The object of this research is drilling process. The key is to ensure safe and efficient drilling operations by proactively identifying and eliminating critical anomalies, such as stuck pipes, that cause downtime, increase costs and degrade performance.

A machine learning model combining Multilayer Perceptron (MLP) and XGBoost was developed to predict critical parameters such as hook weight, minimum weight on bit, effective tension, and torque on bit. The model achieved 86 % accuracy in detecting drilling anomalies, including sinusoidal and spiral buckling. This enabled timely corrective actions and improving drilling efficiency.

The model's accuracy is due to its ability to process large datasets and capture complex, nonlinear relationships between drilling parameters. By training on both historical and real-time field data, it can learn patterns that are difficult to detect with traditional tools which allows to predict of drilling anomalies in real-time.

The distinctive feature of this model is its adaptability to new data, as well as its ability to predict complex phenomena like helical buckling and torque fluctuations, which are challenging for traditional methods. Unlike conventional models that need manual tuning, this model continuously learns from data, improving over time and under varying conditions.

The model can be applied practically in real-time drilling operations to optimize drilling parameters, reduce the risk of stuck pipes, and minimize non-productive time

Keywords: torque and drag, machine learning, drilling efficiency, prediction of drilling parameters, neural network

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DEVELOPMENT OF AN ENHANCED TORQUE AND DRAG MODEL USING MACHINE LEARNING FOR OPTIMIZING DRILLING EFFICIENCY

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1. Introduction

Drilling operations in oil and gas exploration face persistent challenges related to mechanical inefficiencies, including pipe sticking, sinusoidal and helical buckling, and excessive torque, all of which can cause significant operational delays and increased costs. Despite advancements in drilling technologies, these issues continue to impact wellbore stability and the overall success of drilling operations. As a result, the development of new methodologies to mitigate these risks remains essential for ensuring safe, cost-effective, and efficient drilling operations.

Traditional torque and drag (T&D) models, which often rely on empirical relationships and manual tuning, have struggled to capture the nonlinearities and complexities of dynamic drilling environments. However, with the rise of machine learning (ML) techniques that can process vast datasets and make real-time predictions, the potential to optimize drilling parameters and improve operational efficiency has never been greater. Research on leveraging ML to address drilling challenges is increasingly necessary to advance the field [1, 2].

The oil and gas industries are progressively shifting toward real-time data monitoring and automated decision-making to enhance operational safety and efficiency. Machine learning offers the potential to revolutionize drilling by predicting anomalies, reducing non-productive time, and optimizing drilling parameters to minimize risks, such as stuck pipes and buckling [3, 4]. Thus, research aimed at integrating machine learning into drilling operations is both timely and essential for addressing contemporary challenges faced by the industry [5, 6].

Therefore, developing machine learning-based models to optimize T&D and predict operational anomalies is highly relevant. Such research is critical for addressing the ongoing challenges in the oil and gas industry, ensuring the adoption of innovative solutions that enhance both drilling efficiency and safety.

2. Literature review and problem statement

Torque and drag (T&D) prediction has been a key focus in drilling optimization due to its significant role in enhancing drilling efficiency and reducing operational risks. Over the years, T&D modeling has evolved from traditional mechanical approaches to more sophisticated data-driven methods, with real-time applications becoming increasingly prevalent.

The paper [6] presents research on a real-time T&D prediction approach using machine learning models such as random forests and support vector machines (SVMs). This approach effectively handles non-linear data and accurately classifies torque conditions, but unresolved issues remain regarding computational efficiency in real-time field applications. The primary reason lies in the computational demands of machine learning algorithms, which can hinder deployment in environments with limited processing power. A possible way to address these challenges is through optimization algorithms that minimize computational load, yet real-time scalability for field operations remains unresolved.

