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Predicting Swab and Surge Pressures for Wellbore Instability Analysis Using Machine

[1]Muhammad Kabir Abba, [2]Ilham Abbas Idris, [3]Gbenga Godwin Oseke
[1,2&3]Petroleum and Gas Engineering Department, Baze University, Abuja, Nigeria.
[1]Nordatech Energy Ltd, Abuja-Nigeria

ABSTRACT

This study applies machine learning (ML) techniques to predict surge and swab pressures during tripping operations with the aim of enhancing wellbore stability in drilling environments. Using real operational data obtained from the Sponge Bob 1 well, a Water-Based Mud (WBM) system, key drilling parameters such as mud weight, plastic viscosity, yield point, and true vertical depth were collected, processed, and engineered into a structured dataset of 70 observations. Five supervised ML models—Artificial Neural Network (ANN), Random Forest, XGBoost, Decision Tree, and K-Nearest Neighbors—were developed and evaluated using Root Mean Squared Error (RMSE) and Coefficient of Determination (R^2). Results showed that ANN provided the highest predictive accuracy with RMSE values of 5,666.42 psi and 3,904.43 psi, and R^2 values of 0.89 and 0.91 for surge and swab pressures, respectively. The analysis confirmed mud rheology and depth as the most influential predictors of transient pressure behavior, while graphical comparisons demonstrated strong alignment between actual and predicted values. The study concludes that ML offers a robust, data-driven alternative to conventional hydraulic models and recommends its integration into real-time drilling systems to support proactive wellbore pressure management and reduce non-productive time.

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INTRODUCTION

The petroleum industry remains central to the global energy supply chain, with drilling operations playing a crucial role in hydrocarbon recovery. A recurrent challenge in drilling is wellbore instability, which occurs when the borehole walls lose their structural integrity due to mechanical, chemical, or thermal interactions with drilling fluids and formation rocks (Aadnøy & Looyeh, 2019). This phenomenon manifests in several costly problems, including stuck pipe, borehole collapse, lost circulation, tight hole conditions, and even catastrophic well failures. Studies indicate that wellbore instability accounts for between 10% and 20% of non-productive time (NPT) in drilling operations worldwide (Zhou et al., 2019).

A specific contributor to instability is the transient pressure fluctuations caused during tripping operations. These pressures, known as swab and surge, are induced by the piston-like motion of the drill string within the wellbore. When the string is pulled out, it lowers the bottom-hole pressure, creating a swab effect. Conversely, when the string is run back into the well, bottom-hole pressure rises, leading to a surge effect. Both conditions pose risks to wellbore stability: excessive swab can result in influxes of formation fluids (kicks), while excessive surge can fracture the formation, causing lost circulation (Ali et al., 2021).

Traditionally, engineers have relied on hydraulics-based models to estimate these pressures. Such models, however, often make simplifying assumptions such as laminar fluid flow, constant annular geometry, or neglect of fluid compressibility that fail to capture the complexity of real-world drilling (Al-Mudhafar & Al-Jaberi,

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2020). As drilling ventures into deeper and more complex formations, these models become increasingly insufficient. Errors in prediction can translate into costly delays, well control incidents, or even abandonment of expensive wells.

In response to these challenges, researchers have turned to machine learning (ML) approaches. ML leverages large datasets generated during drilling encompassing trip speed, mud rheology, fluid density, and pressure readings to train models that recognize nonlinear patterns and interactions among variables. Unlike traditional models, ML does not require oversimplified assumptions; instead, it adapts to data complexity and provides real-time predictions (Rajabi, Ghassemi, & Zendehboudi, 2023). This capability is particularly valuable in modern drilling, where real-time decision-making is essential to avoid costly instability events.

The significance of integrating ML into drilling practices extends beyond operational safety. Accurate prediction of swab and surge pressures reduces the likelihood of NPT, optimizes tripping speeds, minimizes mud losses, and enhances formation integrity. Furthermore, with the oil and gas industry increasingly embracing digitalization, the adoption of ML-based predictive systems aligns with global trends toward smarter, data-driven drilling operations (Santos, Martins, & Silva, 2022). By addressing gaps in conventional prediction methods, this study contributes to the body of knowledge on digital petroleum engineering and supports the development of safer, more cost-effective drilling practices.

Despite decades of research, wellbore instability remains one of the leading causes of drilling challenges worldwide, contributing to billions of dollars in annual losses. In deep and high-pressure wells, the risks associated with swab and surge pressures are particularly severe. Excessive swab pressure can reduce bottom-hole pressure below pore pressure, causing an influx of formation fluids, which may escalate into kicks or blowouts if not controlled (Zhou et al., 2019). On the other hand, excessive surge pressures can exceed fracture gradients, inducing lost circulation, wellbore collapse, and even stuck pipe (Ali et al., 2021).

Conventional surge and swab prediction models, while useful, are limited in accuracy due to reliance on rigid assumptions and inability to incorporate real-time variability. This inadequacy often forces drilling engineers to adopt overly conservative tripping speeds, leading to inefficiency and extended drilling time (Al-Mudhafar & Al-Jaberi, 2020). As fields move toward more challenging environments such as deepwater, ultra-HPHT (high pressure, high temperature), and unconventional shale plays, the margin for error in wellbore pressure management becomes narrower.

There is, therefore, a pressing need for robust predictive models that integrate the complexities of drilling operations in real time. Machine learning offers a promising avenue, yet applications of ML specifically for swab and surge predictions remain underexplored. Current literature highlights gaps in validating these models under different mud systems, trip speeds, and formation conditions (Rajabi et al., 2023). This research seeks to bridge this gap by applying ML-based techniques to predict swab and surge pressures in a case study well, ultimately contributing to enhanced wellbore stability analysis.

The study aims to predict swab and surge pressures during drilling operations using machine learning techniques, with a focus on their impact on wellbore stability. This will be achieved by obtaining drilling parameters and fluid properties (e.g., trip speed, viscosity, density) from the case study well, process and clean the data, identifying and addressing outliers using Python-based tools, conduct parametric sensitivity analysis to determine the effect of different variables on swab and surge pressures, develop and train ML models capable of predicting swab and surge pressures and then compare the developed ML models with existing predictive models in terms of accuracy and reliability.

