IOSR Journal of Applied Geology and Geophysics (IOSR-JAGG)
e-ISSN: 2321–0990, p-ISSN: 2321–0982.Volume 11, Issue 1 Ser. II (Jan. – Feb. 2023), 13-18
www.iosrjournals.org

Development of Computer Program for Hydrocarbon Reservoir Property Evaluation

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Abstract
A reliable, interactive and efficient computer program is developed for plotting digital well data and evaluation of reservoir rock properties. The program (GeoFutaLog) is meant to compliment its popular, standard but scarce and expensive counterpart. The code was written with python programming language, an aspect of machine learning. This is because of its effectiveness and popularity within the Geoscience and petrophysics domains. The task involves coding and plotting of field data with depth and estimation of petrophysical parameters for reservoir evaluation. Some of the reservoir parameters evaluated included porosity, permeability, volume of shale, water and hydrocarbon saturation etc. The output of the new program was compared with that of Petrel and the range of percentage deviation ranged from 0 to 8.7%. The low deviation lends credence to the high degree of reliability. Consequently, the developed program is considered safe, reliable and efficient for usage in the academia as well as oil and solid mineral industry.

Keywords*: Software, Python, Reservoir, Petrophysical parameter, Histogram*

Date of Submission: 10-02-2023 Date of Acceptance: 22-02-2023

I. Introduction

Hydrocarbon accumulations have been found to mostly occur in pore spaces of reservoir rocks. Therefore, to have an idea of the commerciality of a new accumulation or reservoir, some basic petrophysical parameters such as porosity, permeability, hydrocarbon saturation, and thickness etc., needs to be evaluated (Saarela and Jauhiainen, 2021). These parameters can be inferred from various well logs.

Geophysical data are normally analyzed manually and with the aid of computer software. The common interpretation software is not usually affordable. Also manual interpretation of these data is time-consuming and sometimes unreliable (Abe and Olowokere, 2013). The need to reduce the cost, time and minimize the risk involved in evaluating reservoir properties informed the development of this in-house computer program. It involved incorporating several equations for determining different parameters into a computer program for reservoir analysis. The existing interpretation software are usually time-limited and are subject to renewal. This is sometimes not easy. Several authors have used various programming language to develop software for estimating some reservoir parameters. Mohammed (2021) built a stable machine learning model that could predict volume of shale with minima error with data from the Norwegian North Sea. Enikanselu and Adekanle (2008) developed a Fortran computer program for computing connate water resistivity from spontaneous potential log data and compared the output with field values. The maximum deviations were within ±10%. Cristhian (2020) carried out petrophysical interpretation using an ensemble technique (Supervised Learning model), which is widely known as Random Forest Regression and discovered a high level of correlation between the real and the predicted values.

This paper developes a computer program capable of employing raw digital well data to generate plots of variation of different subsurface physical properties with depth. It also determines the stratigraphic vertical layer structure as well as the horizontal spread. The program codes the relevant standard interpretation equations for the computation of needed petrophysical parameters. It equally makes qualitative and quantitative interpretation of results and compares with a chosen reliable conventional standard.

II. Methodology

The code was written with python programming language which an aspect of machine learning. Machine learning and Artificial Intelligence are becoming popular within the Geoscience and petrophysics domains. Machine learning is a subdivision of Artificial Intelligence and is the process by which computers can learn and make predictions from data without being explicitly programmed to do so. We can use machine learning in a

number of ways within petrophysics, including automating outlier detection, property prediction, facies classification, etc.
The coding was done to allow for the loading of the well data comprising Gamma ray, Resistivity, Self potential, Density and Neutron logs.
The general process involves the following steps:

Importing Libraries & Data
The first step is to import the required libraries. These included pandas for loading and storing the data, matplotlib for visualising the data.
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import matplotlib

