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Integrated Drilling Geomechanics Analysis Using Poro-Elasto-Plastic Finite Elements and Machine Learning

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ABSTRACT

This study will deal with the essential weaknesses of traditional elastic models to predict wellbore instability that in most cases results in expensive drilling procedures. The aim of this study is to develop an integrated drilling geomechanics analysis using Poro-Elasto-Plastic finite elements and machine learning. The objectives are to, integrate drilling operations using a poro-elasto-plastic Finite Element Model; integrate drilling operations using machine learning algorithms. The analysis evolves a synthesized framework that combines a poro-elastoplastic Finite Element Model (FEM) and a Machine Learning (ML) to allow a dynamic and precise geomechanical analysis. A Drucker-Prager yield criterion has been used in the FEM to model the effects of plastic deformation and time-dependent effects of pore pressure around the wellbore in a realistic manner. Afterward, the ML surrogate models are trained using the outputs of the FEM in order to provide fast real-time predictions. Findings indicate that the hybrid model is able to properly measure the plastic yield zone and can give a dynamically updated safe mud weight window, which is much better than the traditional methods of doing so. The conclusion confirms that such integration forms a powerful digital twin, which allows making decisions in advance to increase the safety of drilling, streamline operations, and minimize non-productive time, thereby creating a new paradigm of wellbore stability management.

Keywords: Integrated Drilling Geomechanics, Pror-Elasto-Plastic, Machine Learning, and Agbami Oilfield.

INTRODUCTION

Geomechanical issues like instability of wellbore and breakouts of well-borings continue to be a leading reason of non-productive time in the oil and gas sector and especially in intricate and profound oil reservoirs (Zhang et al., 2022; Osaki et al 2025a). Conventional forms of analysis have difficulties in taking into account the complexity of such problems which are time-dependent, and coupled thermal-hydraulic-mechanical processes. However, Poro-elasto-plastic finite element modeling, which is an advanced numerical model, has proven to have substantial potential in offering a more realistic simulation of wellbore response through modeling of plastic deformation and failure of the rock the rock beyond the yield point (Gladious, et al., 2025). These high-fidelity models are however computation intensive. At the same time, machine learning (ML) has become an effective instrument in geotechnical engineering and can determine complex trends within big amounts of data to improve predictive accuracy beyond the bounds of traditional techniques (Khan, et al., 2025).

In this study, a structure that enhances a fully coupled poro-elastoplastic finite element model was executed and combined with machine learning algorithms. The task is to establish a strong and effective predictive tool that can not only help to increase the accuracy of the forecast of wellbore stability, but also costs a lot less to compute, which, in turn, will allow making real-time geomechanical decisions during the drilling process.

Aim and Objectives

The aim of this study is to develop an integrated drilling geomechanics analysis using Poro-Elasto-Plastic finite elements and machine learning. The objectives are to;

1. integrate drilling operations using a poro-elasto-plastic Finite Element Model;
2. integrate drilling operations using machine learning algorithms.

Location of the Study Area

Agbami Field is a great field to conduct research on integrated drilling geomechanics based on poroelasto-plastic finite element based on machine learning. This large deep offshore field is at the central Niger Delta in Nigeria, about 1,500 meters of water and with a complicated geology, containing a deep-water turbiditic sandstone reservoir with a structural trap which is a four-way rollover anticline cored by a reverse fault and upwardly mobile shale (Emudianughe et al., 2021). This is a geomechanically complex environment, which is enhanced by factors such as seismic data constraints and thrust faults, making it a prime geomechanical environment to be studied through an advanced method (Amadike et al., 2024;Osaki & Oghonyon, 2025b).

This setting is most appropriate with the application of a machine-learning-assisted poro-elasto-plastic Finite Element Method (FEM) (Komijani, 2024). This combined method has the capability of dynamically forecasting wellbore failure and revising safe mud weight margin through the processing of on-the-fly drilling information and offset well information and thus overcoming the constraints of the traditional unchanging models. The model would directly respond to geomechanical risks in Agbami Field, which would help to reduce unproductive time, improve the safety and efficiency of drilling in this complicated deepwater setting (AlBahrani et al., 2021).

