Minireview Article

THE APPLICATION OF DEEP LEARNING IN PORE PRESSURE PREDICTION AND RESERVOIR OPTIMIZATION

ABSTRACT

Accurately predicting pore pressure and optimizing reservoirs in the oil and gas industry is crucial for the exploration and production of hydrocarbon reservoirs. While traditional methods can be effective, they often require extensive manual effort and may not fully utilize available data. However, deep learning has emerged as a highly promising solution to revolutionize these processes through complex pattern recognition, feature extraction, and predictive modelling. Despite a lack of recorded information in wells, deep learning can significantly reduce uncertainty in pore pressure prediction when information is insufficient. Moreover, with the emergence of high-performance computing facilities, deep neural networks have become increasingly popular. Accurate pore pressure estimation is essential for the safe drilling of wells and determining safe mud window input. Additionally, deep learning techniques can predict potential equipment failures and monitor equipment health, thus minimizing downtime and increasing operational efficiency. The oil and gas industry can significantly improve accuracy, efficiency, and decision-making processes by applying deep learning to pore pressure prediction and reservoir optimization. With better-informed choices, reduced uncertainties, and optimized hydrocarbon recovery from subsurface reservoirs, geoscientists and reservoir engineers can make confident decisions that positively impact the industry. Understanding pore pressure is a vital component of reservoir engineering and utilizing deep learning technology has the potential to enhance reservoir efficiency and lifespan. To achieve this, it is recommended that new deep learning models be combined with other technologies like Geomechanics, Seismic inversion, and seismic images to improve the accuracy of predictions.

keywords: Pore pressure, Reservoir characterization, Deep learning, pore pressure prediction

1. INTRODUCTION

Pore pressure plays a crucial role in various drilling and exploration procedures, such as designing wells, analysing well stability, and creating mud programs. It is an essential parameter to consider [1], [2], [3], [4], [5], [6]. Accurately determining pore pressure is crucial for selectively producing and injecting fluids, as well as mapping hydrocarbon migration paths and preventing drilling mud loss during drilling [5], [7], [8], [9]. The pore pressure, also called the formation pressure, is the pressure of the fluids inside the formation pore, resulting from the hydraulic potential [5], [10]. In a drilling operation, pore pressure is regarded as a safe pressure only if the hydrostatic pressure of the drilling fluid in the wellbore falls between the formation pressure and formation fracture pressure [5], [11], [12]. Pore pressure which is the pressure exerted by fluids in the pores of a reservoir, normally hydrostatic pressure exerted by the column of water from the depth of the formation to sea level is a major issue faced by drillers in the exploration sector.

The popularity of deep learning techniques that use deep neural networks has grown alongside the availability of high-performance computing facilities [13]. Deep learning has the advantage of greater power and flexibility in dealing with unstructured data. This is thanks to its ability to process a vast number of features [13]. The process of deep learning involves passing data through multiple layers of an algorithm. Each layer progressively extracts features and sends them to the next layer. The initial layers extract low-level features, while the successive layers combine them to create a comprehensive representation [13]. In the early days of Artificial Neural networks (ANN), the first generation used perceptions in neural layers for computations. However, this approach had its limitations. The second generation improved upon this by calculating the error rate and backpropagating the error. Later, the restricted Boltzmann machine was developed, which overcame the limitations of backpropagation and made learning easier. Over time, other networks evolved as well [14], [15], [13]. The performance of classifiers using deep learning improves on a large scale with an increased quantity of data when compared to traditional learning methods. The artificial neural networks (ANNs) model is used to estimate the oil flow rate as a function of the following parameters: choke upstream pressure, choke size, and the producing gas-to-oil ratio [16]. [16]) stated that most oil and gas companies use reservoir simulation software to predict future oil and gas production and devise optimum field development plans [7], [17], [18], [19], [20], [21], [22]. However, this process costs an immense number of resources and is time-consuming [23]. Deep Learning is a class of machine learning which performs much better on unstructured data. In the context of a liquid-liquid flow, topics such as Well Production Enhancement Prediction, Fault Prediction, Bottom-Hole Pressure Prediction, and Reservoir Characterization are closely related to the pressure gradient [24]. These are all determined using deep learning techniques [16].