Loading Data
This involved importing the libraries, loading the data using the pandas, read_csv function and assign it to the variable df.
Pandas. describe Function
After loading the data, it was stored within a structured object, similar to a table, known as a dataframe. The contents of the dataframe was checked by considering the summary statistics of numeric columns using the .describe() function. From this, we were able to find information about the number of datapoints per feature, minimum, maximum values.
For the purpose of making the table easier to read, we appended the .transpose() function. This puts the column names in the rows, and the statistical measurements in the columns.
Pandas .info Function
This provided a list of all of the columns within the dataframe, their data type (e.g, float, integer, string, etc.), and the number of non-null values contained within each column. It could be seen that we have a column called wellName that was not contained in the dataframe shown above.
Pandas .head and .tail Functions
Data Visualisation
Well Log Plots
This consist of several columns called tracks. Each column can have one or more logging curves within them, plotted against depth. They help us to visualize the subsurface and allow us to identify potential hydrocarbon intervals.
This create_plot function takes a number of arguments (inputs):
wellname: the wellname as a string
dataframe: the dataframe for the selected well
curves_to_plot: a list of logging curves / dataframe columns we are wanting to plot
depth_curve: the depth curve we want to plot against
log_curves: a list of curves that need to be displayed on a logarithmic scale
The following results were generated after coding and loading of data:
1. Well correlation panel
2. Crossplot
3. Histogram
4. Table of petrophysical parameters
Also, the following equations were coded into the software:

$$I_{GR} = \frac{GR_{log} - GR_{min}}{GR_{max} - GR_{min}} \quad (1)$$

where:
I_{GR} = Gamma ray index
GR_{log} = Gamma ray value of thick and clean sand
GR_{max} = Maximium Gamma ray value
GR_{min} = Minimum Gamma ray value

$$V_{sh} = (0.083^{2(3.7*I_{GR}}) - 1.0) \quad (2)$$

where:
V_{sh} = Volume of shale
I_{GR} = Gamma ray index

$$\emptyset_D = \frac{\rho_{ma} - \rho_b}{\rho_{ma} - \rho_{fl}} \quad (3)$$

where:

ϕ_D = Density porosity
ρ_{ma} = Matrix density
ρ_b = Bulk density
ρ_{fl} = Fluid density

$$F = \frac{a}{\phi^m} \tag{4}$$

where:
F = Formation factor
a = tortuosity factor
ϕ = Porosity
m = Cementation exponent