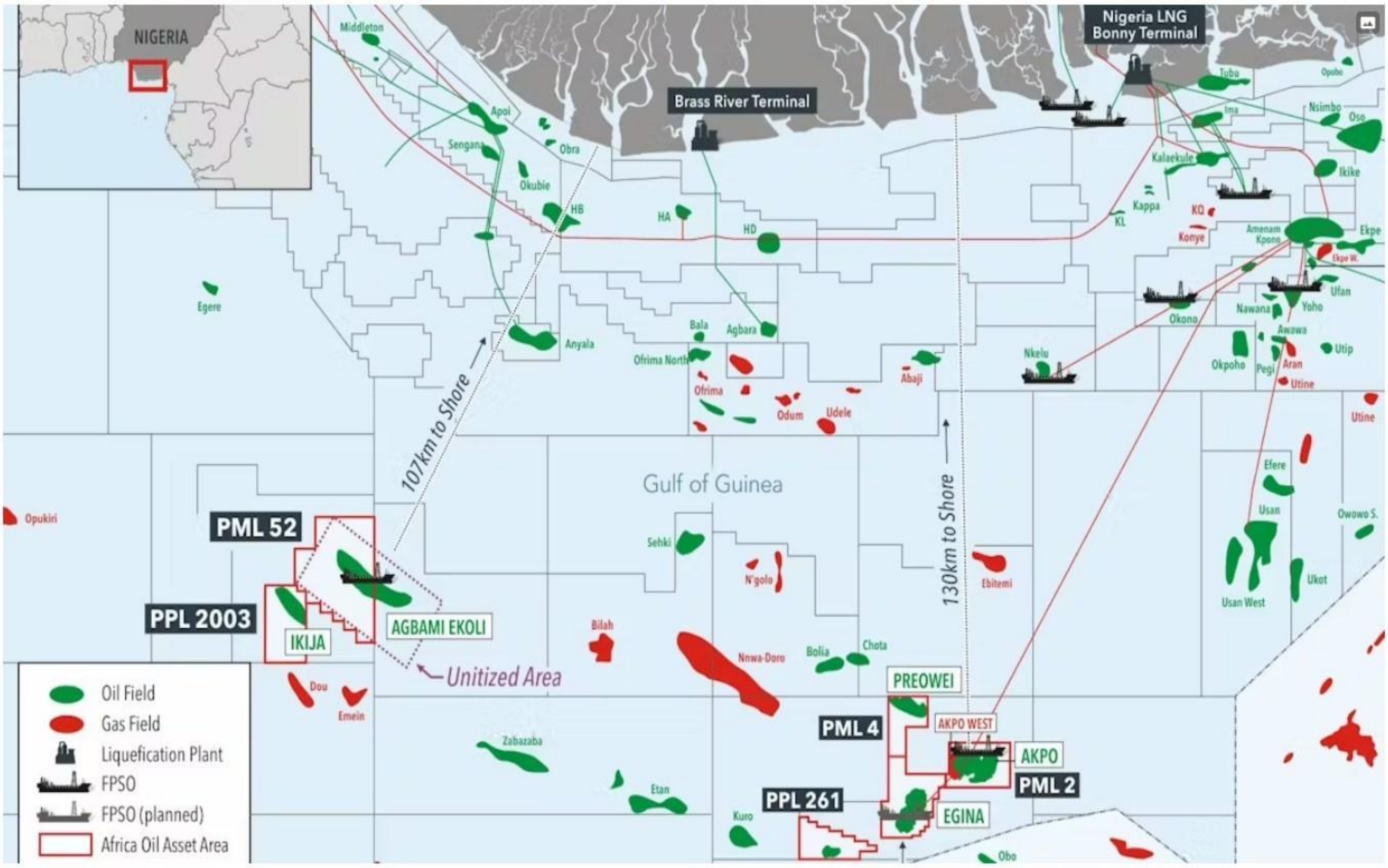

Fig. 1: Map of Agbami Field Showing the Oil Field, Gas Field, Liquification Plant, FPSO, and African Oil Assert Area (Beckman, 2024).

LITERATURE REVIEW

Linear-elastic assumption and analytical solutions are commonly used to describe the traditional wellbore stability analysis and they do not work well to predict the complex, time-dependent Thermo-Hydro-Mechanical (THM) coupled processes in rocks, thus resulting into non-productive time and inaccurate prediction (Jamshidi et al., 2024). In order to overcome these shortcomings, the present-day research trend has changed to more advanced computational models.

One of the major improvements is the creation of poro-elasto-plastic FEM models. The models model the realistic mechanical behaviour of rocks that implicates plastic yielding and post failure behaviour which is

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important in the analysis of wellbore breakout. In addition, they use coupled THM processes to capture the most important effects of redistribution of the pore pressure, and the thermal stresses caused by the temperature difference between drilling fluid and the formation. These thermo-poroelastic effects have a major impact on shear failure and the stable mud window and thus they play a vital role in the modern-day drilling activities Pirhadi, et al., (2025).

Machine Learning has become one of the effective geomechanical analysis tools. Artificial Neural Networks (ANNs), Random Forest (RF) and Support Vector Machines (SVR) are now commonly used as ML algorithms to directly predict rock mechanical properties such as uniaxial compressive strength (UCS), cohesion and friction angle using only drilling data (Liu et al., 2024; Osaki & Oghonyon, 2025). Khan, et al., (2025) noted that, the main advantage of ML is that it can model non-linear, complex relationships that are computational, providing an alternative to physics-based simulation that is fast. The latest line of research development is the combination of these two directions. In a seminal work, AlBahrani et al. (2021) suggested an integrated scheme, such that a poro-elasto-plastic FEM model is employed to produce training data to be used on the ML algorithms. This hybrid model is a continuous updating of the safe mud weight window with real-time drilling data that makes up a dynamic model of geomechanics that by far is more accurate than the traditional models of geomechanics which is described as a pre-drilling model. The goals of this integration are to address the prohibitive cost of high-fidelity FEM simulations as well as capitalize on the speed of ML to generate real-time decisions, which will be a major milestone toward end-to-end intelligent and adaptive drilling optimization (Nautiyal & Mishra, 2023).

METHODOLOGY

Data Collection

Data Sourcing and Integration: The process of using Poro-Elasto-Plastic Finite Elements and Machine Learning for Geomechanics analysis starts with the collection of a multi-scale dataset. These are geophysical well logs (e.g., sonic, density, neutron), direct downhole measurements, such as Leak-off Tests (LOT) to calibrate the stress, and laboratory analyses on core plugs to measure the statically rock strength and elastic properties. One of them involves empirical correlations obtained through statistical analysis of laboratory and log data to estimate at any given time parameters such as UCS and static Youngs modulus over the entire formation interval (Chamanzad et al., 2025).

Pore Pressure and In-Situ Stress Determination: The pore pressure is calculated using a direct measurement of tools such as the Modular Formation Dynamics Tester (MDT) when available. The in-situ stresses magnitudes and direction are tuned by combining LOT data with measurements of wellbore failures (e.g. breakouts, tensile fractures) to make the model reflect the real-world situation (Chamanzad et al., 2025).