The paper [7] describes an automated T&D analysis system that calibrates friction factors and identifies overpull and underpull issues, thus enhancing drilling safety. Although this model reduces the need for manual intervention and increases decision-making speed, unresolved issues include reliance on high-quality real-time data, which is often inconsistent due to sensor limitations or drilling conditions. This inconsistency limits the model's effectiveness in low-data-quality settings. While predictive algorithms can be adjusted to compensate, ensuring continuous data reliability in complex well environments remain a barrier.

The paper [3] integrates a physics-based T&D model with real-time analytics to provide continuous wellbore condition updates, aiding drilling decisions. However, issues arise in environments where automated data inputs may not cover all necessary parameters, leading to gaps in predictive accuracy. This is particularly problematic in remote or harsh conditions, where data transmission can be unreliable. While some automation tools, like the Planned Well Path (PWP) Digitizer, help streamline data entry, further refinement is needed to overcome these operational and connectivity challenges.

This research [8] explores a hybrid approach combining machine learning and mechanical analysis to predict torque and friction in highly deviated and horizontal wells. Although it achieves a relative error of less than 14 %, unresolved issues remain with maintaining this accuracy across varying well conditions. The high dependency on extensive training data (84,000 field samples) makes this model challenging to adapt in cases with limited or incomplete datasets. A possible solution could involve the development of transfer learning models that adapt to new datasets more flexibly, but the fundamental challenge of data availability and quality remains.

The work [9] on Torque-on-Bit (TOB) prediction uses five machine learning algorithms to optimize TOB with minimal error rates. Although boosted trees provided the most accurate TOB predictions, unresolved issues include the high computational cost of these algorithms in real-time settings. Additionally, the effectiveness of the approach depends on algorithm-specific tuning, which can be impractical in field applications where diverse well formations are encountered. Addressing these limitations may require hybrid algorithms that balance accuracy with computational efficiency, though real-time generalizability across diverse drilling environments is still an issue.

The paper [10] introduces a coupled model that integrates multiple metrics, such as ROP, TOB, MSE, and torsional vibrations. This approach enhances drilling efficiency by considering the interactions between downhole phenomena, but it still requires high-quality data and regular updates, which can be difficult to maintain in real-time operations. The complexity and computational demands also limit its adaptability across different formations and drilling conditions. Techniques such as adaptive machine learning models that adjust parameters based on drilling conditions could be explored, but scalability remains a challenge.

This paper [11] introduces a hybrid T&D model combining physical and machine learning methods, tested on ultra-deep and horizontal wells with a 23.19 % reduction in prediction error. However, issues arise from its high data and computational requirements, limiting practicality in resource-limited environments. While algorithm optimization may mitigate some of these limitations, the reliance on high-quality data for model training remains an unresolved issue that impacts real-time application feasibility.

All of these studies demonstrate significant progress but highlight several unresolved issues in real-time T&D prediction, particularly around computational efficiency, data dependency, and adaptability to diverse well conditions. These limitations indicate that further research into an enhanced T&D model – one that optimizes real-time prediction accuracy while minimizing data and computational requirements – is advisable to address the ongoing challenges in T&D prediction within complex and evolving drilling environments.

3. The aim and objectives of the study

The aim of this study is to develop a predictive model that optimizes drilling parameters for efficient well construction, with a focus on preventing pipe sticking and ensuring operational safety.

To achieve this aim, the study focuses on the following key objectives:

– developing and training machine learning models to predict outcomes such as torque, drag, and the likelihood of pipe sticking under various drilling conditions;

– assessing the models' accuracy and reliability by applying them to real-world field data and comparing their predictions with actual operational outcomes.

4. Materials and methods

4. 1. Object and hypothesis of the study

The object of the study is drilling process. The subject of this study is the torque and drag model.

The main hypothesis of the study is the possibility of building models that predict torque and drag. With an increase in the set of historical data, acting as training data, the model will be universal for all wells not only of one field, but also for fields of similar depths and geology.