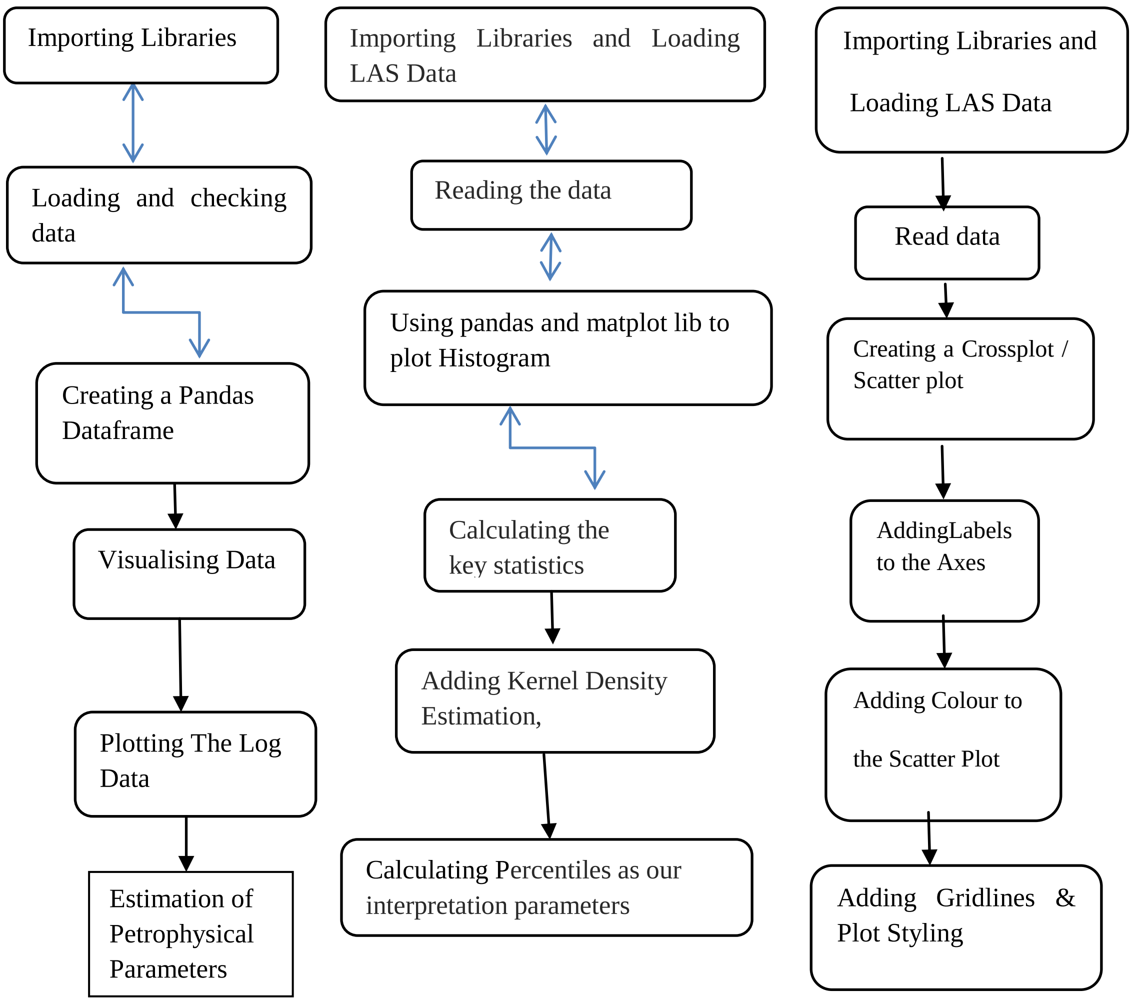
$$R_w = \frac{R_o}{F} \tag{5}$$

where:
R_w = Formation water resistivity
R_O = Resistivity of wet sand

$$\sqrt{S_w} = \frac{F * R_w}{R_t} \tag{6}$$

where:
S_w = Water Saturation
R_t = True resistivity of the formation
R_w = Formation water resistivity

The workflow for coding and generating of well correlation panel, Crossplot and Histogram is shown in Figure 1.



rkflow for Coding and Generation of Well Correlation panel, Histogram and Scatter plot

