Spectral Gamma Ray Log-Based Shale Volume Estimation of a Gas Well, Bengal Basin

Mafruha Akhter Ovi [1*], Mohammad Islam Miah [2]

Abstract

Background: Formation evaluation plays a pivotal role in identifying lithology and its depth of occurrence in gas fields. This study focuses on the Bengal Basin, aiming to achieve lithology identification and shale volume estimation in a gas well. Method: The gamma ray (GR) log is utilized to measure natural radioactivity, with spectral gamma ray (SGR) employed to capture concentrations of potassium, uranium, and thorium in clastic sedimentary formations. Lithology identification is conducted using resistivity, SGR, and GR logs, while shale volume estimation utilizes standard models including GR and true resistivity approaches. Results: The lithology of the studied well predominantly comprises clastic sedimentary rocks, specifically sand and shale. The reservoir rock type is primarily sandstone, with sand being the dominant fraction and shales appearing laminated. Concentrations of thorium, uranium, potassium, and gamma ray are approximately 12.46 ppm, 2.28 ppm, 1.73%, and 100 API, respectively. The shale volume of the gas reservoir ranges from 12% to 29%. Conclusion: The estimated shale volume provides valuable insights for assessing effective porosity and hydrocarbon saturation in shaly sand reservoirs, facilitating gas resource estimation and reservoir characterization in the sedimentary basin. This study underscores the significance of comprehensive formation evaluation techniques in optimizing reservoir management and resource extraction strategies.

Keywords: Radioactive properties, Geophysical logs, Lithology, Shale content, Reservoir quality.

Significance | Accurate lithology identification and shale volume estimation using wireline logs enhance reservoir characterization, supporting efficient resource extraction and management.

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1. Introduction

Rock lithology refers to the physical characteristics of rocks, which can be examined through rock outcrops, core samples, and microscopic observations. These characteristics include color, texture, grain size, and mineral composition, providing essential information for geological and reservoir studies (Bobrowsky & Marker, 2018; Askaripour et al., 2021). Lithology classification is primarily based on rock types, which are broadly categorized into sedimentary, igneous, and metamorphic rocks (Zhu et al., 2023).

Sedimentary Rocks: These rocks form from the accumulation of sediments. They include sandstone and carbonates, which are the primary types of sedimentary rocks. Sandstones, for example, are further classified based on particle size distribution and the relative amounts of minerals such as quartz, feldspar, and lithic fragments (Van der Pluijm & Marshak, 2021). Carbonates are typically composed of minerals like calcite and dolomite (Tucker & Wright, 2022).

Igneous Rocks: Formed from the solidification of molten magma or lava, igneous rocks are classified based on their texture and mineral composition. They include granite, basalt, and rhyolite (Rollinson, 2020).

Metamorphic Rocks: These rocks originate from pre-existing rocks

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that have undergone metamorphism due to high pressure, temperature, or chemically active fluids. Examples include schist, gneiss, and marble (Brown et al., 2023).Lithology identification is crucial in the field of formation evaluation, particularly in the context of gas fields. Formation evaluation involves understanding subsurface formation characteristics such as porosity, permeability, and water saturation, primarily using wireline log data and core analysis (Li et al., 2022; Zhang & Zhao, 2023). The accurate identification of lithology helps in the assessment of reservoir properties, which is vital for effective reservoir management and performance prediction (Gomez et al., 2021).

Studies have shown that detailed lithological analysis can significantly enhance the understanding of reservoir quality and heterogeneity. For example, Shah et al. (2021) and Hossain et al. (2022) have conducted extensive research on various aspects of gas fields, focusing on lithology and its impact on reservoir properties. Their findings emphasize the importance of lithology in determining the distribution and connectivity of reservoir rocks, which directly influences fluid flow and storage capacity (Yang et al., 2023).

