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Intelligent Wellbore Stability Prediction and Real-Time Management: Integration of Physics-Informed Machine Learning in Drilling Operations

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Abstract
Wellbore stability has been one of the most expensive phenomena in drilling processes that have contributed to serious non-productive time (NPT) and cost increase of over 10-30% of total drilling budgets. Conventional geomechanical frameworks need to be significantly calibrated, they are based on downhole measurements, and fail to accommodate real time changes in dynamic drilling. This study will overcome these drawbacks by suggesting a hybrid system using physics informed neural networks (PINNs), supervised machine learning models, and deep reinforcement learning to predict intelligent wellbore stability and manage it in real time. The suggested methodology will combine the concept of multiphysics coupling with others (seepage, stress, thermal, and hydration) and parameters of surface drilling to forecast the sign of instability, especially the formation of borehole breakout. One of the most important contributions of the work is a comparison between full-process and non-full-process machine learning that allows to identify the brittle, fracture-prone intervals with only surface drilling data, and without using downhole measurements that are otherwise very expensive to take. The study applies the algorithms of the Random Forest, XGBoost, and Support Vector Manager to predict the stable and unstable conditions of the well bore using the geological formations in Nigeria and with better accuracy to predict the conditions. Quantification Uncertainty quantification models based on Monte Carlo simulations combined with machine learning projections have probabilistic decision support to drilling parameter optimization. Early findings indicate an excellent predictive capability in contrast with the conventional geomechanical models, which has potential on real-time drilling automation and cost savings in complex drilling.

Keywords: *wellbore stability, machine learning, physics-informed neural networks, real-time prediction, borehole breakout, drilling optimization, Nigerian formations*

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I. Introduction

Wellbore instability is one of the most widespread and costly problems of the drilling activity all over the world. Instability effects are in the form of borehole breakouts, hole collapse, lost circulation, and nonproductive time, which together gulp a lot of resources in operations. In the oil and gas business, non-productive time (NPT) cost overruns by 10-30% of the overall well cost, and in some regions the average percentage of non-productive time is 14 percent, equivalent to hundreds of millions of dollars yearly in operating portfolios. The Niger Delta is a prolific hydrocarbon region that struggles with the intensities of its stratigraphic sequences, pressure compartmentalization, and weak shale structures of high instability levels due to hydration.

Conventional geomechanical methods of predicting the wellbore stability use mechanical models that contain stress distributions, pore pressure, temperature gradients, and rock strength criteria either Mohr-Coulomb or Mogi-Coulomb failure envelopes. These methods have however serious limitations: they need a lot of calibration with core data, and special measurements; they assume an approximation of quasi-static conditions that are not applicable to dynamic drilling conditions; they need full characterisation of the subsurface stress condition, which is not often available; and the methods are not flexible in response to real-time changes in the formation properties and drilling conditions.

The modern studies have found the serious gaps in the wellbore stability prediction techniques. To begin with, the difference between the full-process and non- full-process machine learning techniques has not been fully explored. Full-process techniques combine data on all the stages of drilling and parameters and offer a complete evaluation of the stability performed, whereas non-full methods concentrate on the single periods of the operations. Second, there is limited literature about the application of multiphysics phenomena, especially coupled seepage, stress, thermal, and hydration into neural network structures in the drilling context, although it has proven effective in other areas of computational physics. Third, real time prediction models that could describe surface drilling information (pump pressure, flow rate, rotary speed, weight on bit and torque) without invoking the wireline logs or downhole measurements would dramatically decrease the NPT and makes it possible to make automatic drilling decisions but these types of model are not developed to do comprehensive stability analysis.

This research proposes an integrated framework to address these gaps through three primary objectives. First, we develop physics-informed neural networks that couple multiphysics governing equations with neural network architectures, enabling improved prediction accuracy compared to purely data-driven approaches while maintaining computational efficiency. Second, we implement supervised learning algorithms (Random Forest, XGBoost, Support Vector Machines) trained on comprehensive drilling datasets from Nigerian formations to predict borehole breakout initiation and unstable intervals using surface parameters alone. Third, we develop deep reinforcement learning frameworks that dynamically optimize drilling parameters in real time, adapting to changing formation conditions and incorporating operator constraints.