Table 1: The Core Geomechanical Data and the Parameters used to Measure Them in Drilling Geomechanics

Geomechanical Data	Geomechanical Parameters
Rock Properties	Young's Modulus, Poisson's Ratio, Unconfined Compressive Strength, Cohesion, and Friction Angle.
In-Situ Stresses	Vertical Stress (Sv), Minimum & Maximum Horizontal Stresses (Shmin, SHmax).
Pore Pressure	Pore Pressure

Source: Sanei et al., (2023).

The following are the formulae for the geomechanical parameters;

Young Modulus $E = \frac{\sigma}{\epsilon}$ ………………………………………… i

Where E = Young Modulus

σ = Stress

ϵ = Strain

Poisson's Ratio = $\nu = \frac{\epsilon lateral}{\epsilon axial}$ ………………………………… ii

Where ν = Poisson ratio

$\epsilon lateral$ = Lateral strain

$\epsilon axial$ = Axial strain

Unconfined Compressive Strength (UCS) = $\frac{Pmax}{Ao}$ ………………… iii

Where $Pmax$ = The maximum axial load

Ao = The initial cross-sectional area of the specimen before testing

Friction Angle $\tau = c + \sigma_n \tan\varphi$………………………………….. iv

Where τ = shear strength

C = cohesion

σ_n = Normal Stress φ =

Angle of Internal Friction

C. Poro-Elasto-Plastic Finite Element Analysis

Model Setup and REV Analysis: A 3D finite element model of wellbore and reservoir section is drawn. A Representative Elementary Volume (REV) analysis were done to control the cost of computation. This is to make sure that the simulated volume is large enough to be representative of the entire formation and yet computationally efficient. The calibrated in-situ stresses, pore pressure and rock properties are included in the model (Lindqwister et al., 2025).

Constitutive Model and Simulation: The most important one is a poro-elasto-plastic constitutive model. The model takes into consideration both the time-dependent, fluid-coupled (poro-elastic) creep-deformation of the rock and its passage to irreversible (plastic) failure, which is critical to the successful prediction of wellbore collapse and fracture initiation. A set of simulations are performed in order to produce a rich set of well-boring responses in different conditions that underlie the training of the MLs (Li et al., 2019).

D. Machine Learning Model Development

Artificial Neural Network: An Artificial Neural Network (ANN) is a computer-based model that learns complex nonlinear relationships between geotechnical data to be able to forecast soil and rock behavior, including settlement or strength, that is usually challenging to model using conventional models (Al-Haddad et al., 2025).

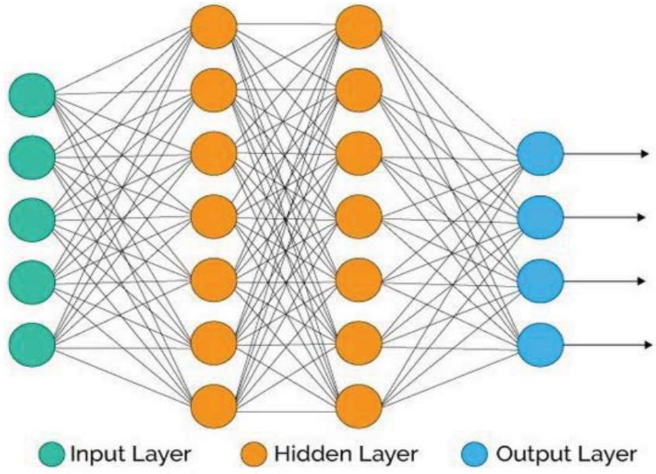

Fig. 2: Artificial Neural Network Showing the Layers fit for Integrating Drilling Geomechanics Analysis

Random Forest Regression: On heterogeneous tabular drilling and geomechanics datasets, such as those with missing values, mixed numeric features, and nonlinear interactions between geology, drilling parameters, and FE-derived predictors include tree methods, which are, Random Forest, XGBoost, and LightGBM that perform exceptionally well. They offer interpretable feature importance and partial-dependence analysis, which are helpful for determining which stress-or-pore parameters have the greatest influence on instability, along with strong baseline predictive accuracy for regression (borehole deviation, ROP) and classification (wellbore stability states). Gradient-boosted trees can be combined with FE outputs as engineered features to capture signals that are informed by physics, and they frequently achieve higher accuracy after careful hyperparameter tuning (Yan et al., 2023).

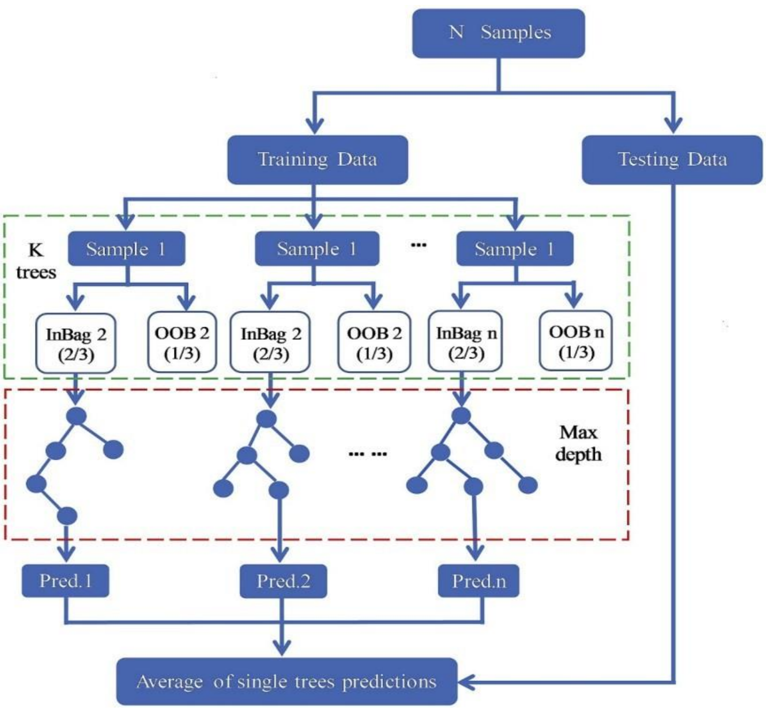

Fig. 3. Random Forest Algorithm Model (Zhang et al., 2021).