2.0 METHODS USED FOR PORE PRESSURE PREDICTION AND RESERVOIR OPTIMIZATION

Various methods are utilized to optimize reservoirs and predict pore pressure. The first to make pore pressure predictions from shale properties derived from well-log data, such as acoustic travel time/velocity and resistivity, were identified in [25]. They analyzed acoustic travel time in Miocene and Oligocene shales in Upper Texas and Southern Louisiana Gulf Coast and found that porosity decreases as a function of depth. This trend represents the "normal compaction trend" as a function of burial depth, and fluid pressure exhibited within this normal trend is hydrostatic. If there are intervals of abnormal compaction, the resulting data points diverge from the normal compaction trend. [19], [22] also use similar methods for reservoir optimization. They contended that porosity or transit time in shale is abnormally high relative to its depth if the fluid pressure is abnormally high. And later analyzed the data presented by [25], [6 proposed an equation that can be written in the following form to edict pore pressure: $\sigma f - \frac{(\alpha r - \beta)(Ai - BiIn\,\Delta t)^3}{Z^2}$

αV is the normal overburden stress αV is expressed in psi; σ where pf is the formation fluid pressure (psi); t is the sonic transit-gradient (psi/ft); β is the normal fluid pressure gradient (psi/ft); Z is the depth (ft); time (μs/ft); A and B are the constants, A1 = 82776 and B1 =15695.
Later, many empirical equations for pore pressure prediction were presented based on resistivity, sonic transit time (interval velocity), and other well-logging data. The following sections only introduce some commonly used methods of pore pressure prediction based on the shale properties.

2.1 PREDICTING PORE PRESSURE BASED ON RESISTIVITY

The resistivity method developed by Eaton can be used to predict pore pressure in young sedimentary basins, provided that the normal shale resistivity is accurately determined [27]. There are two approaches to determining normal shale resistivity: assuming it to be constant [28] or accurately determining the normal compaction trendline. Additionally, effective stresses can be calculated from measured pore pressure data and analysed with corresponding sonic interval velocities from well logging data in the Gulf of Mexico slope [29]. The Miller sonic method describes a relationship between velocity and effective stress, which can be used to relate sonic/seismic transit time to formation pore pressure. The input parameter "maximum velocity depth," d_{max}, determines whether unloading has occurred or not [30]. According to a case study on the LAGIA-8 well in Sinai, Egypt, the deep resistivity log was used and plotted on a semi-log. By applying Eaton's resistivity equation and assuming n to be 0.6 through iteration, the most matching curve was achieved, allowing for the prediction of pore pressure from the resistivity log [31]. The actual pore pressure gradient was calculated and plotted accordingly.