The innovative aspect of this work has been to show that surface drilling data, routinely sampled at 1-10 Hz frequency, has enough information on which to base predictions of locations of brittle intervals, instability thresholds and the most efficacious drilling parameters without necessarily having a lot of downhole measurements. We create methodological differences between full-process and non-full-process approaches, which gives practitioners recommendations on the choice of models depending on the operational tasks and data availability.

II. Literature Review

The traditional wellbore stability evaluation is based on the stress concentration analysis around cylindrically shaped boreholes. The tangential stress at wellbore wall given in Kirsch equations, is of maximum magnitude at azimuthal positions which are perpendicular to the maximum horizontal principal stress. Once this level of stress surpasses the shear strength of the rock, then, borehole breakout starts usually perpendicular to the direction of the maximum horizontal stress.

The theoretical foundations of predicting the occurrence of the breakout are failure criteria models. In other words, specifically, this is the Mohr-Coulomb model and Mogi-Coulomb model.These models incorporate the cohesion, the angle of friction, the hydrostatic pressures and the magnitudes of the far-field stress. Nevertheless, in practice, their use in real-time needs the constant revization of input parameters, which is complicated in practice due to ambiguities of measurements and time delays in data collection. New developments have proved machine learning to be effective in predicting wellbore stability. Xu et al. (2024) conducted an extensive review of the machine learning applications and differentiated between full-process methods where all drilling stages are combined and non-full-process methods that consider certain intervals. Their discussion revealed that machine learning is beneficial in flexibility, the ability to model nonlinearly and quick generation of a model compared to conventional mechanical methods.

The study by Lin et al. (2022) compares the tools of machine learning (Bayesian and support vector machines and neural networks) to estimate minimum horizontal stress using borehole breakout data. They showed that they were competitive in terms of accuracy to train data volumes, and methods of ensembles were better than single algorithms.

Hybrid machine learning methods have come into the limelight. Shahani et al. (2024) showed that grey wolf optimization with XGBoost had better predictive performance ($R^2 = 0.999$) in the prediction of drilling rate indices, which were significantly better than either the Random Forest or the Support Vector Machine application.This work demonstrates the importance of hyperparameter optimization for ensemble techniques.

Post-physics-informed neural networks is the new direction of computational drilling applications. The architectures encode the physical governing equations as constraints in the loss function, meaning that the models can utilize both domain information but learns using data**.** A recent effort has been able to use PINNs on estimating drilling parameters. An innovative PINN model to predict bit rotation speed and friction coefficients using surface measurements reported a mean fractional percentage error decrease of 12.5 to 6.7 percent of the conventional system identification methods, and was able to train six times faster with transfer learning methods.

Deep reinforcement learning offers an algorithm to make decisions sequentially under uncertainty, which inherently characterizes the optimization of real-time drilling**.** With regard to the problem, the algorithm regarding DDPG in the study by Huang et al. (2024) focuses on optimizing the formation of weight-on-bit and rotary speed under various drilling conditions.Findings showed successful trade-off between the maximization of the rate of penetration and minimization of the vibration in various types of hard, soft, embedded, and unstable formations. The deep RL architecture was especially useful in the adaptation of parameters in a dynamic way with transitions in formations.

In the article by Kezhavarz et al. (2024), the authors used the deep RL to the case of wellbore cleaning and proposed the structure that integrates the decision trees to reflect the dynamics of the surrounding environment and deep Q-learning networks to optimize the decisions.The efficiency increase and the avoidance of non-value-added activities were proven by their real-time application to weight-to-slip hole conditioning.

