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# Open Hole-Wireline Logging to Determine the Characteristics of the Reservoir

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## *Abstract*

*Openhole well logging encompasses a diverse range of measurements, including as measurement-while-drilling (MWD) logs, standard wireline logs, and mud logs. These measurements are the major source of formation evaluation data, and they are used in applications ranging from individual drilling-well appraisals to extensive reservoir description studies. They are also known as "logs." The technology for openhole well-logging is continuously being developed in response to the demand for increased precision in determining the features of reservoirs. Recent years have seen a*

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*proliferation of various technical advancements. This article offers a number of recent innovations and applications to demonstrate the current state of technology and to offer insight into the patterns that will guide its future growth.*



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## Introduction

Three-dimensional seismic data is just one piece of the puzzle when assessing a petroleum-bearing reservoir. Mud logging, coring, magnetic and gravity logs, logs on wire, pressure testing, and samples [1]. Although some professionals may choose to specialise in a particular area, such as seismic interpretation, log analysis, or core analysis, understanding all of these topics is essential to the field of petroleum-bearing reservoir appraisal [2-6]. An oil and gas firm's R&D initiatives focus on studying reservoir rocks and fluids for clues about how those materials' attributes map to hard numbers. Borehole and formation properties are measured at known depths using wireline well logging techniques [7-12]. Petroleum industry workers (geologists, geochemists, geophysicists, etc.) care solely about the information provided by wireline measurements, specifically the physical and chemical features of the reservoir, and not the tool's specifics [13].

Well logs are an essential tool for learning about the geology of the subsurface sedimentary formations, which is necessary for finding the petroleum-bearing reservoir. When it comes to describing and characterising reservoirs, wireline well logs shine [14-18]. All of these formation characteristics, including porosity, shale volume, lithology, and water, oil, and gas saturation, can be defined or inferred from log measurements. Permeability estimates, water cut forecasts, over-pressure zone selections, and residual oil estimates can all be made. In a single well setting, log analysis is most useful for characterising formation features. Reservoir properties are often defined by comparing log and core data [19-25]. Log data are typically used as a continuation from core analysis and log comparisons on other wells when cores are unavailable. By describing local geology, stratigraphy, the environment of deposition, and reservoir geometry under current conditions, a suite of logs in the run can be utilised as a geological tool to study subsurface formations [26].

## Literature Survey:

Wireline logging is the practise of continuously monitoring a formation's attributes with electric equipment in order to inform drilling and production decisions [27-31]. With wireline logging, certain instruments are dropped into the borehole to measure characteristics of the formation at depth. logging a well: By inserting a variety of sensors into the borehole, well logging in the petroleum sector can be utilised to detect oil and gas intervals and measure features of reservoir rock [32]. The lithology, geological structure, porosity, fluid saturation, and drilling fluid invasion are just few of the rock features [33]. The sensors can both transmit and receive signals from within the geological formation, and include electric, electromagnetic, acoustic, neutron, and gamma ray devices. The sensors record the transmitted signals, which undergo character changes and attenuation due to the rock qualities and conditions near the borehole. The signals are then evaluated to determine the oil and gas-relevant features of the formation. Caliper logs are also used to measure the internal diameter of the bores [34-39].

Reservoir characterisation is aided by the data provided by certain logging and imaging instruments that highlight faults and fractures. Rock fractures and high permeability "thief" zones can be located with the help of downhole imaging instruments [40-45]. Logging is essential for figuring out how to complete a well for maximum production and how to drill additional wells for reservoir development and management. There are two main types of logging holes: open and cased. Open hole logs are logged in the open borehole of a newly drilled well to determine the rock qualities, such as the presence of hydrocarbons and their saturation levels. After the casing has been installed in the borehole, cased hole logs can be used. Casing integrity and damage detection are two of the primary applications for cased hole logs [46-51]. After a well has been drilled, a string of logging devices is lowered into the well to gather information from below. Sensor data can either be stored downhole in memory mode or transmitted to the surface in real time. In the 1970s, mud-while-drilling (MWD) technology was developed, allowing logging equipment to be fastened to the drill string and sending real-time data to the surface through mud pulses [52-59].

