Review Article

Reservoir Geomechanics: A Data-Driven Approach

Abstract

Reservoir geomechanics is a crucial aspect of optimising and developing oil and gas activities, especially in maximising production. Recent technological advancements have revolutionised reservoir geomechanics studies, including integrating data-driven approaches. This review examines and integrates machine learning, data science, and data twin in reservoir studies. The primary aim is to identify the benefits, limitations, significant advancements, potential challenges, opportunities, and research gaps of data-driven approaches to reservoir geomechanics. Additionally, this study aims to create opportunities for further research to address these challenges. The review identifies cost-effectiveness, improved reservoir characterisation, and reduced operational risks as the benefits of integrating data-driven approaches in reservoir geomechanics. However, the review also highlights the significant challenges of data-driven approaches, such as insufficient datasets, limited interpretability, and limited transferability of models. By shedding light on these issues, this review provides a foundation for future research toward finding solutions to these challenges.

Keywords: Reservoir: Geomechanics; Machine Learning; Data Science; Digital Twin

1.0 Introduction

A better estimation of the reservoir rock elastic and failure properties is instrumental to minimizing wellbore instability problems (Pwavodi et al. 2023; Oguadinma et al. 2014), avoiding differential sticking, improving hole cleaning, improving casing placement, improving hydraulic fracturing operations, minimizing subsidence, and many more. Carrying out mechanical rock tests such as triaxial compression, uniaxial compression, scratch, and impulse hammer is an accurate way to determine these properties. These tests are usually carried out on the downhole samples retrieved from some depth of interest.

However, without core samples and well-log data (Oguadinma et al. 2021; Nwaezeapu et al. 2018), analytical and empirical models determine rock's mechanical properties. In the last two decades, predicting the mechanical rock properties using AI tools were thoroughly investigated.

Production of hydrocarbons leads to changes in reservoir pore pressure, resulting in changes in the stress acting on the reservoir and surrounding rocks (Nwaezeapu et al. 2018; Oguadinma et al. 2016). The increasing stress acting on the rock framework may also lead to the compaction of the reservoir. It may result in problems such as surface subsidence, casing deformation, reactivation of faults, or bedding-parallel slip.

Reservoir geomechanics plays a vital role in optimizing and developing any oil and gas activities, especially those related to maximizing oil/gas production (Oguadinma et al. 2017; Oguadinma et al. 2023). It is well understood that the applications of reservoir geomechanics are entirely relevant to reservoir subduction, reservoir compaction, water flooding management, permeability/porosity reduction, hydraulic fracture, fault reactivation, sand control, and wellbore instability (Denney, 2001; Ibekwe et al. 2023).

The alteration in reservoir rock mechanical properties and the state of stresses during the production should be considered since they affect reservoir performance to deliver hydrocarbon. Therefore, stresses and strain balance are required to mitigate the reservoir properties alteration by sustaining an equilibrium between the extracted hydrocarbons and the amount of the fluid being injected concerning the state of the stresses and the mechanical properties of the reservoir rocks.

2.0 Data-Driven approaches (Digital Twin, Machine Learning, and Data analytics)

The hydrocarbon industry is increasingly aiming to leverage the power of data to improve performance, increase efficiency, and lower costs. It makes the idea of a new generation of digital instruments more advantageous, particularly in the mature and brown fields or developed manufacturing fields. Digitalization has aided the hydrocarbon industry in integrating and automating all its manoeuvres like exploration, drilling, production, and more.

Digital Twin is an advanced 3D model that can be utilised to aid the design phase of an asset. Digital Twin is a combination of cloud computing, machine learning techniques, and high computing power which has made the concept of integrating all data a viable reality. Digital Twin is computer software that takes real-world data about a physical entity or system as inputs and gives outputs. Data is required for analytics, prediction, and automation in a Digital Twin. The data must be of excellent quality, confirmed, and referenced to make a usable twin. To operate in real-time, the Digital Twin needs existing data and models to be up to date with the current asset status and changes.

Machine learning (ML) is a subset of AI that provides statistical tools to explore and analyse big data. Machine learning comprises subsets such as supervised, unsupervised, and reinforced learning (Figure 1). Supervised learning is the data learning technique applied when some past or labelled data is available for future forecasting by function approximation. The unsupervised learning technique is the machine learning technique when the pastlabelledd data is unavailable and is usually used for clustering purposes. Reinforced learning combines supervised and unsupervised learning techniques in which some parts of the data are labelled, and others are not.