A new torque and drag model are developed using machine learning techniques to improve accuracy and predictive capabilities. The model is based on a comprehensive analysis of many factors, including geological characteristics of the well (rock type, well conditions like as temperature, pressure); historical data of drilling operations such as torque, drag, well depth, trajectory data (azimuth, inclinometry and etc.); fluid parameters such as density, viscosity, lubricating properties; and production equipment parameters (pipe diameter, hook weight, type of drilling pipes and coatings and their characteristics. This research explores the application of a chained regression model combining Multilayer Perceptron (MLP) and XGBoost for predicting multiple physical properties in the oil and gas industry.

The stacking model consists of two state-of-the-art models: Multilayer Perceptron and XGBoost regressor. An MLP is a type of neural network that includes an input layer, one or more hidden layers, and an output layer. It is suitable for classification and regression prediction problems and handles tabular datasets effectively.

The XGBoost regressor is a powerful machine learning algorithm known for its efficiency and accuracy in handling regression tasks, excelling in capturing complex relationships between input features and target variables, and providing high predictive performance.

Model building process:

1. Data collection: historical and current data from drilling rigs.
2. Preprocessing: data cleaning, elimination of gaps, normalization and transformation into a suitable format.
3. Training: based on training data sets with known outputs (torques and resistance).
4. Validation: checking the quality of the model on test data.
5. Application: integration of the model into software for monitoring drilling operations.

4. 2. Data preparation and training

The dataset used for machine learning was obtained from both real field measurements and simulated data – output from the WellPlan software. It included key drilling parameters such as wellbore depth, geometric and physical parameters of the well itself and string details, and mechanical parameters such as hook weight, torque, weight on bit during various operations that affect the torque and drag model.

To identify key drilling parameters to create a model, the following work was done:

1) The first and especially important part in completing the task is processing and analyzing data using mathematical statistics methods [12].

2) Combining depths using an algorithm "nearest neighbors".

High-quality data sampling (filtering – filtering out "extra" data and sorting data; calculation of variation, which is characterized by the range of variation ($R=x_{\max}-x_{\min}$), the average linear deviation, dispersion and standard deviation are calculated.

To find hidden connections between data let's use the method "Feature generation".

The Pearson correlation (r) coefficient was calculated, according to which the key parameters (input data) were selected.

Training and evaluation process. The model was trained on data from four oil wells (moldabek2737, aktobe120, gran78, balgimbayev245) and evaluated using train-test split with the model training on 80 % of the data and tested on other 20 %. The primary metric used was the Weighted Mean Absolute Percentage Error (WMAPE), which measures forecast accuracy by accounting for the size of the actual values, providing a more balanced error metric compared to the traditional Mean Absolute Percentage Error (MAPE):

– the first training phase involves training and obtaining cross-validated predictions from the MLP;

– using the linear regression method, the so-called ridge regression, it is possible to estimate the value of a continuous output variable based on the values of the input variables;

– next, using the XGBoost machine learning algorithm, the decision tree makes a prediction to the minimum error:

1) predicts the actual value;
2) predicts its own deviation;
3) predicts variance of variance;
4) predicts a new value with minimal error;

– then, combining the last two methods (Ridge+XGBoost) it is possible to average the prediction value, which results in a decrease in the error of each (each other);

– validation: after training the model on historical data, it built a model for a new, previously unseen well, the drilling parameters of which were identified satisfactorily in comparison with the results of WellPlan software from Haliburton.

4. 3. Model evaluation metrics

The performance and correctness of the built Torque and Drag machine learning model was assessed using the main key metric, which was chosen to provide insight into various aspects of the model's performance.

wMAPE (weighted Mean Absolute Percentage Error) is a metric that is used to evaluate the prediction quality of regression models. Unlike standard MAPE, wMAPE considers the weight of each error depending on the value of the actual observation, which makes it more robust to outliers or small values of the target variable. Chained regression model of forecast accuracy that accounts for the size of the actual values, providing a more balanced error metric compared to traditional MAPE (Mean Absolute Percentage Error):

$$wMAPE = \frac{\sum_{i=1}^{n} |y_i - y_i'|}{\sum_{i=1}^{n} |y_i|}, \tag{1}$$

where y_i – real value of the target variable; y_i' – model predicted value; n – number of observations.