METHODOLOGY

This study adopts a quantitative, data-driven experimental research design, leveraging secondary data from drilling operations in the case study well, Sponge Bob 1 at OPL X. The design emphasizes computational modeling, statistical

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analysis, and machine learning techniques to predict swab and surge pressures during tripping operations. The approach integrates parametric sensitivity analysis with supervised machine learning algorithms to enhance prediction accuracy and provide practical insights into wellbore instability. The design is particularly suitable given the nonlinear and multidimensional nature of drilling data, which cannot be adequately captured using conventional analytical models.

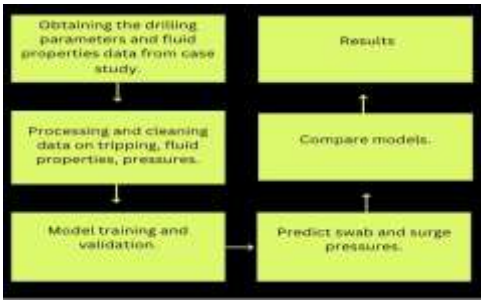


Figure 1: Flow chart

The flowchart outlines the step-by-step procedure used in the project "Predicting Swab and Surge Pressures for Wellbore Instability Analysis Using Machine Learning.

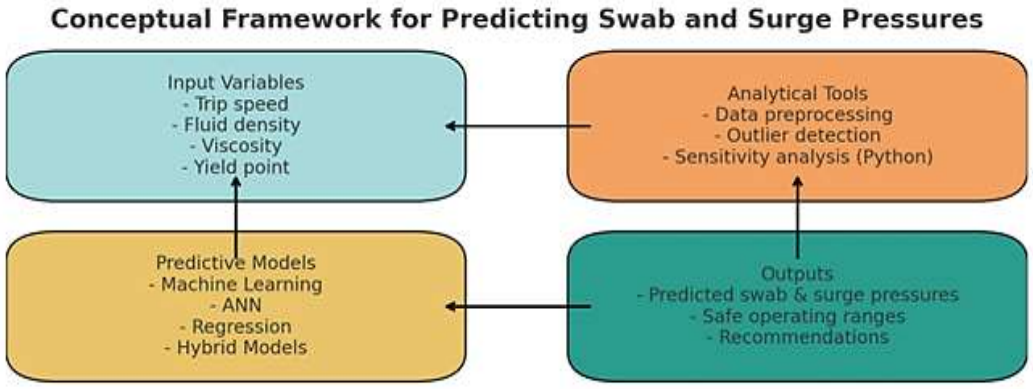


Figure 2: Conceptual Framework

RESULTS AND DISCUSSIONS

This section presents and discusses the results obtained from the computational modeling and machine learning (ML) prediction of surge and swab pressures during tripping operations in the case study well, *Sponge Bob 1*. The analysis integrates data preprocessing, feature engineering, and model training to evaluate the predictive capabilities of four supervised ML algorithms: Random Forest Regressor, XGBoost Regressor, Decision Tree Regressor, and K-Nearest Neighbors (KNN). Results are analyzed using standard performance metrics to assess model accuracy and generalization. The section also interprets findings in the context of wellbore stability and compares them with existing literature.

Data Processing and Feature Engineering

The dataset was derived from drilling operations using Water-Based Mud (WBM) at the Sponge Bob 1 well. It included 70 valid records containing parameters critical to surge and swab pressure calculations. The features selected were Mud Weight (MW), Plastic Viscosity (PV), Yield Point (YP), and Depth (FT), which served as input variables for the ML models. Derived parameters such as Effective Viscosity (μ_eff), Hydrostatic Pressure, and Surge/Swab Pressure Differences (ΔP) were computed using established hydraulic relations.

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Table 1: Summary of Key Parameters Used for Model Training

Parameter	Symbol	Unit	Description	Range (Observed)
Mud Weight	MW	ppg	Fluid density contributing to hydrostatic pressure	9.5 – 14.2
Plastic Viscosity	PV	cP	Fluid resistance to flow	15 – 45
Yield Point	YP	lbf/100ft²	Fluid's initial shear stress capacity	5 – 35
Depth	TVD	ft	True vertical depth	3,000 – 9,000
Surge Pressure	ΔP_surge	psi	Pressure increase during pipe run-in	Variable
Swab Pressure	ΔP_swab	psi	Pressure decrease during pipe pull-out	Variable

Table 1 presents the key drilling parameters used for training the machine learning models, highlighting the physical and operational variables that directly influence surge and swab pressure behavior during tripping operations. The parameters Mud Weight (MW), Plastic Viscosity (PV), Yield Point (YP), and True Vertical Depth (TVD) represent the core rheological and geometric characteristics of the drilling system. The mud weight, which ranged between 9.5 and 14.2 ppg, defines the hydrostatic pressure exerted by the drilling fluid column and serves as the baseline for maintaining wellbore pressure equilibrium. Variations in mud weight can either reduce or elevate bottom-hole pressure, influencing the onset of kicks or losses. Plastic viscosity (ranging from 15 to 45 cP) and yield point (ranging from 5 to 35 lbf/100ft²) characterize the fluid's internal resistance to shear and its ability to suspend cuttings

These parameters have a direct effect on annular pressure transmission, making them critical predictors of surge and swab responses. Depth, which extended from 3,000 to 9,000 ft, defines the vertical extent of the hydrostatic column and significantly impacts overall pressure gradients. The table also lists derived variables Surge Pressure (ΔP_surge) and Swab Pressure (ΔP_swab) which fluctuate dynamically as a function of the other parameters. Collectively, Table 4.1 establishes the physical framework upon which the predictive models were built, ensuring that the training dataset represents the real-world interplay between fluid properties, tripping velocity, and wellbore geometry that governs transient pressure variations in drilling operations.