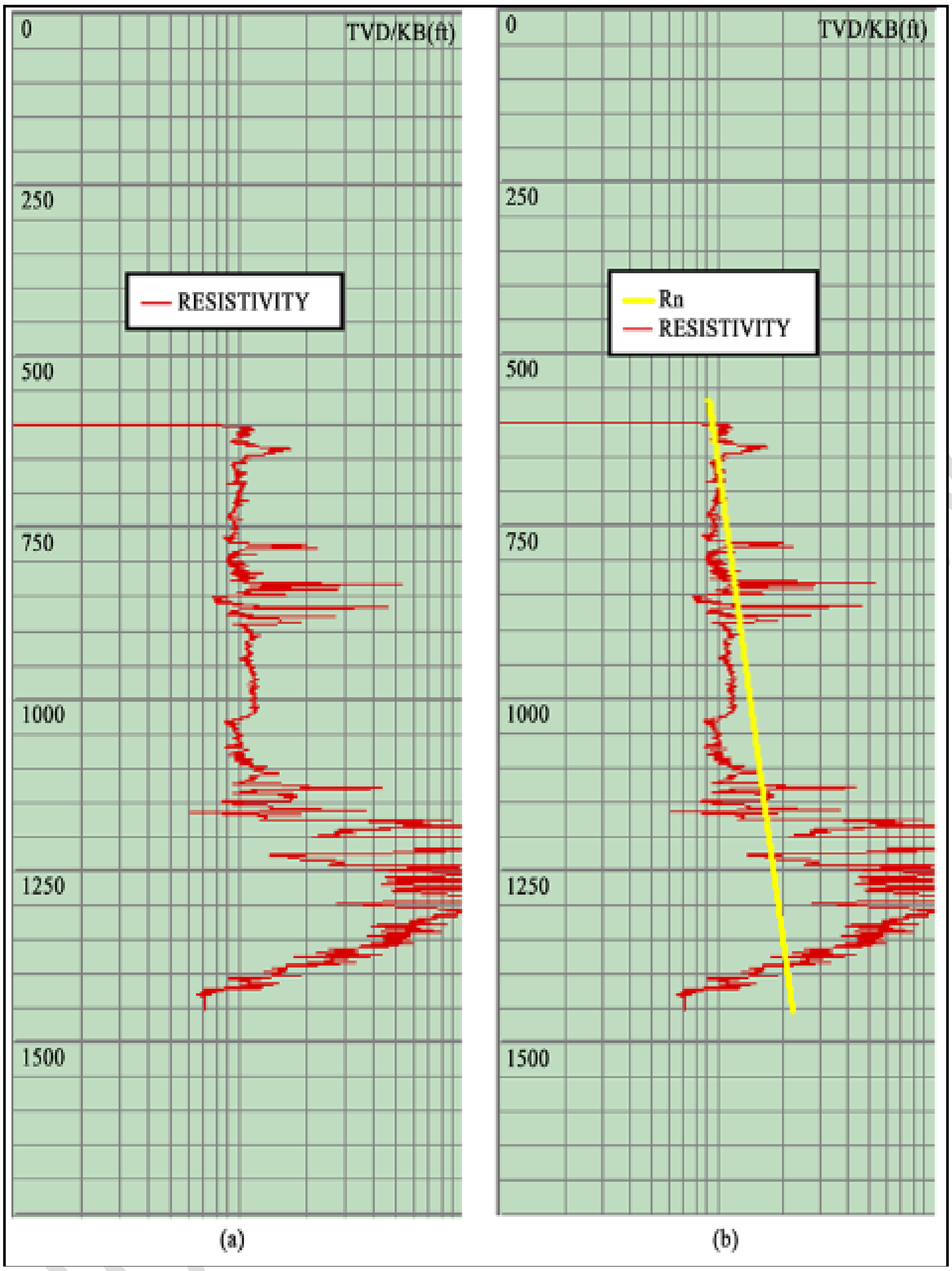

Fig 1: (a) Resistivity of a case study; (b) Normal resistivity of the same case study, in which the red curve, represents the resistivity versus depth, while the yellow straight line represents the normal resistivity, and it best fits the shallow depth to represent the normal pore pressure [31].

2.2 CALCULATING PORE PRESSURE USING SONIC TRANSIT TIME MODEL.

In this case study, we examine a deep-water oil field in the Gulf of Mexico with a water depth of 3850 feet. The formations consist of Tertiary shales and sandstones, and the target zone is in the Middle Miocene sandstones. To calculate the pore pressure gradient, we use a proposed sonic equation with tm = 70 μs/ft, Png = 8.75 ppg, and c = 0.00028. The resulting pore pressure gradient is tml = 200 μs/ft, which we estimate using Bowers' method with tml = 200 μs/ft, Png = 8.75 ppg, A = 14, and B = 0.745. Our proposed sonic method proves to be more accurate than other sonic methods, particularly in the shallow section where overestimation often occurs. This method utilizes a normal compaction trendline, allowing for better pore pressure prediction at both shallow and deep depths.
When dealing with formations like aquifers, hydrocarbon-bearing sandstone, and limestone that are hydraulically connected and permeable, it is possible to calculate the pore pressure at a specific depth by comparing the fluid column difference at another depth where stress is known, as mentioned in [28]. However, shale formations present a challenge as they have over-pressured pore pressures in

deep regions and may not be hydraulically connected. Fluid flow theory cannot be used to determine pore pressures in shale due to compaction disequilibrium, as noted in [28]. Instead, shale petrophysical data or well logs can be utilized to estimate shale pore pressure. [31] recommends using Eaton's resistivity and sonic methods to handle regular compaction trend lines, which makes it easier to estimate pore pressure.

