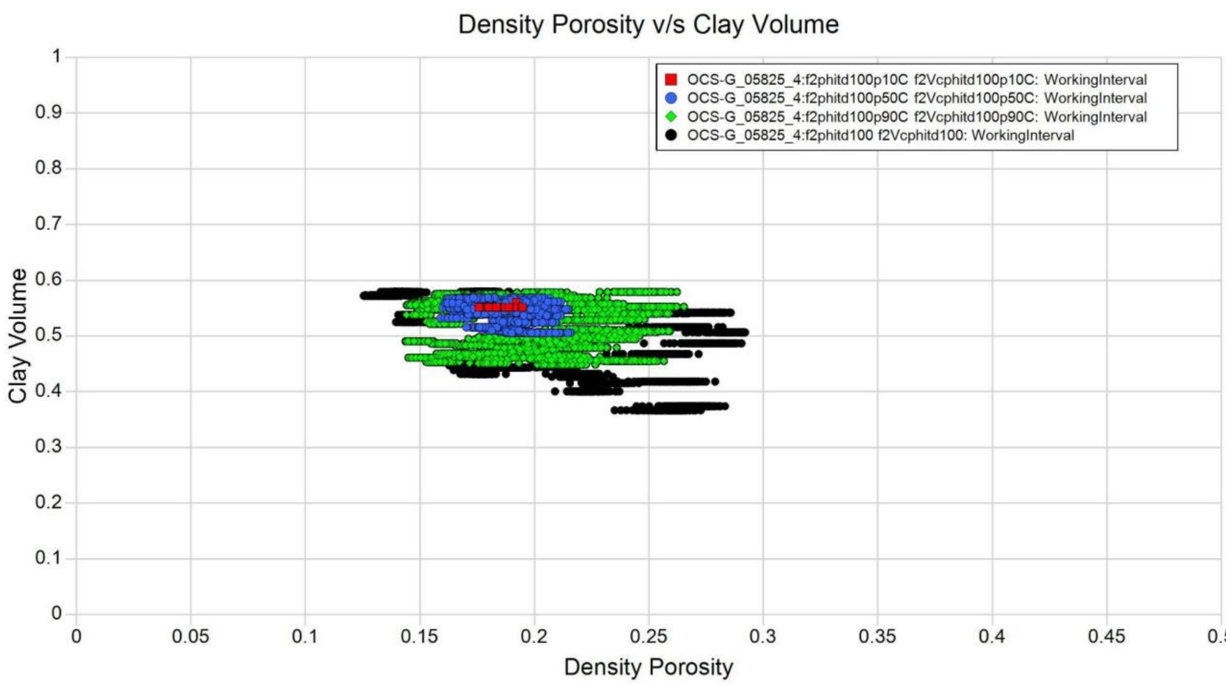


Fig 3.8.6 Density porosity vs. Clay Volume plot for 100 iterations of brine sands

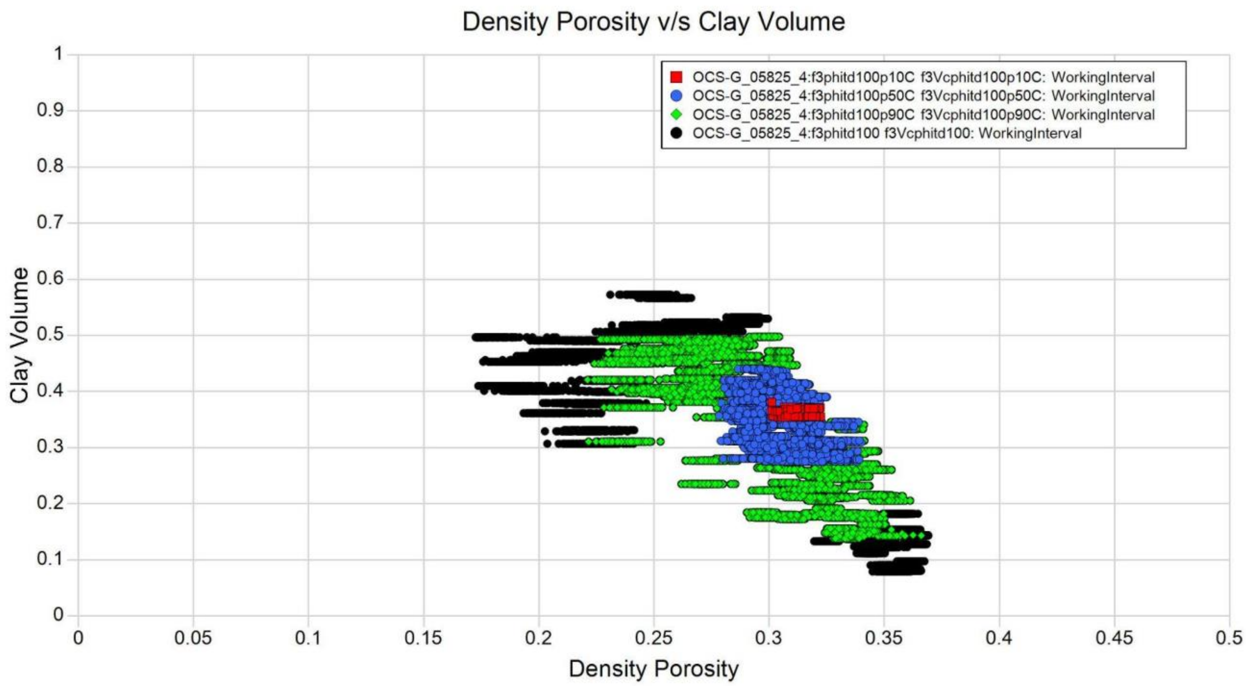


Fig 3.8.7 Density porosity vs. Clay Volume plot for 100 iterations of HC sands

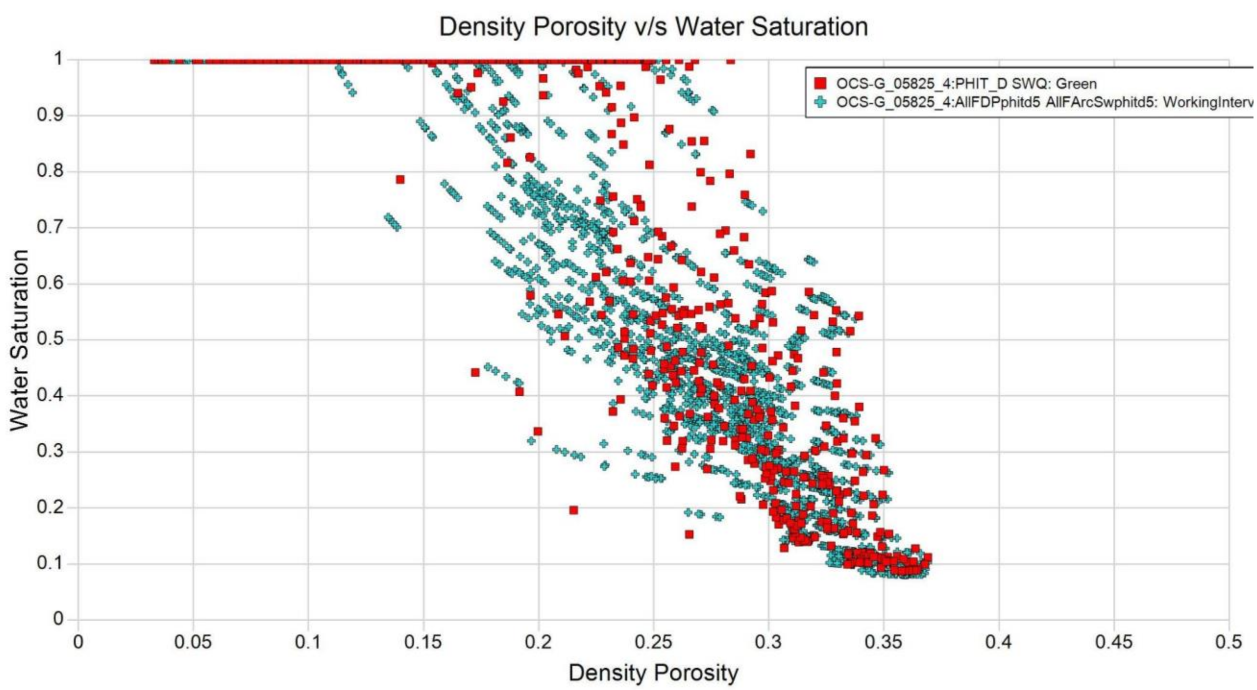


Fig 3.8.8 Density porosity vs. Water Saturation plot for 5 iterations

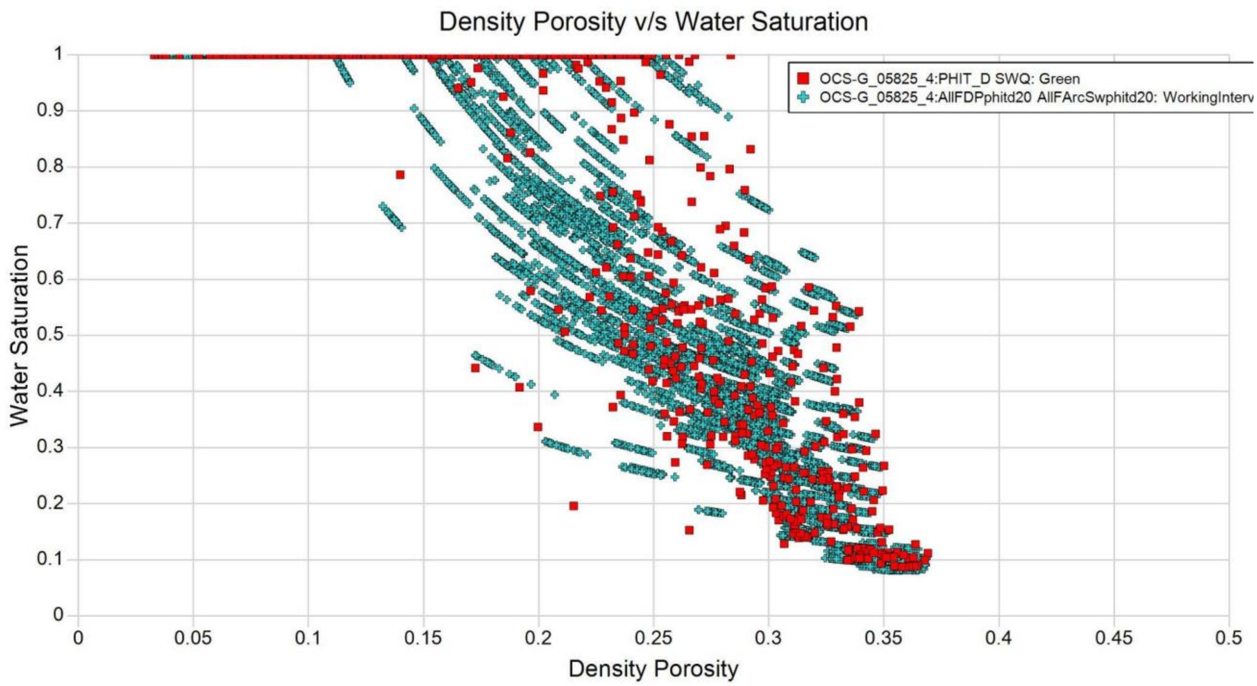


Fig 3.8.9 Density porosity vs. Water Saturation plot for 20 iterations

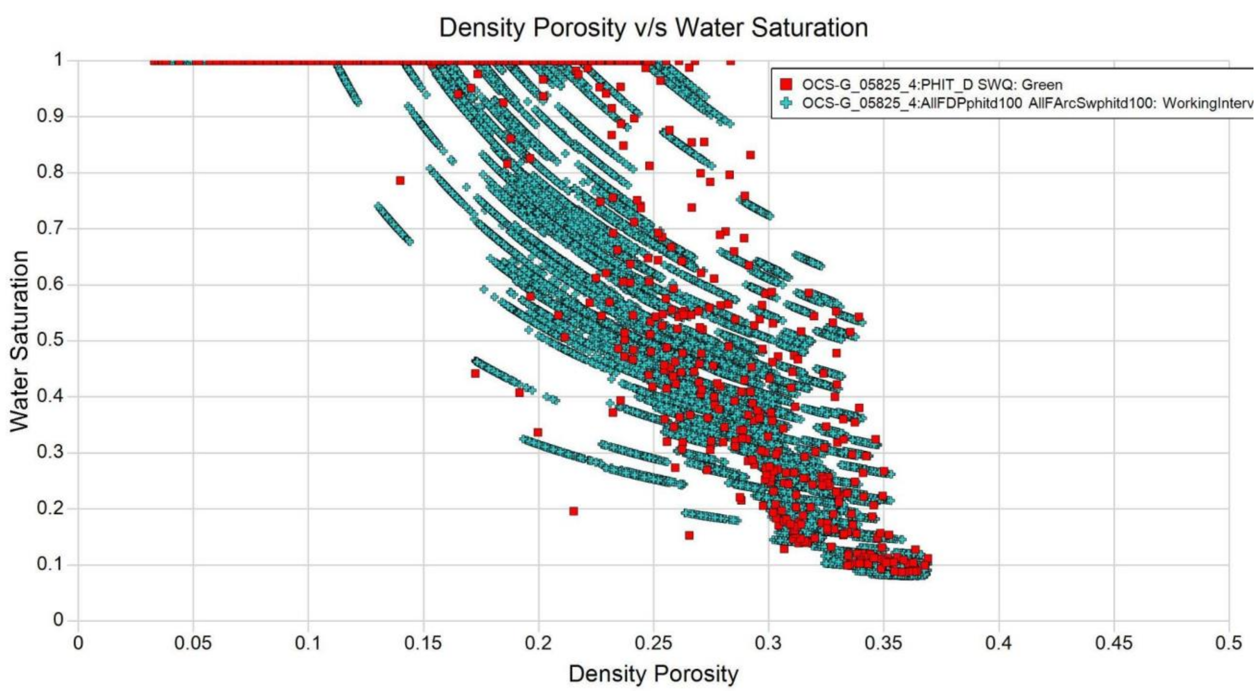


Fig 3.8.10 Density porosity vs. Water Saturation plot for 100 iterations

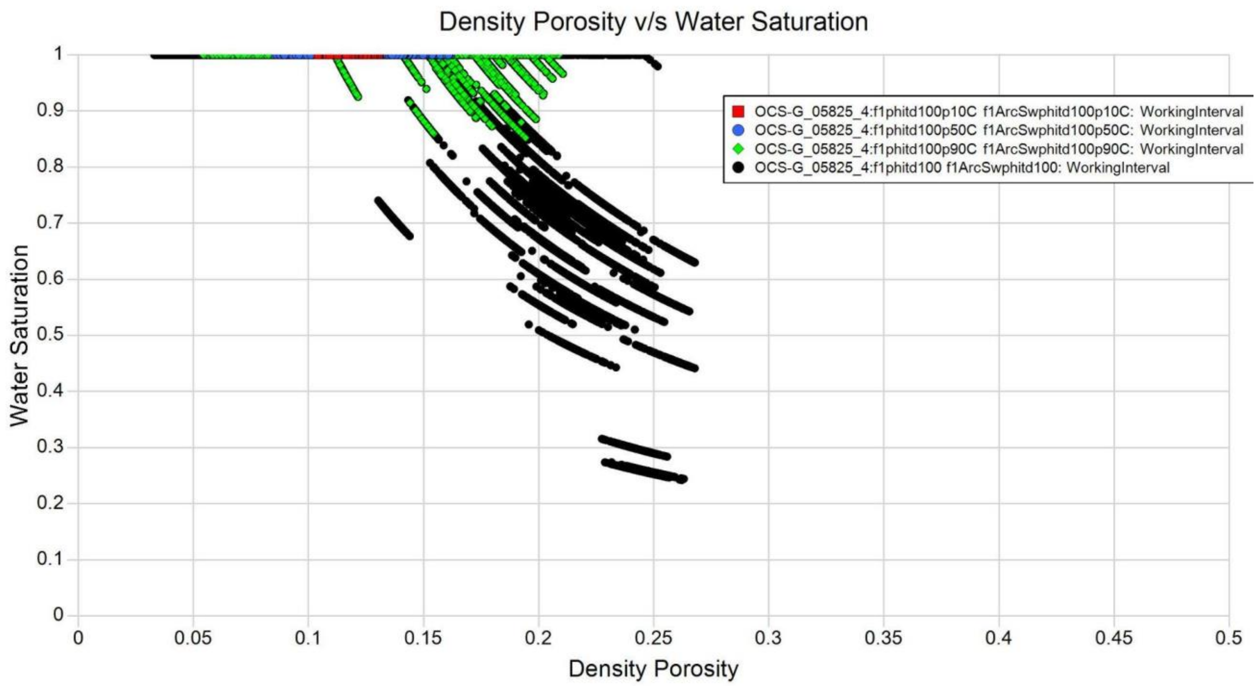


Fig 3.8.11 Density porosity vs. Water Saturation plot for 100 iterations for shale