3.0 Recent advances and evolution of data-driven approaches in reservoir geomechanics

Due to the high degree of variability in natural materials and the physical environment in which they are located, rock mechanical behaviour always exhibits a high degree of nonlinearity. Therefore, in practice, experience, knowledge, and numerical modelling methods have been important tools for understanding rock mass behaviour and predicting its response to its environment and changes in situ stress conditions (Morgenroth et al., 2019; Aniwetalu, et al, 2018), hence, crucial in reservoir stress studies (Figure 2).

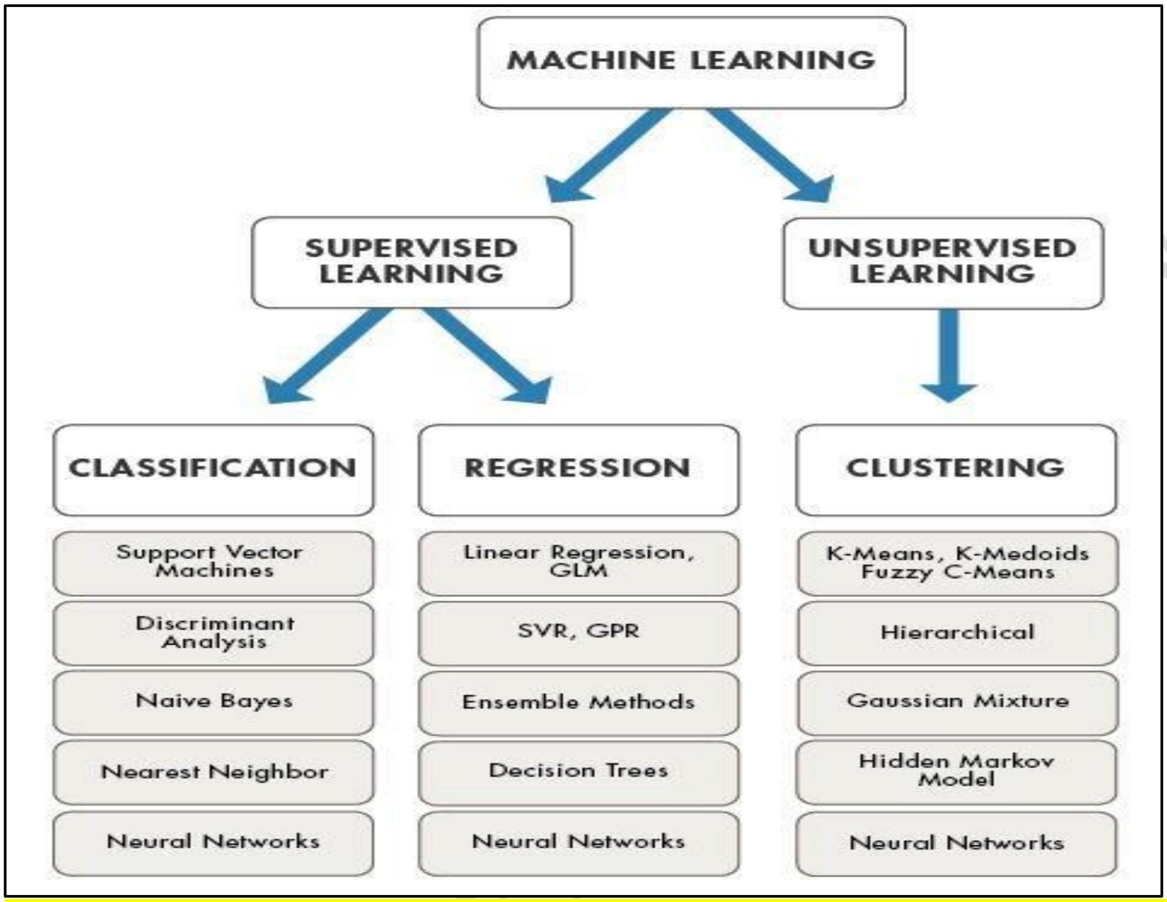

Figure 1: A comprehensive classification of Machine Learning showing statistical frameworks (Diksha & Neeraj, 2017).