The Schlumberger brothers, who established the company around the turn of the century, get most of the credit for pioneering modern well-logging methods. The logging tool was originally designed for use in the mining industry to locate precious metals, but it has since found widespread use in the oil and gas sector as well. Alsace, France was the site of the first downhole application of a resistivity logging equipment in 1927 [60-64]. A log called the spontaneous potential (SP) was developed a few years later to help locate hydrocarbon-bearing permeable zones. Well Surveys, Inc. invented the gamma-ray log in 1939 to quantify the radioactivity of a formation as it occurred naturally. The log functions properly in cased holes and is ideal for locating shale beds. A nonconductive oil-based mud environment can be navigated with the help of an induction log, which was created in the late 1940s [65-71].

According to resistivity charts, water is a more efficient electrical conductor than either oil or gas. When compared to formation water with a noticeable salt, petroleum fluids are far more electrically robust. This is the premise upon which resistivity logs function. There are two electrodes in the resistivity tool. An electric circuit is created when the first electrode discharges electricity into the fluid-filled formation and the current returns to the second electrode at the other end of the tool [72-79]. As the tool is gently raised to the surface, the strength of the current fluctuates according to the conductivity of the formation fluid. High resistivity levels are typically seen in oil-bearing regions. Dual lateral logs and micro-spherically focused logs are two examples of the most often used resistivity instruments. Dual induction logs, which use induction coils to monitor fluid conductivity, are also used to identify the fluid type and the degree of fluid saturation [80-85].

The SP log, one of the earliest logging equipment in the industry, involves lowering an electrode into the borehole and then comparing the resulting potential to a reference electrode at the top to determine the depth of the well. Depending on the clay percentage and water salinity of the formation, an electrochemical potential deflection is observed as the tool approaches a permeable formation. Logs of density: The bulk density of the formation can be measured with density logging equipment [86-99]. The device relies on radioactive materials. The bulk density of the rock is calculated by counting the number of gamma rays emitted as a result of Compton scattering and photoelectric adsorption as the instrument is moved across the formation [100-104]. The latter is useful for gauging the permeability of a formation.

The gamma-ray log uses a device that monitors the radioactivity of the formation to provide this reading. The radioactive potassium in clay found in shale beds sets it apart from the nonradioactive quartz particles that make up sandstone layers. Uranium and thorium can be found in shale in an adsorbed form as well [105-109]. A borehole profile, comprising the borehole's diameter and form, can be obtained with the help of a calliper log. As the instrument moves upward, its two arms press against the bore wall. A potentiometer at ground level is linked to the arms. Borehole shape changes are tracked and documented [110-114]. The acoustic method of spectral noise logging is employed to ascertain well integrity and locate production or injection zones. Fluid flow noise, as well as any leaks, in the subsurface system are captured by the instrument.

The logging tool is a diameter log, and it is used to help characterise the reservoir. The orientation of geologic layers and the orientation of faults and fractures can be determined with the use of dipmeters, which employ imaging techniques to do so [115-121]. Modern-Way Drilling (MWD): This equipment, which has been used in the drilling business since the 1970s thanks to technological advancements, is able to transmit real-time data from the subsurface formation, such as rock porosity, density, fluid pressure, borehole trajectory, and so on. Electric and acoustic logs are just two of the many techniques used in MWD [122-127]. The use of radioactive materials is also permitted. Mud pulse telemetry, which involves sending pressure pulses down a mud column, is used to send the data to the surface. During horizontal drilling, MWD (also known as logging while drilling) gives real-time data on the position and orientation of a lateral segment [128].

