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Geomechanically Modeling for Wellbore Stability Analysis: A Literature Review

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Abstract

Wellbore stability is a critical aspect of drilling operations, directly impacting the safety, efficiency, and cost-effectiveness of resource extraction and subsurface engineering projects. A comprehensive geomechanically model is essential for predicting and mitigating wellbore instability, encompassing the in-situ stress state, rock strength, and the interaction between drilling fluid and the surrounding rock formation. This review synthesizes the current literature on geomechanically modelling techniques for wellbore stability analysis, highlighting the evolution of methodologies, key parameters influencing stability, and the application of these models in both conventional and unconventional reservoirs. Additionally, the review addresses the challenges associated with model calibration and validation, emphasizing the importance of integrating well logs, core data, and field observations to enhance predictive accuracy and optimize drilling practices. Real-time monitoring systems and probabilistic decision algorithms further enhance wellbore stability management by enabling dynamic adjustments to drilling parameters and trajectories. Furthermore, this review identifies gaps in current research and proposes future directions for advancing geomechanically modelling to address the complexities of subsurface environments and improve the overall performance of drilling operations.

Keywords: Drilling, Geomechanically modelling, Rock mechanics, Wellbore stability.

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1. Introduction

The oil and gas industry, despite employing advanced technical analysis, faces a persistent challenge in achieving high success rates in drilling operations, highlighting the critical need for improved decision-making processes to save substantial costs [1]. Wellbore instability is a pervasive problem encountered in drilling operations, leading to increased non-productive time, higher drilling costs, and potential safety hazards [2]. The integrity of a wellbore is compromised when the stresses induced by drilling exceed the rock's capacity to withstand them, resulting in shear or tensile failure [3]. Understanding the in-situ stress state, rock strength properties, and the interaction between drilling fluids and the formation is crucial for predicting and preventing wellbore instability [2]. Geomechanically models serve as essential tools for simulating the stress distribution around the wellbore and evaluating the potential for failure under various drilling conditions.

The construction of reliable geomechanically models for wellbore stability analysis requires a multidisciplinary approach, integrating data from various sources, including well logs, core tests, and field observations. Well logging data has become a primary source for geological interpretation because of the widespread use of coreless drilling in practical engineering scenarios [3]. These models typically incorporate constitutive laws that describe the mechanical behavior of the rock formation, such as the Mohr-Coulomb, Drucker-Prager, or Hoek-Brown failure criteria [4]. The accuracy of these models depends on the quality and completeness of the input data, as well as the appropriate selection of model parameters. As profitability is a key success factor, companies in the industry utilize well logs to explore the subsurface beforehand [5]. The subsurface models are critical inputs to drilling decisions [6].

The complexity of geomechanically models ranges from simple analytical solutions to sophisticated numerical simulations. Analytical models, such as the Kirsch solution, provide a quick and efficient means of estimating the stress distribution around a circular wellbore in a homogeneous, isotropic, and linear elastic medium. However, these models are limited in their ability to account for complex geological features, such as fractures, faults, and anisotropic rock properties [2, 7]. Numerical models, such as finite element and finite difference methods, offer greater flexibility in simulating complex geometries and material behavior. Numerical models can also incorporate the effects of temperature, pore pressure, and chemical reactions on wellbore stability [8, 9]. Rock strength data is essential for designing recovery plans for a reservoir and for developing an appropriate reservoir simulation [10]. The finite element method can be used to create wellbore stability models, leading to increased usage of sophisticated software and computational tools [11].

1D mechanical earth models are also used to characterize the variation of rock mechanical properties with depth. 3D MEMs extend the capabilities of 1D MEMs by incorporating spatial variability in rock properties. Mechanical Earth Models are commonly employed to characterize the vertical variation of key rock mechanical properties as a function of depth, providing a foundational understanding of the subsurface geomechanically environment [12, 13]. Advanced techniques, such as 3D geomechanically modeling, provide a more thorough approach to understanding possible drilling problems in complex carbonate reservoirs [12]. These models not only incorporate spatial variability in rock properties but are often coupled with seismic data to offer a comprehensive understanding of the subsurface. This integration allows for the prediction of stress variations in areas where drilling processes have not yet commenced, enabling proactive risk management and optimized drilling strategies [13].

