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GEOMECHANICAL MODELING OF RESERVOIRS: APPLICATIONS TO WELLBORE STABILITY, SAND PREDICTION, AND OPTIMIZED DRILLING

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Abstract: *This study discusses how the use of the geomechanical advanced modeling can be used to optimize the reservoir management and drilling process. The study combines geological information, rock characteristics and in-situ stress fields to form a powerful model of predicting underground behavior. The key issues, which the model is specifically applied to, are: forecasting wellbore instability to implement safer casing and drilling fluid programs, predicting the risk of sand production to implement effective strategies of completion and optimization of the drilling parameters to increase the efficiency and minimize non-productive time. The results show that the geomechanical method of addressing operational risks, integrity of wellbores, and the maximization of hydrocarbon recovery is incomplete without a thorough geomechanical approach. This modeling is an essential instrument in cost reduction and the improvement of safety during the lifecycle of a field.*

I. Introduction

Geomechanical modeling is a combination of rock mechanics, geology and in-situ stress analysis to solve complex reservoir problems (Bagheri et al., 2021). It enables Engineers to forecast and control the risk of drilling by creating elaborate mechanical earth models (MEMs), minimize non-productive time (NPT) and increase operational efficiency. According to Ounegh et al., (2024) the cause of wellbore instability, which is one of the most significant causes of NPT, is the discrepancy between the in-situ stresses and the pressure of drilling muds, which causes the shear or tensile failures (breakouts or fractures). Recent innovations make use of machine learning to process images of drilling cuttings in real-time, which allows quick detection of instability and adjusting mud weight. Also, in the management of sand production, the geomechanical models play a crucial role that predictions are used to guide the drawdown strategies and perforation designs to avoid expensive erosion and destruction of equipment (Eladj et al., 2022). To optimize the drilling process, 3D geomechanical models that are calibrated using seismic inversion data will offer a clue on safe mud windows, planning of well path and subsidence risks of a reservoir (Shuai et al., 2023). Examples of carbonate and shale formations, including the Dezulf embayment of Iran and the Zubair formation of Iraq, show that acoustic impedance (AI) and reflection coefficient (RC) logs confirm stress regimes and failure modes. With increasingly complex drilling environments, the combination of geomechanics and real-time information and analytics facilitated by AI has the potential to achieve even greater accuracy in management of the reservoirs (Elrayah, 2024; Osaki, L.J. et al., 2025).

II. Literature Review

It has been proven that incorporating multi-source data, including acoustic logging, diagnostic fracture injection tests (DFIT), and formation microscanner imagery (FMI), into 3D geomechanical models improves accuracy of pore pressure and in-situ stress predictions, which, in turn, improves wellbore stability estimates (Chen et al., 2025). From their study, Chamanzad et al., (2025) reported research in the deep shale gas reservoirs of the Sichuan Basin which used the finite element modeling to optimize drilling fluid density and well pathway, shortening the drilling cycles by as much as 67%. Likewise, empirical studies of the Zubair oilfield used the Mogi-Coulomb failure criterion to establish the safe mud weight windows, in order to deal with shear failures of shale formations (Shaban & Hadi, 2020).

Nevertheless, a number of drawbacks are still present. A lot of research is based on two-dimensional static models that are not generalizable to different geologic environments. As an illustration, the empirical correlations to predict rock mechanical properties (e.g., uniaxial compressive strength) are usually site-dependent biased and, as such, the stress measure and failure estimates are erroneous (Noori & Hadi, 2025). Araujo-Guerrero et al., (2024) added that, sand prediction models often neglect temporal effects, including stress effects due to depletion or water ingress effects, which restricts their determination limits of sand production quantitatively. Although core analogues made by 3D printing have been useful in laboratory experiments studying sanding processes, no studies have yet tested their scaling to field environments.

Drilling optimization studies focus on real-time analytics and machine learning in order to adjust mud weight but are limited by the quality of the data (Xu et al., 2025). Some critical gaps are the lack of validation of failure criteria in overburden zone and the lack of adequate integration of thermo-hydro-mechanical couplings in CO2 injection situation (Hosseinzadeh, et al., 2025).

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III. Methodology

A. Log Data Analysis

The analysis of log data is a step towards a solid geomechanical model of reservoirs to predict accurately, stability of wellbores, sand production, and optimization of the drilling process. It is a process of systematic interpretation of well-log measurements to obtain the required geomechanical simulations in the form of mechanical properties, in-situ stresses, and pore pressure profiles (Ibrahim et al., 2021). Advanced machine learning methods have revolutionized the accuracy and performance of these analyses in recent years with the integration of the standard logs, including gamma-ray (GR), density (RHOB), compressional (DTC) and shear wave transit time (DTS) (Bagheri et al., 2021).

1. *Dynamic Elastic Properties:* Dynamic elastic properties are directly calculated from sonic and density logs. Compressional and shear wave velocities (Vp and Vs) are derived from DTC and DTS logs, respectively, using the relations Vp=1/Δtc$Vp=1/\Delta tc$ and Vs=1/Δts$Vs=1/\Delta ts$. These velocities are used to compute dynamic Young's modulus (EdEd) and dynamic Poisson's ratio (vdvd) as follows:

$$Ed = pbV2s\frac{(3V2p-4Vs)}{(V2p-V2s)} \quad \text{..................} \quad (1)$$

2. *Rock Strength Estimation:* Unconfined compressive strength (UCS) and friction angle (ø) are important in measuring shear failure. UCS is estimated with empirical relations to acoustic impedance (AI) or porosity ($ø_p$):

$$UCS = K.\ AI - b \quad \text{..................} \quad (2)$$

Where $AI = pbV_p$

internal friction angle is obtained through UCS or shear modulus correlations. In the case of shale formations, gamma-ray logs can be used to measure a clay content which is inversely related to strength.