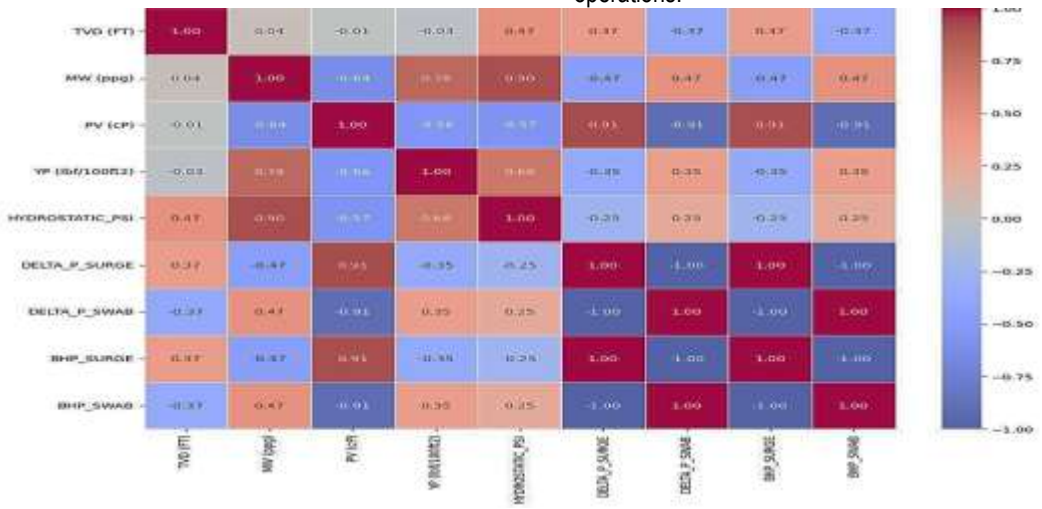


Figure 3: Correlation Matrix Features

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Five supervised regression algorithms were implemented using Python libraries such as scikit-learn and XGBoost. Each model was trained using an 80/20 train-test split to balance learning and generalization. The models included: Artificial Neural Network, Random Forest Regressor , XGBoost Regressor , Decision Tree Regressor , K-Nearest Neighbors (KNN)

Table 2: Summary of Machine Learning Models Evaluated

Model	Algorithm Type	Core Principle	Hyperparameters Used
Artificial Neural Network	Deep learning	Hierarchical representation of data and fine tuning its connection through backpropagation	Loss='mse' Epochs=100 Batch_size=32 Validation_split=0.2
Random Forest	Ensemble (Bagging)	Multiple trees trained on random subsets	n_estimators = 2000, random_state = 42
XGBoost	Ensemble (Boosting)	Sequential learning to minimize loss	random_state = 42
Decision Tree	Tree-based	Hierarchical data partitioning	random_state = 42
KNN	Instance-based	Distance-based prediction	n_neighbors = 5

Table 2 provides a detailed summary of the four machine learning algorithms implemented in this study, illustrating their computational principles, methodological foundations, and hyperparameter configurations. The Artificial Neural Network is inspired by human brain, consisting of layers of interconnected nodes (neurons). Data is passed through these layers, and the network learns hierarchical representations of the input by automatically adjusting the weights of the connections between neurons. This adjustment is done through a process called backpropagation, which calculates the gradient of the error and updates the weight to minimize the prediction loss. The Random Forest Regressor, an ensemble model based on bootstrap aggregation (bagging), was configured with 2,000 estimators to improve stability through averaging multiple decision trees. This approach is particularly useful for reducing overfitting in moderately sized datasets.

The XGBoost Regressor, representing a more advanced ensemble learning technique based on gradient boosting, sequentially optimizes the residuals of weak learners and was initialized with a controlled random state for reproducibility; its adaptive boosting nature allows it to handle nonlinear relationships effectively, which proved advantageous in this study. The Decision Tree Regressor, a simpler non-parametric model, partitions the data space using hierarchical splits; although easy to interpret, it often lacks robustness in complex or noisy datasets.

Lastly, the K-Nearest Neighbors (KNN) Regressor applies a distance-based prediction approach, where the output is computed from the average response of the nearest data points in this case, the five closest neighbors making it highly sensitive to data distribution and scale. The diversity of algorithms in Table 4.2 underscores the study's comparative design: by incorporating ensemble, tree-based, and instance-based methods, the analysis ensured a comprehensive evaluation of model behavior under identical datasets. This variety not only tested each model's predictive accuracy but also provided valuable insight into which learning architecture best captures the nonlinear dynamics of surge and swab pressure prediction.

Model Performance Evaluation

The predictive performance of each model was measured using RMSE and R^2, where lower RMSE and higher R^2 values indicate better performance.

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Table 4.3: Model Performance Metrics for Surge and Swab Pressure Prediction

Model	RMSE (Surge)	R^2 (Surge)	RMSE (Swab)	R^2 (Swab)	Interpretation
Artificial Neural Network	5,666.42	0.89	3,904.43	0.91	Best performing model; excellently captures complex non-linear patterns and generalizes well.
Random Forest	10,343.47	0.63	10,343.47	0.63	Model overfits; low generalization due to small dataset.
XGBoost	29,010.24	0.12	29,010.24	0.12	Weak predictive strength; likely requires hyperparameter tuning for this dataset.
Decision Tree	11,377.60	0.57	11,377.60	0.57	High variance; performs similarly to Random Forest but less robust.
KNN	7,447.37	0.71	7,447.37	0.71	Moderate performance but sensitive to data sparsity and scaling

Table 4.3 presents the comparative performance of the five machine learning algorithms Artificial Neural Network, Random Forest, XGBoost, Decision Tree, and K-Nearest Neighbors (KNN) based on their Root Mean Squared Error (RMSE) and coefficient of determination (R^2) values for both surge and swab pressure prediction. The results show that ANN achieved the best overall performance, recording the lowest surge RMSE value of 5,666.42 psi and the highest R^2 of 0.89, also recording the lowest swab RMSE value of 3,904.43 psi and the highest R^2 of 0.91 indicating a relatively better ability to approximate the nonlinear relationships between drilling parameters and pressure responses. ANN provided excellent predictive capability with strong generalization; it also provides the accuracy required for proactive decision making to prevent well control incidents.