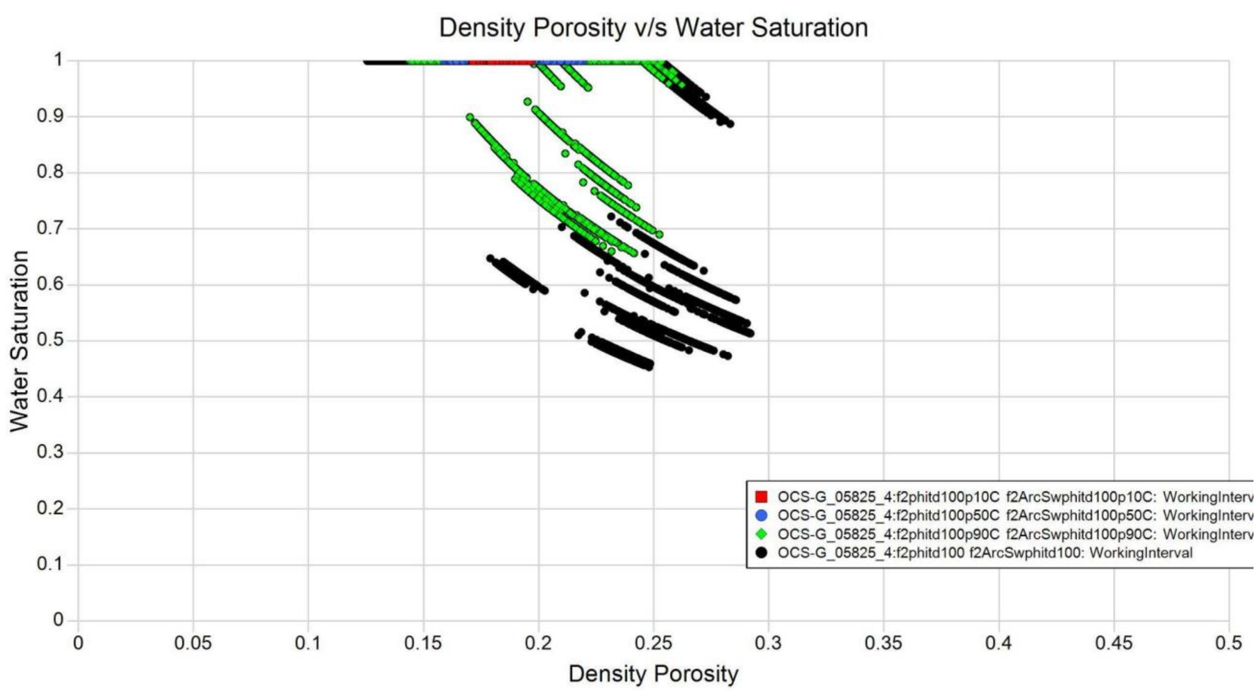


Fig 3.8.12 Density porosity vs. Water Saturation plot for 100 iterations of brine sands

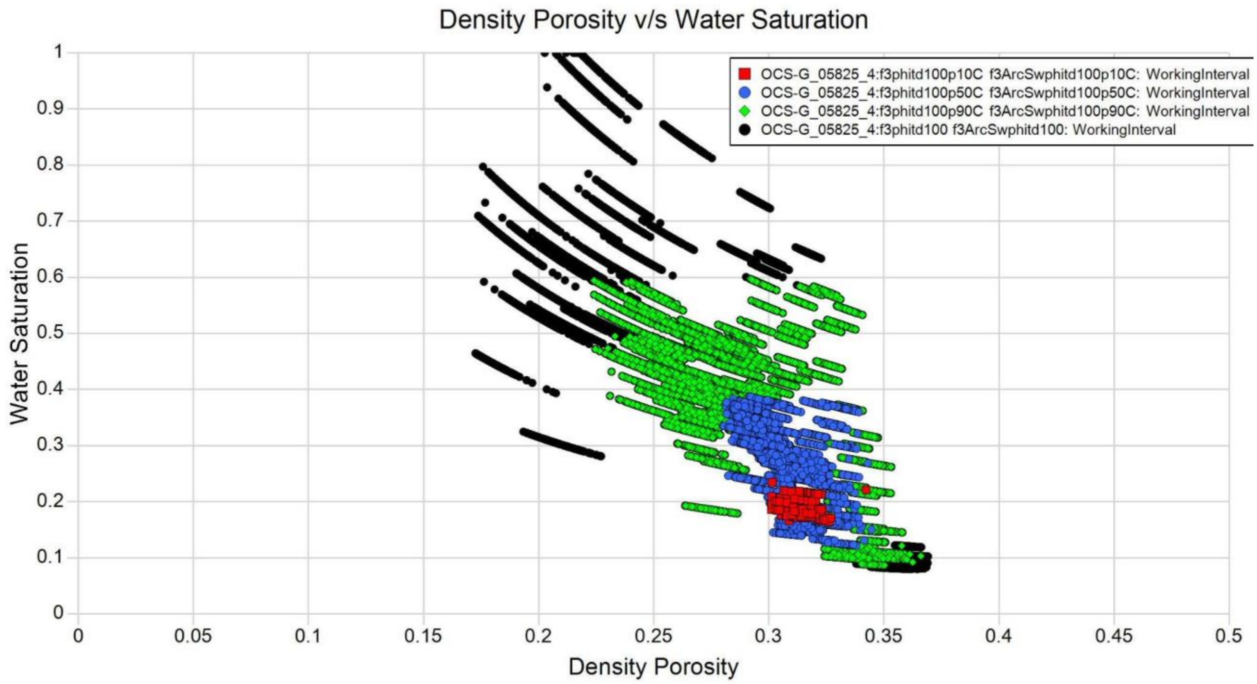


Fig 3.8.13 Density porosity vs. Water Saturation plot for 100 iterations of HC sands

Note:

In Non facies wise plots:

- Represents recorded data and Represents simulated data

In facies wise Confidence level plots:

- Represents 10% confidence of the most likely value
- Represents 50% confidence of the most likely value
- Represents 90% confidence of the most likely value
- Represents entire facies data

## 3.5 Monte Carlo Simulation of Clay Volume

**Overview**:

i) Compute VCL from Gamma ray log data by varying input parameter GRshale (GRSH) by performing iterative M.C. simulations and use this simulated VCL to compute ρmatrix.

ii) This ρmatrix is also "simulated" since the M.C. simulated VCL is one of the input parameters to the ρmatrix equation. We use this ρmatrix to compute Porosity.

iii) To compute Sw, keep Formation Water Resistivity (Rw), Tortuosity (a), Cementation exponent (m) and Saturation exponent (n) as is.

iv) It is done so because a, m, n & Rw are constants which are obtained from Pickett plot and the Formation factor values are determined by using VCL varied Porosity that we have just simulated.

iv) Finally, compute Sw using a, m, n, F & Rw (for n iterations) in Archie's Equation.