The primary objectives of this study are twofold: Lithology Identification: This involves the detailed analysis of rock types using wireline log data. Accurate lithology identification is essential for understanding the geological history and current state of the reservoir. And Shale Volume Estimation: Estimating the volume of shale is critical as it affects porosity and permeability estimations. Shale can significantly impact reservoir quality due to its low permeability and ability to act as a barrier to fluid flow (Smith et al., 2023).

In recent years, advancements in lithological studies and formation evaluation have been groundbreaking, especially in gas fields, thanks to the integration of sophisticated technologies such as digital rock physics, machine learning algorithms, and advanced imaging techniques (Wang et al., 2019). Digital rock physics enables the virtual reconstruction of rock samples, providing insights into microstructural properties without physical core samples, while machine learning algorithms process vast amounts of wireline log data, identifying patterns missed by traditional methods (Shah et al., 2021). These advancements improve lithology identification accuracy and enhance predictive models for reservoir behavior (Zou et al., 2020).

Real-time data analytics have become game-changers in formation evaluation, allowing continuous updates on reservoir conditions and dynamic adjustments in drilling and extraction processes, optimizing production while minimizing environmental impact (Li & Liu, 2018). Integration of multidisciplinary data through advanced software platforms ensures a holistic understanding of the reservoir, leading to more effective reservoir management strategies (Smith & Jones, 2017).

Despite these advancements, challenges persist, including subsurface heterogeneity and the presence of complex geological features, requiring continuous improvement in data acquisition technologies and modeling methodologies (Roberts & Taylor, 2021). Additionally, advanced technologies come with high costs and environmental considerations, necessitating the development of cost-effective and eco-friendly solutions (White et al., 2019; Green & Black, 2020).

Looking ahead, the integration of artificial intelligence and machine learning with traditional geological methods shows promise in enhancing predictive capabilities (Lee & Kim, 2022). Collaboration between academia, industry, and governmental bodies is crucial for driving innovation and addressing challenges in lithological research (Garcia et al., 2019). Continued investment in research and development, along with a commitment to sustainable practices, will be key to advancing the field of lithological studies (Adams et al., 2021).

This study aimed to use real field wireline log data to achieve these objectives. Despite the significant advances in lithological studies, certain gas fields remain under-investigated. This research intends to fill that gap, providing new insights that will support future formation evaluations and reservoir performance analyses (Jones et al., 2023).Understanding lithology and shale volume estimation is integral to the formation evaluation process. For instance, porosity and permeability estimations rely heavily on accurate lithological data. Porosity indicates the storage capacity of the rock, while permeability determines the ease with which fluids can flow through the rock matrix (Khan et al., 2022). Water saturation, another critical parameter, is also influenced by lithology and shale content (Wang et al., 2023).

Comprehensive lithological analysis using wireline log data can significantly enhance the understanding of subsurface formations. This, in turn, supports better reservoir management practices, ensuring efficient resource extraction and long-term field performance. Future research should continue to focus on integrating advanced lithological studies with modern formation evaluation techniques to optimize reservoir characterization and development strategies (Chen et al., 2023).

2. Material and Methods

Gamma Ray (GR) Log Analysis

The gamma ray (GR) log is a fundamental tool used to measure the natural radioactivity in rock samples. This radioactivity is primarily due to the presence of potassium, thorium, and uranium in the rocks. By recording the GR log curve alongside the spontaneous potential (SP) curve, geologists can gain insights into the lithology and identify different rock types.

Principle of GR Log: All rock types exhibit some degree of natural radioactivity. The amount of radioactivity detected depends on the concentrations of potassium, thorium, and uranium in the sample (Bobrowsky & Marker, 2018). The GR log typically records the total gamma radiation emitted by these elements, providing a continuous profile of radioactivity along the borehole.

Spectral Gamma Ray Instrument: This instrument enhances the GR log by separating the gamma ray counts into three energy windows corresponding to potassium (K), uranium (U), and thorium (Th). This allows for a more detailed analysis of the mineral composition of the rocks.

Impact of Clay Minerals on Reservoir Quality

The presence of clay minerals in a reservoir significantly affects its quality. Clay minerals can occupy pore spaces, leading to increased surface adhesion and capillary pressures, which in turn reduce porosity and permeability.