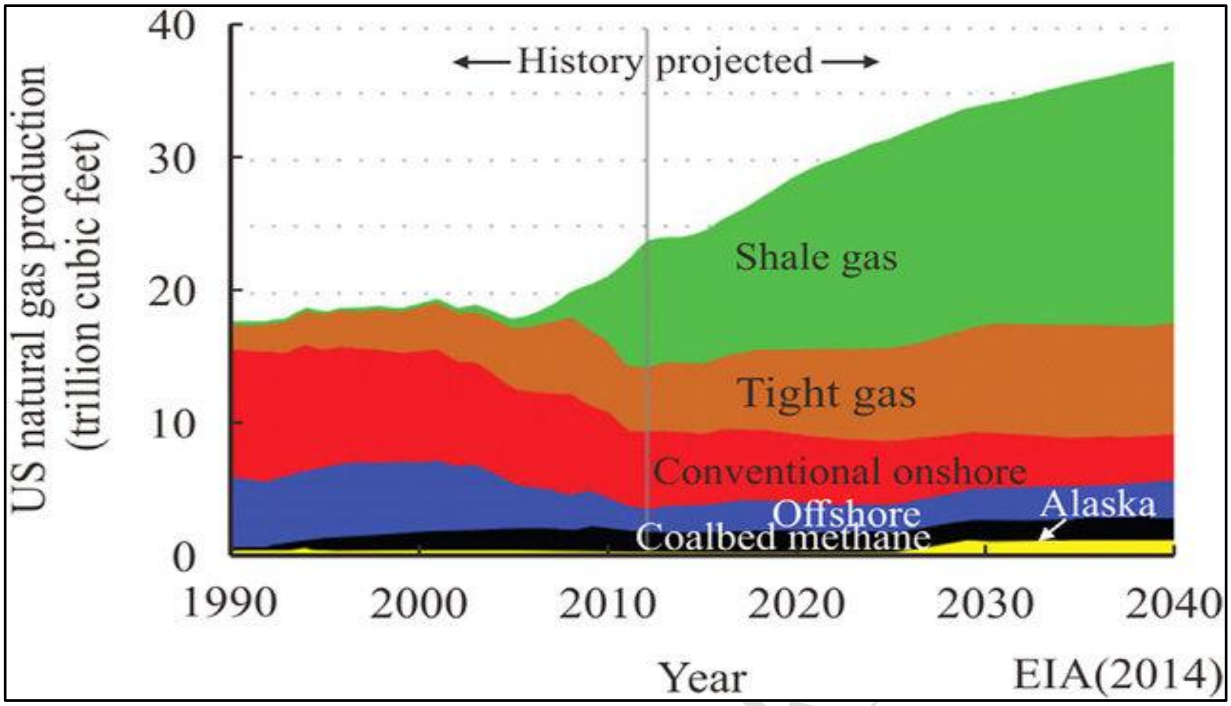

Figure 2: Recent progress and future advancement of artificial intelligence in reservoir geomechanical studies (Fahad et al, 2022).

But from previous applications, we can know that it is often difficult to integrate all the data collected into empirical and numerical models effectively. Furthermore, frequent extrapolation and interpolation techniques are likely to distort the data. Since the 1990s, scholars have noticed the advantages of new computer science research methods applied to the simulation of rock mechanical behaviour.

By integrating machine learning into rock mechanics, we could obtain more meaningful conclusions from data that are collected relatively inexpensively (Zhou & Wu, 1994). As a result, we use computers to find patterns in data, not "manipulate" data.

4.0 The benefits of reservoir geomechanics

Reservoir geomechanics is *a* discipline that combines geology, geophysics, and engineering to study the mechanical behavior of subsurface rock formations that contain hydrocarbons. It is an interdisciplinary field that studies the mechanical behavior of rocks in the subsurface, including their deformation, failure, and fluid flow properties. Integrating geomechanics into reservoir engineering and management has proven beneficial in several ways, including improved reservoir characterization, enhanced reservoir performance, and reduced operational risks.

1. **Improved reservoir characterization:** Geomechanical models can provide valuable information about the mechanical properties of reservoir rocks, including their strength, stiffness, and stress state. This information can help better understand the reservoir's geology and architecture and the potential for deformation and failure during production. A study by Zoback and Gorelick (2012) demonstrated the importance of geomechanical

modeling in improving reservoir characterization and reducing uncertainty in geologic models. Also, Khatibi & Aghajanpour (2020), employed to predict Shear velocity, compressional velocity, and vertical stress relationship of offshore gas fields of which the predicted drilling events matched quite well with the observed drilling reports fromt the Machine Learning algorithm (Figure 3 & 4).