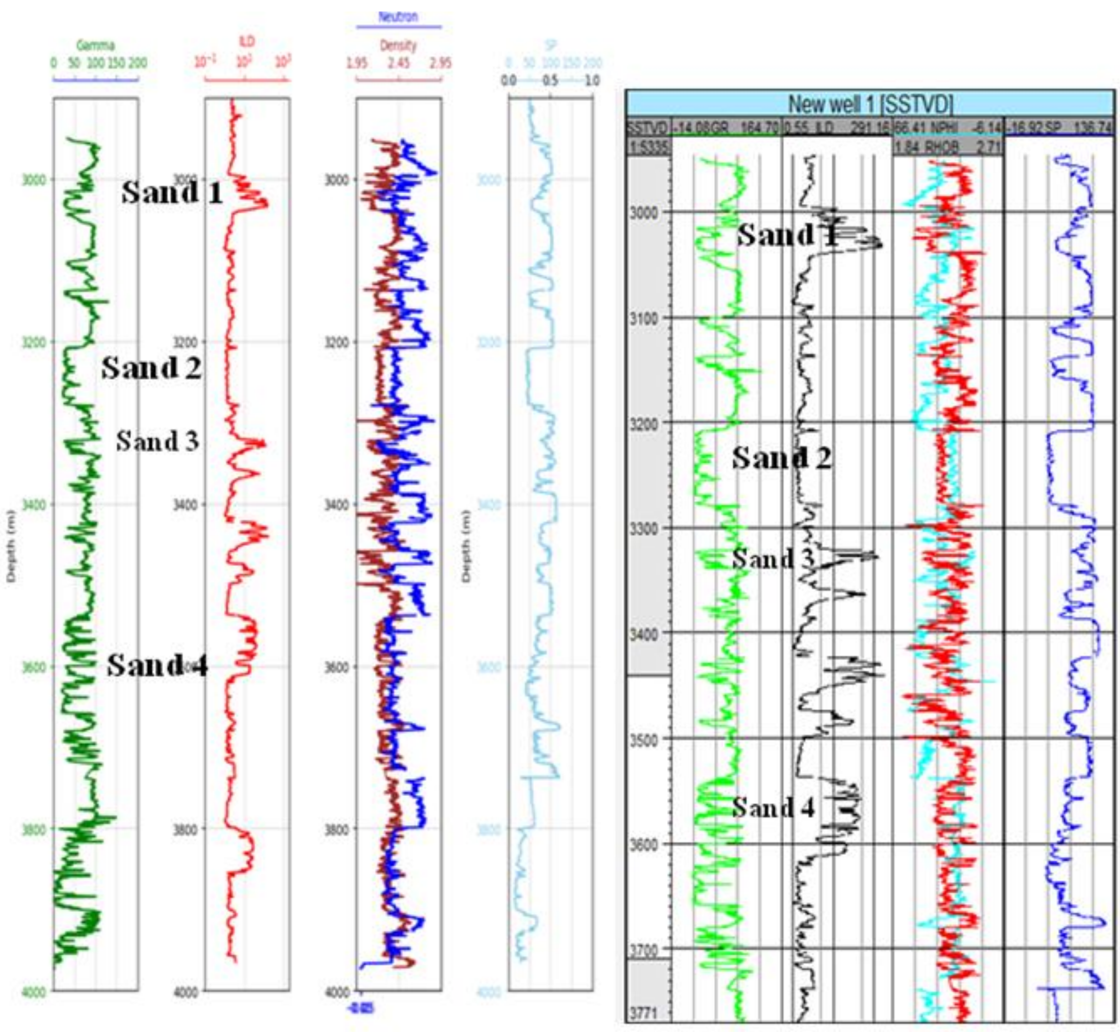
III. Result and Discussion

The results are presented as Well Correlation panel, Histogram , Crossplot and table, as shown in Figures 2, 3, 4 and Table 1.The computed results are compared with that of Petrel. Figure 2 showed the well correlation panel displayed side by side from the two software. It could be observed that log signatures are similar in both cases for Gamma ray, Resistivity log (ILD), Neutron log, Density log and SP log.

In Figure 2a and 2b, Gamma ray log is in track 1 (coloured deep green and light green), the log showed intercalattion of sand and shale that is typical of Agbada Fornation in the Niger Delta. The log motiffs are similar as evident between depth 2800 m to about 4000 m. A thick sand body (Sand 4) between 3500 m and 3800 m is evident in both plots. Track 2 contains resistivity log (ILD), which is coloured in red and black in the new and the reference software. The log gives an idea of the fluid present within the Formation. The log signatures from the new and old software are similar, with high resistivities observed at depths of 3030 m to 3100 m and 3500 m to 3800 m in both plots.

