Asian Journal of Geological Research

Volume 6, Issue 3, Page 160-171, 2023; Article no.AJOGER.104716

The Application of Deep Learning in Pore Pressure Prediction and Reservoir Optimization: A Brief Review

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Authors' contributions

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

Article Information

Open Peer Review History:
This journal follows the Advanced Open Peer Review policy. Identity of the Reviewers, Editor(s) and additional Reviewers, peer review comments, different versions of the manuscript, comments of the editors, etc are available here: https://www.sdiarticle5.com/review-history/104716

Mini-review Article

Received: 12/06/2023
Accepted: 16/08/2023
Published: 08/09/2023

ABSTRACT

Accurately predicting pore pressure and optimizing reservoirs in the oil and gas industry is crucial for the exploration and production of hydrocarbon reservoirs. Traditional geophysical methods of pore pressure prediction and reservoir optimization require extensive manual effort and may not fully utilize available data. However, in order to surmount these constraints, deep learning has revolutionized these procedures by engaging in intricate pattern recognition, feature extraction, and predictive modelling. Deep learning models such as Artificial neural network, convolution neural network, Pore-net, FCN, DeepLab V3 +, LSTM, and BP can capture complex patterns those traditional methods might miss. Despite a lack of recorded information in wells, deep learning has significantly reduce uncertainty in pore pressure prediction when information is insufficient. In pore pressure prediction and reservoir optimization, deep learning models can analyse a vast amount of seismic, well log, and geological data to accurately predict pore pressure distribution in subsurface formations and can assist in making informed decisions about production strategies. This helps maximize hydrocarbon recovery, minimize operational costs, and extend the productive life of the

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reservoir, 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. Despite ongoing obstacles such as scarcity of data in developing countries and the complexity of predicting unconventional formations, it is indisputable that utilizing deep learning offers significant advantages. Further research and integration of deep learning with other technologies is recommended in order to facilitate the creation of more efficient approaches for predicting pore pressure and optimizing reservoirs.

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 [1-6]. 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 [5,7-9]. 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, specifically, 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.

Traditional methods have been widely used in the oil and gas industry for pore pressure prediction and reservoir optimization. They often involve a combination of empirical relationships, physics-based models, and engineering analysis to enhance the understanding and management of subsurface reservoirs.

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 [7,17-22]. 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. TRADITIONAL GEOPHYSICAL METHODS OF PORE PRESSURE PREDICTION AND RESERVOIR OPTIMIZATION

In the realm of oil and gas exploration and production, accurate pore pressure prediction and effective reservoir optimization have long stood as essential pillars for successful and sustainable operations. The challenges of navigating subsurface formations and maximizing hydrocarbon recovery have spurred the development and application of traditional methods that harness geological, geophysical, and engineering insights. Various traditional geophysical methods such as empirical methods, geomechanical models, equivalent depth methods, material balance analysis, decline curve analysis, waterflood performance analysis, reservoir simulation, and economic analysis are utilized to optimize reservoirs and predict pore pressure [3,4,12]. 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]. [19] and [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]. The pioneers in predicting pore pressure from shale properties obtained through well-log data were authors [25-28]. 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:

$$p_f = s_v - \frac{(a_v - ß)(A_1 - B_1 \ln\Delta t)^3}{Z^2}$$

where:

P_f is the formation of fluid pressure, psi,
a_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),

$\ln\Delta t$ is the sonic transit time (m_s/ft).

There are many traditional geophysical methods of pore pressure prediction as noted by [29]. 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 [28]. 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 [30]. 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 [32], [39]. 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 sonic transit time model utilizes a normal compaction trendline, allowing for better pore pressure prediction at both shallow and

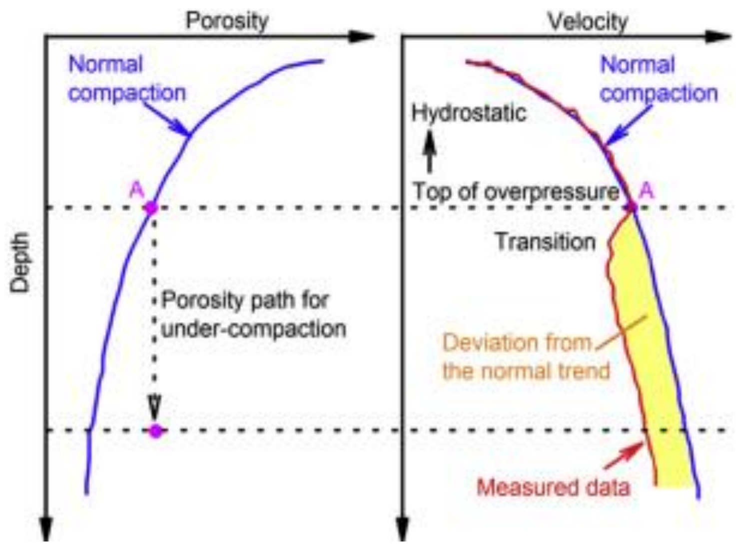

Fig. 1. Schematic for pore pressure prediction based on normal compaction trend using traditional geophysical method [29]