This paper presents a comprehensive review of geomechanically modeling techniques for wellbore stability analysis, covering both theoretical background and practical applications.

2. Material and Methods

This paper evaluates more than 61 articles on different geomechanically modeling techniques applied to wellbore stability analysis. The reviewed articles focus on analytical models, numerical simulations, and empirical approaches used to predict and prevent wellbore instability. While these methods often rely on experimental measurements of mechanical properties obtained from formations near the wellbore, the practicality of such measurements is limited by the high costs and logistical constraints associated with coring operations, which are typically confined to a small number of appraisal or exploratory wells. The limited availability of core data presents a challenge in obtaining comprehensive rock property information, which is crucial for the development of accurate geomechanically models. This highlights the importance of exploring alternative data sources, such as well logs and regional geological data, to supplement the core measurements and improve the predictive capabilities of the geomechanically models.

3. Result

Geomechanically modeling of wellbore stability has evolved significantly with the development of advanced numerical techniques and computational capabilities [14]. Numerical modeling and computer-aided simulation have become increasingly prevalent because field studies, in situ measurements, and realistic modeling require specialized equipment, are expensive, and take time [15]. Initial approaches relied on linear elasticity and simple failure criteria, but modern models incorporate more realistic rock behavior, such as plasticity, anisotropy, and time-dependent deformation.

The accuracy of geomechanically models is highly dependent on the quality and quantity of input data. The traditional deterministic wellbore stability analysis methodologies usually overlook the uncertainty of these key parameters [16].

Characterizing the stress distribution and deformation around a wellbore under various drilling conditions and loading scenarios in geomechanics modeling is essential for proper wellbore stability analysis. One of the most notable advancements involves the integration of sophisticated constitutive models that more accurately represent the non-linear and time-dependent behavior of rocks, enabling more precise predictions of wellbore stability under complex geological conditions. The proper selection of parameters is critical for creating precise geomechanically models, and calibration exercises have to be carried out to reduce model uncertainty [13, 17].

Picture of inclined wellbores, where wellbore stability is critical for ensuring safe and efficient oil and gas drilling. The temperature gradient between the drilling mud and the formation significantly influences stress and pore pressure distribution [8].

The incorporation of anisotropic rock properties is crucial for accurate wellbore stability analysis, especially in shale formations [7]. Analytical solutions have been developed to calculate the stress distribution around a cased borehole in orthotropic formations, considering the welded boundaries and generalized plane strain [18].

Step-by-step to build geomechanically modeling includes: collecting the available data, for example, well log data and core data, to build a 1D MEM for all the wells [19]. Then integrate all the 1D MEM to build the 3D MEM [20]. The construction of a geomechanically model involves several steps, starting with data acquisition and quality control. In-situ stress determination is a critical component of geomechanically modeling. The model is then validated against field observations, such as caliper logs, drilling events, and image logs, to ensure its accuracy and reliability.

Anisotropic wellbore stability analysis was performed targeting an offshore gas field to investigate, in particular, the impact of elastic anisotropy on borehole failure predictions [7]. The results show that borehole failure predictions are significantly affected by Thomsen's parameters, especially the failure mode and the safe mud weight window.

Geomechanically models are essential tools for optimizing drilling parameters, such as mud weight, wellbore trajectory, and casing design [21]. These models play a crucial role in determining the optimal values for these parameters to ensure wellbore stability and efficiency. By accurately predicting the stress state around the wellbore, engineers can design drilling programs that minimize the risk of borehole collapse, breakouts, and other instability issues [22].

Geomechanically models also facilitate the optimization of wellbore trajectory, enabling engineers to design wells that minimize stress concentrations and reduce the risk of instability. Furthermore, geomechanically models are used to optimize casing design, allowing engineers to select the appropriate casing size, grade, and setting depth to withstand the expected loads and pressures during drilling and production operations.