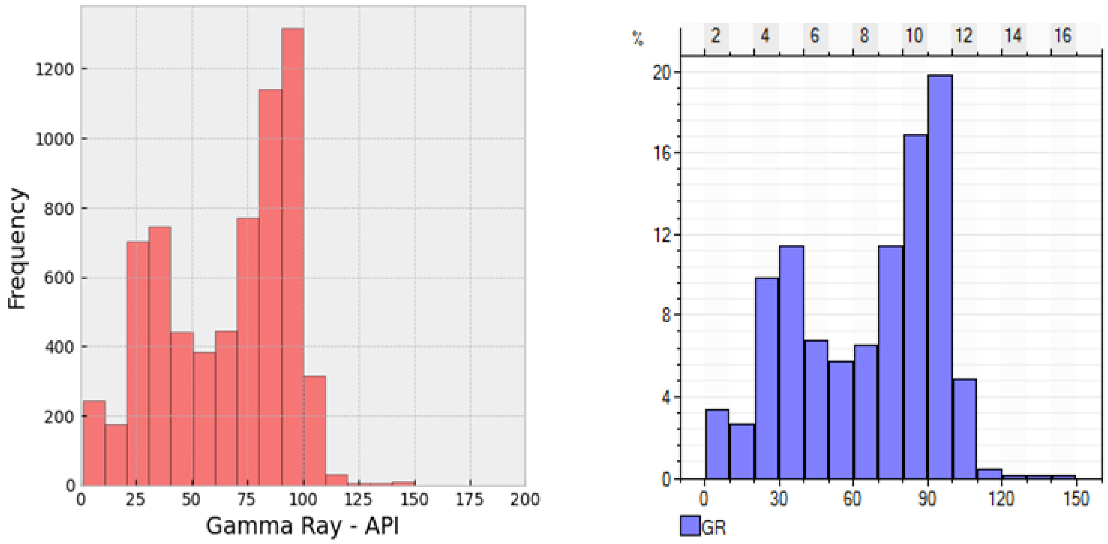
In figure 2a and 2b, neutron and density logs are in track 3 crossploted. The log signatures are similar which gives some level of reliability on the newly developed software. Track 4 in figure 2a and 2b contains SP log which is also a lithology log. The log signatures are also similar showing variation in self potential values from the top to the bottom of the well.

Figure 3a and 3b shows the histogram of the Gamma ray log. This shows the frequency of the Gamma ray count. This also allows us to know the dominant Gamma ray value, which is very important in petrophysical analysis. The histogram plots are very similar in both cases, having the most dominant gamma ray value between 90 API to 100 API. The range of the values is between 0 and 120 API, the two peaks or dominant values at 30 API and 100 API are also evident and similar in both plots.



(a) (b)

Figure 2: Well Correlation Panel Generated with the new Software (a) and Standard Petrel (b)

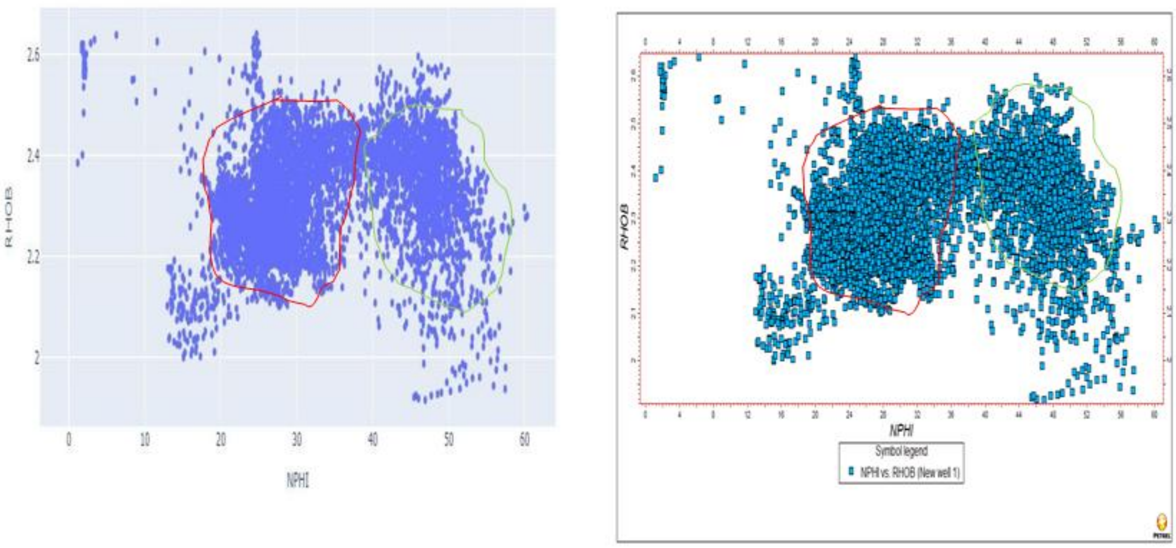


(a) **(b)**

Figure 3: Histogram Generated with the new Software (a) and Petrel (b)