3. Pore Pressure and Data Analysis: The pore pressure, Pp, is estimated based on the Eaton approach that exploits the aberration of sonic or resistivity logs to abnormal patterns of compaction:

$$Pp = Sv - (Sv - Pn)\left(\frac{\Delta tn}{\Delta t}\right]3 \quad \text{..................} \quad (3)$$

4. *Machine Learning Enhancement:* Recent developments use machine learning (ML) to directly predict stresses and properties based on logs. Multi-log data (GR, RHOB, DTC, DTS) are analyzed by random forest (RF), adaptive neuro-fuzzy inference systems (ANFIS), functional networks (FN) to estimate Sh and SH with an accuracy of more than 90 without the complex theoretical modeling (Chamanzad et al., 2025). As an example, ANFIS models are guided by linguistic rules to transcribe log inputs to stresses, saving calibration time by a dramatic factor.

5. *3D Geomechanical Model:* Simulation of reservoir-scale behaviour is performed by constructing 3D finite element models (FEM) with software such as ABAQUS or FLAC3D:

Mesh Generation: Structured grids with faults and layer interface

Property Population: Seismic attributes are used to distribute property population (e.g., acoustic impedance) and kriging interpolation.

Boundary Conditions: In-situ stresses and pore pressure are exerted according to the tectonic constraints in the region.

B. Applications

Wellbore Stability: Failure Criteria: Mohr-Coulomb or Mogi-Coulomb criteria are used to evaluate shear failure (breakout)and tensile failure (fracturing)

Sand Production Prediction: Critical Drawdown Pressure (CDP): Ultimate pressure that may be used without the occurrence of sand ingress is approximated by analytical models or numerical simulations.

Drilling Optimization: Rate of Penetration (ROP) Modeling: Hybrid models: Hybrid methods are analytical (e.g., mechanical specific energy) and data-driven (e.g., machine learning) frameworks to optimize ROP:

C. Research Study Area

Gabo Field in the Niger Delta is one of the study locations having a perfect increase of applied geomechanical models to be applied because of the geological complexity and the high potential of hydrocarbons (Evans et al., 2025). The area is defined by large growth faults and roll-over anticlines, that form heterogeneous stress regimes, which are the best to test wellbore stability, sand production, and optimization of drilling. In the case of the Niger Delta, based on studies of the fields such as Keva, integration of seismic interpretation and petrophysical analysis shows that there are strong reservoir units with good porosity (19-21%) and high hydrocarbon saturation (40-78%), which are important in modeling fluid-rock interactions (Adagunodo et al., 2022).

The Gabo Field geomechanical modelling relies on 1D and 3D static models constructed on the basis of well log data and seismic attributes to model pore pressure, distributions of stresses, and mechanical properties of rocks (Horsfall et al., 2024). These models play a crucial role in forecasting shear and tensile failures in wellbores during the process of drilling and production thus minimizing non-productive time. However, the sandstone constructions in the field are not consolidated, and thus it is subject to sand production, which requires investigation of perforation design and drawdown management to reduce the risk (Sanei et al., 2023; Osaki, L. J. & Oghonyon, R.,2025).

Recent progress in the field of machine learning and deep reinforcement learning in trajectory optimization, studied in other basins, can be applied to the Gabo Field to make drilling more precise and efficient under geomechanical constraints (Iheaturu et al., 2024). Moreover, experimental research of water flooding in analogous reservoirs emphasizes the traits of geomechanical properties development in the course of increased oil recovery and guides the approaches to keeping caprock integrity and fault stability. The multifaceted geology of the Gabo Field, along with accessible data and technological systems, provides an interesting opportunity to further develop the geomechanical applications in the studies of wellbore stability, sand prediction, and drilling optimization (Amupitan et al., 2022; Osaki, L. J. & Oghonyon, R. 2025).