Gaussian Process Regression: For risk assessment drilling decisions, Gaussian Process Regression offers a probabilistic stand-in for FE outputs that directly measures predictive uncertainty e.g., confidence intervals on predicted pore-pressure increase or fracture risk. Due to its nonparametric versatility, GPR can be used as an emulator for costly poro-elasto-plastic simulations in Bayesian calibration or active learning loops, as well as to model smooth spatial/parameter fields such as stiffness and permeability. Contemporary sparse GPR variants allow integrated workflows for sensitivity, inversion, and optimal data acquisition while scaling to larger datasets while maintaining uncertainty estimates (Nguyen et al., 2025).

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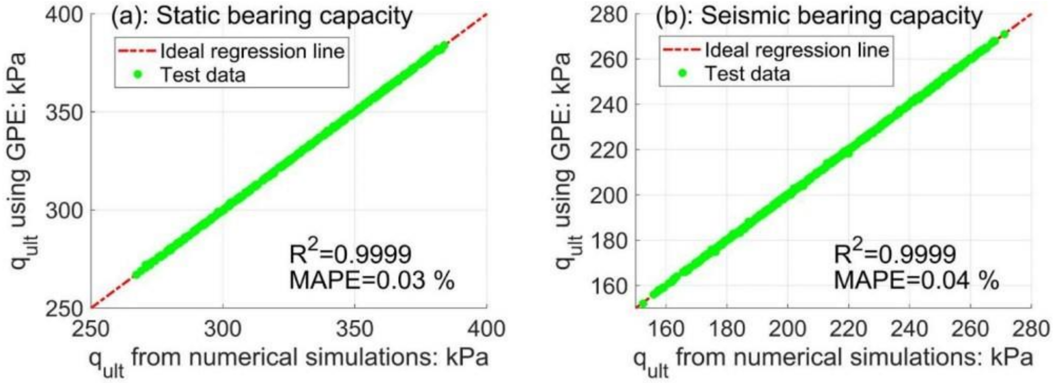

Fig. 4: Gaussian Process Regression (Nguyen et al., 2025).

RESULT AND DISCUSSION

F. Poro-Elasto-Plastic Finite Element

In order to use Poro-Elasto-Plastic Finite Element in integrated drilling operations in Agbami oil field, the precision and consistency of three distinct coupling schemes on the pore pressure and displacement were tested with a variety of permeability, elastic modulus, and Biot coefficient. It is expedient to show that the fixed stress schemes can work with a similar precision like the fully coupled scheme in a computationally efficient manner. Yoon et al., (2022) opined that, the fixed stress scheme needs the refined numerical tolerance to attain a target accuracy at low permeable cases. However, this study revealed that, the fixed stress scheme is numerically far more stable than the fully coupled scheme in the low permeable cases where the fully coupled scheme employs finite elements with the same order interpolation elements in both displacement and pore pressure. One special case of Terzaghi problem of two layers was examined after three base benchmark problems. The fixed stress schemes work relatively well (Figure 5a&b) and extremely well (Figure 5c-d) as indicated in Figure 3. In the cases in Figure 5a&b, the permeability of saline aquifer (A) is less than sandstone (S) and the pressure has to dissipate slowly to the top boundary. This leads to the loss of numerical accuracy, which needs the fine tolerance in specific cases of the fixed stress scheme. It can be stated that the fixed stress scheme is numerically sound and stable as shown in this work. Therefore, this plan will be of great value to very nonlinear problems.