## Flowchart:

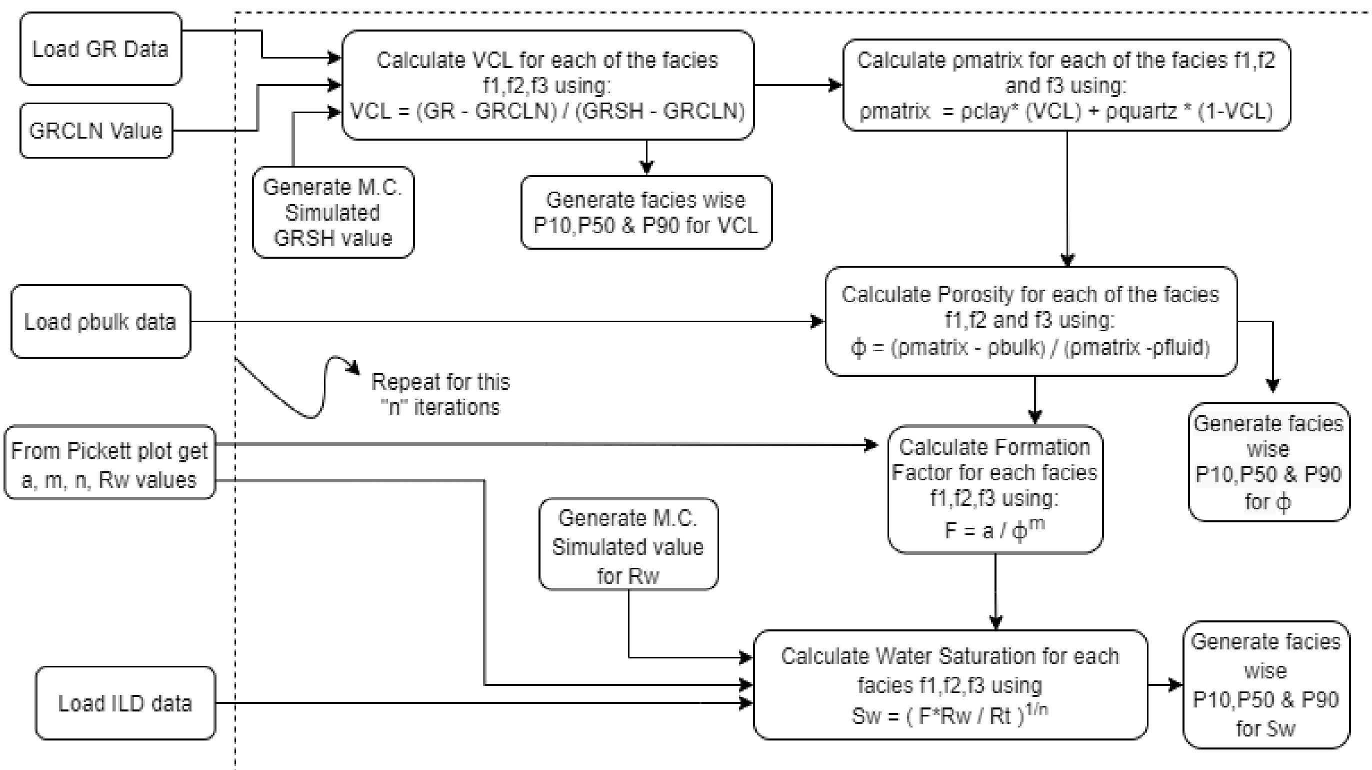


Fig 3.9 Workflow for Clay Volume M.C. Simulation

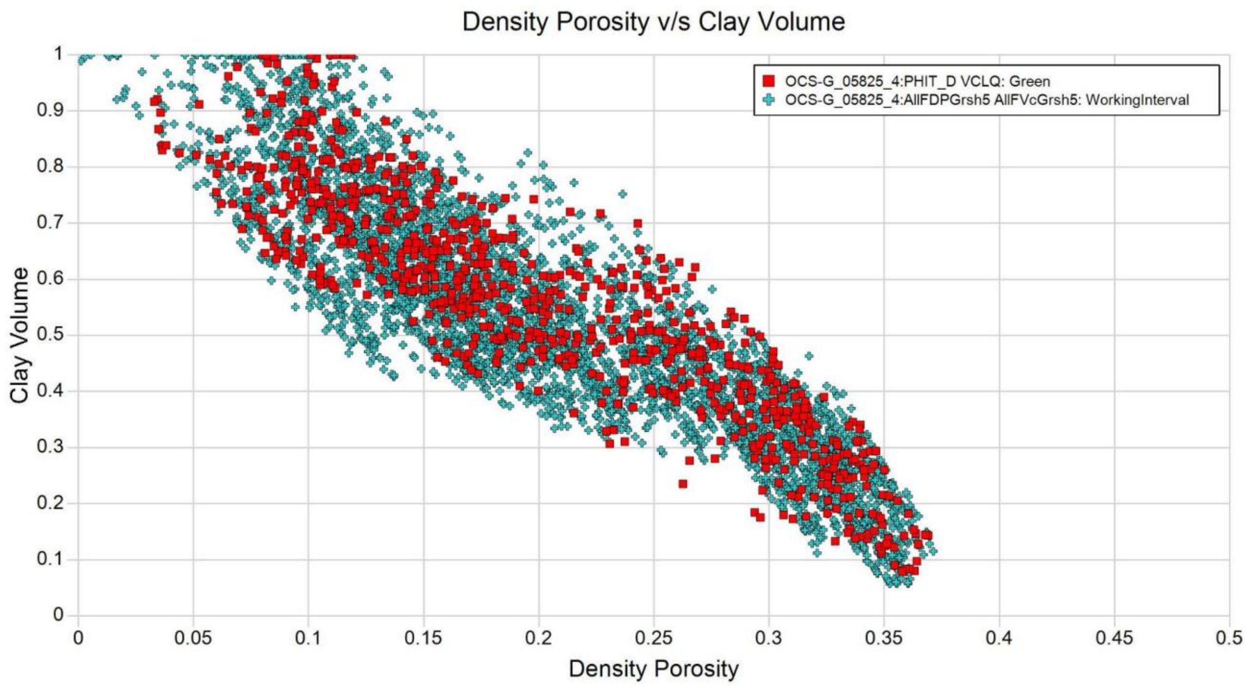


Fig 3.9.1 Density porosity vs. Clay Volume plot for 5 iterations

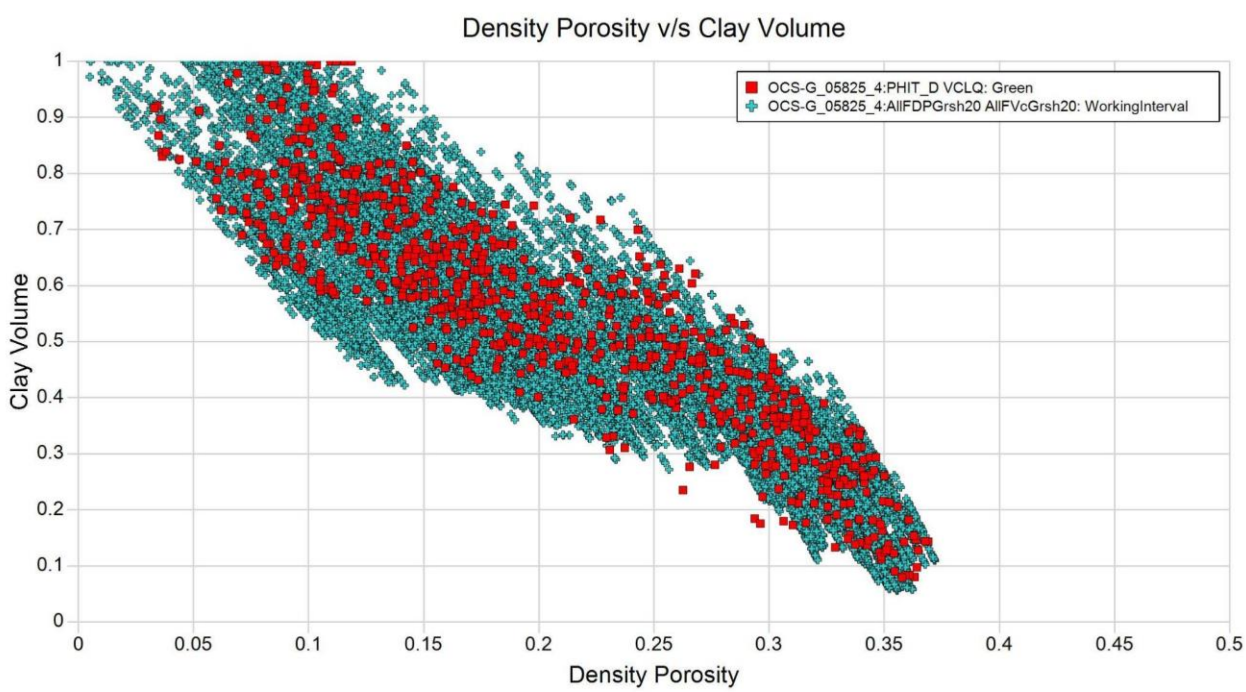


Fig 3.9.2 Density porosity vs. Clay Volume plot for 20 iterations

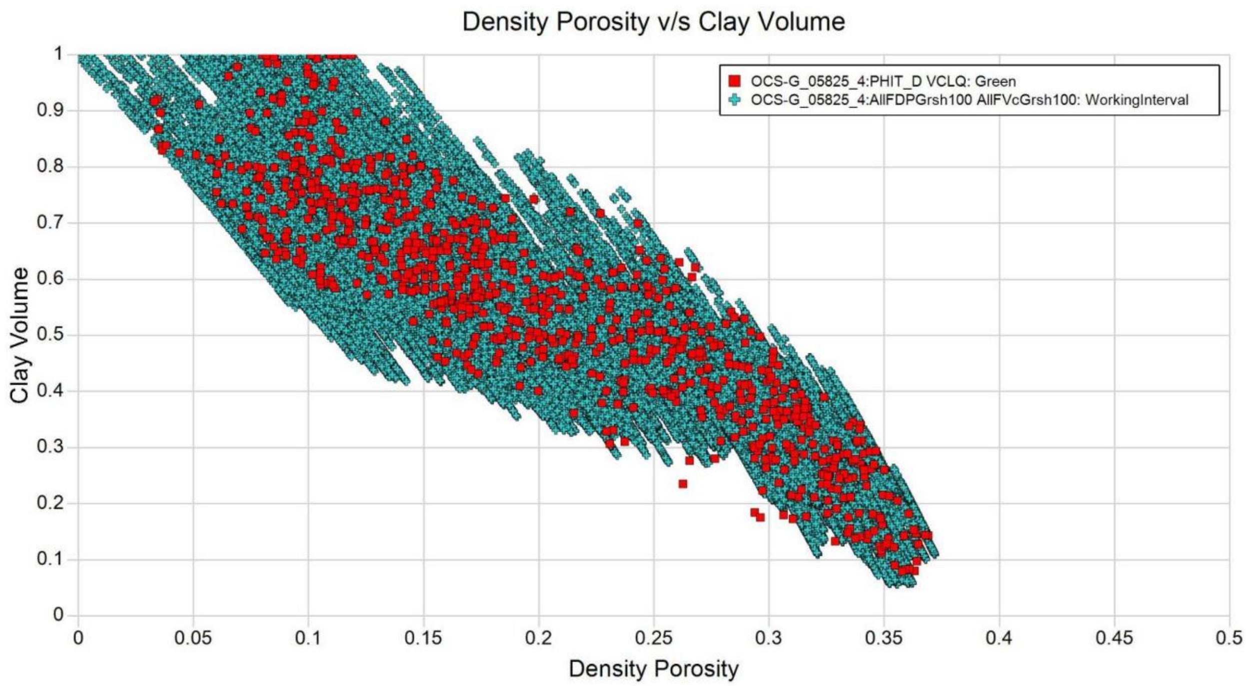


Fig 3.9.3 Density porosity vs. Clay Volume plot for 100 iterations

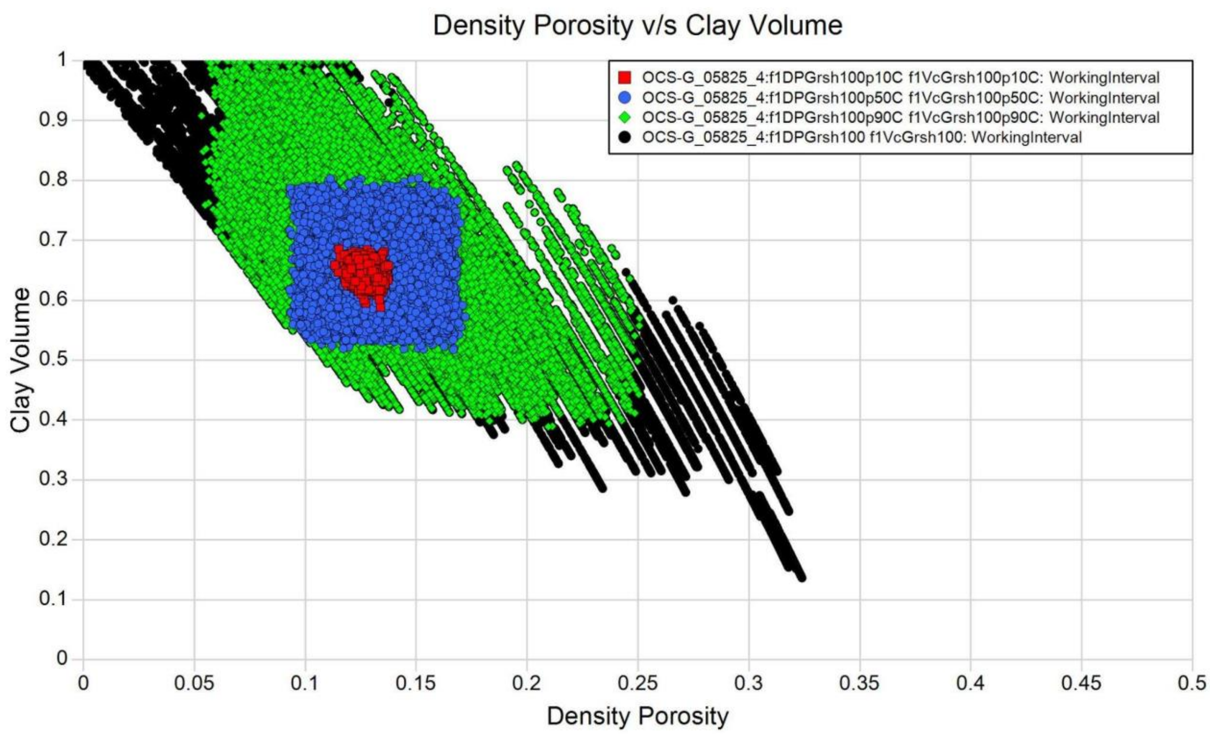


Fig 3.9.4 Density porosity vs. Clay Volume plot for 100 iterations of shale facies

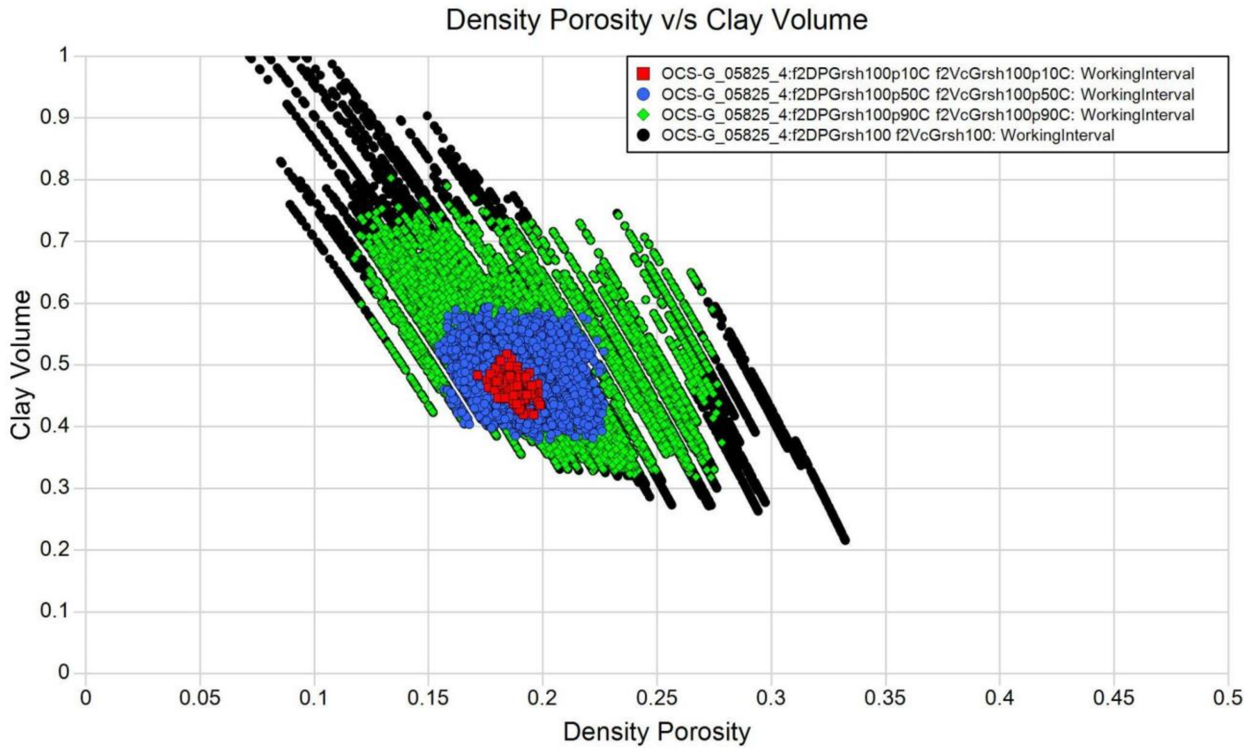


Fig 3.9.5 Density porosity vs. Clay Volume plot for 100 iterations of brine sands