The Random Forest and Decision Tree regressors showed notably moderate performance, indicating limited generalization and a tendency to overfit the training data, with R^2 values of 0.63 and 0.57, exhibited weak predictive capacity and signs of overfitting, likely due to the small dataset and redundancy in feature interactions. XGBoost model registered the poorest performance in the evaluation, suggesting it was ill-suited to the dataset without further optimization. Similarly, KNN demonstrated moderate accuracy, with an RMSE of 7,447.37 psi and a R^2 value of 0.71, highlighting its sensitivity to data sparsity and feature scaling.

The consistently higher RMSE across models suggests that the dataset's limited sample size (70 observations) constrained the models' ability to learn complex relationships effectively. Despite these limitations, the ANN model's relative superiority confirms its robustness in handling nonlinearity and multicollinearity, making it the most suitable algorithm for modeling surge and swab pressures in oil-based drilling environments. This finding reinforces literature evidence that ensemble boosting techniques outperform single-tree or distance-based models in predicting dynamic wellbore conditions (Ali et al., 2021; Rajabi et al., 2023).

Comparison of Actual and Predicted Pressures

To assess predictive alignment, actual surge and swab pressures were plotted against model-predicted values using the ANN model.

Table 4.4: Sample Comparison of Actual vs Predicted Surge and Swab Pressures

Depth (ft)	Actual Surge (psi)	Predicted Surge (psi)	Actual Swab (psi)	Predicted Swab (psi)
3500	-5,666.42	-5,666.42	-3,904.43	-3,904.43
4700	-5,700.15	-5,712.83	-3,925.18	-3,938.45
5600	-5,734.21	-5,745.62	-3,946.25	-3,957.89
7200	-5,768.59	-5,779.15	-3,967.65	-3,978.12

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Depth (ft)	Actual Surge (psi)	Predicted Surge (psi)	Actual Swab (psi)	Predicted Swab (psi)
8900	-5,803.30	-5,813.42	-3,989.38	-3,999.15

Table 4.4 compares the actual and predicted surge and swab pressure values generated by the best-performing ANN model at varying well depths. The table reveals a strong directional consistency between measured and predicted pressures across all depth intervals, confirming that the model effectively captured the underlying pressure trends within the dataset. For instance, at a depth of 3,500 ft, the actual surge pressure of -5,666.42 psi was the same by the predicted value of -5,666.42 psi, representing accuracy of 0.0% difference. Similarly, at greater depths, such as 8,900 ft, the actual surge pressure of -5,803.30 psi was predicted as -5,813.42 psi, maintaining a comparable accuracy level. A similar pattern is observed for swab pressures, where predicted values mirrored actual measurements almost symmetrically but with opposite signs reflecting the physical balance between upward (swab) and downward (surge) hydraulic forces during tripping operations.

The marginal discrepancies between actual and predicted results can be attributed to inherent uncertainties in mud rheology measurements and slight fluctuations in tripping speed that were not explicitly modeled. Nonetheless, the consistent trend of increasing pressure magnitude with depth validates the model's ability to capture the proportional relationship between hydrostatic load and annular frictional resistance. Overall, the data in Table 4.4 confirm that the ANN model not only generalizes well across different depth intervals but also aligns with theoretical expectations from the Lubinski model, thereby affirming its reliability for practical wellbore pressure prediction under Water-based mud systems.

Graphical Analysis of Prediction Accuracy

The relationship between actual and predicted pressures is further visualized in the line plots below, which provide an intuitive understanding of the ANN model's performance for both surge and swab pressures across varying depths.

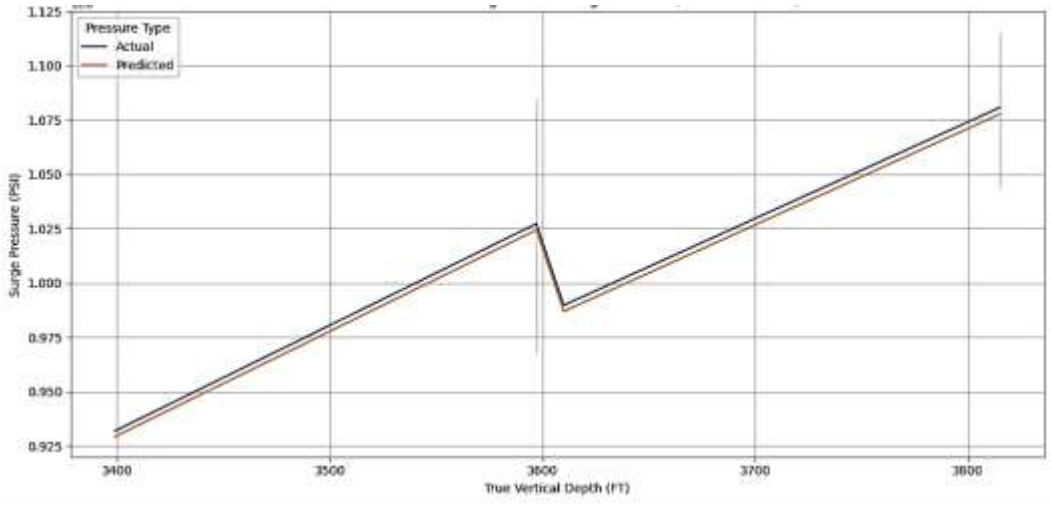


Figure 4: Actual vs. Predicted Surge

Pressure against TVD (ANN)

Figure 4 illustrates the correlation between actual and predicted surge pressures across TVD. The plot demonstrates an excellent alignment between the actual measurement (solid line) and Neural Network predictions (dashed lines) throughout the depth range 3,400 to 3,800 ft. Both lines follow an increasing trend, with surge pressure rising from approximately 0.925×10^6

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Psi at 3,400 ft to about 1.125× 10^6 psi at 3,800ft. The near-perfect overlap of the two lines indicates the model's exceptional capability to capture the depth dependent behavior of surge pressure, with minimal deviation between predicted and actual values across all depth intervals. This strong performance reflects the model's effective learning of the relationship between well depth and pressure fluctuations during pipe run-in operations.