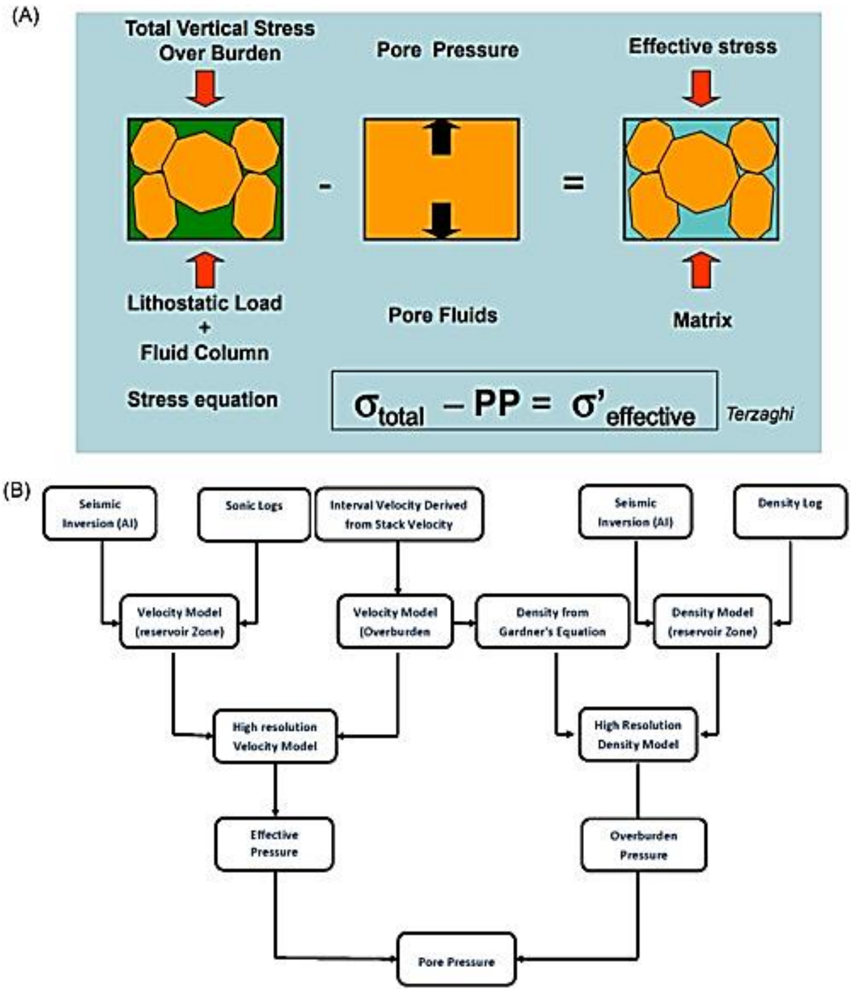

Fig. 2. (A) and (B) pore pressure prediction workflow. Adapted from [31]

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. However, traditional geophysical models often involve complex computations and require manual tuning to achieve optimal training results, consuming a considerable amount of time.

3. DEEP LEARNING MODELS AND PROCESSES USED FOR PORE PRESSURE PREDICTION AND RESERVOIR OPTIMIZATION

Deep learning models use seismic, well-log, and geological data to predict subsurface pressure [38]. The process includes data collection, pre-processing, feature extraction, model selection, training, validation, testing, inference, and fine-tuning. Various deep learning network models are used for pore pressure prediction and reservoir optimization, such as Artificial neural network, convolution neural network, Pore-net, FCN and DeepLab V3 +, LSTM, and BP. [32] proposed a deep learning method for porosity prediction based on a deep bidirectional recurrent neural network. [33] stated that a deep learning algorithm is proposed to accelerate NVT flash 16 calculations with capillary pressure for phase behaviour modelling in nanopores. [33] added that to generate training and testing data for the proposed neural network model, two thermodynamically stable mole and volume evolution equations are established to calculate equilibrium phase compositions. [34] used shale gas well production data to establish a database for training recurrent neural network models. The LSTM model showed accurate production prediction and high conformity with actual shale gas production. It achieved accurate production prediction for neighbouring wells and demonstrated high conformity with actual shale gas production. [35] applied both backpropagation neural network (BP) and LSTM deep learning networks to intelligently predict formation porosity pressure. The test results indicated that the LSTM neural network model had superior predictive performance. [36] stated that during the training process of a neural network, a loss function is typically used to measure the model's ability to fit the training data. The deep learning semantic image segmentation method is suitable for pore recognition of shale SEM images. The fully convolutional neural network model is used to train the manually labelled shale SEM images, and a shale pore recognition model that can automatically identify the pore structure in these images is obtained. [33] stated that Optimization of the network structure and deep learning techniques are needed to accelerate the loss convergence to improve the training efficiency and estimation reliability.