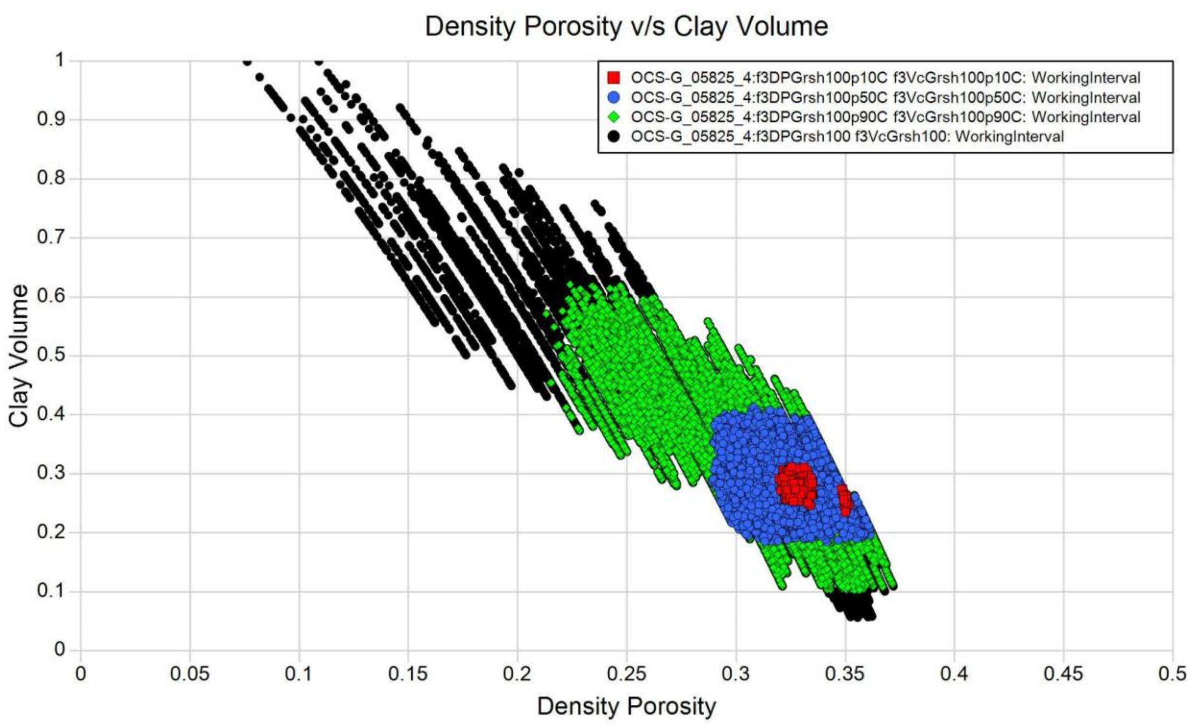


Fig 3.9.6 Density porosity vs. Clay Volume plot for 100 iterations of HC sands

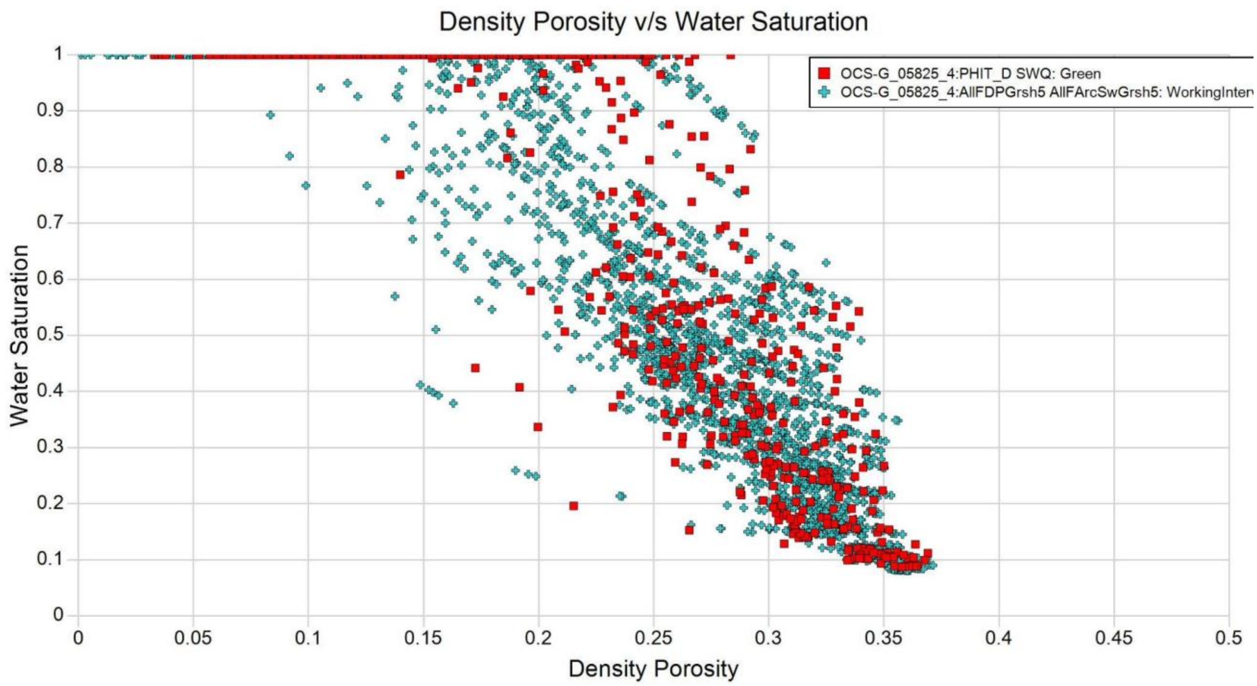


Fig 3.9.7 Density porosity vs. Water Saturation plot for 5 iterations

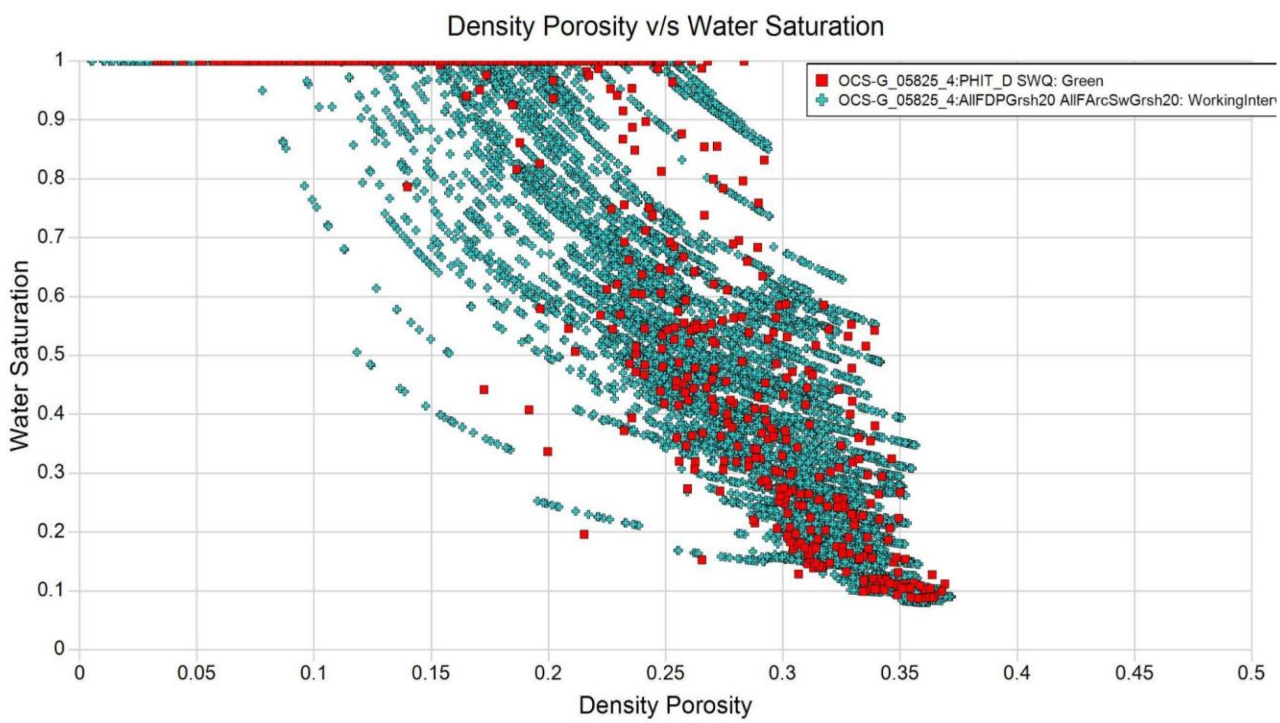


Fig 3.9.8 Density porosity vs. Water Saturation plot for 20 iterations

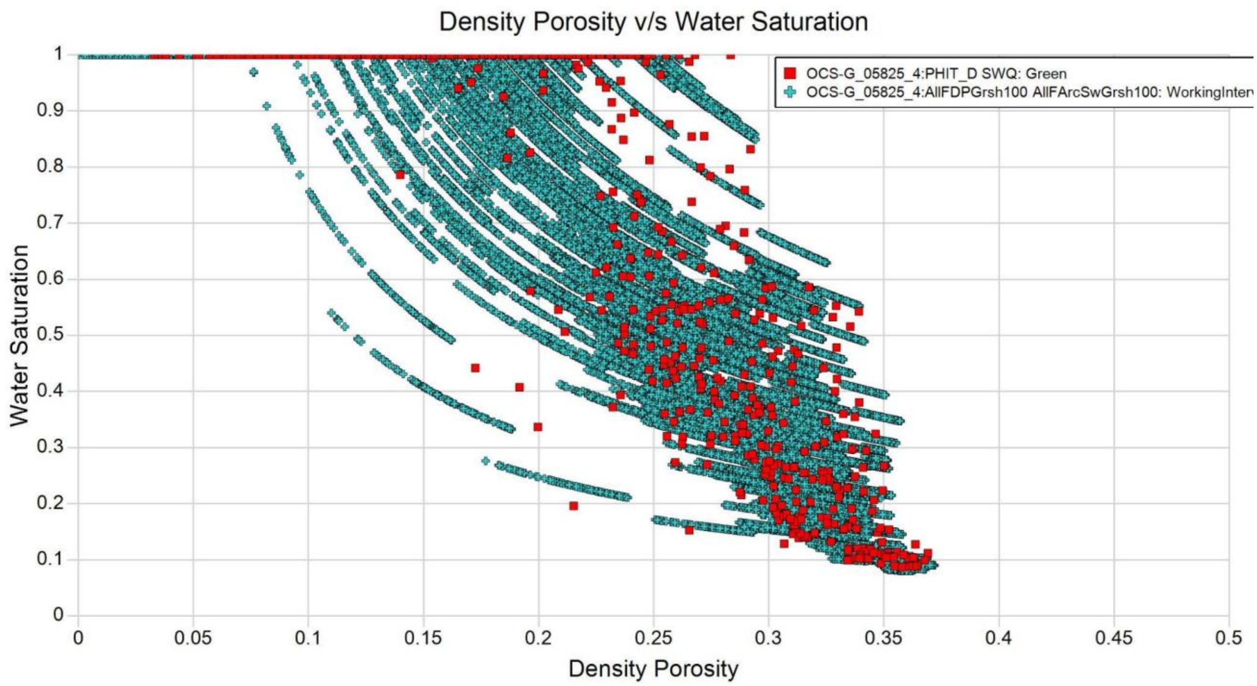


Fig 3.9.9 Density porosity vs. Water Saturation plot for 100 iterations

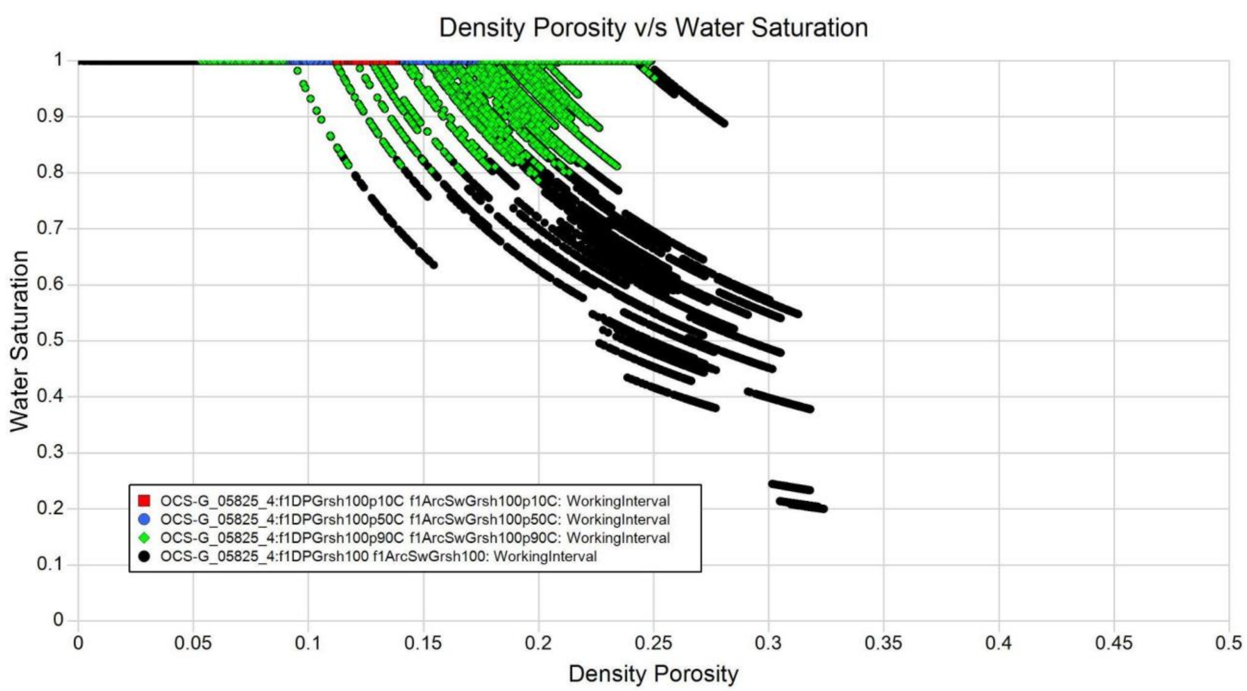


Fig 3.9.10 Density porosity vs. Water Saturation plot of 100 iterations of shale

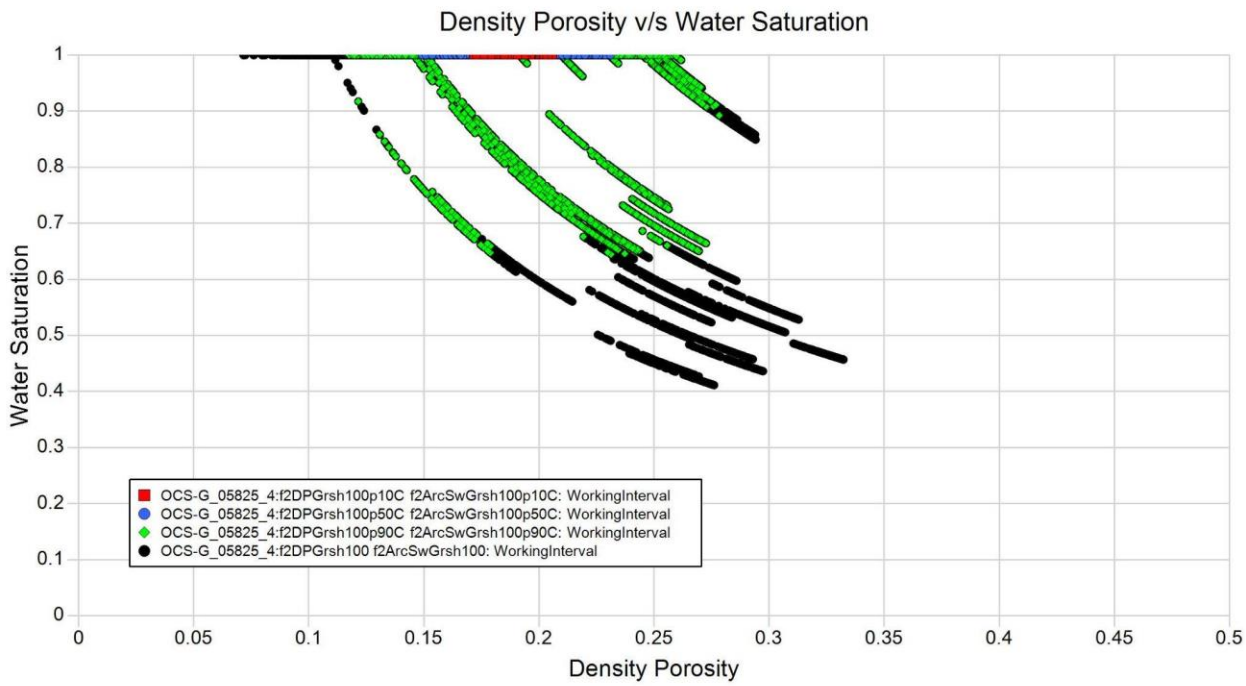


Fig 3.9.11 Density porosity vs. Water Saturation plot of 100 iterations of brine sands

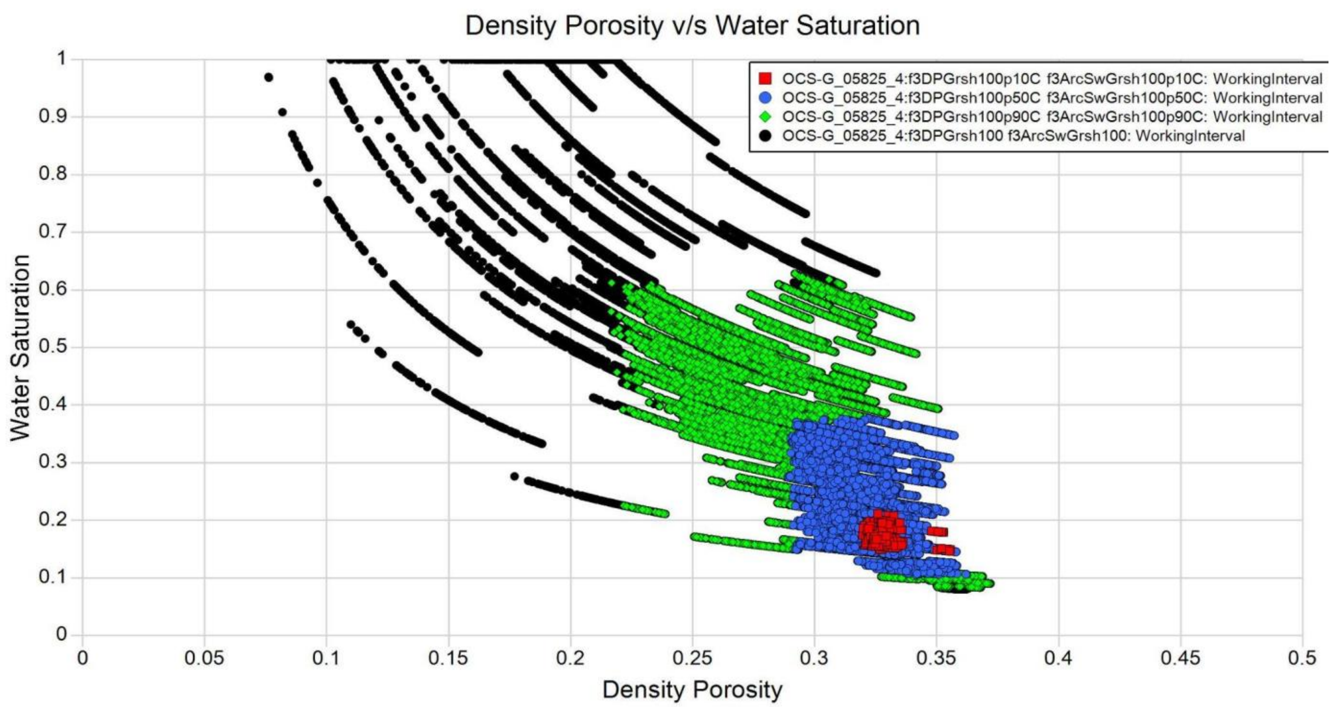


Fig 3.9.12 Density porosity vs. Water Saturation plot of 100 iterations of HC sands

Note:

In Non facies wise plots:

- Represents recorded data and Represents simulated data

In facies wise Confidence level plots:

- Represents 10% confidence of the most likely value
- Represents 50% confidence of the most likely value
- Represents 90% confidence of the most likely value
- Represents entire facies data

### 3.6 Monte Carlo Simulation of Density Porosity

**Overview**:

i) Obtain VCL from Gamma ray log data and use this VCL to compute the ρmatrix.

ii) Here, aim is to vary the input parameter ρclay in order to perform M.C. simulation for ρmatrix which yields M.C. simulated Porosity.

iii) Therefore, we can obtain water saturation (Sw) values, while keeping Tortuosity (a), Cementation exponent (m), Saturation exponent (n) and Formation Water Resistivity (Rw) as is and we take True Resistivity (Rt) values from ILD log data.

iv) It is done so because a, m, n, Rw are constants which are obtained from the Pickett plot and the Formation factor values are determined by using Porosity that we have just simulated.

v) Finally, compute Sw using a, m, n, F and Rw (for n iterations) in Archie's Equation.