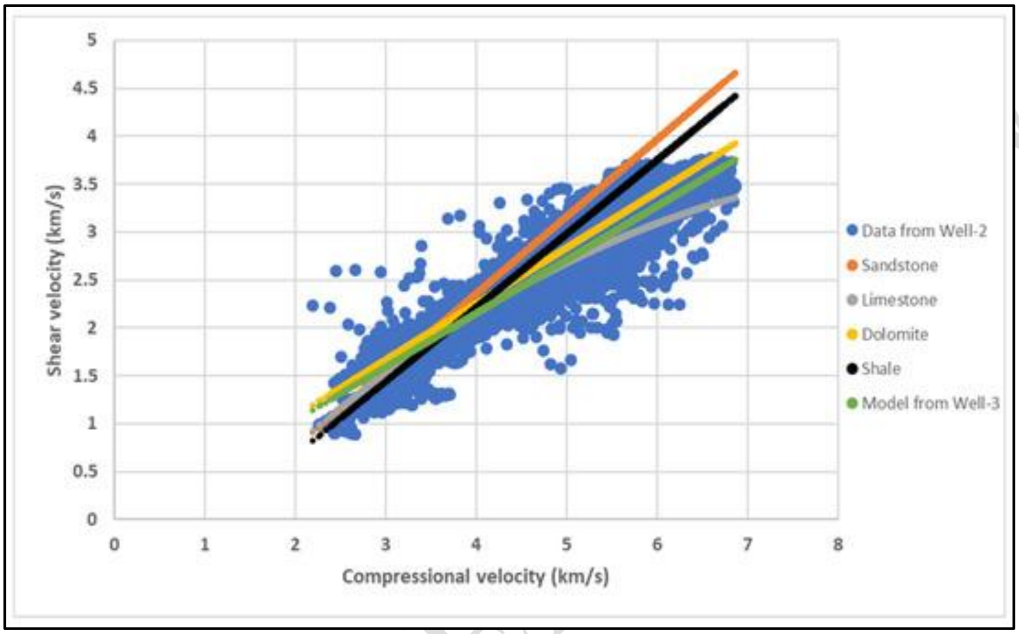

Figure 3: Machine learning employed to predict shear and compressional velocoities of gas reservoir (Khatibi & Aghajanpour, 2020).

2. **Enhanced reservoir performance:** Geomechanics can also help optimize reservoir performance by providing insight into the effects of fluid injection, production, and other operations on the subsurface. For example, geomechanical models can predict the formation of fractures, shear velocity and faults, and other deformation features that can enhance or impede fluid flow. Several studies have shown that incorporating geomechanics into reservoir simulation can lead to more accurate predictions of reservoir behavior and improved production rates (e.g., Rahman et al., 2017; Wang et al., 2020; Khatibi & Aghajanpour, 2020).