4. PREDICTING PORE PRESSURE USING DEEP LEARNING

Predicting pore pressure using deep learning involves training neural network on large datasets of geological and geophysical information. These networks learn complex relationships between various input parameters and pore pressure values, enabling them to make accurate predictions in real time or during drilling operations. The first step in predicting subsurface pore pressure using deep learning involves collecting a diverse dataset that includes seismic data, well logs, and geological information [33], [34], [36]. This data is then pre-processed to ensure consistency, remove noise, and standardize formats. Deep learning models

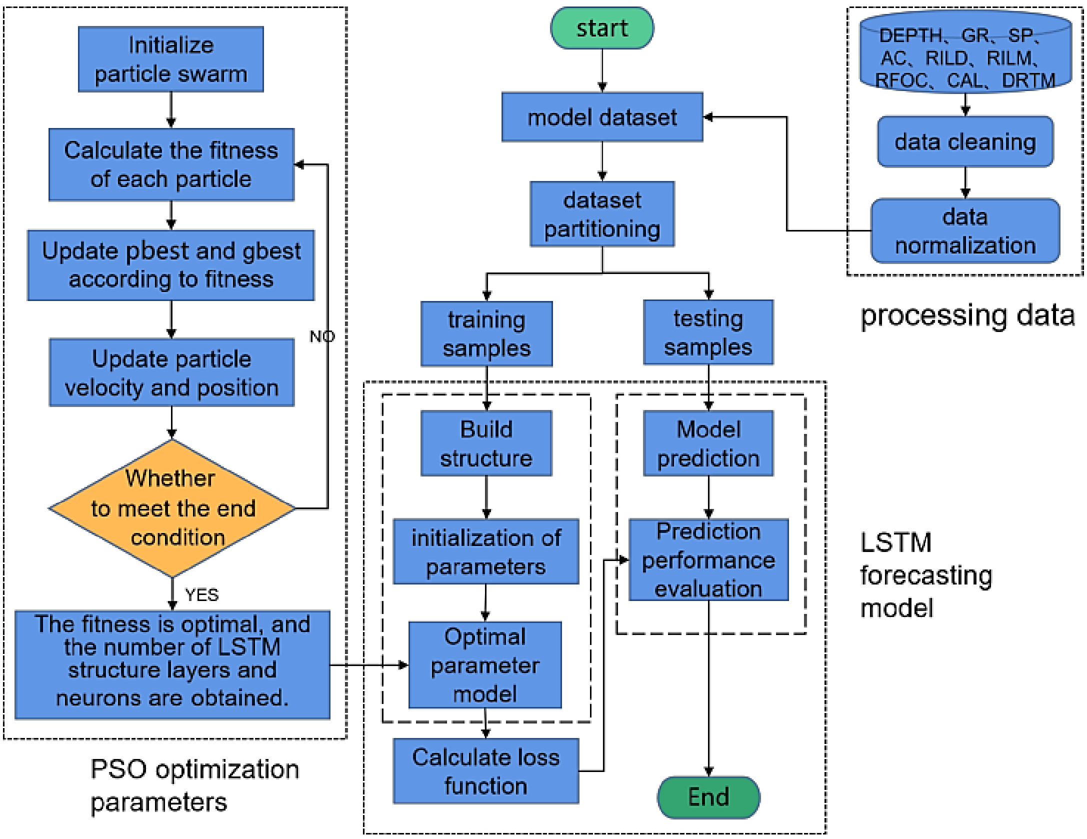

Fig. 3. Block diagram of the PSO-LSTM network implementation process [36]

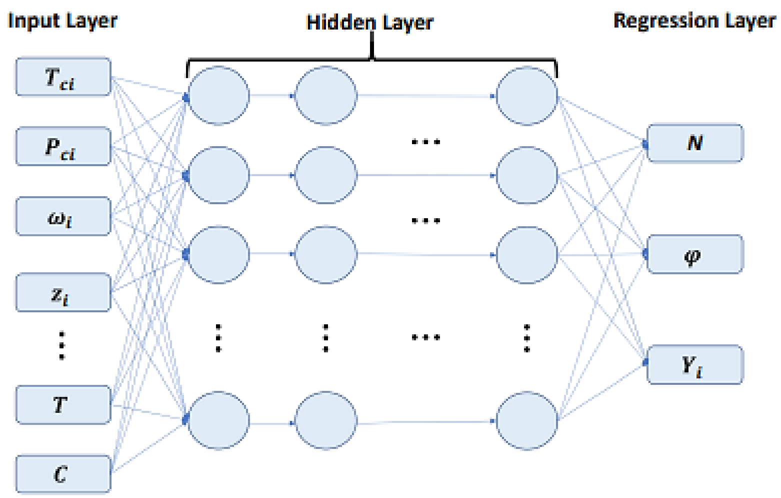

Fig. 4. Schematic diagram of the optimized fully connected deep neural network [33]