## **Flowchart**:

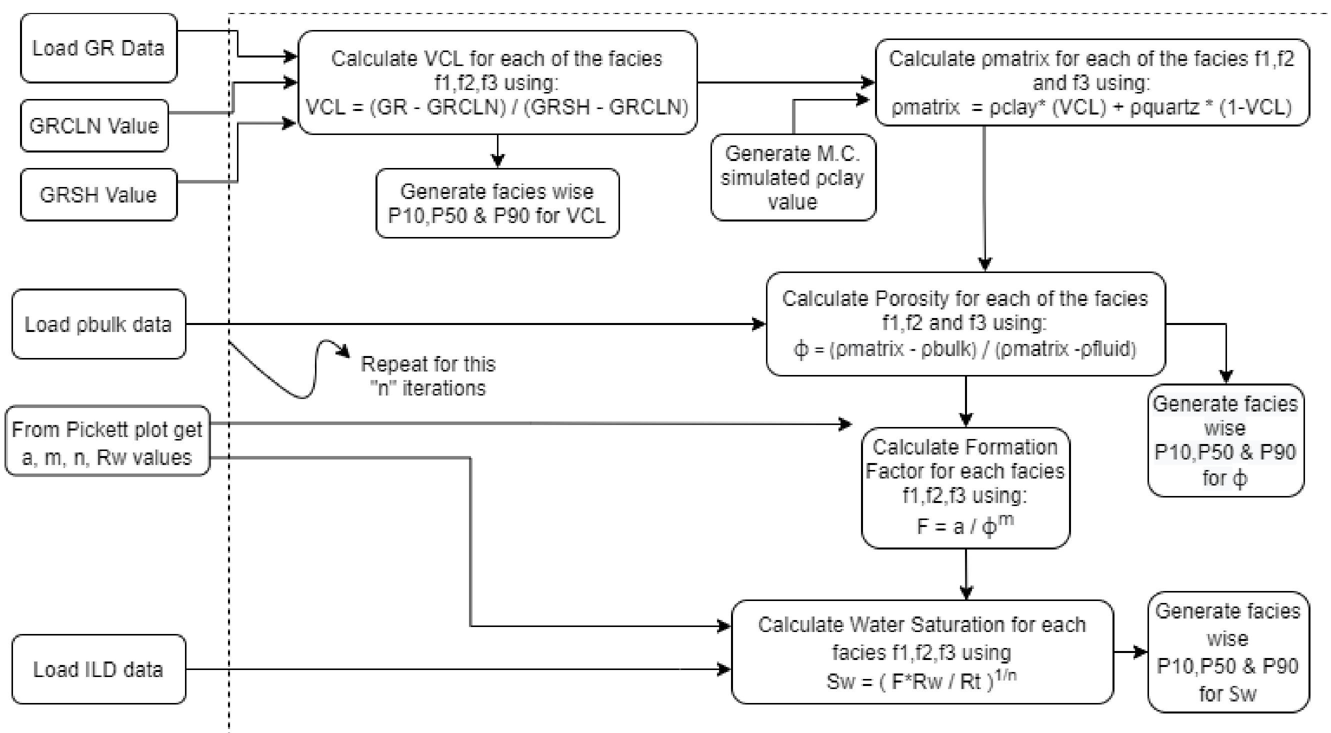


Fig 3.10 Workflow for Density Porosity M.C. Simulation

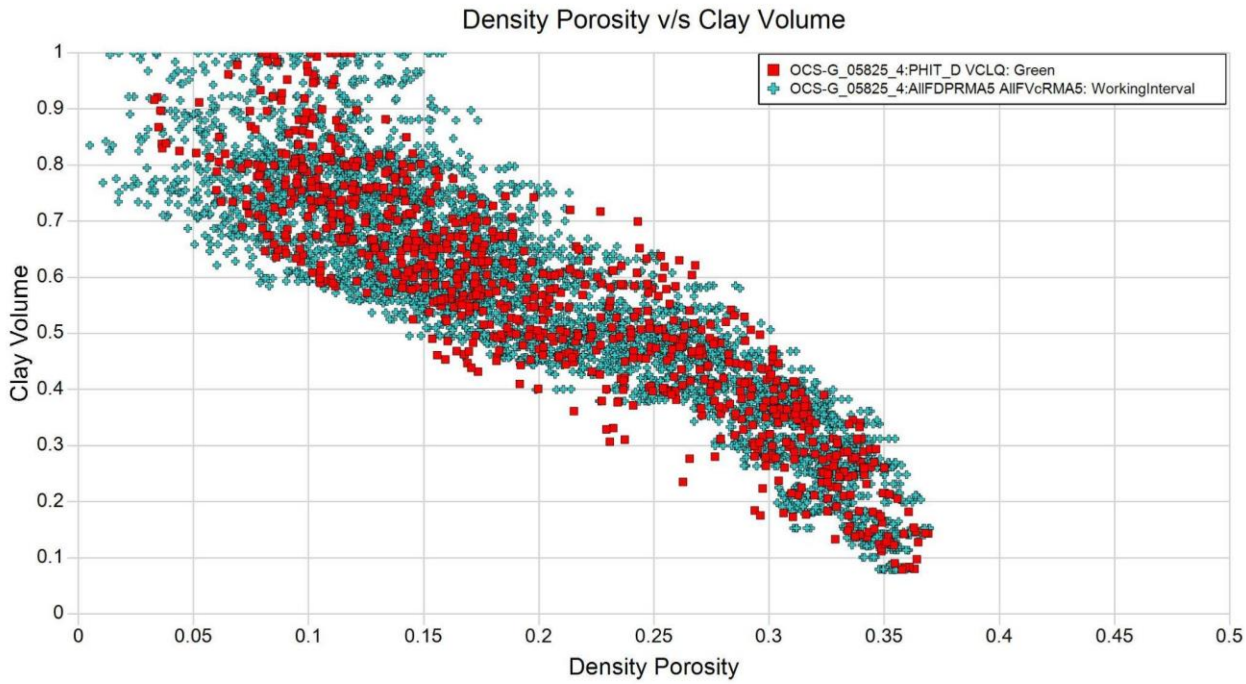


Fig 3.10.1 Density porosity vs. Clay Volume plot for 5 iterations

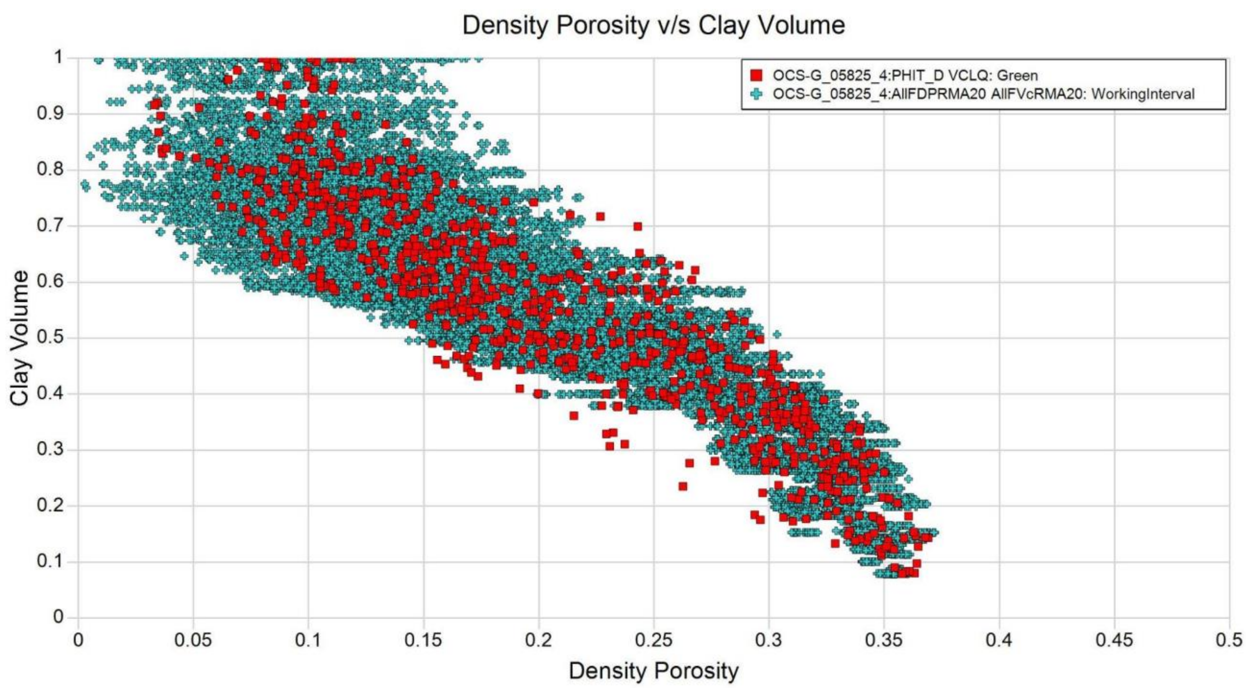


Fig 3.10.2 Density porosity vs. Clay Volume plot for 20 iterations

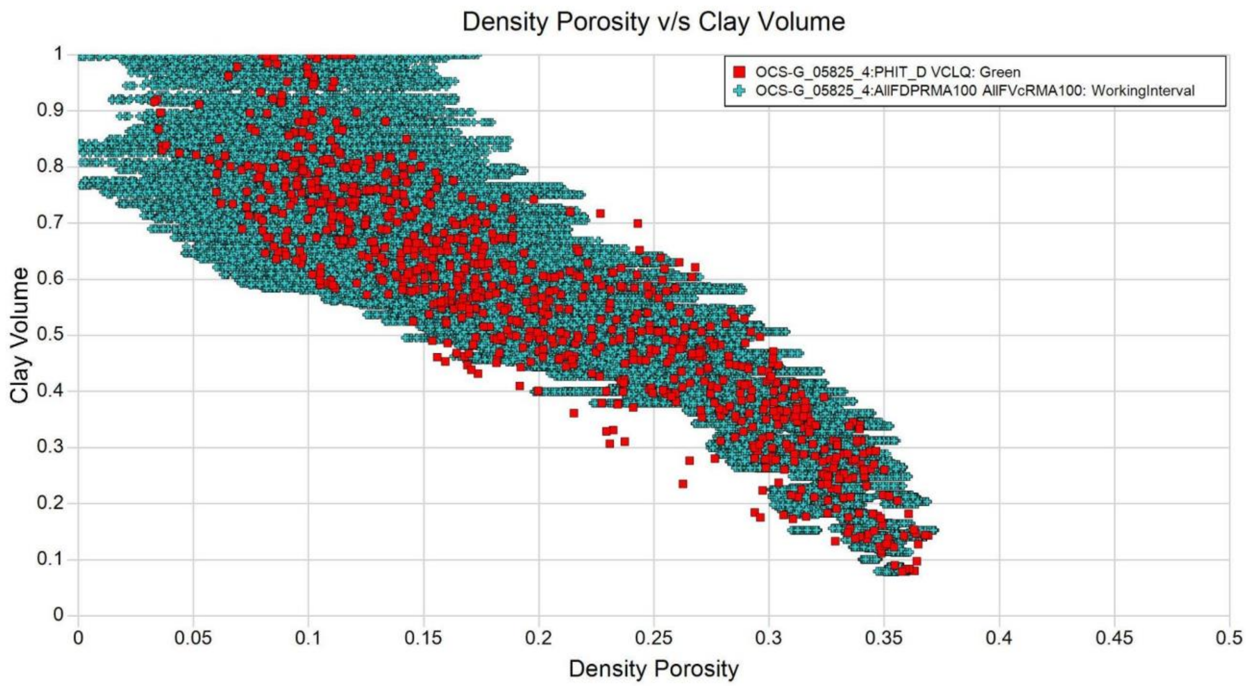


Fig 3.10.3 Density porosity vs. Clay Volume plot for 100 iterations

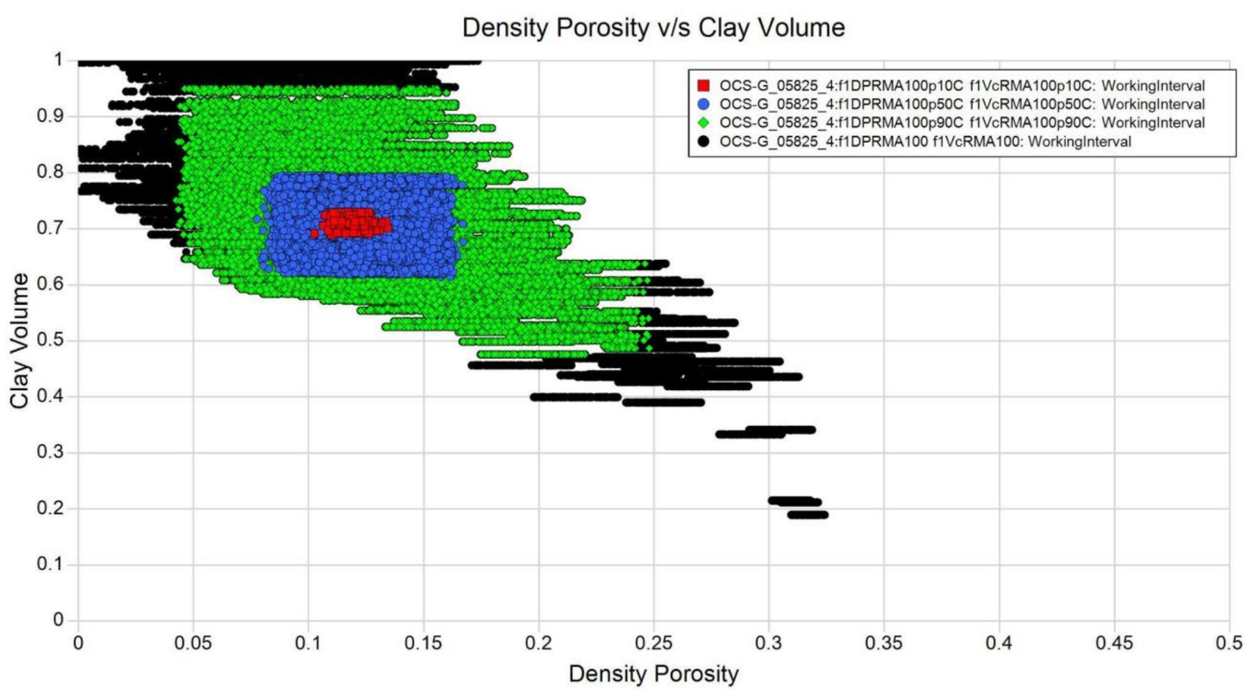


Fig 3.10.4 Density porosity vs. Clay Volume plot for 100 iterations of shale facies