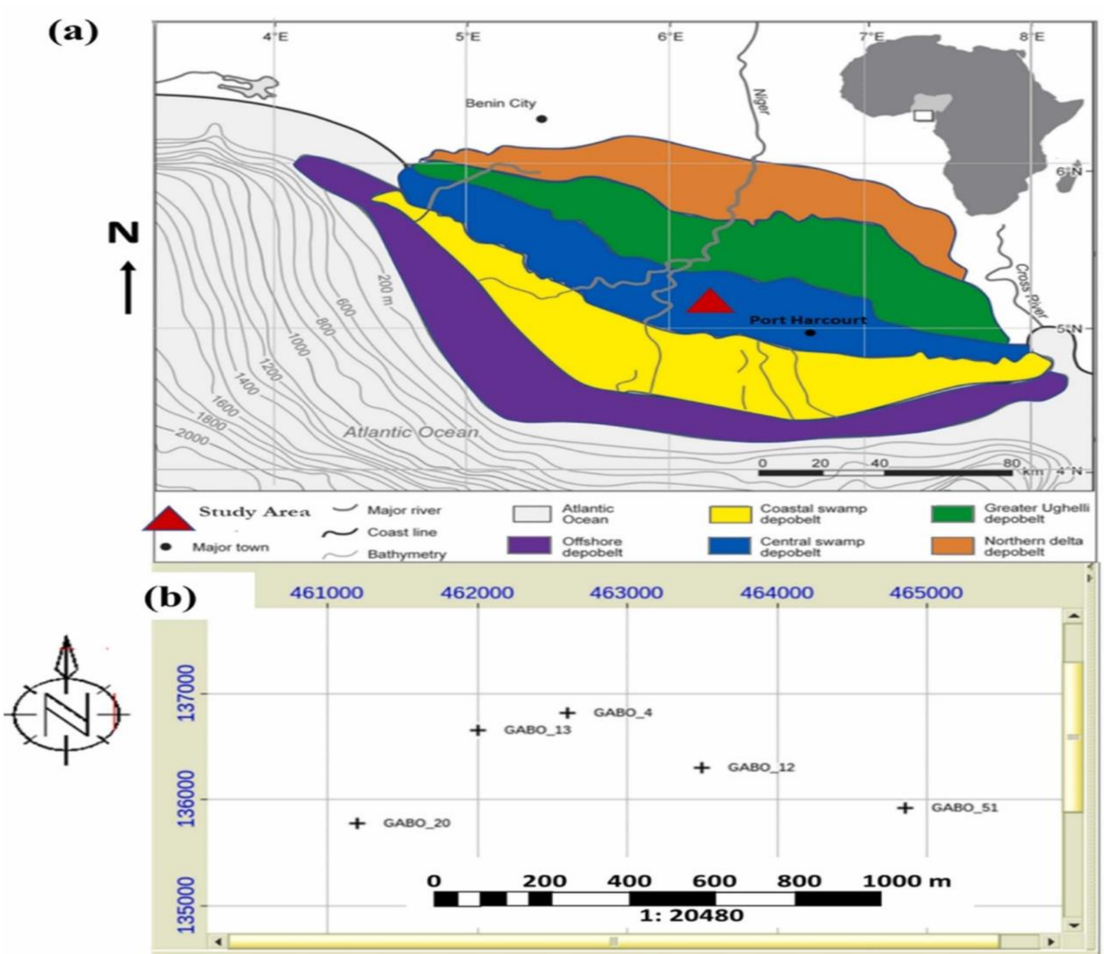

Fig. 1. a. Niger Delta Map showing Gabo Field b. Well Distribution of the Study Area

IV. Results and Discussion

D. Wellbore Stability

Wellbore stability analysis is the determination of the minimum mud weight (shear failure gradient). A mud weight window is necessary in maintaining a stable wellbore in the course of drilling. Drilling at mud loads less than the pore pressure can cause splintering or washout of boreholes and higher mud weights will lead to fracturing. Shear failure will occur as a result of

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an equally drilling at a lower mud weight than the shear failure gradient. This in turn necessitates a safe mud weight prediction to do safe drilling. The optimal mud weight is the weight of the mud that is halfway the maximum and the minimum mud weight. Fig.2 illustrates anticipated mud weight window of the wells to be drilled without borehole collapse and unintended fracturing of the formation in isotropic formations.
There is a heterogeneity and anisotropies of mud weight window with the depth across the field. It is predicted that there will be a mud window of 5.0 -19.0ppg in the field. The minimum and the maximum mud weight are more than the other in certain parts of the wells. Drilling mud weight at these points must be held at fracture gradient limit to prevent the possibility of unintentionally fracturing the formation with resultant mud losses that would be more hazardous than the breakout formation that could occur as a result of excessively low mud weights. Sections that are weak and have very low shear strength can be reinforced to ensure that they do not collapse.