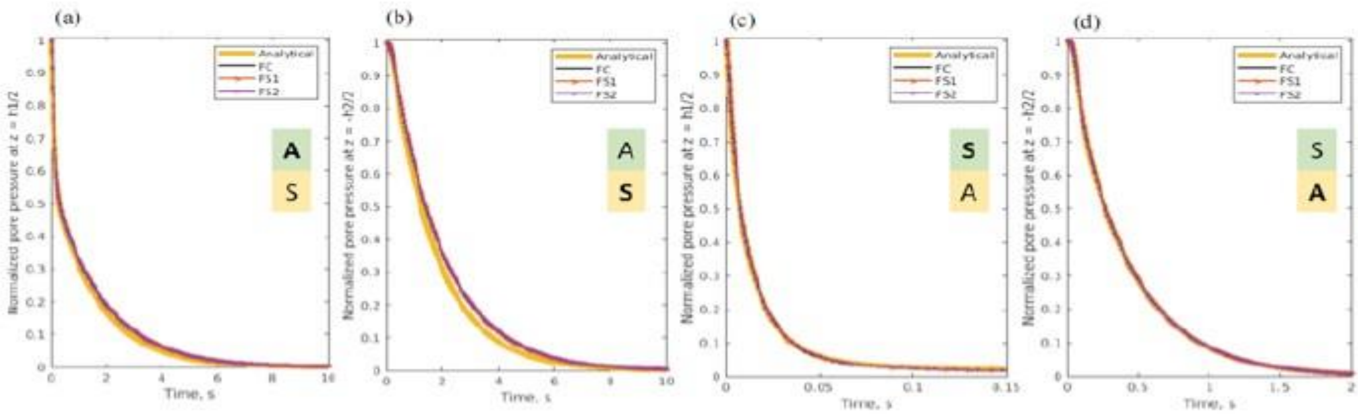

Fig 5: Pore pressure profile for two-layer Terzaghi problem at mid-point of each layer for (a-b) saline aquifer (A) top layer and sandstone (S) base layer and (c-d) sandstone (S) top layer and saline aquifer (A) base layer. Permeability (m^2) and elastic modulus (GPa) for saline aquifer and sandstone are 3×10^{-14} m^2 and 20 GPa, and 3×10^{-12} and 16 GPa, respectively. FC, FS1, and FS2 represent the fully coupled, fixed stress scheme implemented in Sierra/Aria simulation code, and fixed stress scheme implemented in Sierra/ Aria and Sierra/SM, respectively.

G. Elasto-plasticity

This is to test the fidelity of Sierra/Aria and Sierra/SM simulation codes on elasto-plasticity beyond the yield point where elasticity is in force, the behavior of plastic is nonlinear. In the case of 1D Terzaghi problem, we employed a new analytical solution that Liu and Huang (2021) had developed in which plasticity is applied at the drainage boundary and propagates to the undrained end. Another reason why Sierra/Aria lacks a plastic material model is because we can test the coupling solution with Sierra/Arpeggio where Sierra/Aria is resolved in pore pressure and Sierra/SM is resolved in the displacement as stated above. In the case of plasticity, DruckerPrager model was applied. In the case of 2D plate problem, the analysis of elasto-plastic behavior is conducted in the Galin plate with a hole in the center. The pore pressure is passive and hence, only Sierra/SM is employed to solve the mechanics. Plasticity begins at the edges of the hole in the centre and this extends to the plate. Numerical results were compared to analytical solution and the pore pressure, displacement, and the location of elasto-plastic interface are well predicted. Good accuracy of numerical solutions of the 2D plate problem is also evident, although not mentioned here. In the process of validation, the 2D elasto-plastic problem with the wellbore breakout test in which the pore pressure is passive and the wellbore in Mancos shale has a breakout, demonstrating the development of material failure, is also developed. Finalization of failure surface is considered to be the development of plasticity to be compared with the model.

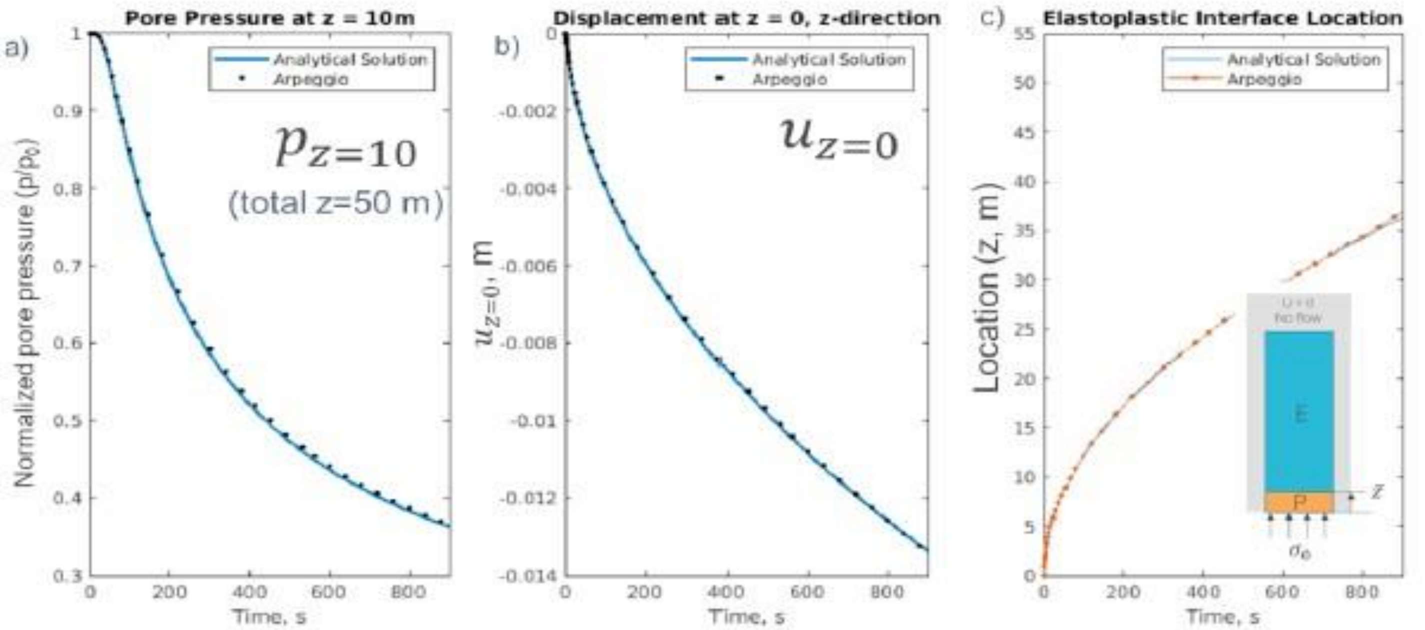

Fig. 6: Comparison of numerical results (Sierra/Arpeggio) with the Analytical solution. a) Time history of the pore pressure at 10m from the drainage boundary, b) Time history of displacement at the drainage boundary (z = 0), and c) Time history of the location of the elasto-plastic interface, showing its progression along the height of the column over time. A schematic of 1D Terzaghi problem is shown in (c).