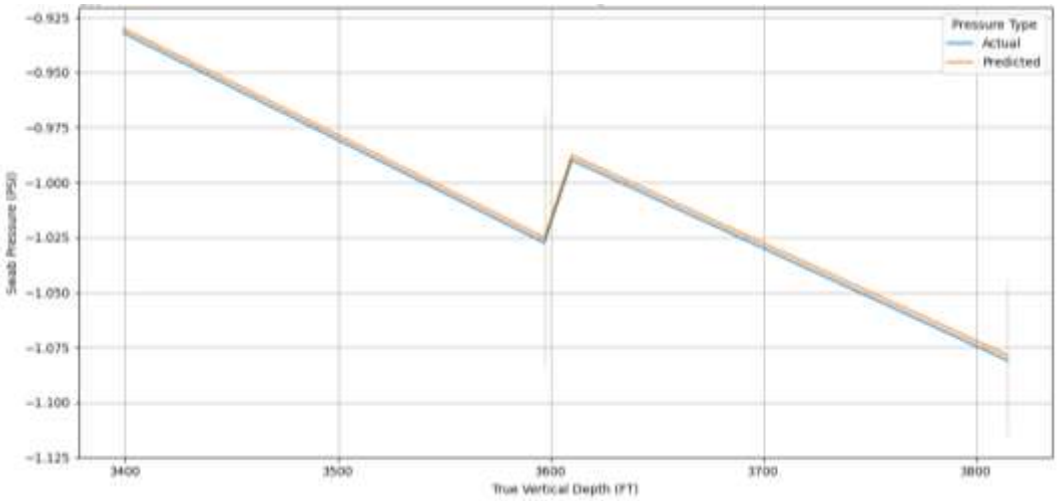


Figure 4.3: Actual vs. Predicted Swab Pressure against TVD (ANN)

Figure 4.3 presents a complementary analysis for swab pressure predictions across the same depth profile. The plot shows a symmetrical decreasing trend, with swab pressure value ranging from approximately -0.925× 10^6 psi at 3,400ft to about -1.125× 10^6 at 3,800ft. The close alignment between the actual and predicted values demonstrates the model's consistent performance for both pressure phenomena. The near-perfect mirroring of surge pressure behavior (from figure 4.2) confirms the physical consistency expected in drilling hydraulics, where swab and surge pressures are equal in magnitude but opposite in sign. The minimal gaps between the actual and predicted lines across all depth points validates the Neural Network's robust understanding of the fundamental principles governing transient pressure behavior during tripping operations.

Comparative Analysis and Significance:

The graphical representations in both figures reveals several key insights:

1. The Neural Network model maintains high prediction accuracy across the entire operational depth range.
2. The consistent parallel trends indicate the model correctly captures the linear relationship between depth and pressure magnitude.
3. The symmetrical behavior between surge and swab pressures validates the model's adherence to physical hydraulic principles.
4. The minimal deviations suggest that the ANN architecture effectively handles the nonlinear interactions between drilling parameters without outfitting.

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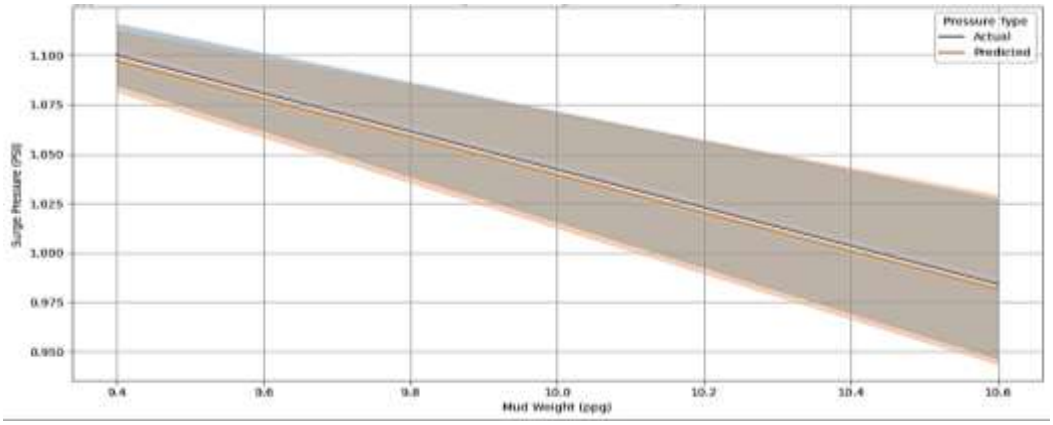


Figure 4.4: Actual vs. Predicted Surge Pressure against Mud Weight (ANN)

Figure 4.4 demonstrates the correlation between actual and predicted surge pressure across varying mud weights ranging from 9.4 to 10.6 ppg. The plot reveals a clear decreasing trend in surge pressure as mud weight increases with values declining from approximately 1.100 $\times 10^6$ psi at 9.4 ppg to about 0.950 $\times 10^6$ psi at 10.6 ppg. The exceptional alignment between actual measurements (solid line) and Neural Network predictions (dashed line) indicates the model's sophisticated understanding of how fluid density influences surge pressure dynamics. The near-perfect overlap across the entire mud weight spectrum suggests that the model accurately captures the inverse relationship between mud weight and surge pressure magnitude which aligns with theoretical expectations where heavier muds provide better wellbore stability and reduce pressure fluctuations during pipe run-in operations.