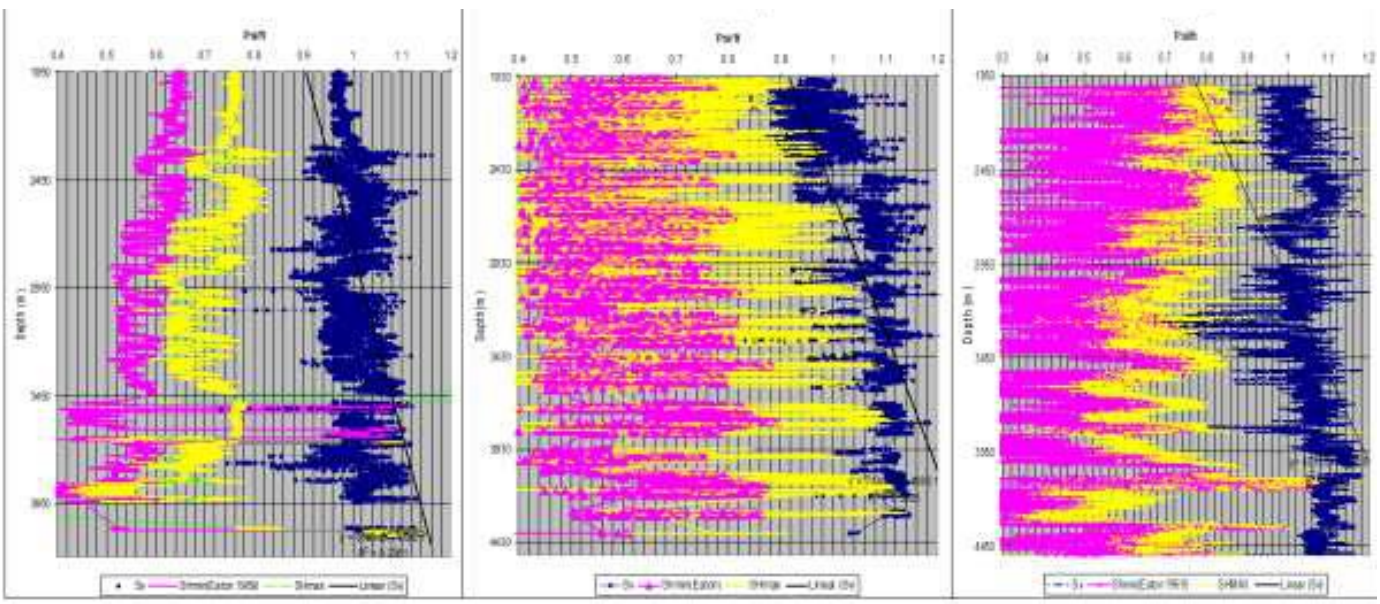

Fig. 2. In situ and wellbore stress

E. Sand Prediction

Geomechanical modelling of sand prediction are presented in figure 3-6 using suitable values of empirical parameters which are: the exponent coefficient (β = 1), maximum erosion strength (λ2 = 0.088 m−1), initial erosion strength (λo = 0.42λ2 m−1) and threshold depth of the λ plateau (Λp = 1.1Λo m). However, the small discrepancy with the experimental data can be neglected.

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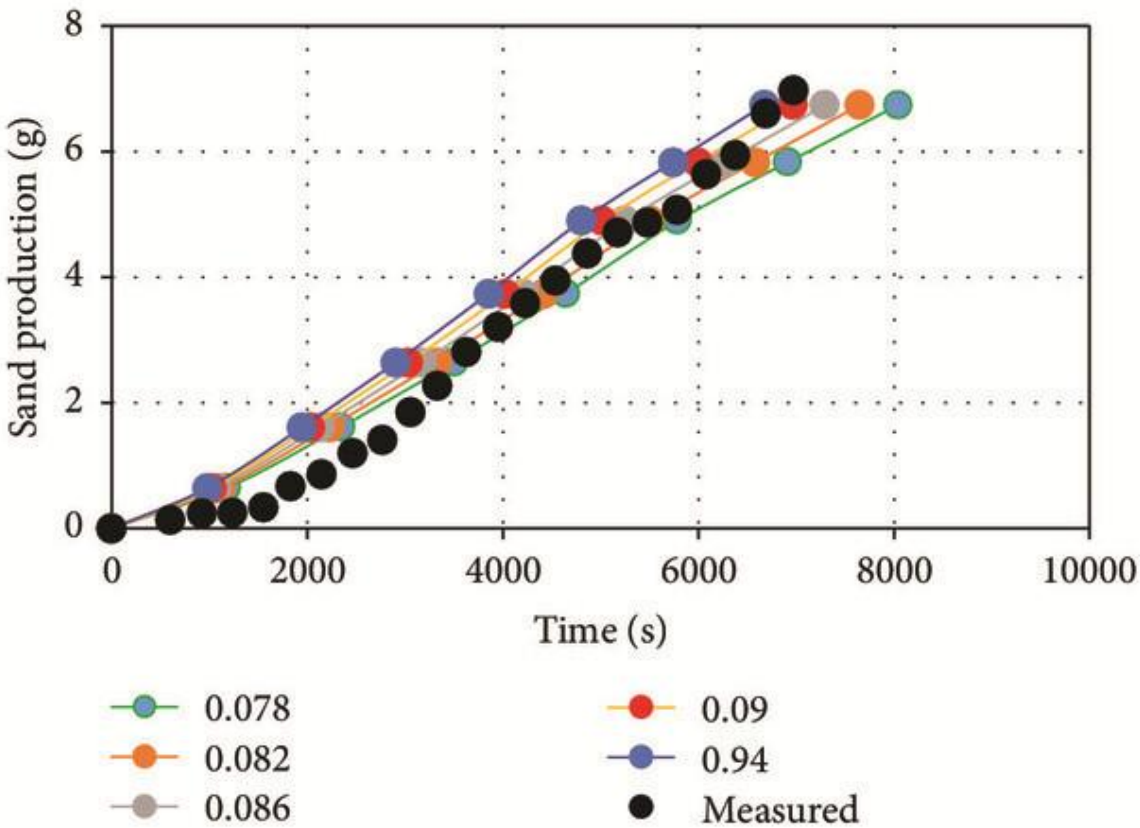

Fig. 3. Sand mass produced over time while maximum erosion strength λ2 varies from 0.078 to 0.94 m^{-1}. $\beta = 1$, $\lambda_o = 0.42\lambda2$, and $\Lambda_p = 1.1\Lambda o$.