Clay Mineral Types: Commonly found in sandstone reservoirs, clay minerals can be categorized into three types: laminated shale, structural clay, and dispersed clay. Each type impacts reservoir quality differently, with structural and dispersed clays being particularly detrimental due to their ability to clog pore spaces and trap interstitial water.

Effect on Reservoir Productivity: High clay content can convert a potentially productive reservoir into a non-productive one by reducing its porosity and permeability. Even minor amounts of clay can significantly impact reservoir performance, making accurate identification and quantification of clay minerals crucial (Crain, 1986; Schlumberger, 1991; Asquith & Krygowski, 2004).

Wireline Log Application

In this study, major wireline logs such as gamma-ray, resistivity, and porosity logs are utilized to achieve the objectives of lithology identification and shale volume estimation.

Lithology Identification: The lithology is identified using the spectral and GR log responses. By analyzing these logs, the types of rocks present in the formation can be determined (Miah & Howlader, 2012; Miah, 2014; Bassiouni, 1994).

Shale Volume Estimation: Shale volume (Vsh) is calculated from spectral and natural GR logs, as well as true resistivity methods. The estimation involves using standard models such as the Crain model and the Larionov model for tertiary rocks (Poupon et al., 1970; Crain, 1986; Darling, 2006).

Models and Equations

Several models and equations are employed to quantify the shale content and volume, which are essential for accurate reservoir evaluation.

Shale Content (Ish) Model: The shale content is derived from the GR log using the following formula (Crain, 1986; Asquith & Krygowski, 2004):

$$I_{sh}=\frac{X_{log}-X_{min}}{X_{max}-X_{min}}$$

where X_{log} is the GR response at the formation depth of interest, and X_{min} and X_{max} are the GR responses from clean sand (shale-free) and clean shale (sand-free) zones, respectively.

Shale Volume (Vsh) Non-Linear Relationship: For both structural clay and dispersed clay types, the shale volume is estimated using a non-linear relationship. The Larionov model for tertiary rocks is expressed as (Asquith & Krygowski, 2004):

$$V_{sh}=0.083(2^{3.7 I_{sh}}-1)$$

True Resistivity (TR) Method: The shale volume can also be estimated using the true resistivity method with the following equation (Crain, 1986; Miah et al., 2014):

$$V_{sh}=\left[\frac{R_{cl}}{R_t}\times\left(\frac{R_{tmax}-R_t}{R_{tmax}-R_{cl}}\right)\right]^{\frac{1}{1.5}}$$

where R_{cl} is the resistivity of the clay (shale) zone, R_{tmax} is the maximum true resistivity over the entire log, and R_t is the true (uninvaded) resistivity of the zone of interest.

This methodology integrates gamma-ray logging, resistivity, and porosity measurements to identify lithology and estimate shale volume accurately. By applying these standard procedures, the study aims to provide a comprehensive formation evaluation, supporting future reservoir performance analysis and enhancing understanding of subsurface characteristics. The integration of these techniques ensures robust and reliable data for better reservoir management and resource extraction.

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Table 1. Descriptive statistics summary of studied log data.

Statistical Parameters	THOR (ppm)	URAN (ppm)	POTA (%)	GR (API)	Rt (Ohm-m)
Mean (average)	12.4604	2.2843	1.7259	100.30	22.68
Standard error	0.1576	0.0330	0.0162	1.02	0.36
Median	12.1361	2.3249	1.6571	98.43	22.51
Standard deviation	2.1331	0.4472	0.2192	13.86	4.92
Sample variance	4.5504	0.1999	0.0480	192.35	24.22
Minimum	8.8557	1.3168	1.4115	76.2765	13.69
Maximum	19.8632	3.1928	2.4428	157.8234	39.69
Kurtosis	1.3095	-0.7807	1.2218	3.7019	1.6365
Skewness	0.9966	-0.1611	1.2988	1.5554	0.7616