5. Results predicting the torque and drag parameters

5. 1. Prediction performance and outcomes of the drilling models

To obtain a universal model that will work regardless of different depths, it is possible to train the model in two steps. First, the model was trained to predict parameter values at subsequent depths of the same well, giving the parameters of previous depths. This is done so that it reveals a pattern in the section. Then they gave training to 4 wells at all depths (Aktobe 120, well depth – 2928 m, Balgimbayev, well depth – 1282 m, Moldabek, well depth – 765 m, Gran 78, well depth – 1646 m), using a neural network and deep machine learning algorithms for predicting learning for absolutely a new, previously unseen well.

The first training phase involves training and obtaining cross-validated predictions from the MLP [13].

In the second phase, MLP predictions are appended to the input data, and the XGBoost Regressor is trained on this augmented input data. The rationale for using the two models is that MLP can be sensitive to noisy data and produce incorrect outputs; therefore, XGBoost is used as the final estimator due to its robustness and resistance to overfitting. The MLP has 2 layers with 64 and 42 nodes, respectively. The XGBoost regressor consists of 100 trees with a depth of 5 and a sub column rate of 0.9. All the input and target data were normalized using normal distribution:

1) Input layer.

Contains input data ($x_1, x_2, ..., x_m$) – these are the input data or features that are fed to the neural network. Each neuron in this layer represents one feature of the data.

2) Hidden layer 1 (64 neurons): the first hidden layer processes the input data. Each neuron in this layer applies weights, that determines the significance of each input feature or neuron for a given neuron (w_n) and an activation function which is applied to the result of the weighted sum of the neuron's inputs ($f(\Sigma_i x_i w_i + b)$ to the data received from the input layer. This layer is responsible for extracting features and creating a representation of the input data. Where b is a bias that is added to the weighted sum of the inputs so that the model can better fit the data. Bias helps a neuron fire even if all input values are zero.

3) Hidden layer 2 (42 neurons): the first hidden layer processes the input data. Each neuron in this layer applies weights and an activation function to the data received from the input layer. This layer is responsible for extracting features and creating a representation of the input data.

4) Output layer: output y(*prediction*).

The following data was selected as input: «MD», «Incl», «Azim», "Sub_Sea", "TVD", "Local_N_Coord", "Local_E_Coord", "Global_N_Coord", "Global_E_Coord", "Dogleg", "Vertical_Section", "Body_OD", "Body_ID", "Body_AvgJointLength", "Stabilizer_Length", "Stabilizer_OD", "Stabilizer_ID, "Weight", "Coefficient_of_Friction", "Minimum_Yield_Stress", that is, the geometric characteristics of the well itself and the parts of the working string that is, the geometric characteristics of the well itself and the parts of the working string. The model produces the following data as output: "Derrick load capacity (effect_na)", "Rotary drilling(effect_na)", "Spiral (helical) buckling(without rotation) (effect_na)", "Lifting (effect_na)", "Sinusoidal buckling (all operations) (effect_na)", "Descent (effect_na)" and so on. That is, it provides optimal parameters for drilling and tripping operations with and without rotation, considering all limits. Also predicts the values when sinusoidal and helical bends begin, which leads to stuck string and tool in the well.

Below let's present the results of machine learning model and WellPlan software results as graphs for visual comparison and analysis of the model.

A detailed comparison of the two variables can be seen in Fig. 1, 2, which highlight the changes of Hook load values over time and measured depth.

Comparison of the Hook load values.