Trucker wireline –Open Hole Wireline Logging

In order to make a comparison, the Tucker Wireline crew followed the RMOTC logging contractor with a set of open-hole logs. The methods used were BHC Sonic porosity, density porosity, Dual Laterolog, and Phased Induction. The Dual Laterlog instrument offers both LLD and LLS, which are measures of resistivity depth. While the flushed, invaded, and transition zones will all contribute to LLS under typical conditions, the virgin zone will have the most impact on LLD. For a reliable reading, it is essential that the least-altered structure contributes the most. Therefore, the resistivity of the mud must be low compared to that of the formation. This instrument was developed at RMOTC's request to improve the quality of deep resistivity (Rt) measurements in the Tensleep formation. Methodology and Results of the Tests: After the contract logger had been gone for nearly two hours, an attempt was made to run the logs on April 5. At around 4400 feet, a bridge was found, and the logging attempt to clean the hole was halted [129-135]. Tucker reentered the well on April 6 with the triple combination string and drilled to the driller's depth of 5947 feet. There were no issues with any of the three logging excursions [136-141].

Properties of Reservoir

Reservoir determination relies on accurate information about the characteristics of rocks and fluids. Properties that can be defined or inferred using log measurements include the following. Water, oil, or gas saturation and permeability; lithology; shale volume; resistivity; [142-145]. The resistivity of a material is defined as the resistance it presents to the flow of an electrical current across a length of 1 m and a cross-sectional area of 1 sq m. Marked by the letter R; its SI derived units are the ohm metre [146].

Rock porosity, lithology, and roughness all affect the speed at which sound travels through rock, which is used to create an acoustic log [147]. To assess the rock's properties, the equipment uses a transmitter to send out sound waves and a receiver to record the elapsed time it takes for the waves to return (fig.1).

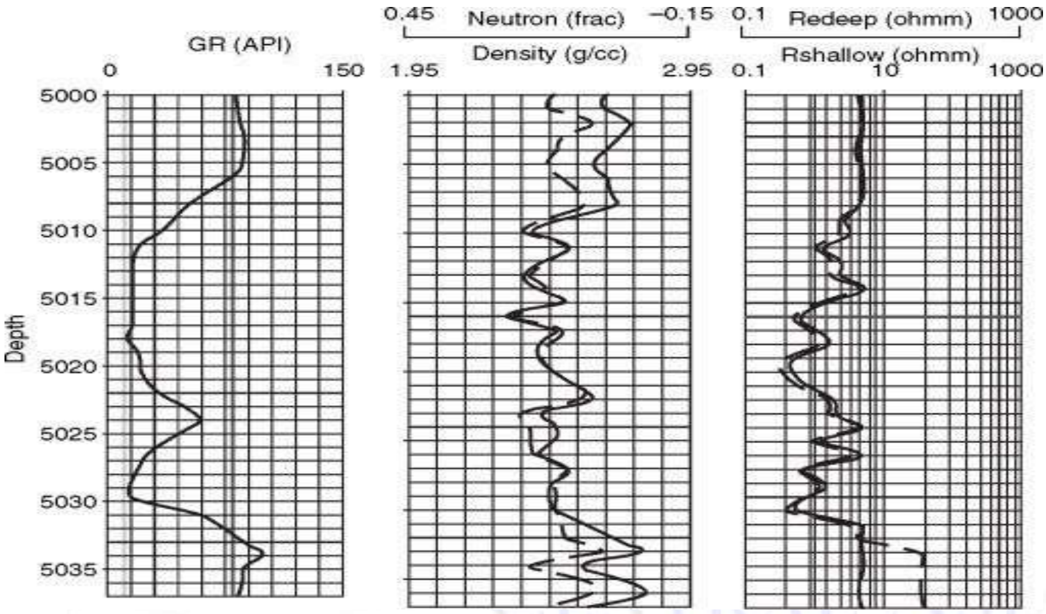


Figure 1: Resistivity Log

The resistivity was the initial formation parameter measured by wireline logging, along with the record depth. Log resistivity readings are a function of rock porosity and fluid conductivity (salinity). It is used to evaluate the fluid permeability of a given formation. A symbol for it is K. It has extremely massive units. Darcy, and the standard unit of measurement is the millidarcy (MD). The pores, capillaries, or fractures in a rock must be interconnected for the rock to be permeable. Therefore, there is a correlation between porosity and permeability on a very rough scale. In general, higher permeability is associated with higher porosity, however this is by no means a hard and fast rule. Although shale and some sands are highly porous, their permeability may be quite low due to the small size of their grains. Limestone is an example of another type of formation that features dense rock that has been shattered by either little fissures or large fractures. A low porosity in such a formation doesn't necessarily mean a low permeability in a crack.