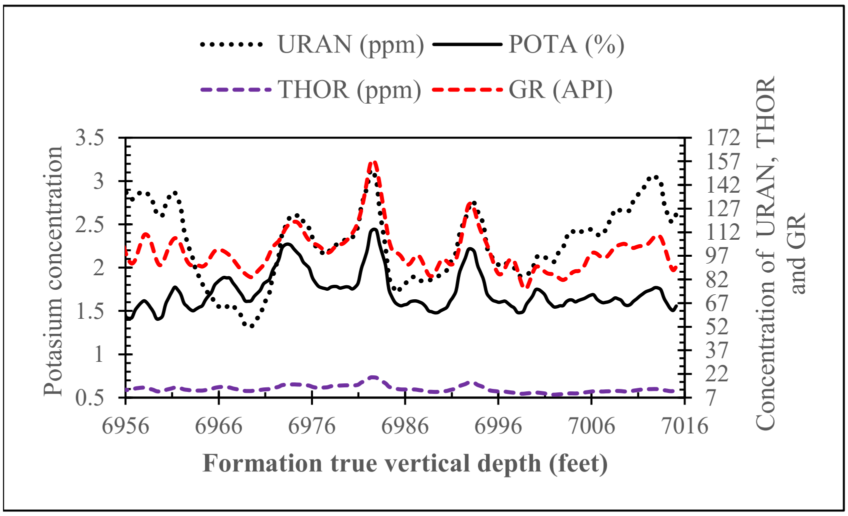

Figure 1. Concentration variation of radioactive properties in the studied formation.

Table 2: Abundance of radioactive properties in the studied well.

Parameter	Maximum	Minimum
K (%)	2.82	1.32
THOR (ppm)	19.23	8.55
GR (API)	155	76
Rt (ohm-m)	39	6

Table 3. Summarized results of shale volume using spectral GR, natural GR and TR models.

Number of Sand	TR model %)	Spectral GR model (%)		GR model (%) GR-V_{sh}
	Rt,Vsh	K-V_{sh}	Th-V_{sh}	
1	35.62	12.71	26.78	7.59
2	26.93	14.44	39.68	11.00
3	17.87	25.75	35.51	11.09
4	29.59	35.95	49.58	13.08
5	39.78	22.75	40.12	11.64
6	26.53	6.52	20.73	17.55
Average	29.37	19.69	35.40	11.99