Current research on 1D MEM is being integrated to build 3D MEMs. The closed-loop framework from 1D MEM to 3D MEM is a key area of current research, as is using 3D MEM to understand spatial variations in rock properties [13, 20]. The integration between 1D and 3D MEM enables anticipation of subsurface conditions for the proactive design and drilling of new wells [23].

Current research efforts concentrate on employing sophisticated machine learning techniques to create more accurate models. ML methods are more reliable and easier to automate than physics-based models, while still having enough accuracy and predictivity [24]. The models can be helpful in performing well-testing, avoiding costly shut-in operations [25]. However, observations are always sparse and only indirectly related to data, and the human processing time involved limits efficiency [26].

One method involves interpretable machine-learning workflows that use surface drilling data to pinpoint brittle, fracture-prone, and productive rock intervals in shale formations, which can then be used for real-time processing of surface drilling data [4]. Other approaches use machine-learning algorithms to evaluate the sensitivity of individual measurements and to cluster the inverted models to acquire more geologically reasonable models of the surrounding formations [27]. The models are trained using a subset of observations while maintaining a disjoint set for evaluation.

The latest studies focus on developing techniques to consider temporal changes in rock properties and stress conditions during drilling and production operations. Real-time monitoring and data assimilation techniques are used to update geomechanically models with new information, allowing for adaptive management of wellbore stability risks [28]. The increasing integration of machine learning and data analytics into geomechanically modeling workflows is enhancing the accuracy and efficiency of wellbore stability analysis [29, 30]. Subsurface data is acquired in the form of physical fluid/solid samples, images, 3D scans, time-series data, waveforms, and depth-based multi-modal signals [31].

A self-supervised pretraining method using a small CNN-transformer-based model can accurately and efficiently predict rock physical properties [32]. The integration of machine learning with image processing is becoming essential for characterizing rock properties from 3D images [33]. Supervised machine learning techniques such as LSTM are being used to improve the petrophysical workflow for shear wave velocity prediction [34]. Transfer learning is also used to address the challenge of limited labeled data, which is a common problem in well log analysis [35].

The Table 1, this text shows the focus area for current studies in geomechanics with artificial intelligence, including topics from drilling parameter optimization and rate of penetration prediction to reservoir characterization and production optimization, data-driven modeling and machine learning techniques, real-time monitoring and control, and uncertainty quantification.

Table 1.
Geomechanics Current Study Focus Area.

Area of Focus	Description	Example Studies/Approaches
Real-Time Data Integration	Dynamically updating mechanical earth models with real-time data from LWD, DTS, and other monitoring systems to improve accuracy and adapt to changing drilling conditions.	Strategies for near real-time prediction of borehole stability using LWD data Bloch and Gupta [36].
3D Mechanical Earth Models	Creating detailed 3D MEMs to understand stress distributions and potential failure zones around wellbores, especially in complex geological settings.	Building 3D MEMs for optimized wellbore stability, as demonstrated in a case study Abdulaziz, et al. [23]. Predicting wellbore stability using 3D finite element model Ahmed, et al. [37].
Probabilistic Wellbore Stability Analysis	Using probabilistic methods, such as Monte Carlo simulations, to account for uncertainties in input parameters provides more robust predictions.	Developing probabilistic models to predict critical drilling fluid pressure while considering various in-situ stress regimes [38].
Wellbore Stability for Inclined Wells	Assessing wellbore stability for highly inclined, extended-reach, and horizontal wells, where stress distributions are less favorable.	Methodologies for assessing wellbore stability in inclined wells with limited rock mechanics data [39].
Coupled Thermo-Hydro-Mechanical Modelling	Integrating thermal, hydraulic, and mechanical effects in wellbore stability models to account for the complex interactions between temperature, pore pressure, and rock deformation.	Coupled THM modeling considering drilling unloading, fluid flow, and thermal effects [40].
Shale Wellbore Stability	Investigating the effects of mechanical, chemical, and thermal parameters on borehole stability in shale formations, including time-dependent effects and wellbore configuration.	Examining the effects of thermal, mechanical, and chemical parameters on well design in shale formations [41].
Finite Element Analysis	Utilizing finite element methods and software to simulate stresses and deformation around the wellbore provides a more detailed understanding of potential instability issues.	Numerical wellbore stability analysis for vertical and deviated wells using finite element method Halafawi and Avram [11]. Prediction of Wellbore Stability Using 3D Finite Element Model Ahmed, et al. [37].
Mud Weight Window Optimization	Developing models and strategies to widen the operating mud weight window, increase wellbore stability, and reduce the risk of collapse or fracture.	Geomechanically models to increase the thin mud weight window in vertical and deviated wellbores Bassey, et al. [41].
Machine Learning Applications	Applying machine learning techniques, such as neural networks, to enhance the accuracy and efficiency of geomechanically modeling workflows, handle large datasets, and improve predictive capabilities.	Incorporating machine learning methods in well-log data processing to enhance data quality [EDITOR]. Development of neural network models for predicting wellbore instability Okpo, et al. [42]. Application of machine learning for horizontal wells optimization and risk assessment [43].
Reducing Well Construction Costs	Applying geomechanics technology can help reduce costs in well construction and optimize drilling parameters.	Sustainable Deployment of Geomechanics Technology to Reduce Well Construction Costs Mody, et al. [44].