H. Machine Learning

The machine learning algorithm used to integrate the drilling geomechanics was based on the artificial neural network (ANN) which can learn and model complex and non-linear relationships and is reported to create good fitting functions. ANNs are a group of artificial neurons, which are constructed in a way that they communicate through signals on the communicational connections. The input layer nodes do not alter the data, however, pass them to the hidden layer. At the hidden layers, certain form of transformations is done to the input data using some weight functions and then connected to the output layer that is related to the results we need.

To eliminate the impact of bad data (e.g., null value, bad log measurements) available data were filtered. The model was built by creating a three-layer feed forward neural network with hidden neurons having sigmoid functions and output neurons having linear functions. Training of the network was done using the LevenbergMarquardt backpropagation algorithm.

The reason for this conversion is due to the difference in the measurement condition. Uniaxial compressive strength (UCS) and friction angle (φ) were also estimated based on Plumb's correlation. Calculated rock properties for Well-1 are presented in figure 7.

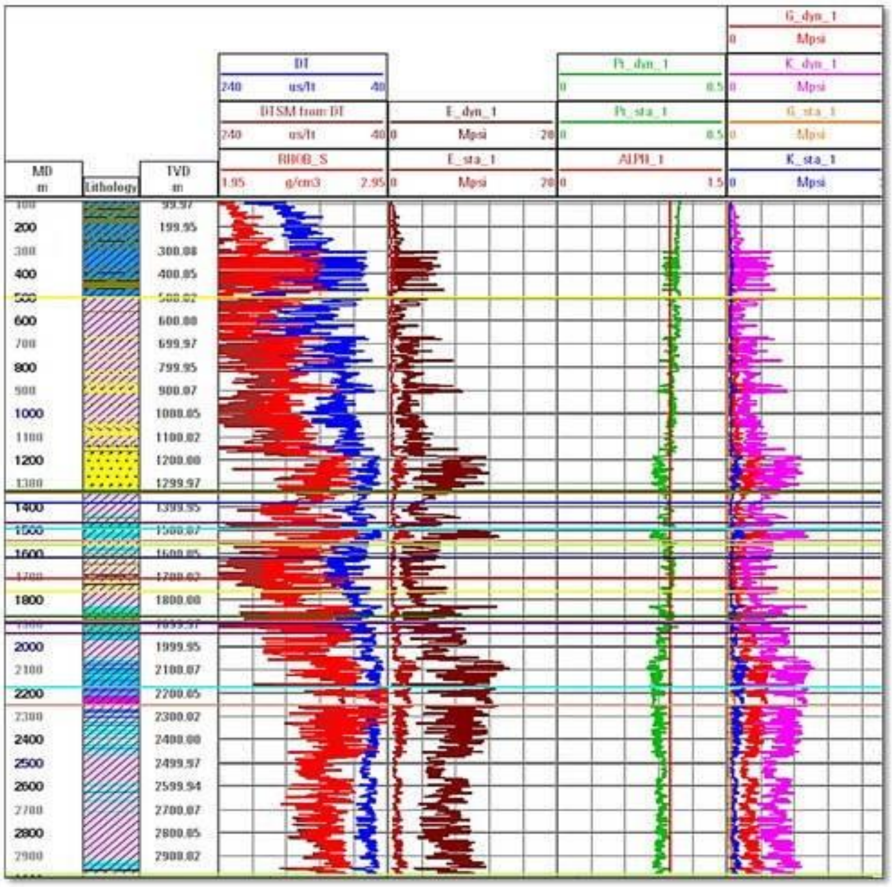

Fig. 7: Various elastic parameters for Well-1 after predicting the DTS; First track is showing: DT and DTS in µs/ft along with RHOB (density) in g/cc, Second track is showing: Dynamic and static Young's modulus in MPsi, Third track is showing: Dynamic and static Poisson's Ratio along with Biot's coefficient, Forth track is showing: Dynamic and static Bulk and shear Modulus in MPsi.