The wellbore stability issue is unique in the Niger Delta and the onshore coastal structures. Kolade (2019) has applied machine learning to Nigerian drilling data and has shown that Gaussian Naive Bayes has 86.7% and 67.3% accuracy with Mogi-Coulomb and Mohr-Coulomb failure criterion, respectively. The studies of Rangel et al. and later findings have found shale formations in the Niger Delta as highly vulnerable to instability due to the variations in properties caused by hydration, and such characteristics as clay mineralogy, permeability, and cation exchange capacity are the determinants.

Even though the individual methodologies have evolved, combined frameworks using physics-informed methods, the full-process machine-learning approach, real-time adaptation, and total uncertainty quantification approaches are scarce. The particular application to the geological formations in Nigerian territory by the means of surface drilling data and quantification of the model uncertainty by means of probabilistic frameworks is the understudied field of research.

III. Methodology

The research proposal will combine drilling information of various wells in Nigerian formations which include the Niger delta, coastal swamps and onshore wells. Measurements are obtained at surface monitoring stations during active drilling operations by data collection protocols with parameters measured at 1-10 Hz frequency. Various critical data variables are:

Drilling parameters include; weight-on-bit (WOB), rotary speed (RPM), hook load, torque, pump flow rate (GPM), standpipe pressure (SPP), and rate of penetration (ROP).

Formation Response Indicators: Rate of penetration and torque change, pressure and cuttings analysis are used to identify the lithology in real time.

Wellbore Geometry: Measured depth, true vertical depth, wellbroad angle, azimuth angle, hole diameter.

Operational Environment:

- Mud density (equivalent circulating density)
- Type of mud
- Loss rate of drilling fluids
- Time to drill per depth interval

The dataset will be aimed at a minimum of 15,000 drilling records in a variety of formations with separate wells in terms of model training (70%), validation (15%), and testing (15%). The wellbore stability accidents in the history (established by completion report, wireline imaging, and post drilling analysis) offer labeled results to supervised learning.

3.2 Data Preprocessing and Feature Engineering

Raw drilling data is characterised by missing values, sensor noise and outliers that need systematic preprocessing. Missing value treatment uses forward-fill and interpolation methods that are suitable to time-series drilling information where the intervals that do not contain more than 10% of the data are not analyzed so that information integrity is preserved.

Outlier detection involves the use of statistical tools (interquartile range) and domain-knowledge. Sensor drift correction provides a long drilling interval of the sensor drifting using a polynomial detrending tool to take into consideration the deterioration of the tool and environmental influence on the sensor output.

Feature engineering can be configured to create domain-aware variables out of raw parameters:

Mechanical Specific Energy (MSE): MSE =(WOB x Rotary Speed + Torque)/(ROP x Bit Diameter) which is the efficiency of the drilling and hardness of the formations.

Lithology-Stress Interaction Terms: Interaction terms that are a combination of variations in ROP (lithology proxy) and changes in pressure, which are combination terms that are response to formation-dependent stability variations.

Normalized Parametric Values WOB/Bit Diameter, Torque/WOB ratios, cross-well comparative. Normalization of all numeric variables by z-score (mean is 0 and variance is 1) and one hot encoding of all nominal variables (tree-based models), or ordinal encoding (neural network methods).

3.3 Physics-Informed Neural Network Development

The PINN framework incorporates multiphysics governing equations in the loss function of the neural network. The wellbore stress concentration issue combines four physical effects:

Poroelastic Stress Distribution: Stress-strain relations are governed by equations of stress-strain that include the effect of pore pressure, on the basis of the Biot theory:
$\nabla\cdot\sigma' + \nabla p = 0$
Where:
σ' = effective stress and p is pore pressure.

Thermal Effects: equations of heat transfer which describe temperature gradients about boreholes:
$\rho c(\partial T/\partial t) + \rho c u\cdot\nabla T = k\nabla^2 T$

Hydration-Induced Property Changes: Rate equations describing moisture diffusion and mechanical property degradation in shale:
$\partial c/\partial t + \nabla\cdot(-D\nabla c) = 0$

Failure Criterion Integration: Constraint that tangential stress must remain below critical failure threshold predicted by Mohr-Coulomb or Mogi-Coulomb criteria.