4. Discussion

Despite the advancements in geomechanically modeling for wellbore stability analysis, there are still notable gaps in the literature that need to be addressed. Especially for 1D MEM, there is a need for more research on the integration of real-time data into geomechanically models. This includes incorporating data from logging-while-drilling tools, distributed temperature sensing, and other monitoring systems to update the models dynamically and improve their accuracy.

Moreover, more work needs to be done on developing robust and reliable methods for validating geomechanically models, particularly in complex geological settings [30].

Another gap in the literature is the limited research on the application of geomechanically models to unconventional reservoirs.

Another opportunity for research is to investigate the use of machine learning techniques to improve the accuracy and efficiency of geomechanically modeling workflows [45, 46].

Geomechanically modeling in fractured basement reservoirs presents major gaps in the literature due to the complex nature of the fractures [47]. The models need to accurately characterize the geometry, connectivity, and mechanical properties of fracture networks in order to predict wellbore stability and optimize drilling operations.

Existing research faces challenges such as limited data processing capabilities and insufficient model generalization capabilities [30]. Advanced deep learning algorithms show promise for parameterizing complex geological structures and non-Gaussian fracture and permeability fields [48].

Another aspect to be improved is the integration of different data types, such as geological, geophysical, and engineering data, into a unified geomechanically model [49].

Furthermore, there is a need for more research on the development of user-friendly software tools that can facilitate the application of geomechanically models in the field. The integration of petrophysical behavior, geological statistics, and characterization of unconventional resources needs further exploration [50].

The effective utilization of geomechanically models requires the development of software tools that are not only accurate but also easy to use and interpret [51, 52].

Geomechanically modeling remains particularly challenging for unconventional reservoirs, such as fractured basement reservoirs. The complex nature of the fracture networks in these formations makes it difficult to accurately characterize the geometry, connectivity, and mechanical properties required for reliable wellbore stability predictions. Existing geomechanically models often struggle to adequately capture the heterogeneity and anisotropy of fractured basement reservoirs, leading to uncertainties in the analysis and optimization of drilling operations [19]. It is essential to further investigate the influence of natural fractures and bedding planes on fracture propagation in the vicinity of a borehole, especially under the joint impact of these factors [53]. Additionally, innovative approaches are needed to overcome the limitations of traditional geomechanically modeling techniques when applied to unconventional reservoirs.

The use of machine learning in geomechanics shows promise, particularly for predicting rock properties and optimizing drilling parameters. For example, one study developed a machine learning-based method to predict subsurface brittleness by integrating multidisciplinary data sets, such as seismic attributes, rock physics, and petrophysics information [54].