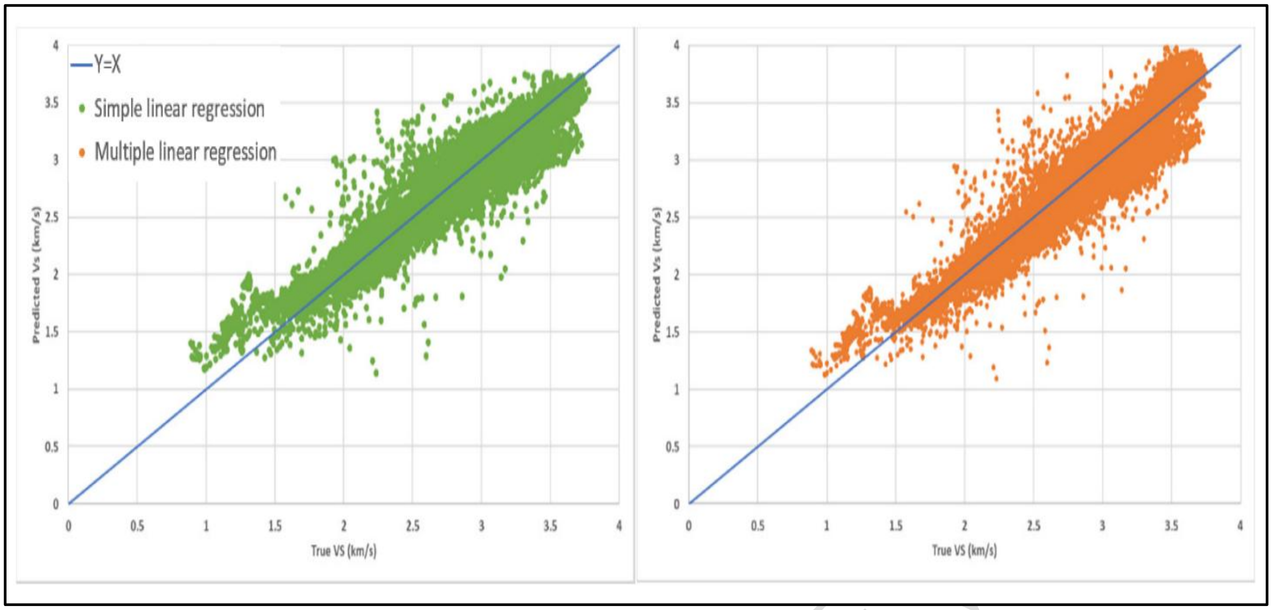

Figure 4: Predicted vs. True shear velocity for Well-2 using (**left**) Simple linear and (**right**) multiple linear regression methods from Well-3. (Khatibi & Aghajanpour, 2020)

3. **Reduced operational risks:** Drilling, completion, and production risks can also be assessed using geomechanical models. For example, they can help identify potential drilling hazards, such as lost circulation, wellbore instability, and casing collapse. Geomechanical analyses can also help optimize hydraulic fracturing operations by predicting the extent and orientation of fractures and minimizing the risk of induced seismicity. For example, a study by Maxwell et al. (2015) showed that geomechanical modeling could optimize hydraulic fracturing and reduce the risk of micro-seismic events.

Reservoir geomechanics has several benefits for reservoir engineering and management, including improved reservoir characterization, enhanced reservoir performance, and reduced operational risks. These benefits are supported by a growing body of research and case studies demonstrating the importance of geomechanics in modern reservoir management.

5.0 Benefits of data-driven approach in reservoir geomechanics

Research on reservoir geomechanics has been revolutionized by machine learning, data analytics, and digital twin technologies in recent years. As a result, data-driven approaches have become increasingly crucial in reservoir geomechanics due to their ability to provide more accurate and reliable predictions of subsurface behaviour. Some of the benefits of data-driven approaches in reservoir geomechanics include the following:

1. **Improved prediction accuracy**: Data-driven approaches can incorporate vast amounts of data from various sources, including geological, geophysical, and reservoir

engineering data. This enables more accurate predictions of reservoir behavior and helps mitigate the uncertainties associated with reservoir characterization.

2. **Enhanced reservoir management**: Data-driven approaches can optimize reservoir management strategies by predicting future reservoir behavior based on current and historical data. For example, predictive models can identify the most productive well locations and the best strategies for managing water and gas injection (Zhang et al., 2019).

3. **Improved well design and completion:** Data-driven approaches can help engineers design and complete wells more effectively by predicting the behavior of reservoir rocks under different conditions. For example, machine learning algorithms can predict the mechanical properties of rock formations and identify the most effective completion methods (Song et al., 2019).

4. **Increased efficiency and cost savings**: Data-driven approaches can help reduce the time and cost associated with reservoir management by providing more accurate and timely information. For example, predictive models can optimize production schedules and reduce the frequency of well interventions (Wang et al., 2020).

6.0 Limitations of using data-driven approaches in reservoir geomechanics modeling

Several technologies, such as machine learning, data analytics, and digital twins, are being adopted in reservoir geomechanics to analyze and predict subsurface reservoir behavior. However, their use is subject to several limitations.

1. **Lack of high-quality data**: Machine learning and analytics require high-quality and reliable data to generate accurate predictions. However, the data available in reservoir geomechanics often need to be completed, noisy and uncertain. Therefore, in order to avoid inaccurate predictions, it is essential to preprocess the data before analyzing it (Acar & Unler, 2020).

2. **Computational complexity:** Digital twin models can be computationally expensive, and the simulation time can be extended. This limits the applicability of digital twin models to real-time monitoring of reservoir geomechanics (Guo et al., 2021).

3. **Limited Interpretation:** Machine learning and data analytics tools can use large datasets to identify patterns and make predictions. However, they do not explain why a particular outcome was reached. This may limit the ability to interpret results and make informed decisions.