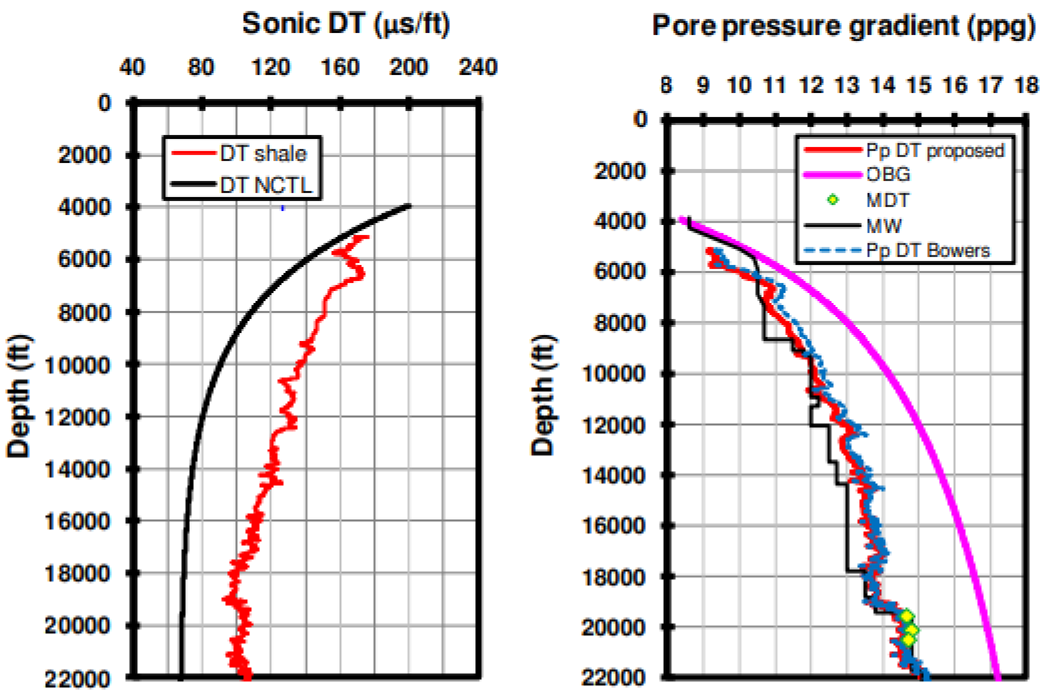

Fig 2: Pore pressure calculations from the sonic transit time method proposed by Oer's method. The left tack presents the transit time of shales obtained from the sonic log and the normal compaction trend line of transit time calculated from Eq $\Delta t_n = \Delta t_m(\Delta t_{ml} - \Delta t_m)_e^{-cz}$. e right track plots the overburden stress gradient, mud weight used while drilling, measured pore pressure from MDT, and pore pressure profile calculated from the transit time by Bower's method [28].

2.3 PREDICTING PORE PRESSURE USING LOGS

The pioneers in predicting pore pressure from shale properties obtained through well-log data were authors 25 and 28. They utilized acoustic travel time/velocity and resistivity to make their predictions. [26] presented an equation that can be expressed as follows for pore pressure prediction:

$$p_f = \sigma_v - \frac{(\alpha_v - \beta)(A_1 - B_1 \ln \Delta t)^3}{Z^2}$$

where:
P_f is the formation of fluid pressure, psi,

α_v is the normal overburden stress gradient (psi/ft),

β is the normal fluid pressure gradient (psi/ft),
A and B are the constants, A_1 = 82.776 and B_1 = 15.695,

σ_v is expressed in psi,
Z is depth (ft),
Dt is the sonic transit time (m_s/ft).