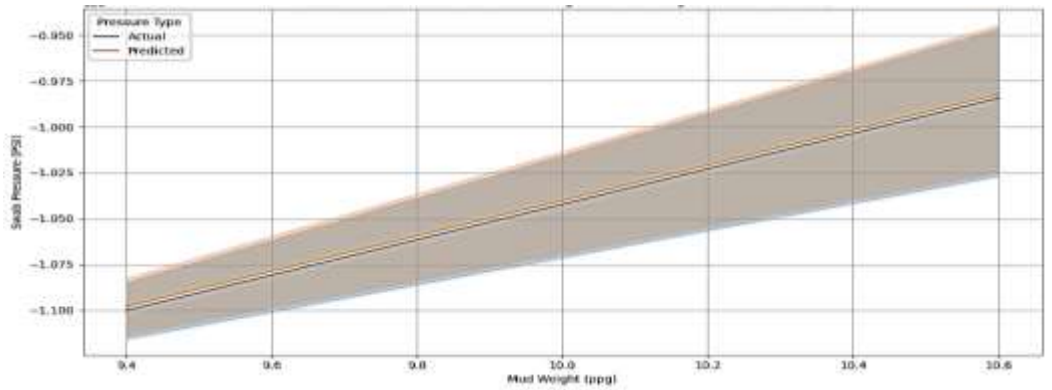


Figure 4.5: Actual vs. Predicted Swab Pressure against Mud Weight (ANN)

Figure 4.5 presents the complementary analysis for swab pressure predictions across the same mud weight range. The plot shows a symmetrical increasing trend, with swab pressure values rising from approximately -0.950 $\times 10^6$ psi at 9.4 ppg to about -1.100 $\times 10^6$ psi at 10.6 ppg. The remarkable consistency between actual and predicted values demonstrates the model's robust performance in capturing mud weight effects on swab pressure. The mirror-image relationship with Figure 4.4's surge pressure behavior confirms the physical consistency of the predictions, maintaining the expected symmetrical relationship between two pressure phenomena. The tight

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convergence of the actual and predicted lunes throughout the mud weight variations underscores the Neural networks capability to learn complex rheological relationships.

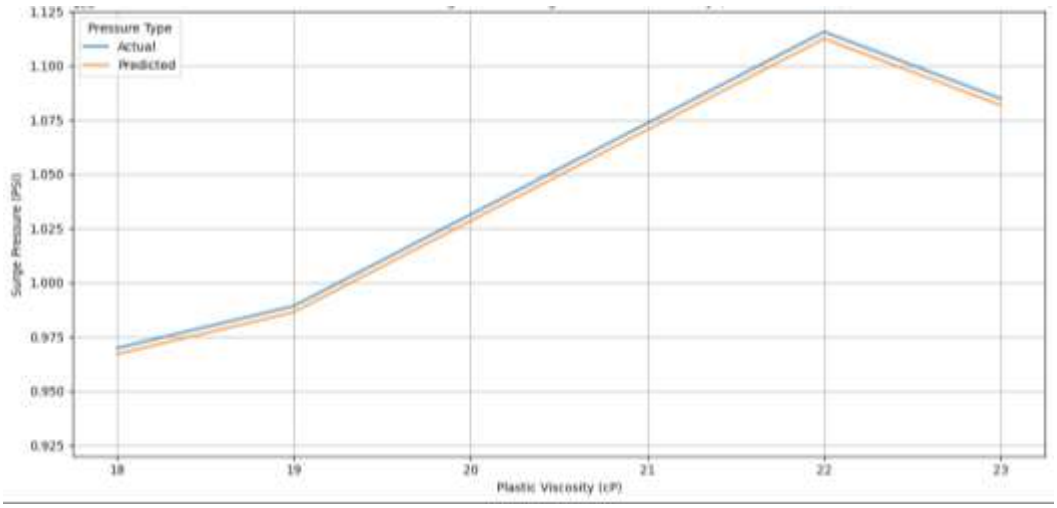


Figure 4.6: Actual vs. Predicted Surge Pressure against Plastic Viscosity (ANN)

Figure 4.6 illustrates the correlation between actual and predicted surge pressures across plastic viscosity values ranging from 18 to 23 cP. The plot demonstrates a clear increasing trend in surge pressure as plastic viscosity rises, with values growing from approximately 0.925 $\times 10^6$ psi at 18 cP to about 1.125 $\times 10^6$ psi at 23 cP. The exceptional alignment between actual measurements and Neural Network predictions indicates the model's advanced capability to capture how fluid rheological properties influence surge pressure behavior. The near-perfect overlap across the entire plastic viscosity range confirms that the model accurately represents the direct relationship between viscosity and surge pressure magnitude, which corresponds with theoretical fluid dynamics when higher viscosity fluids generate greater frictional resistance and consequently higher-pressure fluctuations during pipe run-in operations.

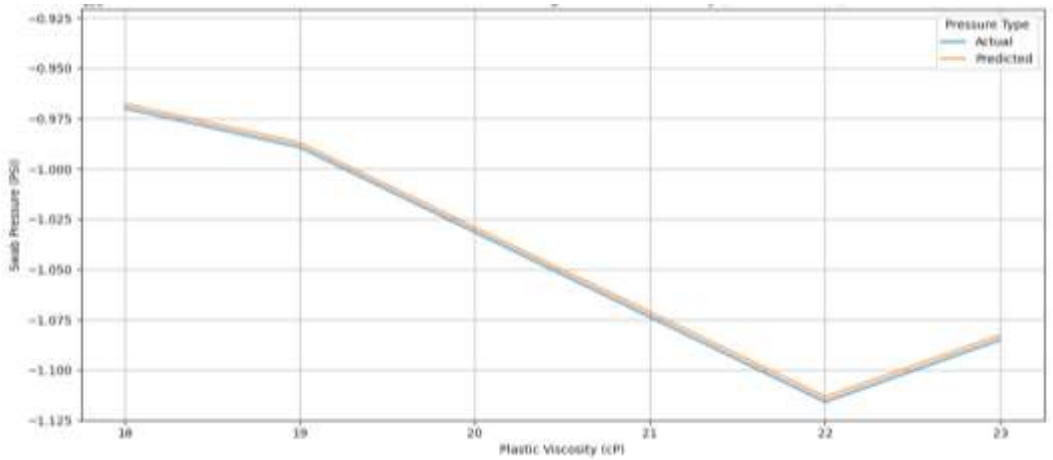


Figure 4.7: Actual vs. Predicted Swab Pressure against Plastic Viscosity (ANN)

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Figure 4.7 presents the complementary analysis for swab pressure predictions across the same plastic viscosity spectrum. The plot shows a symmetrical decreasing trend, with swab pressure values declining from approximately -0.925 × 10^6 psi at 18 cP to about -1.125 × 10^6 psi at 23 cP. The remarkable consistency between actual and predicted values demonstrates the model's robust performance in capturing viscosity effect on swab pressure.