It is quantified as the ratio of fluid volume to total pore volume.

Saturation with water is the amount of formation water present in a given volume of pores. Sw represents saturation.

Saturation with hydrocarbons refers to the extent to which hydrocarbons fill a certain volume of pores. Saturation is represented by the sign Sh.

The percentage of its pore volume that contains oil or gas is its saturation. Some sort of fluid must fill the pores. Therefore, the total of all saturations in a particular formation rock must equal 100%.

$Sh = 1 - Sw$

When attempting to estimate the hydrocarbon saturation of a reservoir, water saturation is the most crucial metric to consider.

Shale with thin layers of clay interbedded with sand that is a few hundredths of an inch thick is called laminar shale (Figure 2.1). Due to its negligible permeability and effective porosity, shale has a significant impact on the overall reservoir rock permeability and porosity.

Shale that has been dispersed typically takes the place of the pore fluid within the sand's pores. This distribution is extremely detrimental to reservoir quality because it suffocates pores and lowers the reservoir unit's effective porosity and permeability.

In the field, wireline logging is performed in a mobile laboratory logging truck. Surface instrumentation is required to provide power to the down-hole instruments, receive and analyse their signals, and to record the log permanently. It carries the down-hole measurement devices, the electrical line, and the winch needed to lower the instruments into the borehole.

Depending on the setting (onshore or offshore) and the specifics of the logging job, logging service providers may employ a wide range of logging units. The following elements will be included in each package:

- Logging cable
- Winch to raise and lower the cable in the well
- Self-contained 120-volt AC generator
- Set of surface control panels
- Set of downhole tools (sondes and cartridges)
- Digital recording system

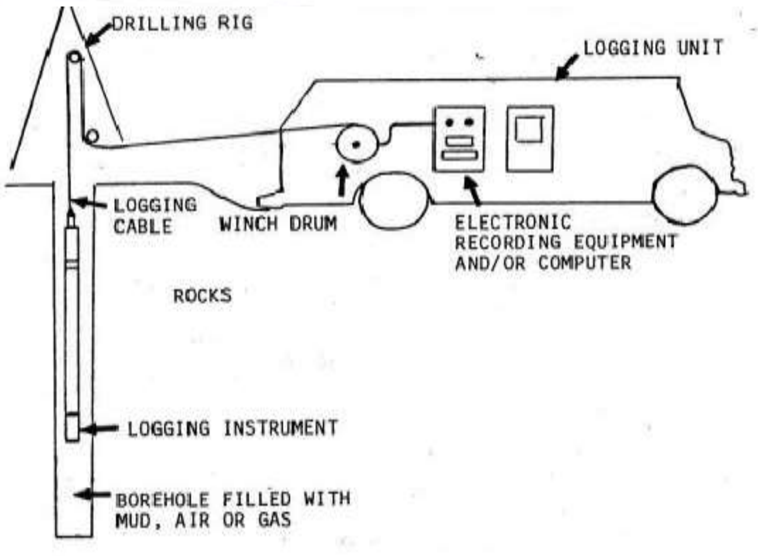


Figure 2: logging Unit

Logging is a wireline process that involves lowering logging equipment as a function of depth to collect data on the physical properties of the various formations encountered in the well (fig.2). The behaviour of the well and reservoir formations can be better understood using these measurements. Finally

- A high-quality log is an unbroken string of readings taken inside a borehole that reflects changes in the physical properties of the rocks being penetrated.

• As can be seen in the illustration, Logs are often presented on the girded paper.
• The record can be captured on film, as still photographs, or digitally.