4. **Dependence on Historical Data:** Machine learning algorithms rely heavily on historical data for training models. This may limit their effectiveness in predicting events that have yet to occur or in analyzing new reservoirs.

5. **Black box nature**: Machine learning models can be challenging to interpret and explain, leading to a lack of transparency in decision-making. This can create trust issues among stakeholders (Koehrsen, 2018).

6. **Limited applicability to new scenarios:** Machine learning models are trained on historical data, and their performance can deteriorate when applied to new scenarios. Therefore, it is necessary to retrain the models regularly to ensure their accuracy in new situations (Wang et al., 2020).

7.0 Challenges of data-driven approaches in reservoir geomechanics studies

Data-driven approaches, including machine learning, data analysis, and digital twin, have become increasingly popular in reservoir geomechanics studies. The late popularity of these approaches is due to their ability to analyze and interpret large datasets generated from subsurface measurements and simulations (Tariq et al., 2021; Tariq et al., 2017a, b; Anifowose, 2012). Also, Sun and Zhang (2020) agree that the use of modeling and simulation techniques for subsurface porous media can aid in decision-making for managing oil and gas reservoirs.

While utilizing these approaches, several challenges have been encountered. Some of these challenges have been overcome through the advancement of research and technological capabilities. Nonetheless, certain challenges are being managed, while others, such as the effects of bias, remain unaddressed (Tariq et al., 2021).

This review aims to consolidate the challenges of data-driven approaches in reservoir mechanical studies, with the objective of providing a foundation for future research to explore ways of addressing and managing these challenges. As such, this study comprehensively summarizes these challenges and provides detailed discussions of each of them.

Previous literature, including Tariq et al. (2021) and Khatibi and Aghajanpour (2020), have identified insufficient and poor-quality data as a major challenge to data-driven approaches, particularly machine learning, data science and digital twin, in reservoir geomechanics. The effectiveness of these approaches is heavily reliant on the quality and quantity of historical data provided for future predictions. Since these approaches are data-oriented, the accuracy of the models can be significantly impacted by the quality and quantity of the data used. Limited and noisy data pose challenges to the accuracy of the models, and the data wrangling process may introduce overfitting of the dataset, another critical hindrance to data-driven approaches in reservoir geomechanics.

Also, Tariq et al. (2021) identified the recurrent challenge of inadequate data for training machine learning models, particularly in the context of reservoir characterization studies. Furthermore, the study identified the unavailability of large datasets as a concern in training models. In line with the above statement, Khatibi and Aghajanpour (2020) opined that the data-driven approaches have the highest accuracy in predicting reservoir geomechanics parameters. However, the study further identified the poor and unavailability of data to be a significant hindrance to the data-driven approaches to reservoir mechanics.

Again, limited interpretability is another critical challenge of data-driven approaches in geomechanics studies. Data-driven models, especially machine learning and data science algorithms, are often black boxes, making it difficult to understand how they arrived at their predictions (Tariq et al., 2021). This is particularly challenging in reservoir geomechanics, where understanding the underlying physical processes is crucial. Integrating physical and data-driven approaches is the best bet in solving this challenge.

Furthermore, Virginia (2018) highlighted that the limited transferability of models is another obstacle to using a data-driven approach in reservoir geomechanics. The study emphasized that AI models have a narrow range of applications and cannot be effectively generalized to predict outcomes from various datasets. Similarly, Ramamoorthy and Yampolskiy (2018) pointed out that models struggle to provide precise predictions when utilized on a dataset that differs from the one on which they were trained. The authors explicitly underlined that the reusability of machine learning and data science models poses a significant challenge, as models trained on one geological field may not be as dependable when applied to other geological fields.

However, Mohaghegh (2017) strongly advises implementing the model only when the input parameters of the given dataset fall within the range of input parameters for which the model is designed. Mohaghegh's (2017) suggestion is reasonable; however, researchers should strive to find solutions to such issues. In fact, one of the primary objectives of this review is to identify potential challenges and research gaps in data-driven approaches to reservoir geomechanics to create opportunities for further research toward finding solutions to these challenges.

The challenges associated with using machine learning, digital twin, and data analysis approaches in reservoir geomechanics studies include data quality and quantity, complexity and interpretability, computational resources, integration and interoperability, and regulatory challenges. Researchers are developing novel approaches to overcome these challenges and leverage the benefits of these approaches to improve the understanding and management of hydrocarbon reservoirs.