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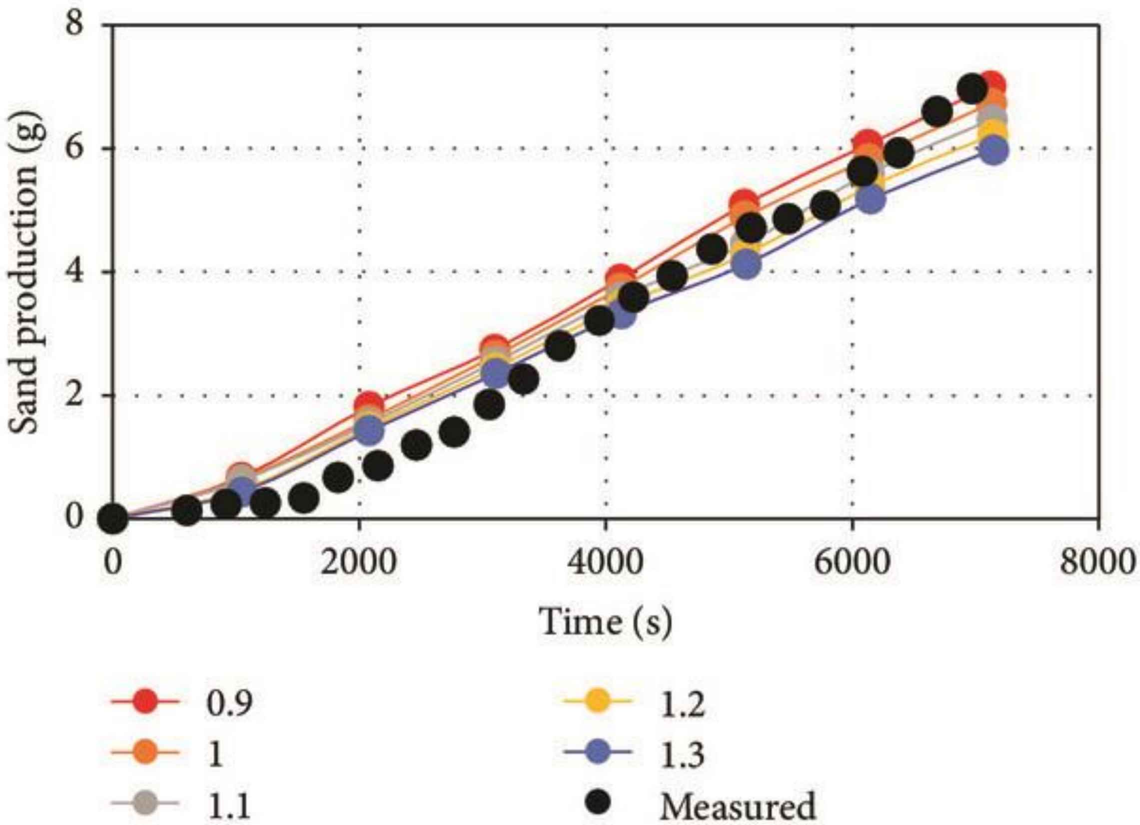

Fig. 4. Sand mass produced over time while changing exponent coefficient β from 0.9 to 1.3. λ2 = 0.088, λ0 = 0.42λ2, and Λp = 1.1Λ0

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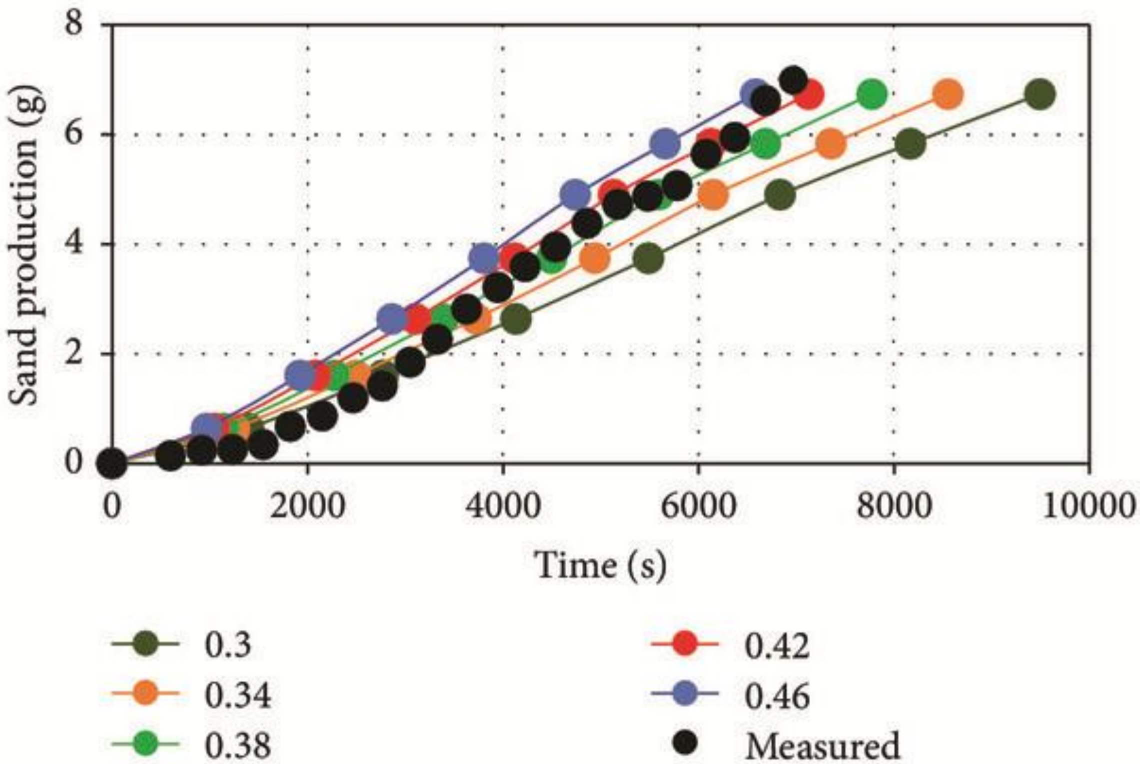

Fig. 5 Sand mass produced over time while changing ratio of initial to maximum erosion strength $\lambda 0/\lambda 2$ from 0.3 to 0.46. $\lambda 2 = 0.088$, $\beta = 1$, and $\Lambda p = 1.1\Lambda 0$.