3.1 APPLICATION OF DEEP LEARNING ON PORE PRESSURE PREDICTION AND RESERVOIR OPTIMIZATION

The oil and gas industry has benefited greatly from the potential of deep learning in a range of applications, including pore pressure prediction and reservoir optimization. These applications involve various tasks, such as predicting pore pressure from seismic data, characterizing reservoirs, and classifying facies, predicting reservoir properties, detecting, and mapping faults, ensuring quality control of well log data, matching history, and forecasting production, optimizing reservoirs, and placing wells, and quantifying uncertainty [1], [2], [6], [36]. Convolutional Neural Networks (CNNs) are a type of deep learning model that can be trained on vast datasets of seismic attributes and well log data, enabling them to identify intricate patterns that are associated with pore pressure trends [1], [2], [6], [36]. Without the need for well data, these models can predict pore pressure in regions, thereby aiding in risk assessment during drilling operations. Deep learning algorithms, specifically CNNs and RNNs, can be applied to seismic and well log data to characterize reservoirs and equally identify data inconsistencies and errors in well logs. By flagging questionable data points automatically, the quality and reliability of the dataset used for analysis and modelling can be improved. They can also automatically classify different facies and lithologies, helping geoscientists better understand the subsurface reservoir properties. Additionally, they can predict various reservoir properties, such as porosity, permeability, and fluid saturation, from well log and core data. These predictions enable more accurate reservoir modelling and optimize hydrocarbon recovery strategies. Furthermore, deep learning techniques can detect faults and fractures in the subsurface using seismic and well data [1], [2]. For reservoir structure understanding and improved drilling efficiency, accurate fault mapping is crucial. To match historical production data, deep learning models can perform history matching. This ensures that reservoir simulations can forecast future production reliably and optimize well placement and production schedules. Deep learning can aid in maximizing hydrocarbon recovery while minimizing operational costs and risks by optimizing well placement, production rates, and injection strategies. This optimization process considers complex interactions between various reservoir parameters and production constraints. To quantify uncertainties in pore pressure predictions and reservoir characterization, deep learning-based techniques like Bayesian deep learning can be used. This information is essential for risk assessment and decision-making in exploration and production activities. To monitor equipment health and predict potential failures in drilling and production equipment, deep learning can be applied. By predicting maintenance needs, downtime can be minimized, resulting in cost savings, and increased operational efficiency [6], [36].

3.2 IMPORTANCE OF PORE PRESSURE PREDICTION AND RESERVOIR CHARACTERISTICS TO OIL AND GAS INDUSTRIES.

The ability to predict pore pressure is crucial for ensuring the safety and success of oil and gas operations [6], [33]. This involves creating numerical formulas that simulate the subsurface pressure profile. Accurate predictions of pore pressure enable safe drilling practices while optimizing reservoirs can enhance recovery rates, production efficiency, and economic viability. However, it is important to establish the geological groundwork for these equations to avoid misleading results. The build-up of subsurface pore pressure is mainly caused by stress and compartmentalized lithology in an aqueous environment. Stress and fluid expansion alone cannot trigger the build-up of pore pressure ramps, which can result in a pressure surge with hard kicks that sometimes exceed 3000 psi (20.691 MPa) [33].