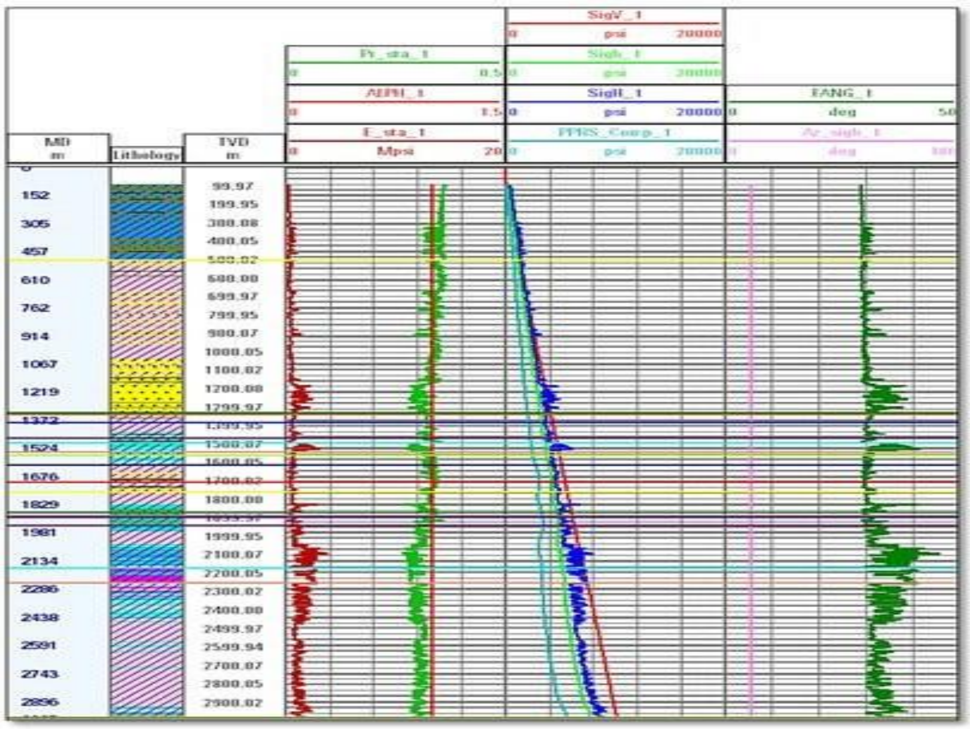

Fig. 8: In-situ stresses of Well-1 of Agbami field. The first track is showing: Poisson's Ratio, Biot's coefficient and Young's modulus, the second track is showing: Vertical stress, minimum horizontal stress, maximum horizontal stress along with the pore pressure, the third track is showing friction angle and horizontal stress azimuth.

I. Comparative Performance

The comparative performance of the traditional and hybrid methods are presented in table 2 below.

Table 2: Comparative Performance Table Showing the Advantages of Hybrid Method over Traditional Method

Attribute	Traditional	Hybrid
Core methodology	Depends on a single modelling technique, like the independent Finite Element Method (FEM) for geomechanical analysis.	Incorporates several approaches. For example, Poro-Elasto-Plastic FEM and Machine Learning (ML) algorithms are combined in one known hybrid approach to produce an integrated model.
Model Integration and Workflow	Employs sequential, segregated solution processes in which distinct problem components, such as soil deformation and fluid flow are resolved independently.	Strives for a system that is more cohesive. The hybrid model is intended to be an "Integrated Drilling Geomechanics Model" in the drilling context, combining FEM and ML.
Objective and Result	focusses on using well-established physical models to forecast soil response and pore pressure coupling under load.	aims for real-time application and improved predictive capabilities. The combined FEM-ML model is appropriate for a real-time setting and is used to forecast failure limits for new wells.
Flexibility and Adaptability	The model is based on constitutive relations (like Mohr-Coulomb) and fixed physical parameters. It can take a lot of computing power to update the model with new data.	Through the use of machine learning, the model may be able to learn from data and gradually enhance its predictions, becoming more flexible when dealing with fresh field data.
Implementation and Efficiency	For complex, real-time scenarios, highfidelity traditional FEM can be computationally demanding, despite its effectiveness in forecasting reasonable soil responses.	The efficient prediction capabilities of the hybrid FEM and ML approach suggest that the ML component could aid in optimizing computational resources for tasks such as real-time forecasting.

CONCLUSION AND RECOMMENDATION

The study shows that poro-elasto-plastic Finite Element Modeling (FEM) and Machine Learning (ML) are the next generation in the paradigm in drilling geomechanics. The FEM physics model is good at modeling complex time-dependent behaviour of wellbores, such as plastic yield and pore pressure, and stretches past the limitations of simplistic elastic models. ML algorithms optimally convert this high-fidelity output into real-time predictive tools that can be used rapidly on wellbore stability.

The combination of such technologies forms a strong digital twin, which allows dynamically updated safe mud window, which reacts to the real downhole conditions. This is a direct transfer to safer drilling, more efficient mud programs, and a huge decrease in non-productive time due to instability of the wellbore. This combined strategy is creating a new standard of preparation-driven and economical well building by closing the disconnect between complicated simulation and operational decision-making, initiating the process of autonomous drilling geomechanics in hard-to-reach locations.

The following recommendations are hereby made;

High-Fidelity Data Acquisition and Curation: Accuracy of the model is purely based on quality of the data. It is important to develop a multi-well database of the Niger Delta that will be systematized and comprise logs, core tests, and drill events. Removal of extraneous data and ability to extreme features is sensitive towards training strong, dependable machine learning programs.

Development and Validation of Real-Time Model Updating Protocols: The theoretical framework has to be converted into an operational tool in the present time. There should be a design of automated processes in which LWD data (e.g. pore pressure, wellbore shape) is automatically fed into the FEM and ML model. This gives rise to a dynamic digital twin of the wellbore to be used in proactive decision-making.

Implement Advanced Hybrid Modeling Techniques: To overcome computational limits, there should be a development of a hybrid modeling framework. Here, the high-fidelity FEM generates massive training datasets for a faster, surrogate ML model (e.g., a deep neural network). This surrogate can then be deployed for instant, real-time predictions at the rig site.