There are two parts to the instruments used for taking measurements while down the hole. The sonde-shaped sensor is housed in one section. The down-hole tool consists of a cartridge containing the electronics that power the sensors, process and communicate signals to the truck; a cable with either seven insulated copper conductors or six copper conductors and one fibre optic conductor is used to lower and withdraw the tool from the well.

Short normal tool spacing is 16 inches (0.40 m) and long normal tool spacing is 64 inches (L62 m). Zero represents the middle of the A and M electrodes and serves as a point of reference. The current flows between electrodes A and B in a lateral device. Electrodes M and N are used to measure the resulting potential difference (Figure 4). Electrodes with this kind of potential can be found on the sonde. In this case, the inscription is located directly in the middle between electrodes M and N. The AO distance is 18 feet and 8 inches (5.7 m). The current and potential electrodes have been switched in this device compared to a standard device. The larger the gap, the greater the instrument's depth of field. As a result, the lateral device can probe more deeply than the standard device.

Tools that measure localised resistance Conventional electrical logging systems' responses are sensitive to the borehole and surrounding formations. These impacts are reduced to a minimum by a class of resistivity instruments known as "focusing current" instruments.

Laterolog 7, Laterolog 3, deep Latero log, and Dual Latero log device are all deep-reading instruments (DLL). The Dual Induction Laterolog (DIL) tool's Latero log 8 and the Deep Learning Laterolog (DLL) tool's shallow Laterolog are the medium to shallow reading devices, respectively.

Measure the resistivity of the flooded zone (Rxo) and define permeable beds (Pbs) by identifying the presence of mud cake using a micro-resistivity device. The micro log is one such device.

One can utilise a focused micro-resistivity tool to determine the resistivity of the flushed zone (Rxo) and to identify mud cake in order to define the boundaries of permeable beds. Microscopically focussed logging is one such instrument (MSF). The micro later log and proximity tools have been replaced by the pad-mounted spherically focused logging device known as the Micro SFL.

It outperforms the other Echo products in two key ways. The DIL and DLL are just two examples of different logging tools that can be used in conjunction with the first. Since the micro later log measurement is less sensitive to mud cake, this avoids the requirement for a separate logging run. The mud coating has no effect on the proximity logs.

Methods and materials: Choose the electrode spacing and bucking current control to reduce the mud cake effect. Bucking currents, travelling between the electrodes Ao and Al, flow in the mud cake and, to a lesser extent, in the formation. The surveying current runs outward from a central electrode, Ao. Lo, the measuring current, follows a straight line into the formation, "bells" out, and then travels back to a far-off electrode (B). By adjusting the bucking current, the voltage on the display can be brought to zero.

First developed for use in both oil-base mud and air-drilled boreholes, induction logging is a method of determining the formation's resistivity. Multiple coils are used for both transmission and reception in induction tools. Using a sonde with a single coil for both transmission and reception helps illustrate the concept.

A transmitter coil is used to transmit the high-frequency current, and the resulting alternating-current magnetic field induces currents in the geological formation surrounding the borehole. These currents are produced by a transmitter coil and a ground loop. This results in a voltage being induced in the receiver coil by a magnetic field. The ground loop currents are proportional to the formation conductivity because the alternating current in the transmitter coil is both constant in frequency and amplitude.

The conductivity of the formation can be measured by the voltage induced in the receiver coil, which is directly proportional to the ground loop currents. Both the sender and receiver coils are directly coupled to one another. The "bucking" coils can be used to get rid of the signal caused by this coupling. As long as the mud isn't too salty, the formations aren't too resistant, and the borehole diameter isn't too huge, the induction tool works effectively even when the borehole contains conductive mud. The radioactivity of the rocks in the area is measured. The shale composition of sedimentary rocks is reflected in where it settles. Clays and shales, rather than pure rocks, are where radioactive materials are most likely to be found in concentrations. Radioactive elements such as U, Th, and K in the rock can be identified with a gamma ray detector (usually a scintillation detector, with an active length of 8 to 12 inches). Each gamma ray identified by the detector triggers a single electrical pulse. Number of pulses detected per unit of time is the recorded parameter.