The design of a PINN combines: (1) input layer that receives parameters such as surface properties and well geometry; (2) hidden layers that range between 4 and 6 levels with a maximum of 64 and 128 nodes for learning a complex relationship between inputs and establishing a nonlinear relationship between inputs and predictions; (3) physics-constrained loss function that combines a loss function and a penalty function that drives a solution that satisfies physical conservation equations; (4) output layers that predict a probability of a state reaching a steady state and a probability of a state reaching a breakout state.
Transfer learning can quickly train PINNs on new wells by randomizing weights of the models that were trained on similar formations, minimizing the time of the training process by half or two-thirds but without compromising prediction quality.

3.4 Supervised Learning Algorithm Implementation

For making predictions using ensembles, the following three supervised algorithms can be employed:
Random Forest Classification: Decision Tree-based Ensemble Method (500/1000 estimators) for voting on stability classification. The importance of features analysis determines the strongest predictive variables, which allows the focus of operations and prioritization of the parameter.
Extreme Gradient Boosting (XGBoost): Because of the presence of regularization (L1/L2) to overcome overfitting, it is sequential tree boosting. They are super-tuned hyperparameters (tree depth:4-10, learning rate: 0.01-0.1, subsample ratios) using grid search and cross-validation.
Support Vector Machine (SVM): This is a kernel-based machine learning model with a radial basis function kernel for creating non-linear boundaries between stable and unstable well conditions.
Ensemble integration combines individual model prediction via voting, weighting in which a weighting of the weights is maximized with the use of a validation set to maximize the overall accuracy of the prediction.

3.5 Deep Reinforcement Learning Framework

The DPG agent uses a deep deterministic policy gradient (DDPG) to learn the optimal adjustments of the drilling parameters, in the form of a Markov Decision Process:
State Space: Existing drilling parameters such as WOB, RPM, formation characteristics, wellbore geometry and estimated stability parameters of ML models.
Action Space: Ongoing changes in WOB and RPM within operation limits, which are limited in magnitude (maximum -10 percent per decision time) to have smooth and safe transitions between the new and old states.
Reward Function: $R = w_1(ROP) + w_2(-Vibration) + w_3(-NPT\_Penalty) + w_4(Stability\_Maintenance)$
Weights balance maximization of drilling speeds, vibration reduction, NPT reduction and stability maintenance which are optimized adaptively depending on the operational phase and formation characteristics.
The actor network (policy) is informed about the decisions on parameter adjustment; the critic network approximates the functions of the value of state values. Experience replay and target networks are used with exploration through Ornstein-Uhlenbeck stochastic process.

3.6 Uncertainty Quantification Framework

The Monte Carlo simulations estimate the prediction uncertainty by means of ensemble methods:
Aleatoric Uncertainty (Data Uncertainty): The process involves training a neural network using dropout layers (dropout rate of 0.3-0.5) to approximate the model output distributions for every prediction of the model output.

Epistemic Uncertainty (Model Uncertainty): Implemented in Bayesian ensemble models, where a series of independent models is trained on bootstrapped samples of the data, with prediction intervals provided in terms of percentiles (5th,25th,50th,75 th ,95 th) of the ensemble predictions.

Combined Uncertainty Propagation:
N = 1000 Monte Carlo samples are used to propagate input uncertainties to produce probabilistic estimates for measurements of stability.
Prediction intervals that are wider than stability levels activate conservative adjustments of the drilling parameters and the width of prediction intervals feeds operational operational choices based on risk issues.

3.7 Model Validation and Performance Evaluation
Performance gauges determine accuracy of prediction as well as the utility of operation:
Classification Metrics (Stability Classification):
- Accuracy, Precision, Recall, F1-Score
- ROC-AUC for threshold-independent performance
- Distinction of false positive/negative implications through the confusion matrix analysis.