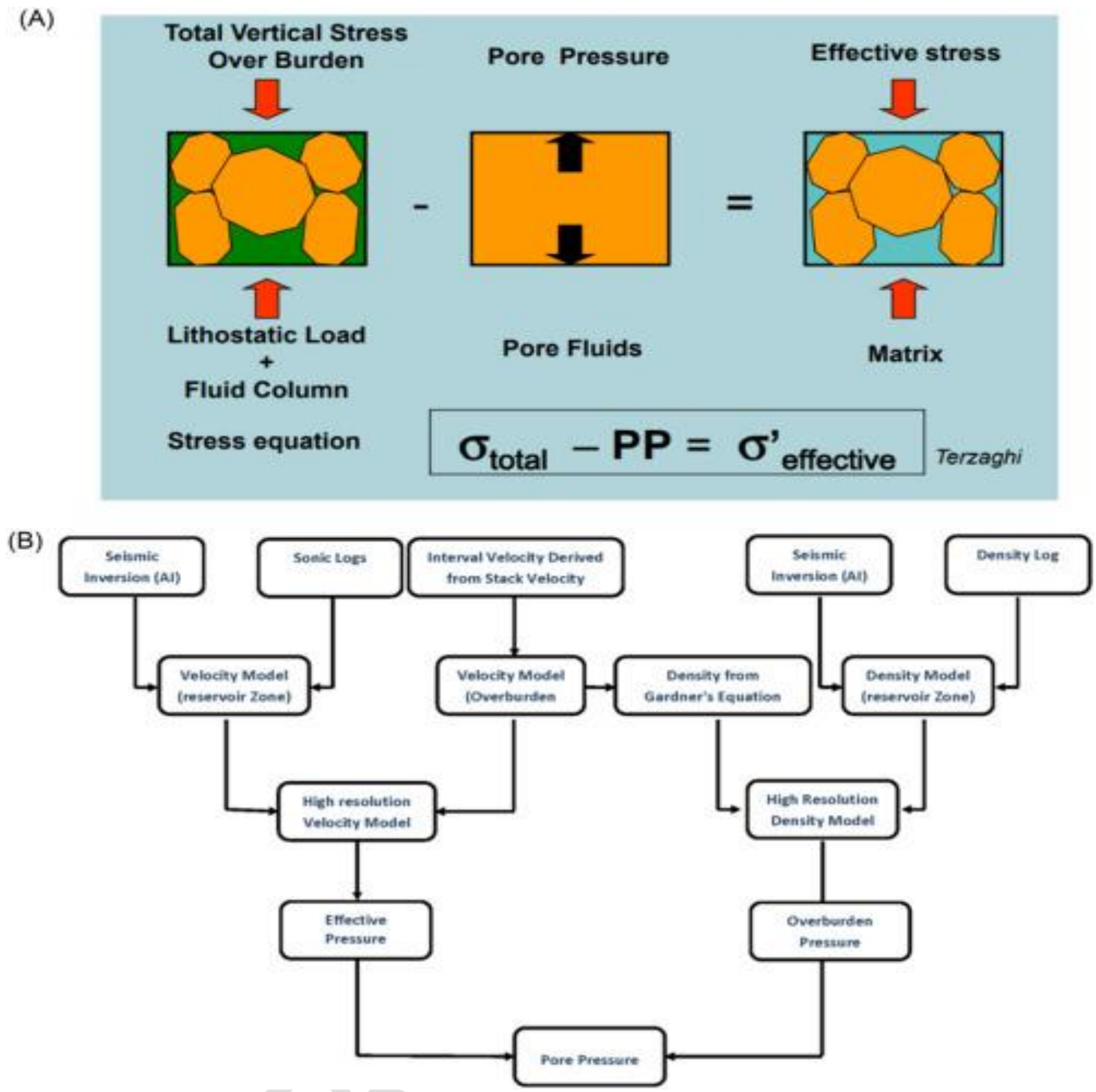

Fig. 3. (A) and (B) pore pressure prediction workflow. Adapted from [33].

4.1 LIMITATIONS OF THE METHODS AND HOW DEEP LEARNING CAN ADDRESS SOME OF THESE LIMITATIONS.

Predicting pore pressure is extremely important in drilling operations to prevent wellbore instability, formation damage, and blowouts. However, the methods currently used to predict pore pressure have limitations that can affect the accuracy of the predictions. These limitations include a lack of sufficient data, complex geological structures, non-linear relationships between pore pressure and geological parameters, and uncertainty.

Deep learning algorithms can address some of these limitations and improve the accuracy of pore pressure predictions. These algorithms can automatically learn complex relationships between input data and output pore pressure, making them suitable for modelling non-linear relationships. They can also handle large and complex data sets, as well as work with incomplete or noisy data, which makes it possible to use data that may be insufficient for traditional methods. Additionally, deep learning can also quantify and propagate uncertainty in pore pressure predictions.

Recent studies have shown promising results using deep learning for pore pressure prediction. For example, research conducted by [6] and [34] used a deep neural network to predict pore pressure in offshore fields, achieving better performance than traditional regression methods. Similarly, [35] utilized a convolutional neural network to predict pore pressure from seismic data, resulting in high accuracy.

4.2 RECENT RESEARCH ON THE USE OF DEEP LEARNING FOR PORE PRESSURE PREDICTION AND RESERVOIR OPTIMIZATION

Several studies have explored the potential of deep learning techniques in the oil and gas industry. One such study, published in the Journal of Petroleum Science and Engineering [36], proposed a method that combined convolutional neural networks (CNNs) and long short-term memory (LSTM) networks to accurately predict pore pressure in shale formations. This method outperformed traditional machine learning methods and showed promising results in improving pore pressure prediction accuracy and reliability.