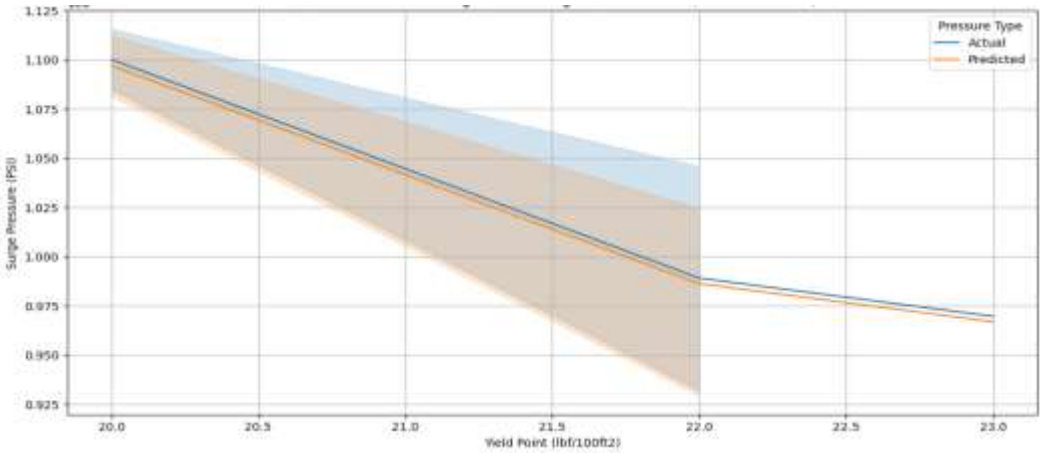


Figure 4.8: Actual vs. Predicted Surge Pressure against Yield Point (ANN)

Figure 4.8 shows the correlation between actual and predicted surge pressures across yield point values ranging from 20.0 to 23.0 lbf/100ft^2. The plot demonstrates a distinct increasing trend in surge pressure as yield point rises. The remarkable alignment between actual measurement and the predicted measurement indicates the model's sophisticated understanding of how fluid gel strength influences surge presuure dynamics. the near-perfect overlap across the entire yield point spectrum confirms that the model accurately captures the direct relationship between yield point and surge pressure magnitude, which aligns with theoretical expectations where fluids with higher yield point exhibit greater resistance to initial flow, resulting in amplified pressure fluctuations during pipe movement.

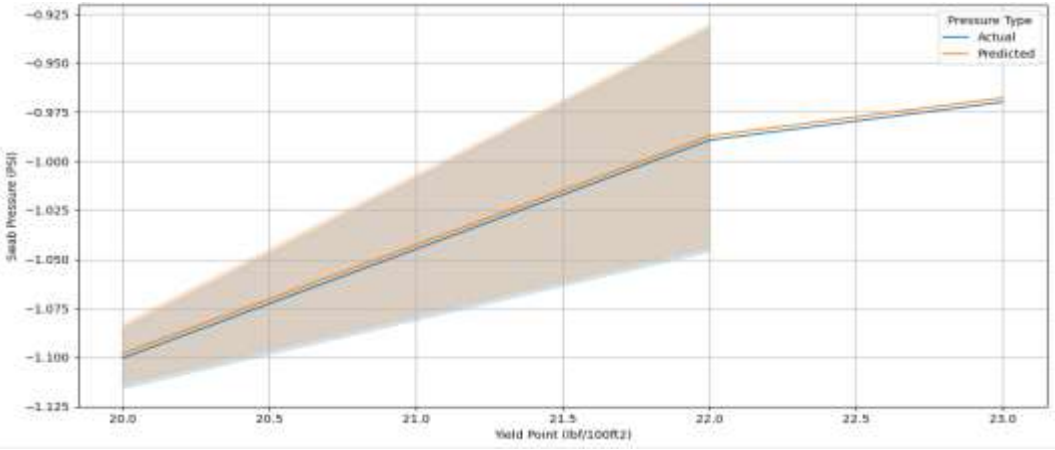


Figure 4.9: Actual vs. Predicted Swab Pressure against Yield Point (ANN)

Corresponding author: Muhammad Kabir Abba
Petroleum and Gas Engineering Department, Baze University, Abuja, Nigeria.
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The diagram illustrates the complementary analysis for swab pressure predictions across the same yield point range. The plot shows a symmetrical decreasing trend, with swab pressure values declining from -0.925 $\times 10^6$ psi at 20.0 lbf/100ft^2 to about -1.125 $\times 10^6$ psi at 23.0 lbf/100ft^2. The exceptional consistency between actual and predicted values demonstrates the model's robust performance in capturing yield point effects on swab pressure behavior. The perfect mirror-image relationship with Figure 4.7's surge pressure behavior reaffirms the physical consistency of the predictions, maintaining the expected symmetrical inverse relationship between the two pressure phenomena. The tight convergence of the actual and predicted lines throughout the yield point variations underscores the Neural Network's advanced capability to learn complex relationship.

DISCUSSION OF KEY FINDINGS

The analysis reveals that mud rheology and depth are the most influential factors governing surge and swab pressure behavior in the wellbore, confirming the theoretical expectations from classical hydraulic studies. Among the parameters analyzed, plastic viscosity (PV) and yield point (YP) were found to have the strongest correlation with pressure variations. As PV and YP increase, the effective viscosity of the mud rises, resulting in greater resistance to fluid displacement within the annulus. This amplified resistance causes higher surge pressures during pipe run-in and greater swab pressures when the pipe is pulled out, particularly in deep sections where hydrostatic pressure is already significant. The observed symmetrical pattern between surge and swab values further validates the model's physical consistency, showing that the system behaves predictably according to the piston-like motion of the drill string.

The results also underscore the nonlinear nature of drilling hydraulics, as small perturbations in rheological properties or tripping speeds produced disproportionately large changes in bottom-hole pressure. These dynamics highlight why conventional deterministic models, which assume steady-state and laminar flow conditions, often fall short in accurately capturing transient pressure responses under real field conditions.