Table 1. Training data set and training times using Deep neural network application [37]

Training datasets	Number of pseudo-logs	Δ P × ΔS_w × ΔS_g Realizations per Pseudo-Log	Total number of samples	Average training times (minutes)
1	300	1130	339,000	~17
2	300	475	142,500	~7
3	12,944	7	30,608	~4
4	12,944	100	1,294,400	~60

require relevant features to identify patterns and various deep learning architectures can be chosen based on the nature of the data. The chosen model is trained using labelled data, where input seismic, well log, and geological data are paired with corresponding pore pressure values. The trained model is validated using data it has not seen before to ensure it generalizes well and is ready for testing on unseen data. [37] added that deep neural networks (DNNs) trained exclusively using synthetic data can provide good solutions to the problem of inverting time-lapse seismic data to the simultaneous changes in pressure, water saturation and gas saturation. In the upstream oil and gas industry, LSTM is widely used in production forecasting. Deep learning often requires large datasets to be effective. These datasets typically consist of wide range of geophysical, geological and reservoir engineering data, core samples, production history and more. By training on diverse and comprehensive datasets, deep learning models can learn intricate patterns and contribute to accurate predictions and optimized reservoir management strategies.

5. APPLICATION OF DEEP LEARNING IN 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, placing wells, and quantifying uncertainty [1], [2], [6], [42]. 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], [42], [42]. Without the need for good 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], [42], [47].

6. IMPORTANCE OF PORE PRESSURE PREDICTION AND RESERVOIR CHARACTERIZATION TO OIL AND GAS INDUSTRIES

Characterization of reservoir fluid saturation and pressure distribution is a very difficult task. The ability to predict pore pressure is crucial for ensuring the safety and success of oil and gas operations [6], [31]. Pore pressure is crucial in oil and gas industries to prevent wellbore instability, formation damage, and blowouts during drilling operation. Accurate predictions of pore pressure enable safe drilling practices while optimizing reservoirs can enhance recovery rates, production efficiency, economic viability, and extend the life of the reservoir, leading to improved profitability for oil and gas industries. [30] stated that an accurate pore pressure prediction can help us to reduce drilling risk or hazard, increase wellbore stability, optimize casing seat selection and for mud program design.

7. LIMITATIONS OF THE TRADITIONAL GEOPHYSICAL METHODS AND HOW DEEP LEARNING CAN ADDRESS SOME OF THESE LIMITATIONS.

Traditional methods rely on well-established techniques like seismic survey and well log analysis for pore pressure prediction and reservoir optimization and these methods involves empirical relationship and physical models. 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 [37], [38], [40].

Deep learning methods leverage complex neural network to analyse vast dataset and identify patterns that might be challenging for traditional geophysical methods to detect. They have potential to provide more accurate and robust predictions by learning from diverse data source. Deep learning algorithms can address some of these limitations and improve the accuracy of pore pressure predictions [38]. 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 [33], [37], [38]. 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 [40] used a deep neural network to predict pore pressure in offshore fields, achieving better performance than traditional regression methods. Similarly, [41] utilized a convolutional neural network to predict pore pressure from seismic data, resulting in high accuracy.

8. 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 of such study published in the Journal of Petroleum Science and Engineering [42], 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 [43], 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 [44], 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 [45] 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 [46] 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.

9. 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 [35], [36], [37], [38], [42], [43], [44], [46]. Traditional methods of pore pressure prediction rely on geological and geophysical data, such as seismic data and well logs [24], [28], [29], [39]. 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.

10. 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.

11. 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. Deep learning techniques can help fill research gaps, improve prediction accuracy, and speed, and identify patterns and relationships in data. Future research can focus on developing accurate deep-learning models for predicting pore pressure in unconventional and data-limited regions

12. INTEGRATION WITH OTHER TECHNOLOGIES

To improve prediction accuracy, deep-learning models must be integrated with other technologies to incorporate more data and information resulting in better results [47].

13. CONCLUSION

Reservoir engineering heavily depends on pore pressure. Deep learning can enhance reservoir efficiency and longevity, but accuracy is limited and may not always match ground truth examples due to imprecise datasets and image resolution, which increases costs. However, further research on deep learning could overcome these limitations and improve reservoir optimization accuracy. Such research could revolutionize the oil and gas industry by making processes more efficient.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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