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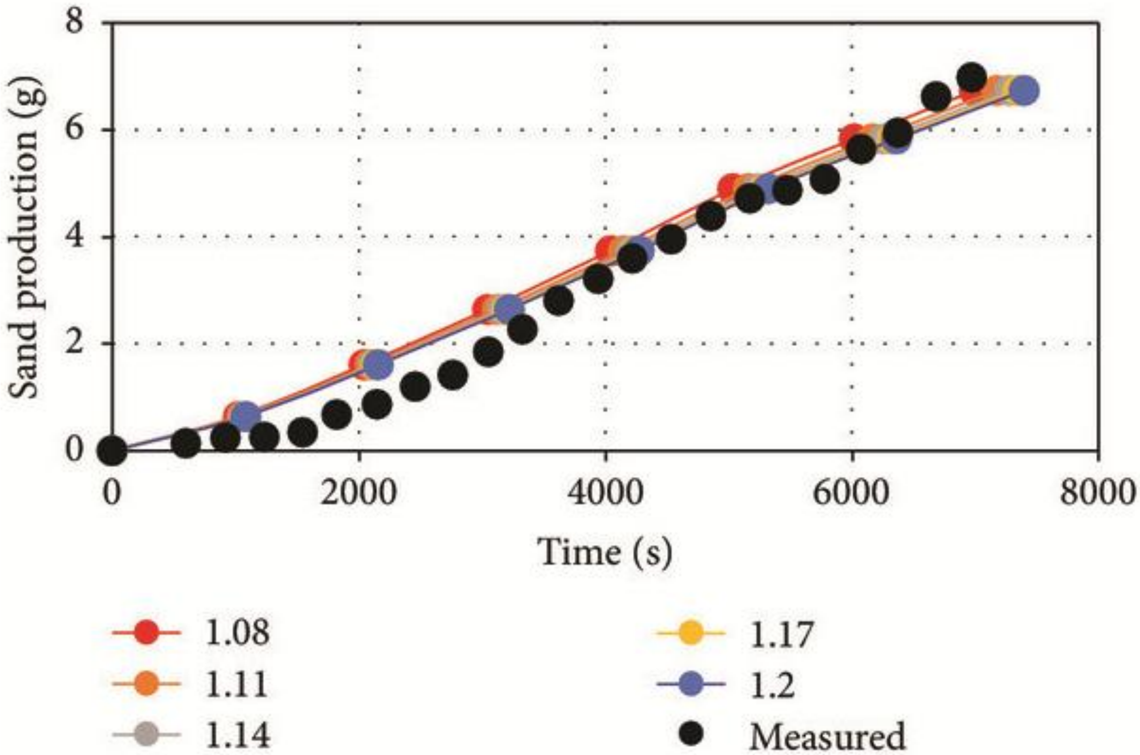
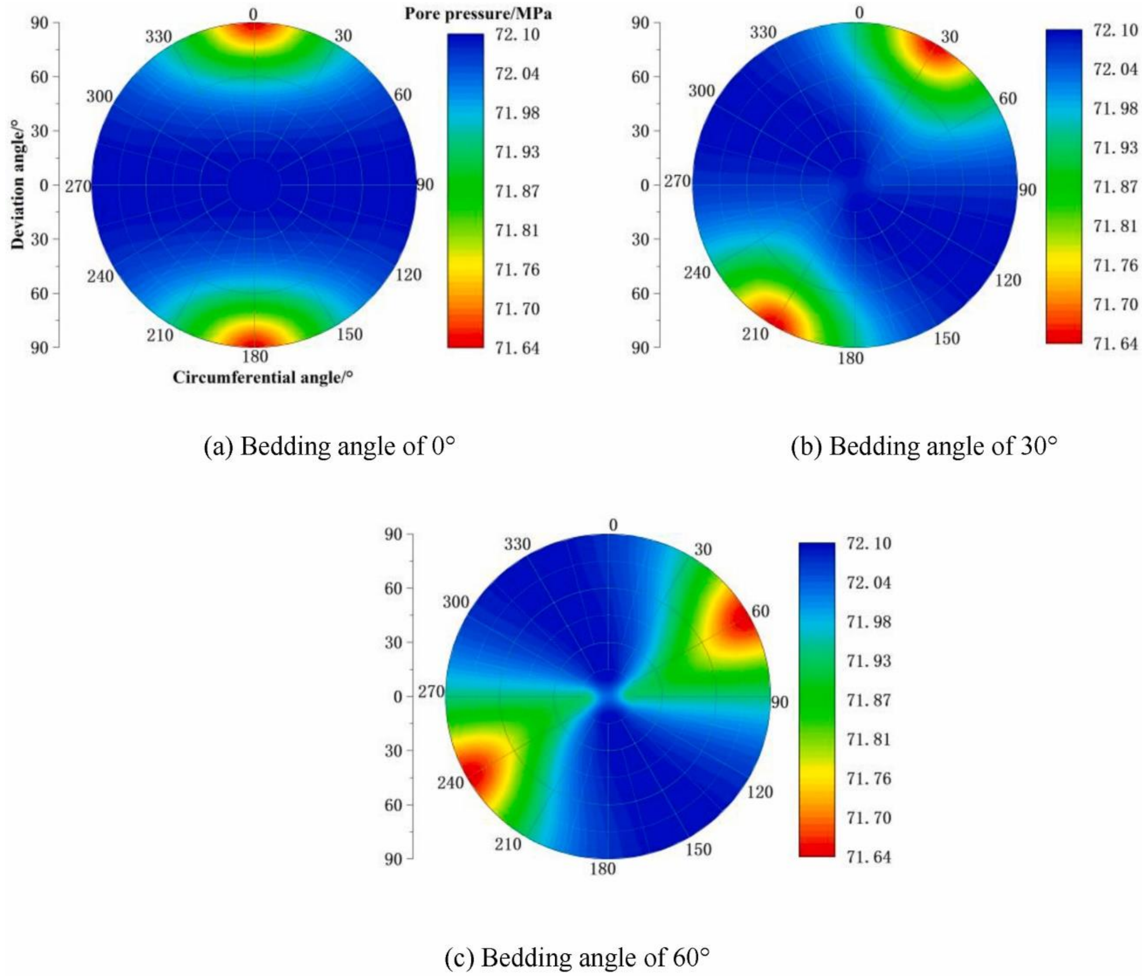


Fig. 6. Sand mass produced over time while changing ratio of threshold depth and initial plastic region Λp/Λo from 1.08 to 1.2. β = 1, λ2 = 0.088, and λo = 0.42λ2.