REFERENCES

1. AlBahrani, H., Papamichos, E., & Morita, N. (2021). Building an integrated drilling geomechanics model using a machine-learning-assisted poro-elasto-plastic finite element method. SPE Journal, 26(04), 18931913. https://doi.org/10.2118/205497-PA
2. Al-Haddad, S. A., Abbas, H. A., Al-Haddad, L. A., & Al-Karkhi, M. I. (2025). Application of artificial neural networks for predicting soil settlement in geotechnical applications with plastic waste reinforcement above buried pipes. Discover Geoscience, 3(1), 1-17.
3. Amadike, M. P., Nwanesi, F. O., Ogbonna, C. G., Ohale, U. U., Okoli, A. E., Jacob, O. J., & Okeke, O. C. (2024). Principles and Applications of Seismic Reflection Geophysical Technique In Petroleum Exploration And Production: A Review. DOI: 10.5281/zenodo.14265732
4. Beckman J. (2024). Agbami field offshore Nigeria set for renewed drilling. https://www.offshoremag.com/regional-reports/africa/news/55243211/agbami-field-offshore-nigeria-set-for-renewed-drilling
5. 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. https://doi.org/10.1007/s40948-025-01006-5
6. Emudianughe, J. E., Eze, P. M., & Utah, S. (2021). Porosity and Permeability Trend In Agbami-Field Using Well Log, Offshore, Niger Delta. Communication In Physical Sciences, 7(4), 531-541. https://orcid.org/0000-0002-1217-4599
7. Gladious, J., Paul, P. S., & Mukhopadhyay, M. (2025). Machine learning based prediction of geotechnical parameters affecting slope stability in open-pit iron ore mines in high precipitation zone. Scientific Reports, 15(1), 21868. https://doi.org/10.1038/s41598-025-99026-4
8. Harle, S. M., & Wankhade, R. L. (2025). Machine learning techniques for predictive modelling in geotechnical engineering: a succinct review. Discover Civil Engineering, 2(1), 1-21.
9. Jamshidi, E., Kianoush, P., Hosseini, N., & Adib, A. (2024). Scaling-up dynamic elastic logs to pseudostatic elastic moduli of rocks using a wellbore stability analysis approach in the Marun oilfield, SW Iran. Scientific Reports, 14(1), 19094. https://doi.org/10.1038/s41598-024-69758-w\
10. Khan, A., Li, Y., Shoaib, M., Sajjad, U., & Rui, F. (2025). Utilizing machine learning and digital twin technology for rock parameter estimation from drilling data. Journal of Intelligent Construction, 3(2), 123.
11. Komijani, M. (2024). A mixed nonlocal finite element model for thermo-poro-elasto-plastic simulation of porous media with multiphase fluid flow. International Journal for Numerical Methods in Engineering, 125(17), e7466. https://doi.org/10.1002/nme.7466
12. Li, X., El Mohtar, C. S., & Gray, K. E. (2019). 3D poro-elasto-plastic modeling of breakouts in deviated wells. Journal of Petroleum Science and Engineering, 174, 913-920. https://doi.org/10.1016/j.petrol.2018.11.086
13. Lindqwister, W., Peloquin, J., Dalton, L. E., Gall, K., & Veveakis, M. (2025). Predicting compressive stress-strain behavior of elasto-plastic porous media via morphology-informed neural networks. Communications Engineering, 4(1), 73. https://doi.org/10.1038/s44172-025-00410-9
14. Liu, H., Su, H., Sun, L., & Dias-da-Costa, D. (2024). State-of-the-art review on the use of AI-enhanced computational mechanics in geotechnical engineering. Artificial Intelligence Review, 57(8), 196.

15. Liu, M., & Huang, H. (2021). Finite element modeling of spherical indentation in a poro-elasto-plastic medium via step displacement loading. International Journal for Numerical and Analytical Methods in Geomechanics, 45(10), 1347-1380.
16. Nautiyal, A., & Mishra, A. K. (2023). Machine learning application in enhancing drilling performance. Procedia Computer Science, 218, 877-886.
17. Nguyen, H. C., He, X., Nazem, M., Chen, X., Xu, H., Sousa, R., & Kowalski, J. (2025). Gaussian process emulators for the undrained bearing capacity of spatially random soils using cell-based smoothed finite element method. Journal of Rock MechanicsandGeotechnicalEngineering. https://doi.org/10.1016/j.jrmge.2025.04.042
18. Osaki, L. J. & Oghonyon, R. (2025a) Synthesizing Geophysical Well Logging and Spatial Modelling for
19. Reservoir Analysis Optimization: A Dynamic Approach. African Journal of Engineering and Environment Research Vol.7(2) 2025 pp 22- 44 ©2025 CEFPACS Consulting Limited. www.cefpacsconsultingltd.org.ng ISSN: 2714-2264.
20. 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) Volume 14 Issue 8 August Pages PP 20-29 2025 ISSN (e): 2319 – 1813 ISSN (p): 2319 – 1805.
21. 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
22. Pirhadi, A., Kianoush, P., Varkouhi, S., Shirinabadi, R., Shirazy, A., Shirazi, A., & Ebrahimabadi, A. (2025). Thermo-poroelastic analysis of drilling fluid pressure and temperature on wellbore stresses in the
23. Mansouri oilfield, SW Iran. Results in Earth Sciences, 3, 100061. https://doi.org/10.1016/j.rines.2025.100061
24. Sanei, M., Ramezanzadeh, A., & Delavar, M. R. (2023). Applied machine learning-based models for predicting the geomechanical parameters using logging data. Journal of Petroleum Exploration and Production Technology, 13(12), 2363-2385.
25. Yan, B., Zhang, X., Tang, C., Wang, X., Yang, Y., & Xu, W. (2023). A random forest-based method for predicting borehole trajectories. Mathematics, 11(6), 1297.
26. Yoon, H., Kucala, A., Chang, K. W., Martinez, M. J., Bean, J. E., Kadeethum, T., & Fuhg, J. N. (2022). Computational Analysis of Coupled Geoscience Processes in Fractured and Deformable Media (No. SAND2022-12824). Sandia National Lab. (SNL-NM), Albuquerque, NM (United States). https://doi.org/10.2172/1890064
27. Zhang, W., Wu, C., Zhong, H., Li, Y., & Wang, L. (2021). Prediction of undrained shear strength using extreme gradient boosting and random forest based on Bayesian optimization. Geoscience Frontiers, 12(1), 469-477.
28. Zhang, L., Zhang, H., Hu, K., Chen, Z., & Yin, S. (2022). Thermoporoelastoplastic wellbore breakout modeling by finite element method. Mining, 2(1), 52-64. https://doi.org/10.3390/mining2010004