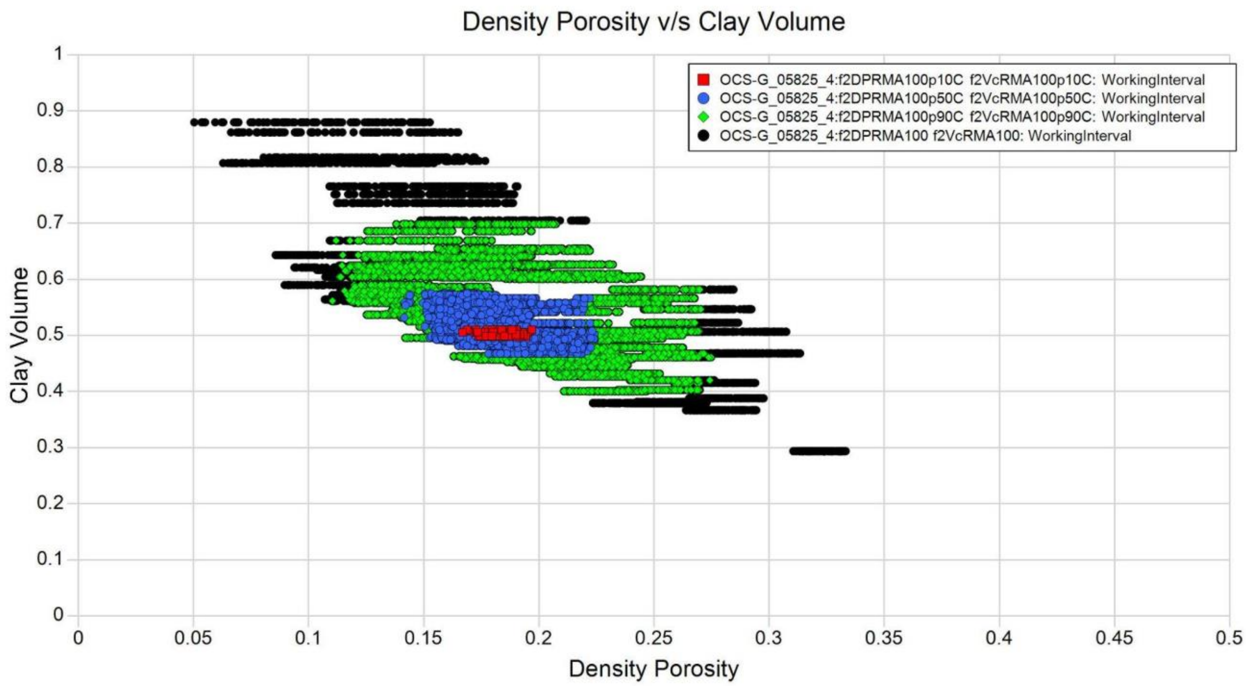


Fig 3.10.5 Density porosity vs. Clay Volume plot for 100 iterations of brine sands

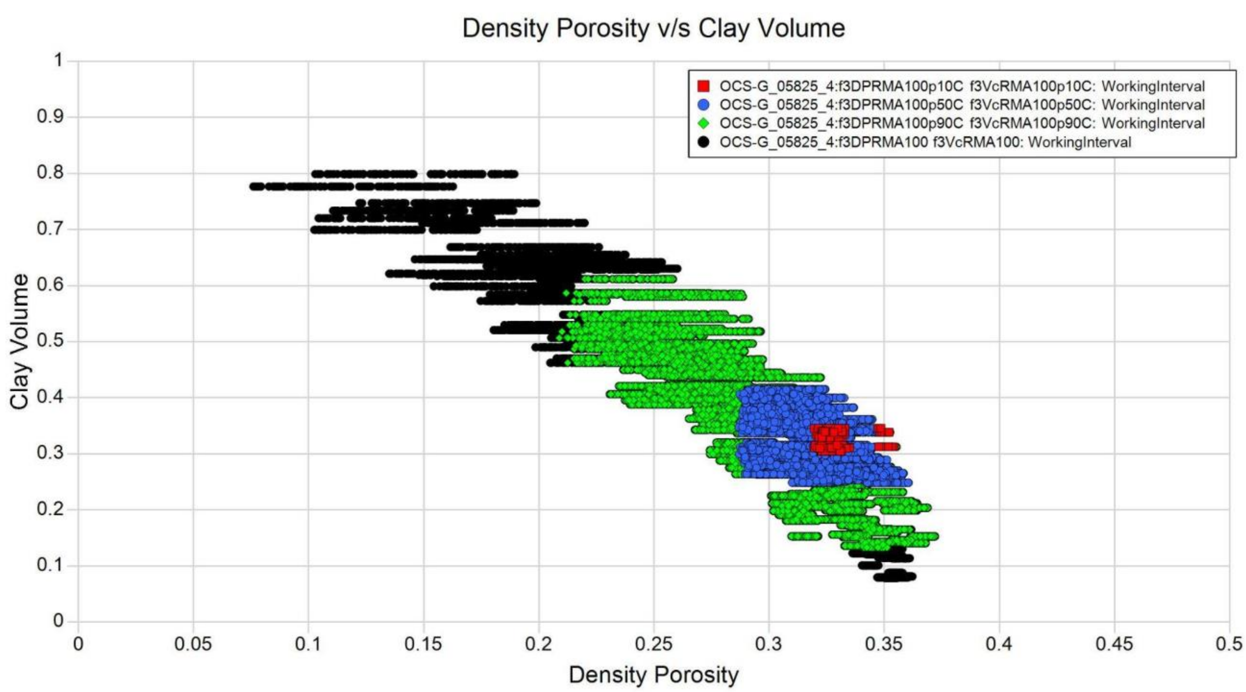


Fig 3.10.6 Density porosity vs. Clay Volume plot for 100 iterations of HC sands

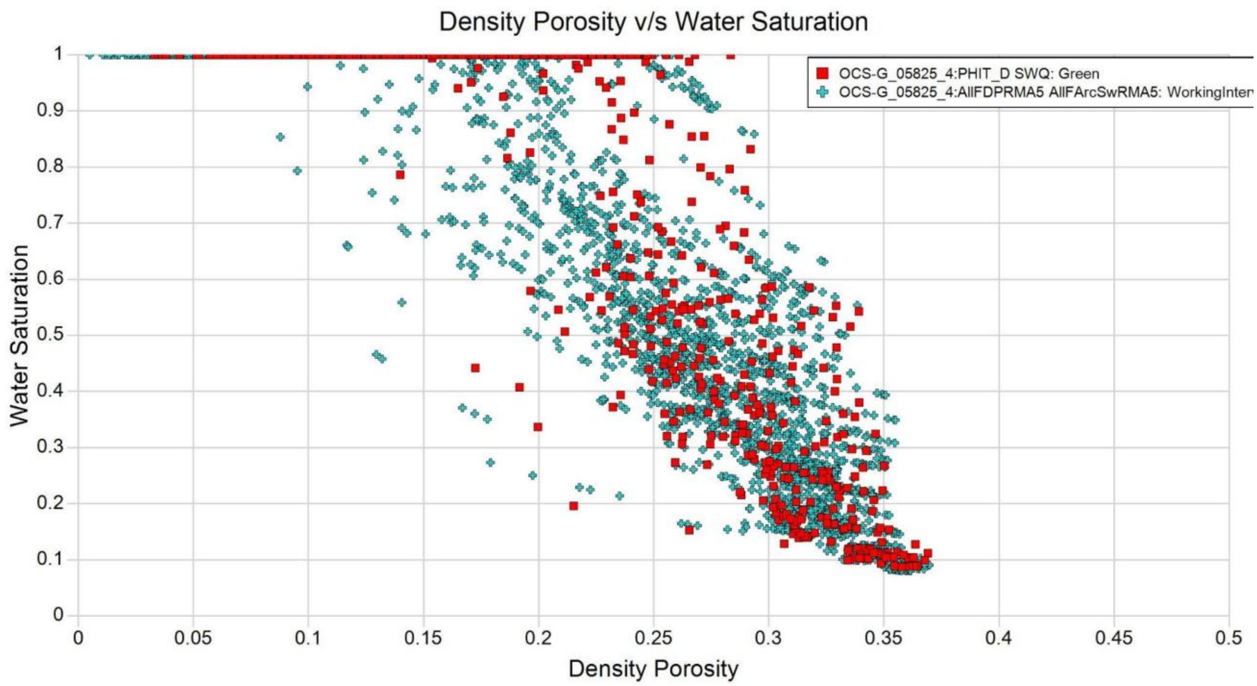


Fig 3.10.7 Density porosity vs. Water Saturation plot for 5 iterations

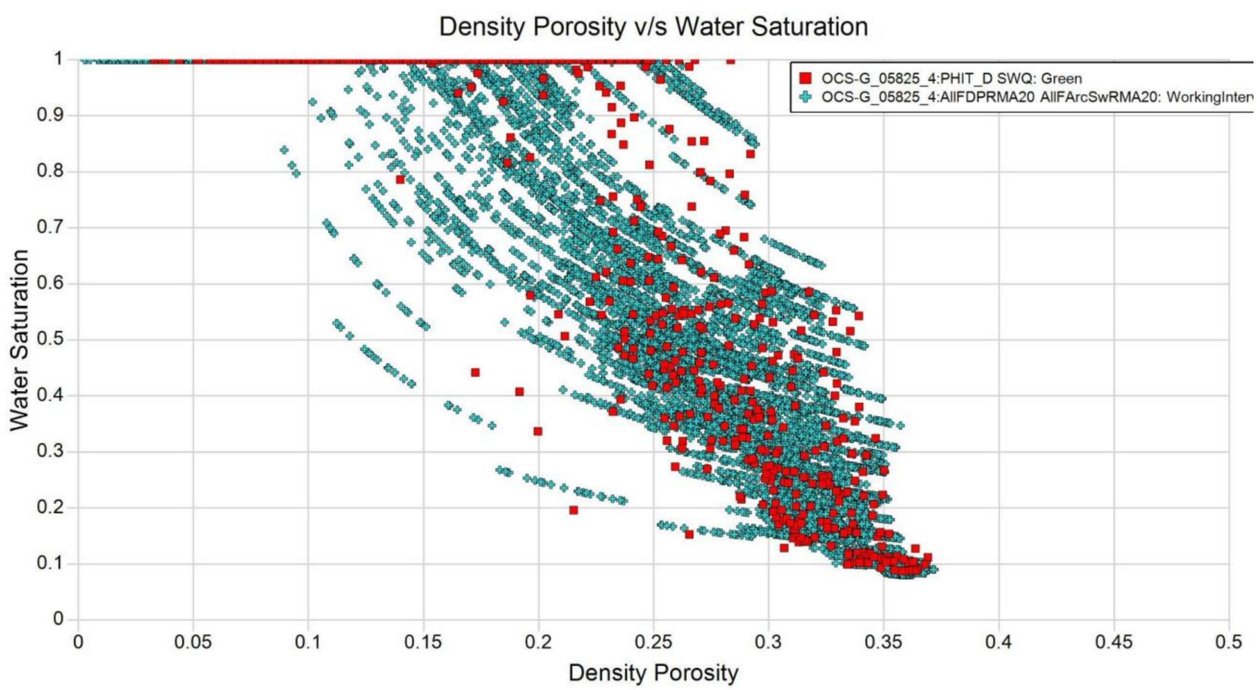


Fig 3.10.8 Density porosity vs. Water Saturation plot for 20 iterations

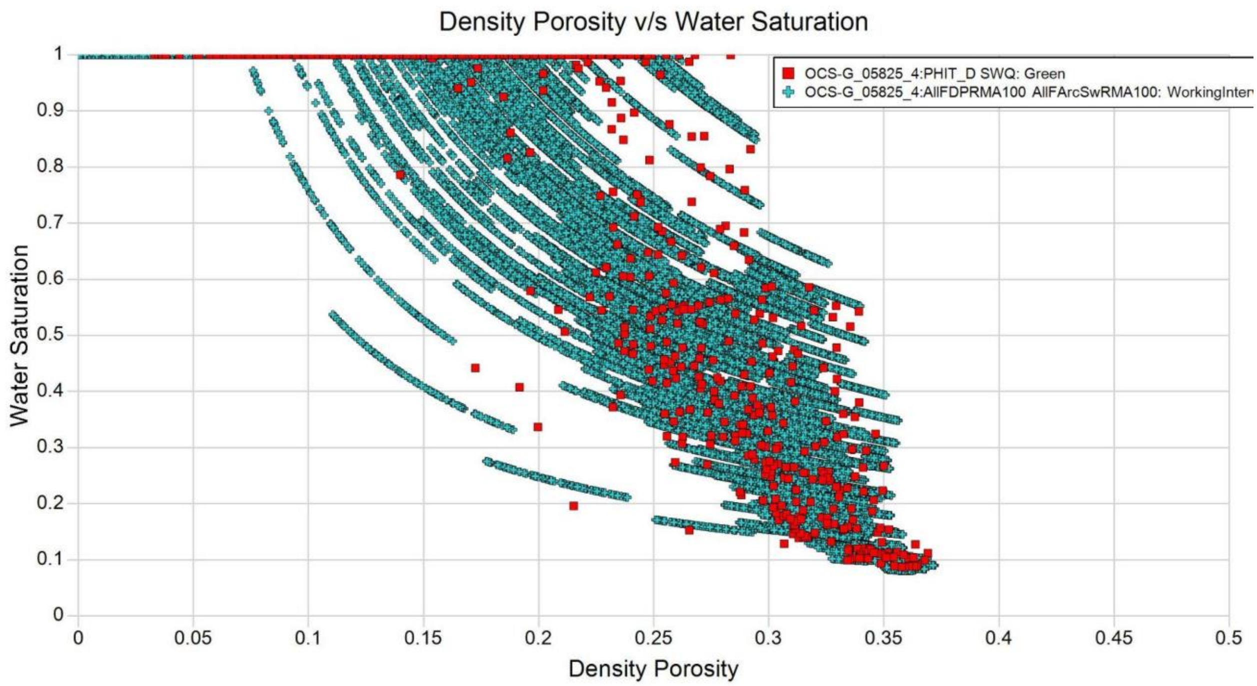


Fig 3.10.9 Density porosity vs. Water Saturation plot for 100 iterations

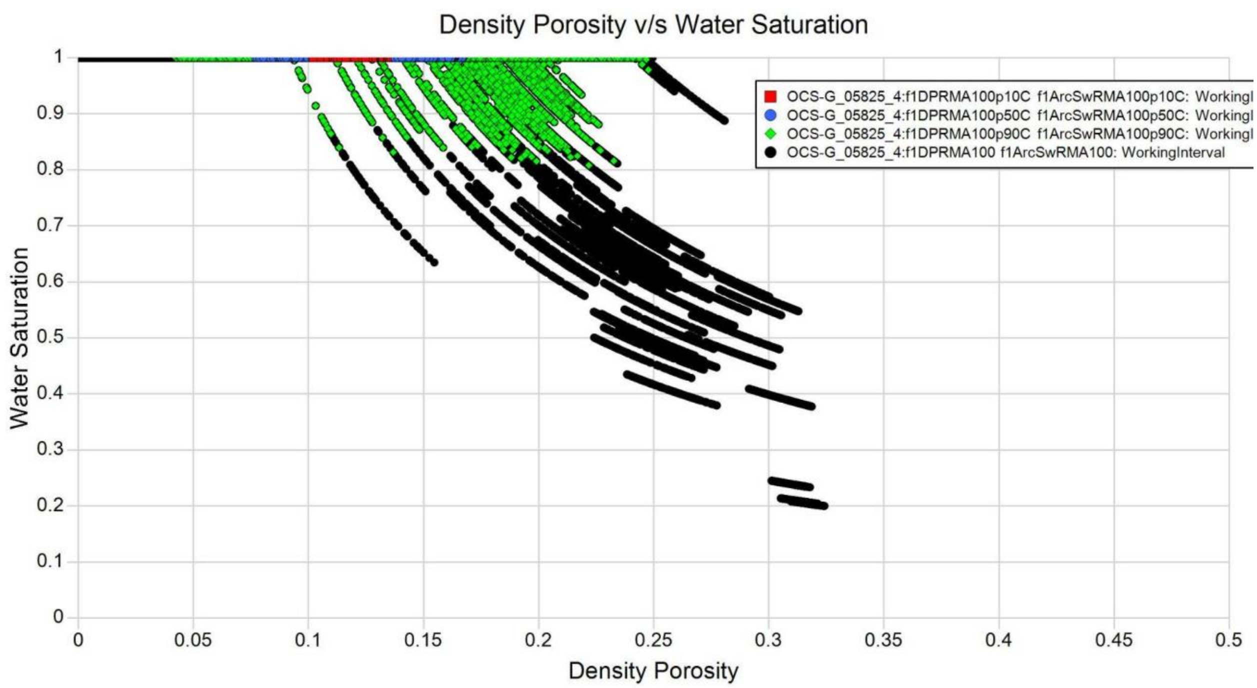


Fig 3.10.10 Density porosity vs. Water Saturation plot of 100 iterations of shale