As it is possible to see, the values of all parameters, including critical ones according to the constructed model, agree very well with the values from WellPlan. In Fig. 2, the red line that indicates lifting (Tripping out) shows the actual data 72.5 tones on the MD 2400 m, and also the red line in Fig. 1 indicates lifting shows the predicted data 70.45 tones at the same depth. The wMAPE is equal to 2.83 %, which shows good convergence of the model with the real processes.

The maximum weight up to the yield point according to machine learning model was 131.36 tons at the MD 2900 m, and according to the WellPlan results it was 132.5 tons at the same depth, that is, the value of wMAPE is 0.67 %, which also means good model performance.

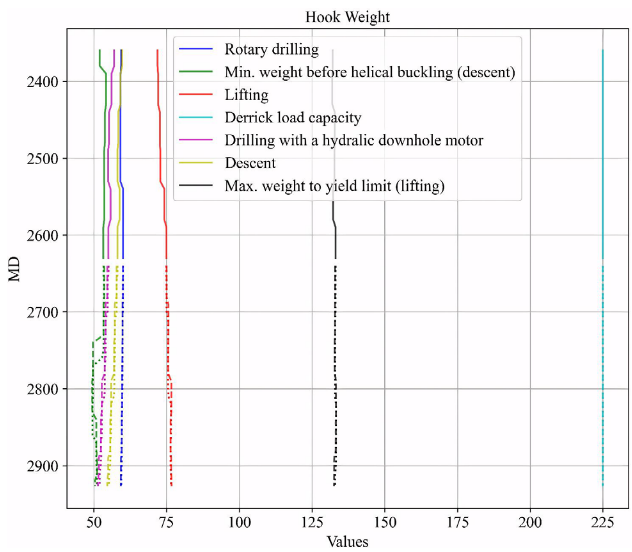

Fig. 1. Hook load vs MD from ML (aktobe120)

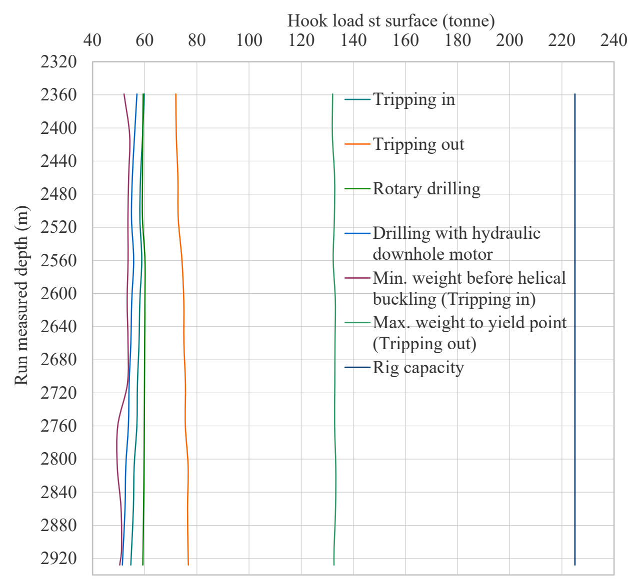

Fig. 2. Hook load vs MD Wellplan results (aktobe120)

As shown in Fig. 3, 4, the results demonstrate a significant change in torque values with measured depth.

In Fig. 4, the green line that indicates rotary drilling shows the actual data 6.25 kN·m on the MD 2600 m, and also the green line in Fig. 3 indicates rotary drilling shows the predicted data 6.44 kN·m at the same depth. The wMAPE is equal to 2.9 %. It is also possible to see an excellent convergence in the initial values. According to the results, wMAPE is no more than 7 %, which is in acceptable limits.

Comparison of weight on bit results shown in Fig. 5, 6 bellow.

In Fig. 6, the red line that indicates Min. WOB before helical buckling shows the actual data 9.375 kN·m on the MD 2600 m, and the blue line in Fig. 5 indicates Min. WOB before helical buckling (rotary drilling) shows the predicted data 9.22 kN·m at the same depth. The wMAPE is equal to 1,65 %. As it is possible to see, it is in this parameter also means good model performance.