8.0 Opportunities of integrating data-driven approaches into reservoir geomechanics workflows.

Integrating machine learning, digital twin, and data analysis approaches in reservoir geomechanics studies presents significant opportunities for improving the understanding and management of hydrocarbon reservoirs. These opportunities are based on the capabilities of these approaches to analyze and interpret large, complex datasets and to identify patterns and insights that may not be apparent through traditional methods (Tariq et al., 2021; Tariq et al., 2017a, b).

However, Busetti (2019) agrees that a key advantage of these approaches is the ability to analyze vast amounts of data, including seismic data, well logs, and field measurements, to gain insights into reservoir properties and behavior under stress. In addition, machine learning algorithms can identify patterns and relationships in the data that may not be apparent through traditional analysis, allowing for more accurate reservoir geomechanical studies.

Moreover, digital twin models can provide real-time monitoring and visualization of reservoir behavior, enabling operators to optimize production and reduce costs. Digital twin technology can also facilitate decision-making processes by simulating various scenarios and predicting the impact of different parameters, including stress/pressure, compaction, etc., on reservoir performance (Sircar et al., 2022).

Furthermore, integrating machine learning, digital twin, and data analysis approaches can enhance reservoir modeling and simulation, improving the accuracy of predictions and reducing uncertainty (Khatibi and Aghajanpour, 2020). In addition, by incorporating physical constraints into machine learning models and digital twins, these approaches can provide more realistic representations of reservoir behavior and enable better estimation of reservoir properties (Chen et al., 2021).

Another opportunity is the potential for cost savings, as these approaches can improve production efficiency and reduce the need for expensive well interventions (Tariq et al., 2021). Additionally, integrating data from multiple sources can provide a more comprehensive understanding of the reservoir, reducing the risk of costly errors and increasing the potential for successful drilling and production (Tariq et al., 2021).

In summary, integrating machine learning, digital twin, and data analysis approaches in reservoir geomechanics studies presents opportunities for more accurate reservoir characterization, improved prediction of reservoir performance, enhanced reservoir modeling and simulation, real-time monitoring and visualization, cost savings, and reduced risk.

Conclusion

Reservoir geomechanics plays a crucial role in optimizing and developing oil and gas activities, particularly in maximizing production rates and improving recovery efficiencies. Recent technological advancements have led to the emergence of novel and innovative data-driven approaches in reservoir geomechanics studies, such as machine learning, data science, and data twin. These approaches have the potential to revolutionize the field by enabling a more comprehensive understanding of reservoir behavior and optimizing operational planning and decision-making. A multitude of literature has applied, examined, and integrated these approaches in reservoir studies, highlighting their potential benefits and limitations.

This review aims to provide a comprehensive and critical overview of data-driven approaches in reservoir geomechanics by analyzing and synthesizing past literature. Specifically, the objectives of this study are to identify the benefits, limitations, significant advancements, potential challenges, opportunities, and research gaps in data-driven approaches to reservoir geomechanics. Additionally, this study aims to create opportunities for further research to overcome the identified challenges and expand the knowledge of data-driven approaches in reservoir geomechanics.

The integration of data-driven approaches in reservoir geomechanics offers several potential benefits. Firstly, these approaches provide a more cost-effective and efficient alternative to traditional methods that rely on extensive and expensive fieldwork. Secondly, data-driven approaches can improve and enhance reservoir characterization, leading to a more accurate and detailed understanding of reservoir properties and behavior. This allows for more precise decision-making and operational planning. Finally, data-driven approaches can reduce operational risks by providing real-time information and insights into reservoir performance, enabling timely intervention and management of potential hazards.

However, data-driven approaches are not without limitations. A significant challenge is the availability of sufficient and reliable datasets, particularly in emerging oil and gas regions. Insufficient data can lead to inaccurate and unreliable models, which can negatively impact operational planning and decision-making. Another limitation is the interpretability of data-driven models, which can be difficult to understand, leading to skepticism and mistrust among stakeholders. Finally, the transferability of models between different reservoirs can be limited, reducing the generalizability and practicality of these approaches.

Overall, this review suggests that data-driven approaches in reservoir geomechanics hold significant potential for optimizing and developing oil and gas activities. By addressing the identified challenges and limitations, further research can expand our understanding of reservoir behavior and enhance operational planning, leading to the maximization of oil/gas production.

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