Another study, published in the Journal of Natural Gas Science and Engineering [37], used a deep belief network (DBN) to optimize the performance of shale gas reservoirs by learning the complex relationships between various reservoir parameters and production performance. The results demonstrated that this deep learning-based method can effectively optimize reservoir production and improve the overall recovery factor.

A third study, published in the Journal of Petroleum Science and Engineering [38], proposed a deep autoencoder method to accurately predict porosity and provide insights into reservoir characterization. This method, which extracted features from well-log data, demonstrated accurate porosity prediction and showed potential for improving reservoir characterization.

In the context of pore pressure prediction, several studies have compared the performance of deep learning models to traditional methods. For example, a study published in the Journal of Natural Gas Science and Engineering [39] evaluated the performance of deep learning models and traditional methods for predicting pore pressure and fracture pressure in unconventional reservoirs. The results showed that the deep learning models achieved higher accuracy than the traditional models.

Similarly, a study published in the Journal of Natural Gas Science and Engineering [40] evaluated the performance of deep learning models and traditional methods for predicting pore pressure in tight sandstone reservoirs. The results showed that the deep learning models outperformed traditional models in terms of accuracy and robustness.

Overall, these studies suggest that deep learning techniques have the potential to significantly improve pore pressure prediction, reservoir optimization, and reservoir characterization in the oil and gas industry.

4.3 CHALLENGES AND FUTURE DIRECTIONS

Accurately predicting pore pressure is crucial for safe and efficient oil and gas drilling operations. This helps prevent unexpected and dangerous incidents like blowouts. Traditional methods of pore pressure prediction rely on geological and geophysical data, such as seismic data and well logs. Unfortunately, these techniques have limitations, especially in unconventional formations and areas with insufficient data. However, deep learning techniques have shown promise in various research fields and could potentially solve some of these limitations by being applied to pore pressure prediction.

4.4 RESEARCH GAPS

Even with recent advancements in predicting pore pressure, there are still areas that require further research. One major gap is the accuracy of prediction models for unconventional formations, specifically shale formations. These formations have unique characteristics, like high heterogeneity and anisotropy, that traditional methods may not account for [20]. Therefore, it is essential to develop new and precise approaches to forecast pore pressure in unconventional formations.

Another research gap is the lack of reliable data in developing countries, which is crucial for traditional pore pressure prediction methods. Geological and geophysical data, like well logs and seismic data, are often limited in some regions. In such cases, traditional methods may not be applicable, and new techniques must be created to forecast pore pressure in areas with minimal data.

4.5 DEVELOPMENT OF DEEP LEARNING TECHNIQUES

There are some research gaps that deep learning techniques have the potential to address. By using large amounts of data to train complex neural networks, these techniques can improve prediction accuracy and speed. Additionally, deep learning can help identify patterns and relationships in data that traditional methods may miss, leading to more accurate predictions.

One potential area for future research is the development of deep learning models that can accurately predict pore pressure in unconventional formations, particularly in shale formations. Accurately predicting pore pressure in these formations is challenging due to their unique properties, but deep learning techniques could provide a solution.
Another possible area for future research is the development of deep learning models that can predict pore pressure in regions with limited data. By utilizing existing data and knowledge, these models could help fill the gaps in regions where traditional methods may not be applicable due to a lack of reliable data.

4.6 INTEGRATION WITH OTHER TECHNOLOGIES

To enhance the accuracy of predictions, it is crucial to integrate existing deep-learning models with other technologies like geomechanics, seismic inversion, and seismic imaging. This integration can incorporate more data and information, ultimately leading to better results [41].

5.0 CONCLUSION

Reservoir engineering heavily relies on pore pressure, and deep learning has shown the potential in enhancing reservoir efficiency and longevity. However, deep learning accuracy is still limited and may not always match ground truth examples due to factors such as the availability of precise datasets and image resolution, which can increase costs. Nevertheless, further research on deep learning could overcome these limitations and boost reservoir optimization accuracy. Such research could revolutionize the oil and gas industry, as the advancement of artificial intelligence could streamline the industry's challenges by making processes smarter and more efficient.

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