Gauge of Density: Medium-energy gamma rays from a radioactive source are used in this method. You could think of these gamma rays as high-velocity particles that crash into the formation's electrons. The term "Compton scattering" is used to describe this sort of interaction.

By measuring the number of Comptonscarrering collisions, we may infer the density of the formation from the scattered gamma rays that reach the detector from a fixed distance from the source. The density of the rock matrix, the density of the fluids, and the density of the formation all affect the real bulk density, p., which in turn affects the electron density. The density tool only goes so far in its research. Less than 8 inches from the borehole wall is where the density tool's signal is strongest. Most of the data collected by the CNL instrument is within a 12-inch radius of the borehole wall. Consequently, light hydrocarbons have less of an impact on the density tool than they do on the CNL instrument.

Information regarding the company, the well, the tools used, the intervals recorded, and the mud records are all examples of what can be found in a Log Header. Stats on Variations The drawing of the logging tool indicates the method that was used to create the log. In need of a toolkit Offsets in sensors (fig.5).

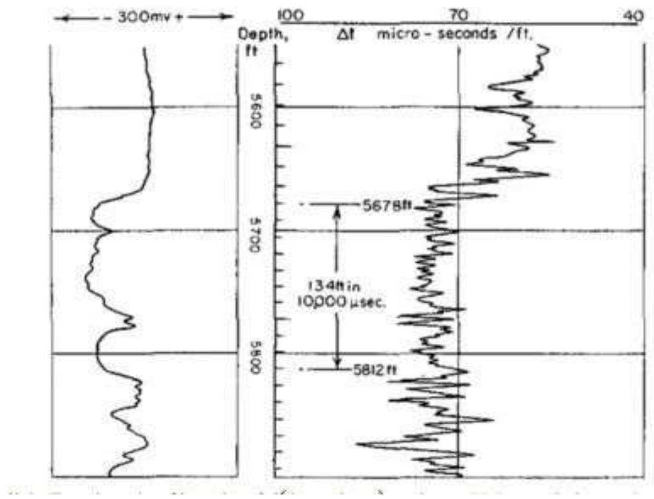


Figure 5: Porosity Resistivity Log

The data included in a Log The main log is a comprehensive record of all necessary data in relation to well depth. The client-defined colour codes and scales are displayed in multiple dimensions (1/500 and 1/200).

A Log Remark contains a caveat and supplementary data to aid with understanding. The data contained in the Log Calibrations document the successful completion of all pre- and post-operational inspections. The reading in the air from the tool wax is accurate. The instrument's most recent reading was well within specifications when it was tested at home base under controlled conditions. A Tech Log tells an engineer whether or not the tool was functioning normally at the time of logging. Hardware health monitoring (voltages, current) The colour green is wonderful. Don't wear red! The last part of a log is called the Tail. A small selection of logs (GR, SP, Neutron, Formation density, Sonic, Focused, Induction, Micro resistivity log, and Caliper) were used for this report.

The logging equipment is sensitive to both pore materials and chemical composition (rock matrix) of the rock. Log analysis benefits most from using a rock categorization based on its chemical composition. Typically, identifying rocks in a well is as simple as looking at the log responses they produce.

Knowledge of additional data linked with logs is helpful in understanding log measurements and the procedures used to gather these data. The log documents everything that takes place before, during, and after a borehole is drilled. Not all of the data in the log header came from the wireline logging tool's measurements. Some of the information measured by the logging team at the surface is often valuable in determining the formation evaluation. Accurate data collection and dissemination is essential.