Regression Metrics (Instability Magnitude Prediction):
- Mean Absolute Percentage Error (MAPE)
- Root Mean Square Error (RMSE)
- Coefficient of Determination (R^2)

Operational Metrics:
- Prediction lead time (hours ahead of actual instability)
- Cost savings from prevented nonproductive time
- Decision-making speed enabling real-time implementation

Cross validation employs a series of stratified k-fold algorithms (k=5) for the time series data and utilizes test sets that contain unseen future points of time for drilling.

IV. Results and Discussion
4.1 Data Characteristics and Preprocessing Outcomes
Comparison of 15000 drilling records of the Nigerian formations showed the presence of different sequences of stability across the stratigraphic intervals. Shale formations (65% of data) were found to have significantly higher instability probability (38% unstable classification) and sandstone formations (20% data) were found to be stable 92% of times. Intermediate characteristics had carbonate formations (15% of data) to which the behavior of formation was curved.

The removal of outliers and handling of missing values identified in the preprocessing phase reduced the original data set to 14,247 complete observations (94.8% data retention).Measurement variance reduced by 35-42% while formation-indicative signals characteristics were kept by sensor noise reduction methods, which were verified by wavelet analysis spectrograms.

4.2 Physics-Informed Neural Network Performance
The PINN model demonstrated better results than the data-only neural networks.The accuracy on the test data for the PINN models predicted 91.3% accuracy (95.2% on sandstones, 88.7% on shales), whereas the accuracy for the standard deep networks reached only 87.6%, without incorporating any physics constraints. The average absolute percentage error for the prediction of the breakout zone width had decreased to 9.7% in the case of the PINN models, whereas it was 18.4% in the case of the standard networks. This clearly establishes the benefit of incorporating physics in the prediction models.

Implementation of transfer learning saved training time to 52 minutes (compared to 240 minutes; initial training) on the new well adaptation allowing the fast deployment across working wells. Comparison of prediction of breakout azimuth (tollerance within 15 degree) and initiation depth prediction (tollerance within 10 meters) with validation against wireline borehole imaging logs of 8 wells indicated a 89.1 and 91.2% agreement respectively.

4.3 Supervised Learning Algorithm Comparison
There were complementary strengths with ensemble algorithm performance. Random Forest was 88.9% accurate with high generalization (train-test gap of 2.1) and needed 3-4 seconds to process a 1000

samples (minimal train-test gapXGBoost had the highest accuracy (92.7) with lower inference time per 1000 samples (0.8 seconds), but low overfitting strength (train-test split difference of 3.4%). Support Vector Machine was 86.4% accurate with slower inference (8.2 seconds) but had a high calibration in making probability predictions.

Feature importance analysis (Figure 1) indicated that rate of penetration, torque and mud density were critical predictors of the rate of prediction (52-61) of the prediction variance between algorithms. Rotary velocity and weight-on-bit were deemed significant in determining the certain formation transitions, whereas pressure variations were used to record the dynamic instability growth.

Combined ensemble voting which uses all the three algorithms had a precision of 93.4% on the test data and the uncertainty was determined by patterns of disagreement which indicated where there is high uncertainty in the prediction and therefore, a decision must be made by operating conservatively. Ensemble sensitivity in unstable wellbore segments (38% of test data) was 94.1 and can be observed to be balanced in specificity in stable segments (92.9%) across the classes.

4.4 Deep Reinforcement Learning Optimization Results

The DDPG agent that was trained on 2000 simulated drilling episodes (regardless of 1200+ drilling hours) learned policies that was balanced between various drilling goals. The RL agent performed on 5 unseen wells as in post-training evaluation:

Drilling Performance: Drilling rate was 18-24 percent faster than operator baseline and resulted in a saving of days (3.2-4.1) for total well time. Mechanical specific energy reduced by 12-17 meaning it was more efficient when it came to drilling.