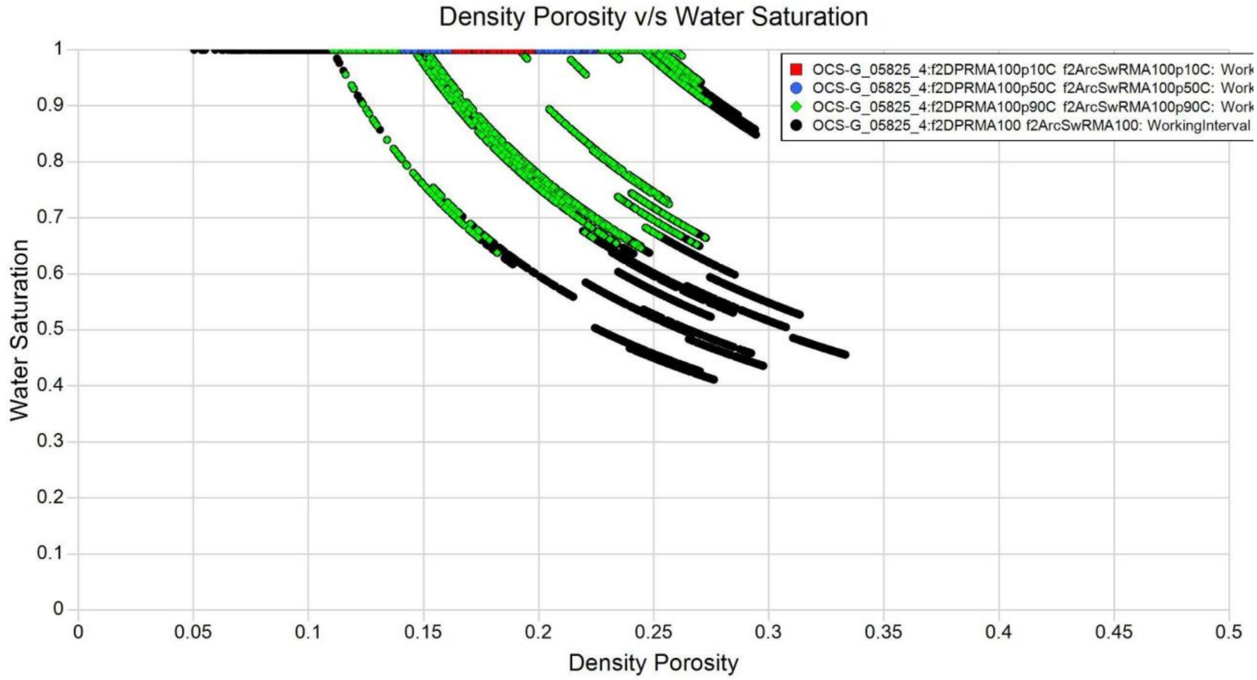


Fig 3.10.11 Density porosity vs. Water Saturation plot of 100 iterations of brine sands

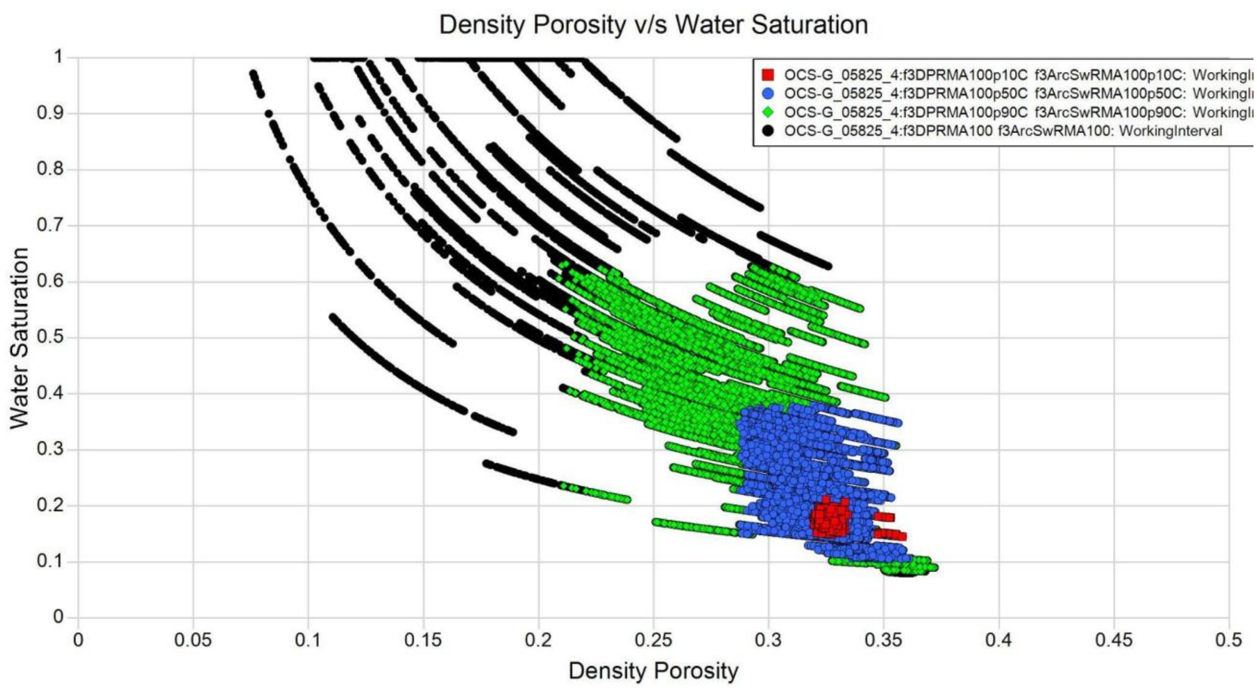


Fig 3.10.12 Density porosity vs. Water Saturation plot of 100 iterations of HC sands

Note:

In Non facies wise plots:

- Represents recorded data and Represents simulated data

In facies wise Confidence level plots:

- Represents 10% confidence of the most likely value
- Represents 50% confidence of the most likely value
- Represents 90% confidence of the most likely value
- Represents entire facies data

## 3.7 Monte Carlo Simulation of Water saturation

**Overview**:

i) Obtain VCL from Gamma ray log data and use it to compute the ρmatrix. Using these ρmatrix values we compute Density Porosity (ϕ) which is used for Formation factor (F).

ii) For Water Saturation, use Archie's equation.

iii) In order to simulate for only water saturation (Sw) values, we do iterative simulations only for Formation Water Resistivity (Rw) while keeping Tortuosity (a), Cementation exponent (m), Saturation exponent (n) and Formation factor (F) as is.

iv) It is done so because a, m, n are constants which are obtained from Pickett plot and the Formation factor values are determined by Porosity which we are not Simulating for over here. Therefore, the only uncertain parameter to vary here is Rw.

v) Finally, compute Water Saturation using a, m, n, F and Rw (for n iterations) in Archie's Equation.

**Flowchart**:

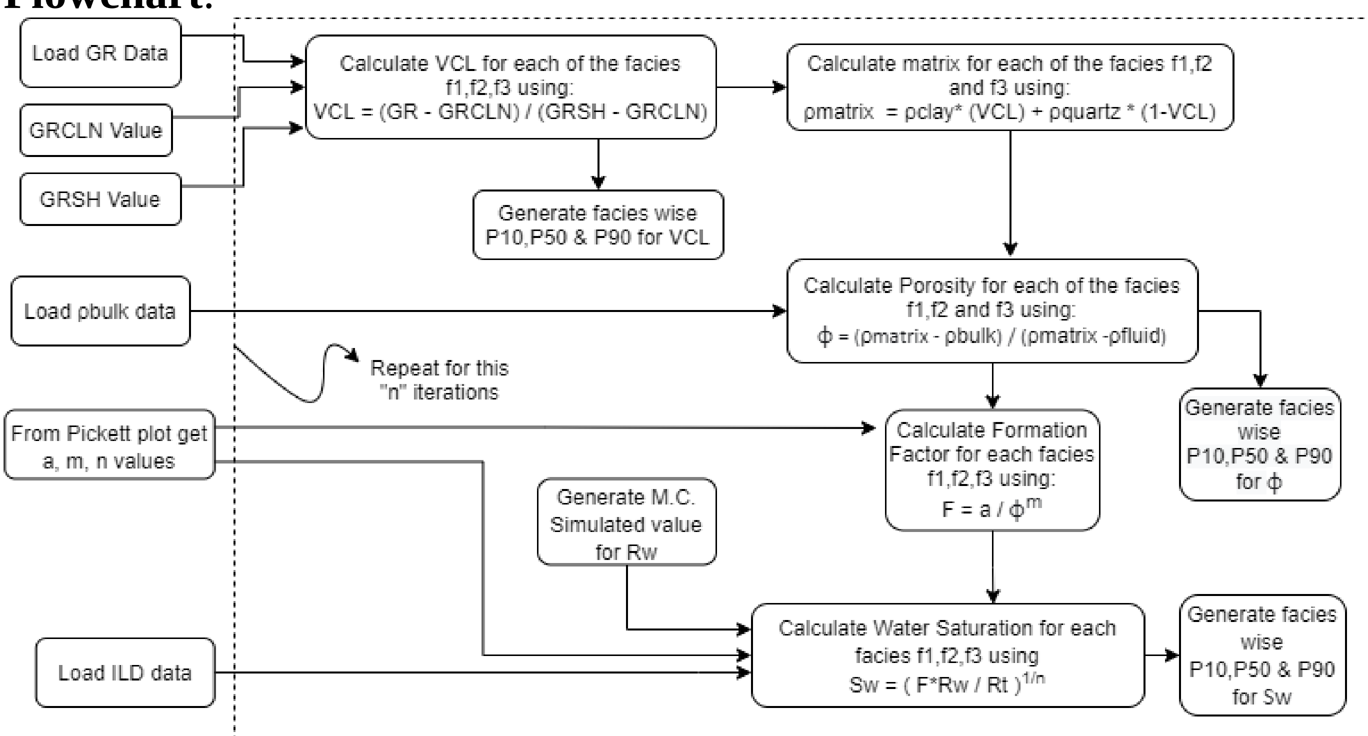


Fig 3.11 Workflow for Sw M.C. Simulation

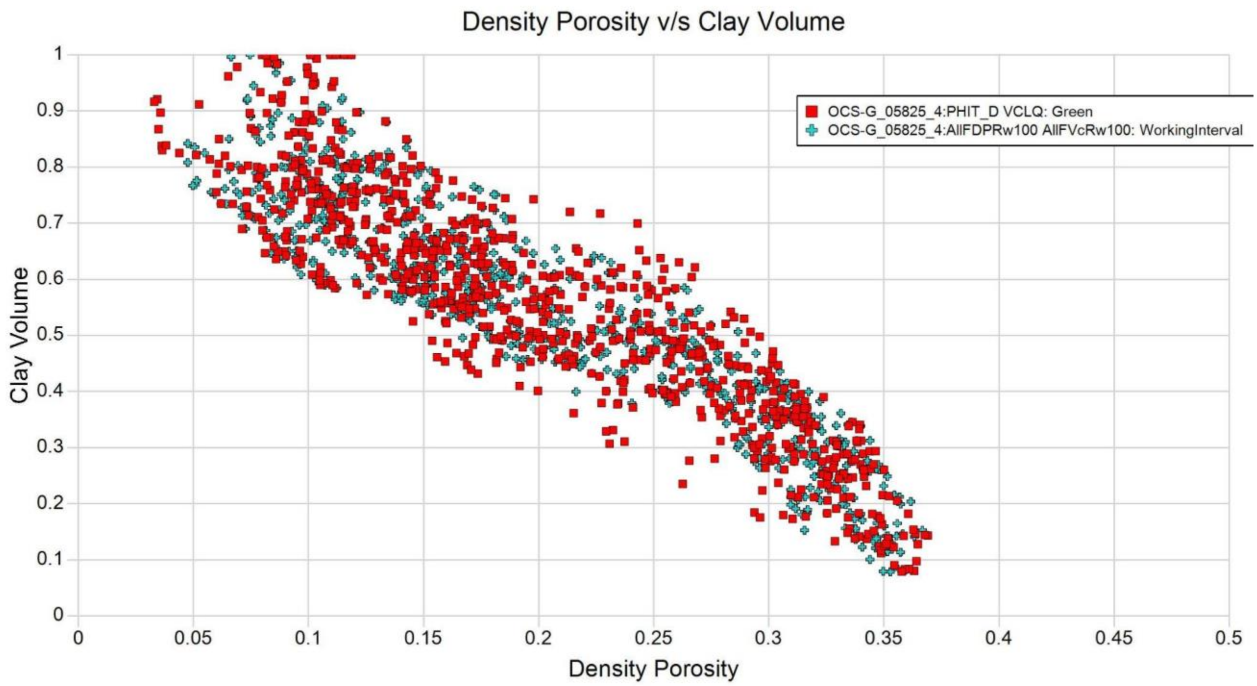


Fig 3.11.1 Density porosity vs. Clay Volume plot for 100 iterations of shale facies