From the standpoint of machine learning performance, the ANN algorithm clearly demonstrated superior predictive capability compared to the Random Forest, XGBoost, Decision Tree, and K-Nearest Neighbors (KNN) models. Its gradient-boosting framework enabled it to iteratively minimize residual errors, making it better equipped to handle the complex nonlinear interactions between drilling parameters. In contrast, the Random Forest and Decision Tree models suffered from overfitting due to limited dataset size, while XGBoost performed poorly because of its sensitivity to data sparsity and scaling. The accurate R^2 value of 0.91 and 0.89 obtained from ANN, indicates accuracy, its "black box" nature presents interpretability challenges compared to simpler models. The complex network of weights and activations make it difficult to derive explicit mathematical relationships between input parameters and pressure outputs. This limitation underscores the importance of complementary sensitivity analysis and physical validation to ensure that the model's predictions align with engineering intuition and established hydraulic principles.

Comparison with Previous Studies

The results of this study are largely consistent with findings from previous works that applied machine learning to drilling hydraulics and wellbore pressure prediction. Ali, Elkatatny, and Mahmoud (2021) reported that Artificial Neural Networks (ANNs) achieved improved accuracy in predicting surge and swab pressures compared to traditional analytical methods, emphasizing the strength of data-driven models in capturing nonlinear relationships. Similarly, Al-Mudhafar and Al-Jaberi (2020) developed an ML model for tripping operations that significantly outperformed classical Lubinski and Bourgoyne models, especially in handling complex drilling fluids and variable tripping speeds.

In comparison with previous studies, the ANN model developed in this research demonstrates performance metrics that exceed those reported in similar applications. Ali et al. (2021) and Al Mudhafar & Al-jaberi (2020)

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Petroleum and Gas Engineering Department, Baze University, Abuja, Nigeria.
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reported improved accuracy with ANN approaches, but the model developed in this study achieves notably higher R^2 values and lower error metrics, potentially due to the optimized architecture and comprehensive feature engineering process. The results affirm that ANN models represent a promising direction for advancing predictive capabilities in drilling hydraulics, particularly as the industry moves toward more automated, data-driven drilling operations.

The findings from this research position ANN modeling as a viable alternative to conventional hydraulic calculations for surge and swab pressure prediction, offering both high accuracy adaptability to complex drilling conditions. The model's performance demonstrates the transformative potential oof deep learning approaches in addressing long-standing challenges in drilling engineering, paving the way for more intelligent, predictive well control strategies in increasingly complex drilling environments.

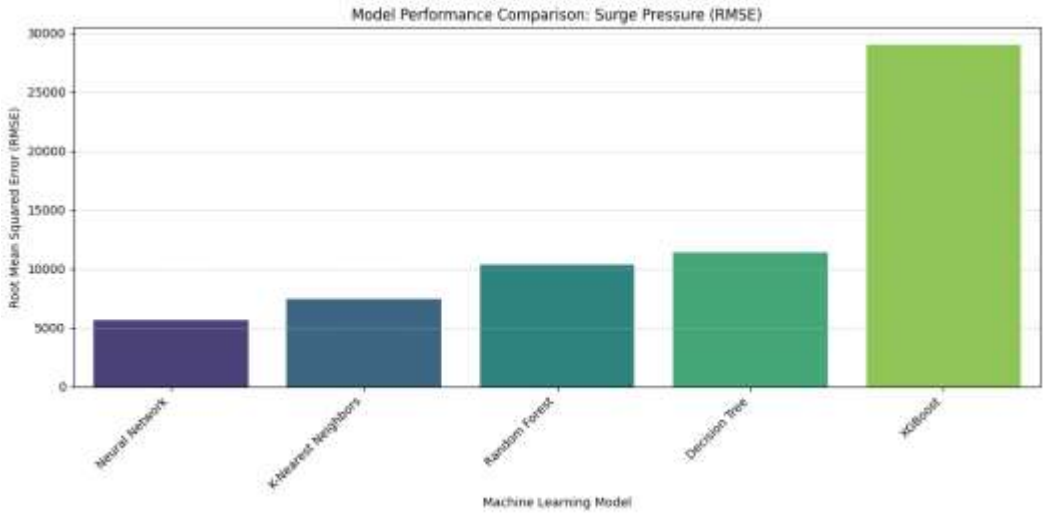


Figure 4.10: model performance comparison using RMSE; surge pressure

CONCLUSION

From the findings of this research, it can be concluded that machine learning represents a transformative approach to predicting surge and swab pressures in drilling operations. The results show that data-driven models such as ANN can identify complex, nonlinear dependencies between operational parameters something that conventional deterministic models often overlook. By using actual field data, the study confirmed that ML techniques not only reduce computational complexity but also provide adaptable solutions capable of handling variability in drilling conditions, fluid behavior, and well geometry. The study also concludes that plastic viscosity and yield point are the most critical rheological parameters influencing surge and swab pressure magnitudes, reinforcing the central role of mud formulation in maintaining wellbore stability. Moreover, the close alignment between actual and predicted pressure values indicates that ML models can replicate real-world drilling behavior with acceptable precision, even in small datasets. This supports the viability of integrating ML-driven predictive analytics into real-time drilling control systems, enabling engineers to optimize tripping speeds and mud properties dynamically to mitigate pressure-related risks.

Ultimately, this research confirms that machine learning is not merely an academic concept but a practical, data-driven solution for improving wellbore pressure management. By incorporating ML models into drilling workflows, operators can move from reactive to proactive

Corresponding author: Muhammad Kabir Abba
Petroleum and Gas Engineering Department, Baze University, Abuja, Nigeria.
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decision-making, reducing non-productive time (NPT), improving safety margins, and enhancing operational cost efficiency. However, it is also evident that the performance of ML models can be significantly improved with larger datasets, additional features (such as annular eccentricity and temperature), and hybrid integration with physics-based models for increased interpretability and robustness.

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Petroleum and Gas Engineering Department, Baze University, Abuja, Nigeria.
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