Despite the advancements in geomechanically modeling for wellbore stability analysis, there remain notable gaps in the literature that warrant further research. Key areas for improvement include:

- Integrating real-time data from logging-while-drilling tools, distributed temperature sensing, and other monitoring systems to dynamically update and improve the accuracy of 1D mechanical earth models.
- Developing robust and reliable methods for validating geomechanically models, particularly in complex geological settings.
- Expanding the application of geomechanically models to unconventional reservoirs.
- Leveraging machine learning techniques to enhance the accuracy and efficiency of geomechanically modeling workflows.
- Addressing the challenges in modeling fracture basement reservoirs, including characterizing the geometry, connectivity, and mechanical properties of complex fracture networks.
- Improving the integration of diverse data types, such as geological, geophysical, and engineering data, into unified geomechanically models.
- Creating user-friendly software tools to facilitate the practical application of geomechanically models in the field.

Overall, continued research in these areas can help advance the state of the art in geomechanically modeling and optimize drilling operations in a wide range of geological settings.

The synthesis of existing literature on geomechanically modeling for wellbore stability analysis reveals a trajectory of continuous improvement, driven by technological advancements and the increasing complexity of drilling environments. Integrating data from diverse sources, such as well logs, seismic surveys, and laboratory tests, is crucial for building comprehensive and accurate models.

The shift towards real-time modeling and dynamic updating of geomechanically models is essential for adapting to changing conditions during drilling and production operations [55].

As the industry ventures into more challenging and unconventional reservoirs, the need for sophisticated geomechanically models becomes even more pronounced [56, 57].

Future research directions should focus on several key areas.

First, the integration of advanced machine learning techniques, such as deep learning and neural networks, can significantly enhance the predictive capabilities of geomechanically models.

Second, the development of more robust and efficient numerical methods is crucial for handling the computational demands of complex 3D models, particularly in fractured reservoirs.

Third, more work needs to be done on developing reliable methods for validating geomechanically models, especially in the absence of extensive field data.

Fourth, the development of user-friendly software tools that can facilitate the application of geomechanically models in the field is essential for wider adoption. The models will be able to describe the actual case studies of wellbore instability in the field [11].

Fifth, integrating real-time data acquisition and analysis techniques into geomechanically modeling workflows can further enhance the accuracy and reliability of wellbore stability predictions.

Lastly, as the oil and gas industry increasingly adopts digital technologies, machine learning can be used to accurately predict future outcomes, thereby significantly advancing optimization in complex drilling operations [58].

The evolution of geomechanically modeling for wellbore stability analysis has been marked by significant advancements in data integration, numerical methods, and computational power.

Looking forward, the integration of advanced machine learning techniques, robust numerical methods, and real-time data acquisition systems holds great promise for further enhancing the accuracy and reliability of geomechanically models.

These advancements can lead to increased drilling cost efficiency by optimizing well placement, reducing non-productive time, and minimizing the risks of wellbore instability. Improved geomechanically models can help operators make more informed decisions during the drilling process, leading to more efficient operations and ultimately reducing overall drilling costs.

5. Conclusions

geomechanically models are essential for predicting and mitigating wellbore instability, which is a major concern in drilling operations. The literature review reveals a progression from basic analytical solutions to sophisticated numerical simulations that account for a wide range of geological and operational factors. The accuracy of geomechanically models depends on the quality and quantity of input data, including well logs, core data, and drilling parameters [3].

The integration of advanced techniques, such as finite element analysis and computational fluid dynamics, enables a more detailed understanding of stress distribution and fluid flow around the wellbore. Furthermore, the use of data-driven approaches, such as neural networks, can further enhance the accuracy and efficiency of geomechanically modeling [59].

In recent years, the application of machine learning has gained prominence as a method for handling large datasets and improving the predictive capabilities of models [60]. However, developing robust and reliable geomechanically models remains an ongoing process that requires continuous research and validation against field data. This includes studying the stability of inclined wellbores under the effect of coupled thermo- geomechanically [8].

In conclusion, geomechanically modeling plays a critical role in ensuring wellbore stability and optimizing drilling operations. Incorporating machine learning methods in well-log data processing can help enhance the quality of well log data and reduce the costs associated with re-logging or manual correction [3]. Advancements in numerical methods, data integration, and machine learning have significantly improved the accuracy and efficiency of geomechanically models, which have proven valuable in optimizing drilling parameters, minimizing non-productive time, and ultimately reducing overall drilling costs.

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