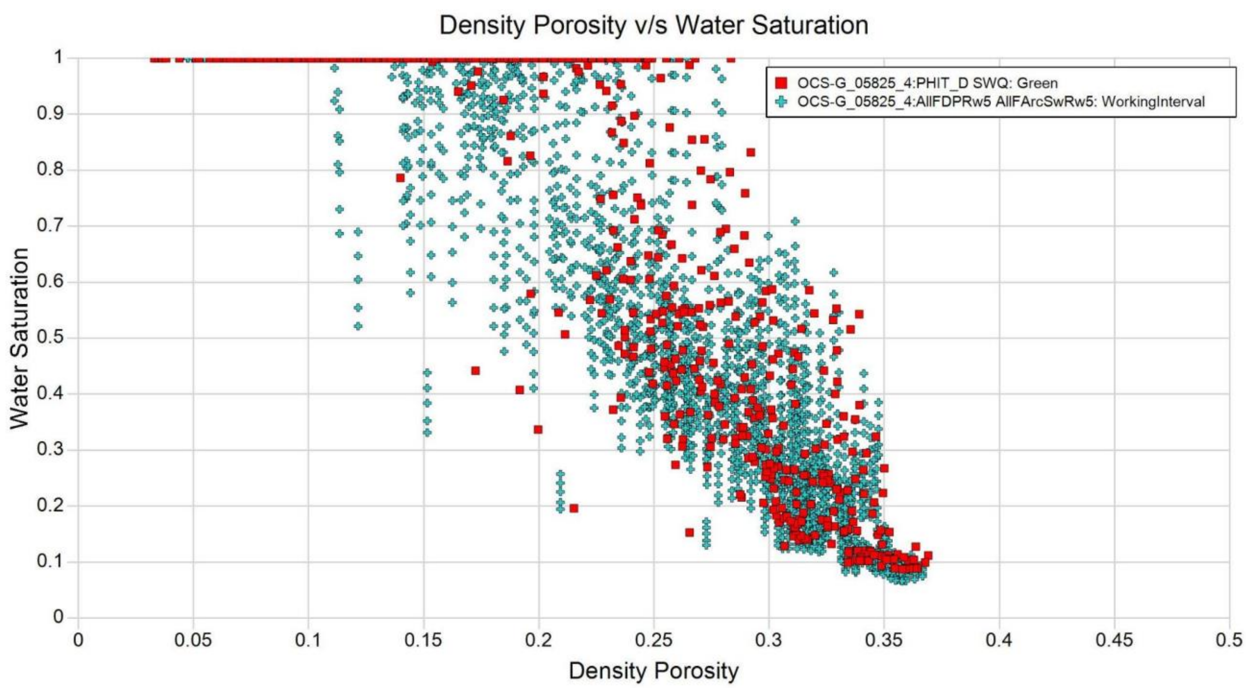


Fig 3.11.2 Density porosity vs. Water Saturation plot for 5 iterations

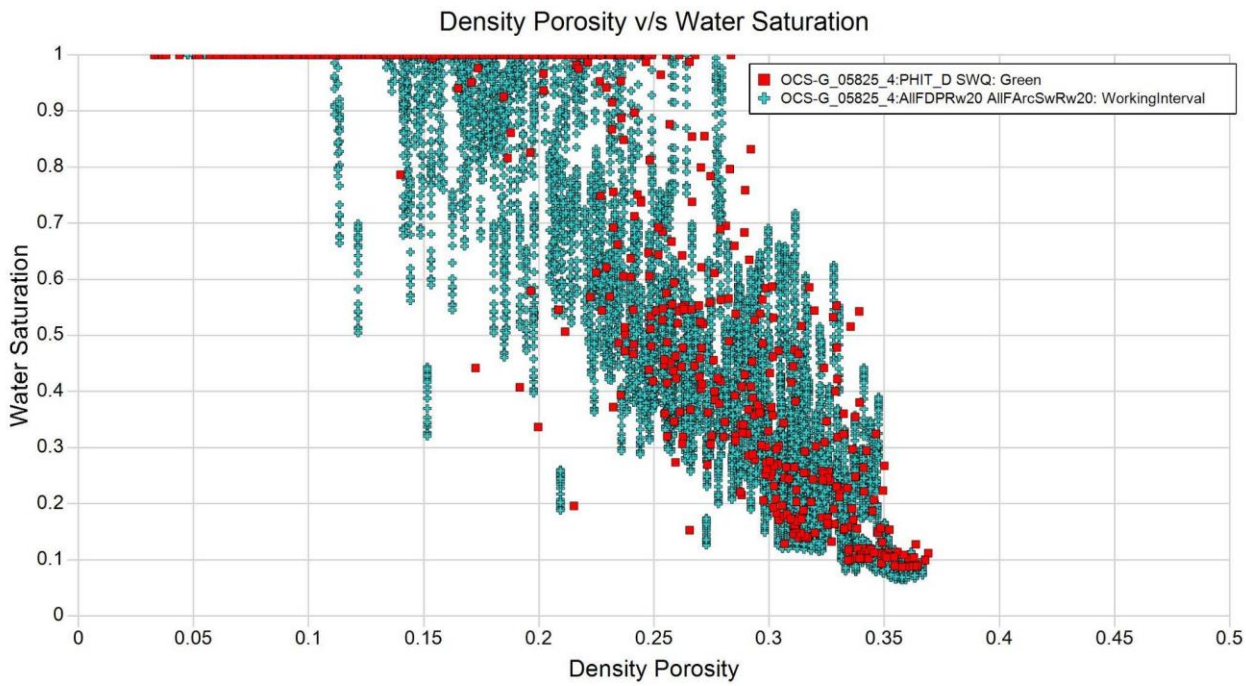


Fig 3.11.3 Density porosity vs. Water Saturation plot for 20 iterations

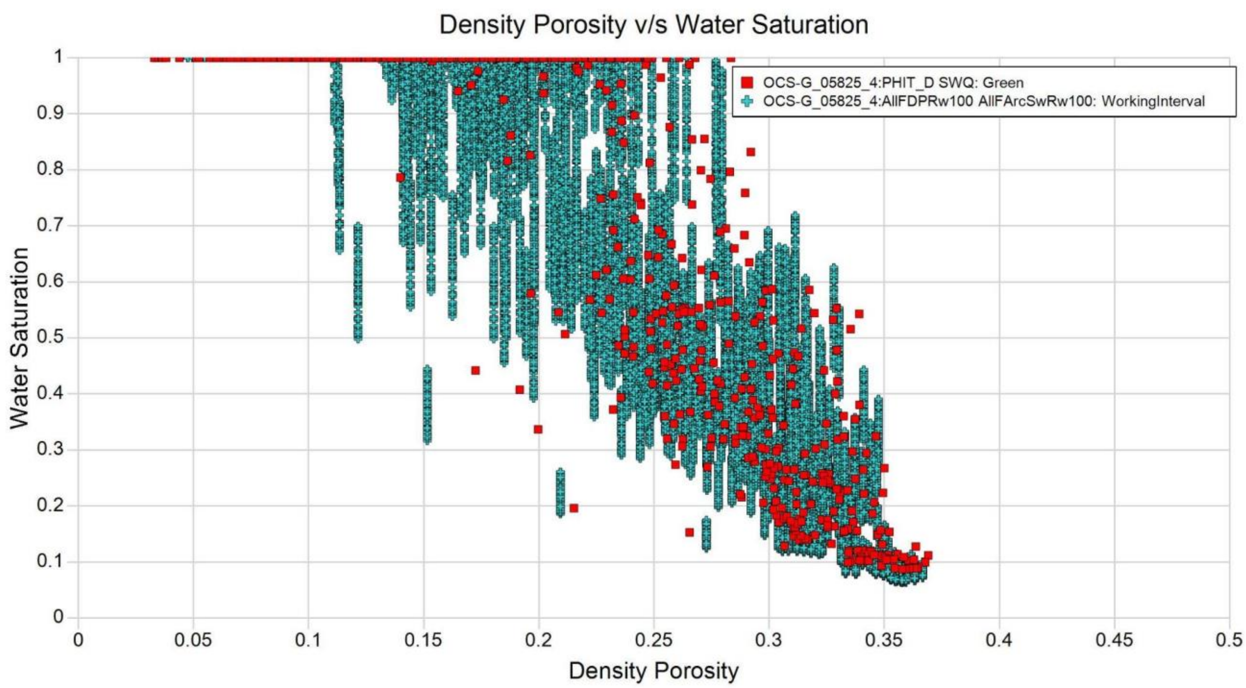


Fig 3.11.4 Density porosity vs. Water Saturation plot for 100 iterations

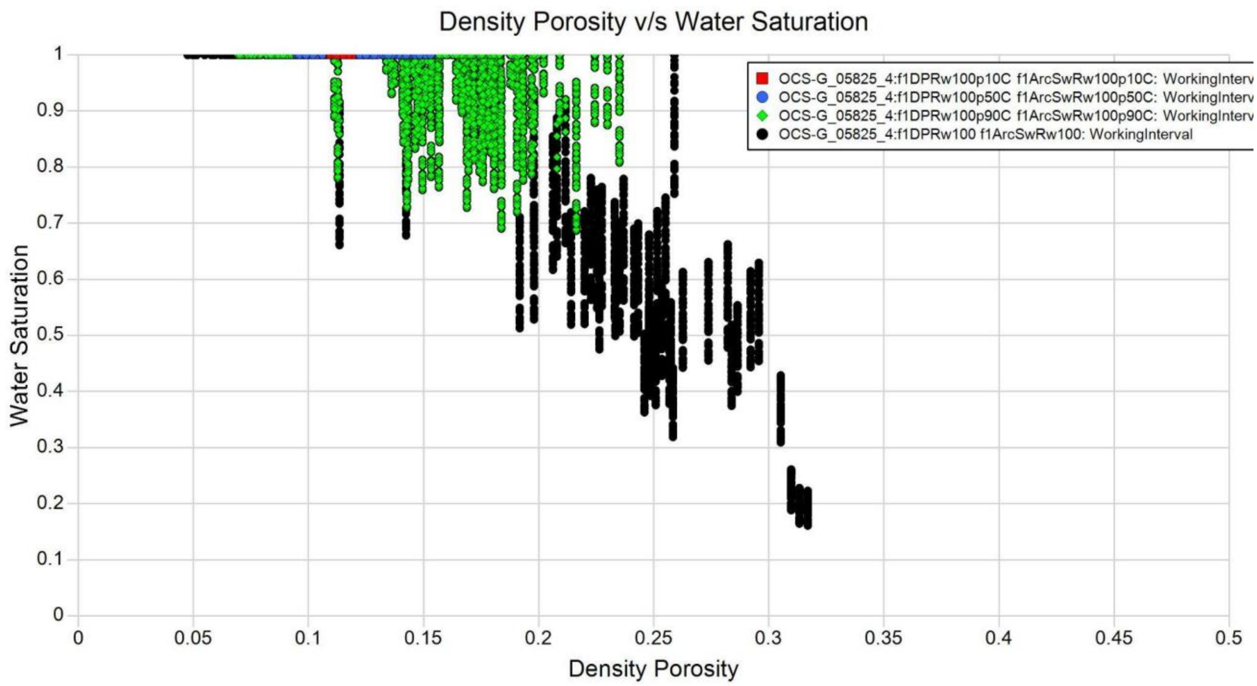


Fig 3.11.5 Density porosity vs. Water Saturation plot of 100 iterations of shale

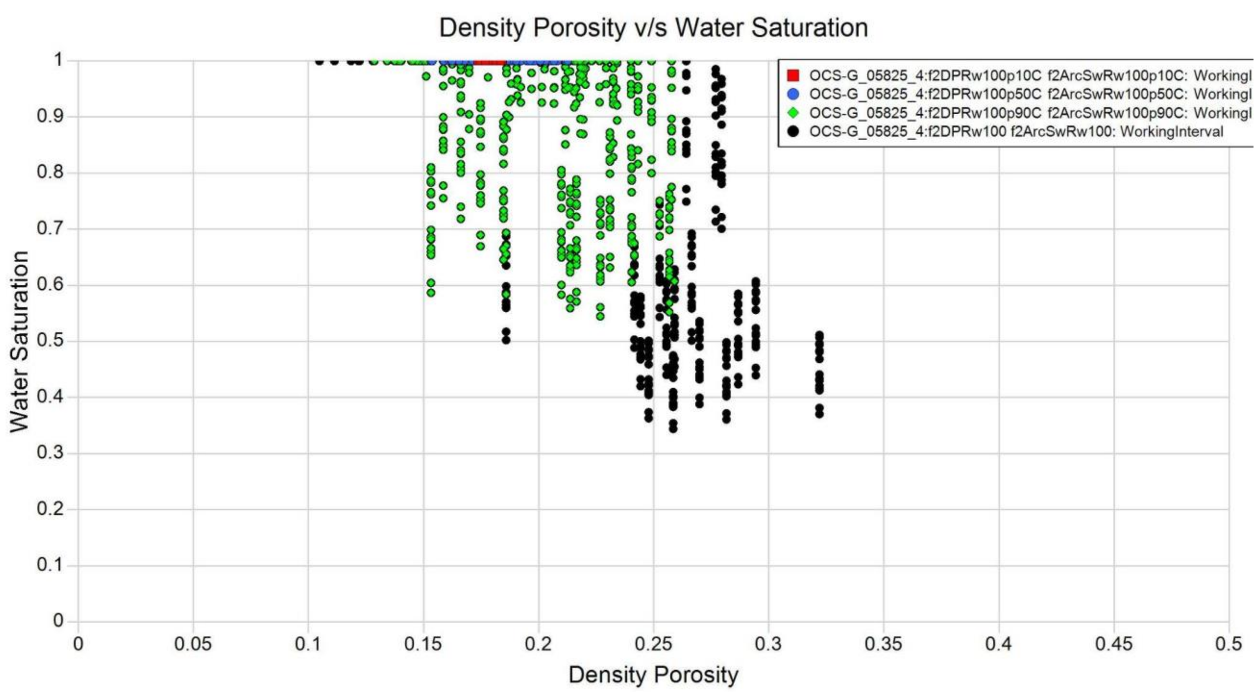


Fig 3.11.6 Density porosity vs. Water Saturation plot of 100 iterations of brine sands

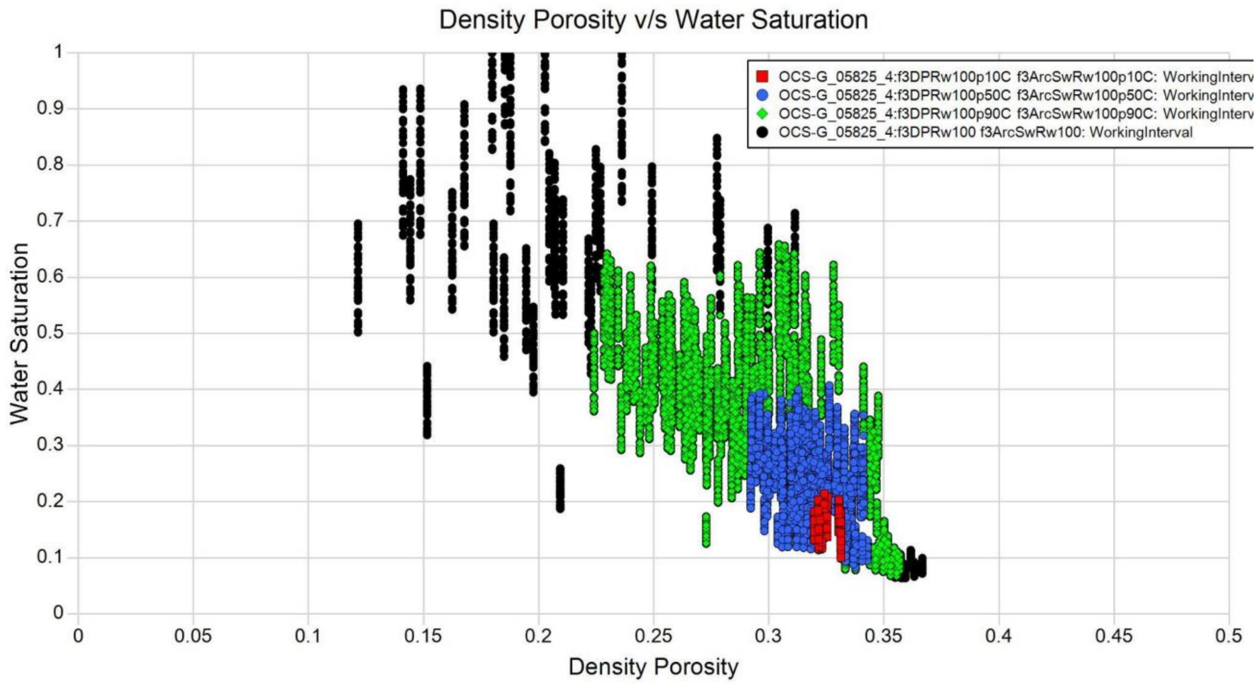


Fig 3.11.7 Density porosity vs. Water Saturation plot of 100 iterations of HC sands

Note:

In Non facies wise plots:

- Represents recorded data and Represents simulated data

In facies wise Confidence level plots:

- Represents 10% confidence of the most likely value
- Represents 50% confidence of the most likely value
- Represents 90% confidence of the most likely value
- Represents entire facies data

# 4. CONCLUSIONS

- Monte Carlo simulation helps address the challenges of dealing with uncertainty in assessing risk by deterministic method. As the no. of M.C. samples increase, we can more clearly demarcate the facies wise VCL, φ and Sw in a range with a certain confidence level.

- Accurate estimates of P10, P50, P90 for each of the facies were made according to the no. of iterations used as well as the estimates based on confidence intervals were quantized as 10% confidence, 50% confidence and 90% confidence respectively.

- Uncertainty of Water Saturation, Porosity and Clay Volume was precisely assessed since the Monte Carlo Simulated parameters yielded outputs of the transfer functions which followed a similar trend of recorded Water Saturation, Porosity and Clay Volume as seen in crossplot.

- The Simulations provide better visualizations of the uncertainty in risk parameters Rw, ρmatrix and GRshale of how they could be and their effects. We can have a better understanding of Water Saturation, Porosity and Clay Volume by the Monte Carlo Simulation not just for given data but we may utilize the same code to analyze the parameters for any data we encounter for them in future.

- By M.C. Simulation, our facies wise cutoffs for pay flag Vclmax, ϕmin and Swmax changes. In general, pay flag is calculated by:

  $$(Vcl <= Vclmax) * (\phi >= \phi min) * (Sw <= Swmax) * (Perm >= Permmin) = 1.$$

  Hence, we can have a better pay summary.

# 5. REFERENCES


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