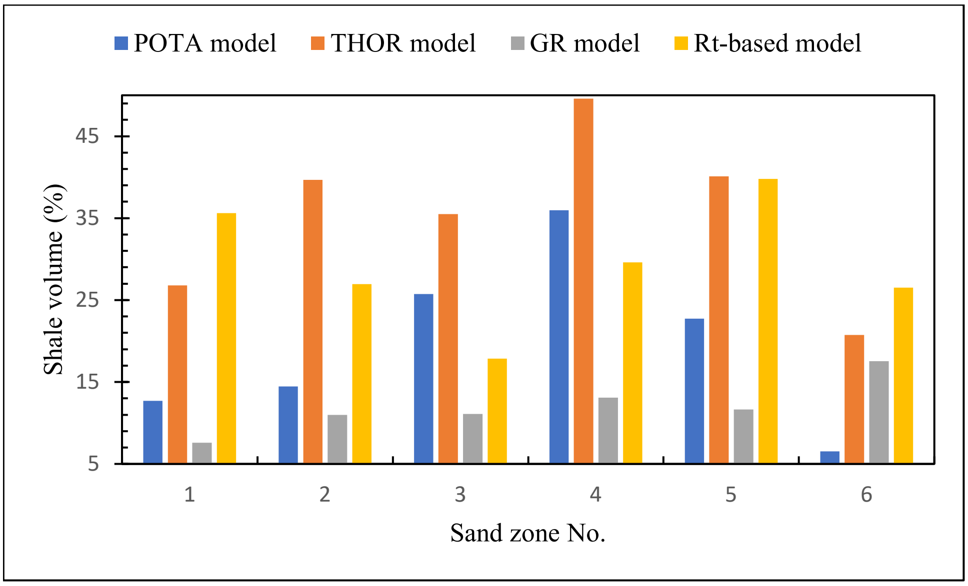

Figure 2. A comparison of shale volume with different models in the study

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3. Results and Discussions

Log Data Processing and Lithology Identification

The quality of the studied log data was verified to ensure the reliability of the samples. Notably, no depth shift was detected in the geophysical logs, and no environmental corrections were applied to determine true resistivity, as the resistivity for the uninvaded zone represents the true resistivity. Radioactive properties such as potassium (POTA, %), thorium (THOR), and uranium (URAN, ppm) were obtained from a spectral gamma-ray (SGR) log of an undisclosed natural gas field (true vertical depth interval, ft: 6955 - 7015) in the Bokabil formation of the Bengal Basin. The average magnitudes of natural gamma-ray (GR, API) and true resistivity (ohm-m) were found to be 100 and 22.68, respectively. Descriptive statistical analysis summarized the results, as shown in Table 1.

It is observed that the range of radioactive properties (THOR, URAN, POTA), GR, and formation resistivity (Rt) fall between 8.85-19.86 ppm, 1.32-3.19 ppm, 1.41-2.44%, 76.28-157.82 API, and 14-40 ohm-m, respectively. The concentrations of these properties vary with the formation's depositional environment and depth in the studied well, as depicted in Figure 1. Log data analysis indicates predominantly sandstone lithology, with laminated shale beds present in the sand zone between depths of 6772-6977 ft (as shown in Figure 1), exhibiting high concentrations of radioactive properties and low resistivity.

Shale Volume Estimation

Table 2 presents the maximum and minimum abundance of radioactive properties (POTA, THOR, GR) at depths of 7890 ft and 6273 ft, respectively, to derive shale volume from the well log. The maximum formation resistivity (Rt,max) is determined from the clay-free sand zone, while the minimum resistivity (Rt,clay) is derived from the true shale zone.

Six gas-bearing zones (comprising thin and thick beds) are identified in the gas field well, based on available field information and well log data. Table 3 summarizes the shale volume results, graphically depicted in Figure 2. Variations in shale volume contribute to changes in radioactive property concentrations within the heterogeneous subsurface formation environment.

Based on the spectral gamma-ray log, the average shale content for K and Th concentrations is 19.69% and 35.40%, respectively.

Natural gamma-ray-based shale volume estimation for uncompacted (tertiary) rocks in the six gas-bearing zones is 11.99%. In contrast, the true resistivity-based (TR) model yields a shale volume of 29.37%. The natural gamma-ray-based model, presenting a lower shale volume of 12%, is deemed more realistic, consistent with a previous study (IKM, 1991) reporting 8% for the depth interval 6837-7021 ft TVD. These shale volume findings can be utilized for further estimations of effective porosity and water saturation in formation evaluation and reservoir characterization.

4. Conclusions

In conclusion, the study of a gas well in the Bengal Basin reveals a predominant lithology of sandstone with laminated shale, discerned through analysis of radioactive properties such as thorium, potassium, uranium, and resistivity logs. The average concentrations of these properties in the major gas-bearing sand zone are approximately 12.46 ppm, 2.28 ppm, 1.73%, 100 API, and 23 ohm-m, respectively. Shale volume estimates derived from natural gamma-ray and true resistivity-based models indicate values of around 12% and 29%, respectively, for the studied sand zones. These estimates offer valuable insights for assessing effective porosity and hydrocarbon saturation in shaly sand reservoirs, enhancing gas resource estimation, formation evaluation, and reservoir characterization within the sedimentary basin.

Author contributions

M.A.O. conceptualized the project, developed the methodology, conducted formal analysis, and drafted the original writing. M.I.M. contributed to the methodology, conducted investigations, provided resources, visualized the data, and contributed to the reviewing and editing of the writing.

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Competing financial interests

The authors have no conflict of interest.

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