F. Optimized Drilling

Figure 7 revealed that fluid migration between the wellbore and the formation has a significant effect on the pore pressure in the formation around the well during the drilling and completion processes. In the process of drilling, the wellbore pressure is higher than the formation pore pressure, and the drilling fluid migrates to the formation, which increases the borehole pressure in the borehole wall. However, the increase in amplitude is different at different positions around the well and depends on the angle relationship between the radial direction of each point and the bedding surface.



(a) Bedding angle of 0°

(b) Bedding angle of 30°

(c) Bedding angle of 60°

Fig. 7. When the Borehole Trajectory Azimuth is 90°, the Pore Pressure in the Borehole Wall of Shale Reservoir Changes during the Drilling Process

In the process of completion, as presented in figure 8, the wellbore pressure is lower than the formation pore pressure; the formation fluid flows into the wellbore, and the pore pressure in the wellbore decreases. The variation amplitude of the pore pressure in the wellbore depends on the radial seepage capacity of the rock in the wellbore.

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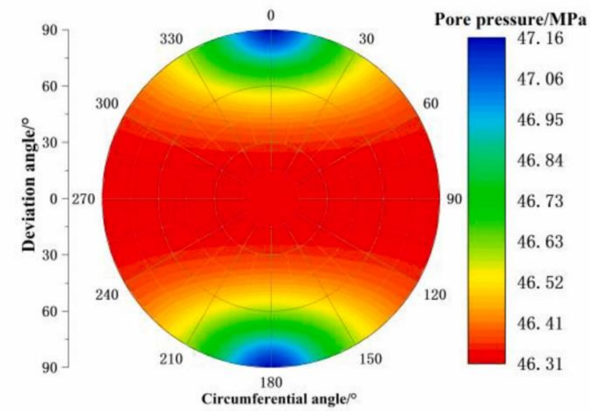
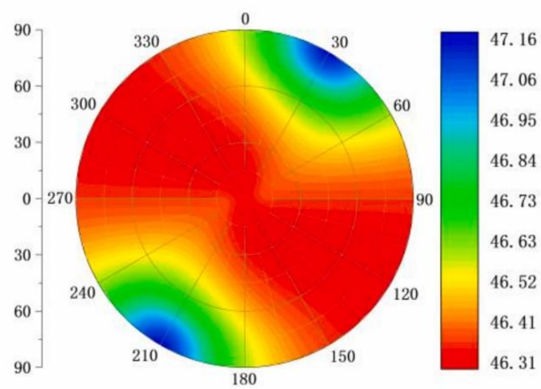
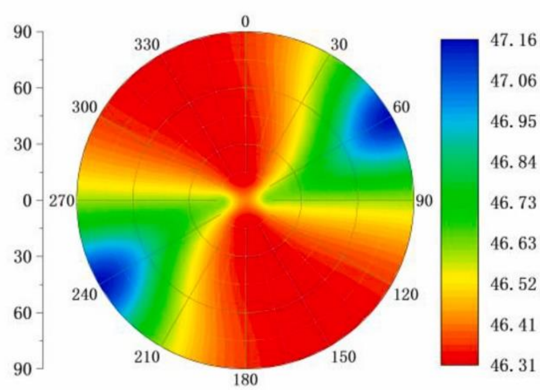


(a) Bedding angle of 0°



(b) Bedding angle of 30°



(c) Bedding angle of 60°

Fig. 8. When the Borehole Trajectory Azimuth is 90°, the Pore Pressure Changes in the Borehole Wall of the Shale Reservoir during completion Production

V. Conclusion

This study revealed that geomechanical modeling is an indispensable tool for modern reservoir management. Through the integration of geological, petrophysical, and stress data, a robust model was developed that successfully enhances wellbore stability forecasts, accurately predicts sand production risks, and provides a scientific basis for optimizing drilling parameters. The application of this model led to a significant reduction in non-productive time and operational costs while markedly improving safety. The adoption of a geomechanical approach is not merely a technical exercise but a critical strategy for mitigating risks throughout the field lifecycle, ensuring well integrity, and maximizing economic recovery from hydrocarbon assets. Future work will focus on real-time model updating using machine learning algorithms.

References

Adagunodo, T. A., Bayowa, O. G., Alatise, O. E., Oshonaiye, A. O., Adewoyin, O. O., & Opadele, V. O. (2022). Characterization of reservoirs and depositional study of JP Field, shallow offshore of Niger Delta Basin, Nigeria. Scientific African, 15, e01064.

Amupitan, F. G., Odigi, M. I., & Ugwu, S. (2022). Petrophysical evaluation of GABO Field, Niger Delta. Quest: Journal of Research in Environmental and Earth Sciences, 8(4), 27–38.