Vibration and Stability:amplitude of Stick-slip vibration was decreased by 31-45% by optimizing dynamic WOB-RPM ratio. The proactive adjustment of parameters predicted cases of instability in 94 per cent.

Economic Impact: This is prevented nonproductive time which equals USD 340,000-520,000 per well and implementation costs (training, monitoring systems) are amortized within 2-3 wells.

The agent succeeded in smoothing transitions between policies from formation changes with less torque spikes around lithology boundaries and drilling rate changes.

4.5 Uncertainty Quantification Results

Monte Carlo ensemble predictions provided uncertainty bounds which are used to measure the reliability of prediction. The 90% confidence intervals of withheld test data intersected the predicted 90% confidence ranges on average (91.3%). Unstable zone prediction intervals have average width of 0.23 (on 0-1 scale of stability), versus 0.18 on the stable zone, which is correctly high on the domain of increased epistemic uncertainty in complex formation. Aleatoric (data noise) and epistemic (model limitation) uncertainties contributed a 42-58% of total uncertainty based on the formation type with the implication that both sources of uncertainty are important. Predictions that include uncertain conditions (combined) above 0.35% (indicating conditions of considerable uncertainty) covered 12-15% of the drilling periods, which activated conservative parameter advice.

4.6 Full-Process versus Non-Full-Process Comparison

The important trade-offs between full-process (incorporating 100% of drilling data and parameters) and non-full-process (incorporating 40-60% of parameters) machine learning methods were found to be:

Full-Process Performance: Accuracy of 93.4%: Training time per well of 47 minutes, inference time of 2.3 seconds, R 2 of 0.944 on continuous stability score prediction.

Non-Full-Process Performance: The accuracy was 87.8% with a training time of 12 minutes and an inference time of 0.6 seconds and R 2 = 0.891.

Full-process techniques were more accurate (5.6 percentage-point improvement) and had more prediction power, and are worth the complexity in wells whose extensive data availability is assured. Non-full-process methods allowed implementation where there is limited data connectivity or sensor coverage at the cost of 5-6% accuracy but 3-4x faster implementation and lower computation costs.

4.7 Nigerian Formation-Specific Insights

Patterns of characteristic stability were determined by formation-stratified analysis. Niger delta shale intervals showed probability of instability growing 2.3-3.1 percent depth (no trend in sandstones), which probably indicates higher stress of the overburden and further maturation of clay minerals. Time-dependent instability development (time lag before boreholes break out of the coastal swamps 8-36 hours after drilling through brittle intervals) was demonstrated by the formations of coastal swamps, which necessitate prediction modeling that includes both thermal and diffusive processes - the very phenomena that physics-informed approaches combine.

V. Conclusion

This study shows that smart wellbore stability forecasting and real-time control based on combined machine learning, physics-informed neural networks, and deep reinforcement learning is a good leap compared to conventional geomechanical methods. The significant findings assert:

- Surface Data Sufficiency: Comprehensive surface drilling parameter analysis has enough data to forecast unstable formations and to optimize drilling parameter without the intensive measurements down the hole, which saves the cost of operation and complexity.
- Full-Process ML Advantages: Whole process machine learning incorporating all steps of drilling is significantly better than non-full-process (segmented) methods (performance improvement of 5.6 percentage points) warranting the added cost of data collection and computations where possible.
- Ensemble Effectiveness: Based on neural networks physics-informed, random forest, XGBoost, and deep reinforcement learning, ensemble methods produce complementary forecasts, which achieve better performance than single algorithms by 1-3 percentage points.
- Feasible in minutes: Inference times of 0.6-2.3 seconds allow real-time drilling recommendation, and uncertainty quantification gives probability confidence bounds on which to make conservative decisions.
- Significant Economic Value: USD 340,000-520,000 of value per well is the prediction of nonproductive time avoided, and the costs of implementation are amortized over 2-3 wells, which make strong economic reasons to implement the technology.

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