The crossplot of density against Neutron is shown in Figure 4a and 4b. Scatter plots are a commonly used data visualisation tool. They allow us to identify and determine if there is a relationship (correlation) between two variables and the strength of that relationship. Within petrophysics, scatterplots are commonly known as crossplots. The crossplot of density and neutron are normally used as fluid discriminator within the reservoir. The crossplot of the two parameters, as displayed by the new and existing software in figure 4a and 4b are also similar. The two major clusters are evident on the two plots. The presence of gas within the reservoir lowers the neutron values due to the low hydrogen ion content. A look at the crossplots showed the presence of oil and water within the Formation.

The hydrocarbon- bearing reservoir between 3550 m and 3730 m were analysed petrophysically for both plots in figure 2a and 2b. Gamma ray log showed deflection to the left while the resistivity log reads high value at the top of the reservoir. The reservoir parameters estimated are gross thickness, porosity, volume of shale, water and hydrocarbon saturation. Table 1 shows the petrophysical parameters estimated within this interval by both the new and the reference software, Petrel.



(a) **(b)**

Figure 4: Crossplots Generated with the new Software (a) and Petrel (b).

In table 1, the gross sand thickness for Sands 1 to 4 is 160 m, 70 m, 40 m and 180 m respectively. The porosity values vary from 0.18 to 0.30 for the standard and computed software. Volumes of shale and water resistivity values are within the acceptable range for a good reservoir.

Table 1: Table of petrophysical parameters generated with the standard softwatre (STD) and the new software (Computed)

Parameters/ Sands	Gross Thickness(m)			Porosity (%)			V_{sh} (frac.)			S_w (%)			S_h(%)		
	STD	Computed	% Deviation	STD	Computed	% Deviation	STD	Computed	% Deviation	STD	Computed	% Deviation	STD	Computed	% Deviation
Sand 1	160	160	0	20	19.5	2.5	0.04	0.037	7.5	14	13	7.1	86	84	2.3
Sand 2	70	70	0	25	23	8	0.01	0.01	0	100	100	0	0	0	0
Sand 3	40	40	0	23	21	8.7	0.03	0.029	3.3	35	33	5.7	65	68	3.1
Sand 4	180	180	0	25	24	4	0.07	0.068	2.9	24	23	4.2	76	73	3.9

IV. Conclusion

A simple, interactive, stand-alone and reliable computer program (in Python language) for plotting of digital well data and estimating petrophysical parameters has been developed. It is meant for subsurface data interpretation for both hydrocarbon and solid mineral exploration. The interpreted logs included the Gamma Ray, Spontaneous Potential, Resistivity, Neutron and Density, while the petrophysical parameters computed were the Gross thickness, Porosity, Volume of shale, Water saturation and Hydrocarbon saturation. Other log types are easily adaptable. The outputs of both the 'standard (Petrel) and the developed programs were compared both qualitatively (visual) and quantitatively. The maximum percentage deviation between both was less than 10 percent; acceptable within the scientific domain. This lends credence to the high level of reliability of the developed program. The authors therefore feel safe recommending same for the usage of both the academia and the industry.

Acknowledgement

The authors wish to appreciate the Tertiary Education Fund (TETFUND) for approving and funding this research. We are also grateful to the management of Federal University of Technology, Akure under whose platform the project was approved. Our profound appreciation also goes to the Department of Applied Geophysics, Federal University of Technology, Akure, Nigeria, for permission to use the reference software (Petrel) employed in the validation of computed results. We are equally grateful to Mr Ajayi Olawale for providing the highly needed computing technical support at the program development stage.

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Enikanselu, P.A, et. al. “Development of Computer Program for Hydrocarbon Reservoir Property Evaluation.” *IOSR Journal of Applied Geology and Geophysics (IOSR-JAGG)*, 11(1), 2023, pp. 13-18.