Araujo-Guerrero, E. F., Alzate-Espinosa, G. A., Chalaturnyk, R., & Zambrano-Narvaez, G. (2024). Geomechanical laboratory testing for sand production characterization using 3D-printed core analogues. Geomechanics and Geophysics for Geo-Energy and Geo-Resources, 10(1), 195.

Bagheri, H., Tanha, A. A., Doulati Ardejani, F., Heydari-Tajareh, M., & Larki, E. (2021). Geomechanical model and wellbore stability analysis utilizing acoustic impedance and reflection coefficient in a carbonate reservoir. Journal of Petroleum Exploration and Production Technology, 11(11), 3935–3961.

Chamanzad, M., Nikkhah, M., Ramezanzadeh, A., Shi, X., Pezeshki, M., & Mostafavi, I. (2025). Proposing an approach for geomechanical model construction based on laboratory and wellbore test results and wellbore instability assessment in the Kangan and Dalan formations. Geomechanics and Geophysics for Geo-Energy and Geo-Resources, 11(1), 1–23.

Chen, Y., Li, W., Wang, X., Wang, Y., Fu, L., Wu, P., & Wang, Z. (2025). Research and application of geomechanics using 3D model of deep shale gas in Luzhou Block, Sichuan Basin, Southwest China. Geosciences, 15(2), 65. https://doi.org/10.3390/geosciences15020065

Eladj, S., Doghmane, M. Z., Lounissi, T. K., Djeddi, M., Tee, K. F., & Djezzar, S. (2022). 3D geomechanical model construction for wellbore stability analysis in Algerian Southeastern petroleum field. Energies, 15(20), 7455.

Elrayah, A. A. I. (2024). Enhancing drilling operations: Prioritizing wellbore integrity, formation preservation, and effective mud waste control (case study). Journal of Engineering and Applied Science, 71(1), 86.

Evans, K. T., Osinowo, O. O., Odufisan, W., Koledoye, B. A., Odusanwo, Y., Ude-

Akpeh, T. O., & Tiele, G. Y. (2025). Seismic and petrophysical data analysis for geological interpretation and subsurface modeling of Keva Field, onshore Niger Delta, Nigeria. Energy Geoscience, 6(2), 100382.

Horsfall, O. I., Akpan, M. J., & George, N. J. (2024). Reservoir characterization of GABO field in the Niger Delta Basin using facies and petrophysical analyses. Results in Earth Sciences, 2, 100038.

Hosseinzadeh, B., Amour, F., Hajiabadi, M. R., Ferreira, C. A., Abdollahi, A., & Nick, H. M. (2025). Validated thermo-hydro-mechanical modeling framework for CO_2 storage in chalk reservoirs: A case study from the Harald East field. International Journal of Greenhouse Gas Control, 146, 104426.

Ibrahim, A. F., Gowida, A., Ali, A., & Elkatatny, S. (2021). Machine learning application to predict in-situ stresses from logging data. Scientific Reports, 11(1), 23445. https://doi.org/10.1038/s41598-021-02959-9

Iheaturu, T. C., Abrakasa, S., Jones, A. E., Njoku, I. O., Ideozu, R. U., & Ugwueze, C. U. (2024). Assessment of sealing potential of fault-bounded hydrocarbon prospect in Gabo Field, Niger Delta, Nigeria. Journal of Applied Sciences and Environmental Management, 28(4), 1061–1068.

Noori, A. F., & Hadi, F. (2025). Geomechanical modeling and wellbore stability analysis for studying the shale rock failure. Iraqi Journal of Chemical and Petroleum Engineering, 26(1), 35–43.

Osaki, L. J., & Oghonyon, R. (2025a). Synthesizing geophysical well logging and spatial modelling for reservoir analysis optimization: A dynamic approach. African Journal of Engineering and Environment Research, 7(2), 22–44. https://www.cefpacsconsultingltd.org.ng

Osaki, L. J., & Oghonyon, R. (2025b). An integrated deep learning solution for petrophysics, pore pressure, and geomechanics property prediction. The International Journal of Engineering and Science (IJES), 14(8), 20–29.

Osaki, L. J., Onwubuariri, C. N., & Agoha, C. C. (2025). Optimizing unconventional reservoir performance in Niger Delta: A 3D geostatistical driven geomechanics evaluation-integrated approach to characterization. Journal of Scientific and Engineering Research, 12(2), 138–154.

Ounegh, A., Hasan-Zadeh, A., Khanaposhtani, M. M., & Kazaemzadeh, Y. (2024). Wellbore stability analysis based on the combination of geomechanical and petrophysical studies. Results in Engineering, 24, 103016.

Sanei, M., Ramezanzadeh, A., & Asgari, A. (2023). Building 1D and 3D static reservoir geomechanical properties models in the oil field. Journal of Petroleum Exploration and Production Technology, 13(1), 329–351.

Shaban, S. D., & Hadi, H. A. (2020). Geomechanical analysis to avoid serious drilling hazards in Zubair Oilfield, Southern Iraq. Iraqi Journal of Science, 1994–2003.

Shuai, D., Xian, C., Zhao, Y., Chen, G., Ge, H., & Cao, H. (2023). Using 3-D seismic data to estimate stress based on the curvature attribute integrated mechanical earth model. Geophysical Journal International, 233(2), 885–899.

Xu, K., Zhang, H., Ning, W., Liang, J., Qiang, J., Wang, X., ... & Yuan, F. (2025). Geomechanical parameter-driven evaluation of ultra-deep reservoirs: An integrated methodology and its application to the Kuqa Depression, Tarim Basin. Energy Geoscience, 100433.