The water that permeates the porous formation rock is called formation water, connate water, or interstitial water depending on its location. Since resistivity is needed to determine saturation (water and hydrocarbons) from basic logs, it is an essential interpreting characteristic for formation water. Formation water Resistivity data can be obtained from a number of different places. Some examples are lists of known water quantities, the spontaneous potential (SP) curve, and calculations and diagrams of predicted resistivity. The SP-curves recorded in pristine water-bearing rocks make it straightforward to determine the wool value of Rw. A formation's static SP (SSP) value is proportional to the sum of the chemical activity (aw and am) of its water and its mental filtrate. SSP = -log(aw/am) * K

For NaCl solution, K=71 at 77/ (25°C): k varies in direct proportion to temperature:
K=61+0.1337 F K=65=0.24 TC

Need a dilute NaCl solution for scientific experiments. The resistances decrease with increasing activity. This inverse proportionality holds true for low concentrations and most water types, but it breaks down for higher concentrations. So, we utilise Rw and Rmf, whose resistivities are comparable but which are counter-proportional to the activities. Both Rw and Rmf are measures of the equivalent resistivity of formation water and mud filtrate, respectively. For example, SSP = -K log (Rmfe/Rwe). In order to calculate the resistivity ratio (Rmf /Rw), we need to know the formation temperature and the static SP value recorded against a porous, permeable, non-shaly formation. We provide the surface Rmf value. Using the formula presented below, one may get the Rmf value at a given depth.

Temp gradient =(Td-Ts) (100)/depth difference. Where,
Td - Temp in the borehole at bottom depth Ts - Temp at the surface

Surface temperature plus temperature gradient multiplied by a specified depth = ((Ts+6.77)/Temperature at that depth plus 6.77) / 100 Rmf At the surface, *Rmf If we know the SP value at a specific depth on SP chart-1, we can calculate the corresponding Rmfe/Rwe value. The Rmf value at a specific temperature and depth is shown on SP chart-2, and from there the Rmfe value is estimated. The ratio of Rmfe to Rwe will give us the Rwe value. Then, based on the Rwe value depicted on SP chart-2, the matching Kw value is estimated at a specified depth and temperature.

Key to formation: A formation's resistivity is found to be directly related to its brine saturation level, as demonstrated by Archie's experiment. The formation resistivity factor is the proportionality constant (F). In addition, an empirical connection between formation factor and porosity is established as the final step of his experiment.

Method of Resistivity Ratio: Drilling a borehole introduces mud filtrate into the nearby deposit. A low resistivity zone typically exists in close proximity to the borehole in an oil-bearing zone. And a distant one with greater resistance. Therefore, hydrocarbons can be detected by comparing a deep resistivity device to a shallow one. Saturation in water can be expressed as a function of the ratio of these positive curves using Archie's equation.

Porous reservoirs can have their shale volume estimated using the natural gamma ray log. Vshale is the volume of shale as a percentage or decimal fraction.

Calculating the gamma-ray index is the first step needed to determine the volume of shale from the gamma-ray log.

For clean formation:

$\Phi e = \underline{2\ \Phi N + 7\ \Phi D}$

Without any other channels of signal interference, log data processing is a competitive method for detecting wellbore features. The flowchart explains the processes involved in confessing and interpretation. The petroleum reservoir is the geological formation that houses the petroleum pool, and every reservoir is different. Certain metrics must be estimated in order to characterise a server. Porosity, permeability, and saturation are the primary reservoir characterisation characteristics.

**Conclusion**

Since the reservoir describes the formation as being invaded by mud filtrate near the formation wellbore, this may make logging ineffective for gathering information about the formation, as the shale's response to logs will vary depending on the distance from the formation wellbore that the mud occupies. Water resistivity and saturation volume as a function of porosity are demonstrated as a result. In water-bearing and hydrocarbon-bearing formations, effective porosity (eff), shale volume (Vsh), and saturation (Sw) can be determined from sample data taken in the well. In Well Logging Services, the Geoframe software suite is used on workstations to process the same log data sets. The parameter logs indicate the presence of gas oil contacts (GOC), oil water contacts (OWC), and gas shale contacts (GSC) when they are discovered. Logging medium and reservoir depth indicate the presence of oil and gas as well as water contact in the reservoir, as well as the presence or absence of clean sand.

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