As shown in Fig. 7, 8, the results demonstrate a significant change in effective tension with measured depth.

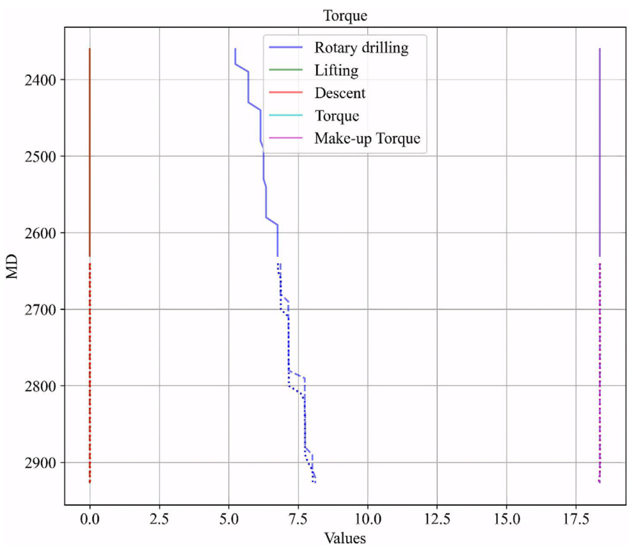

Fig. 3. Torque vs MD from ML (aktobe120)

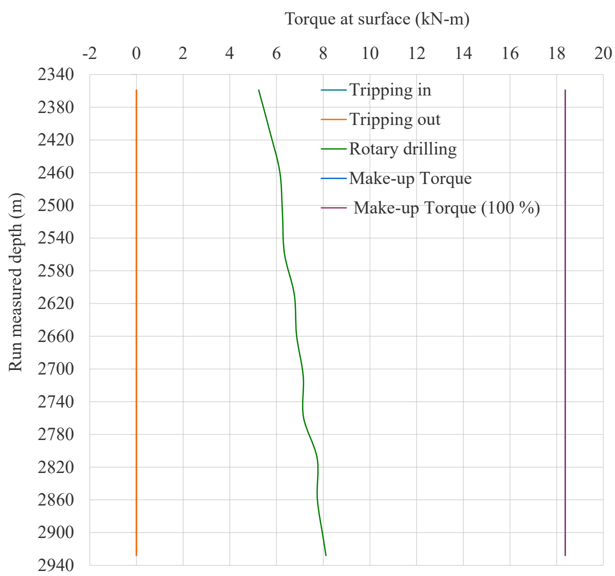

Fig. 4. Torque vs MD Wellplan results (aktobe120)

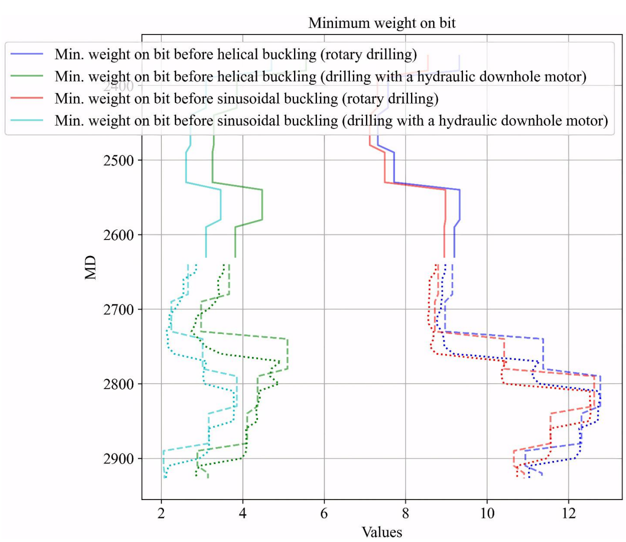

Fig. 5. Weight on bit vs MD from ML (aktobe120)

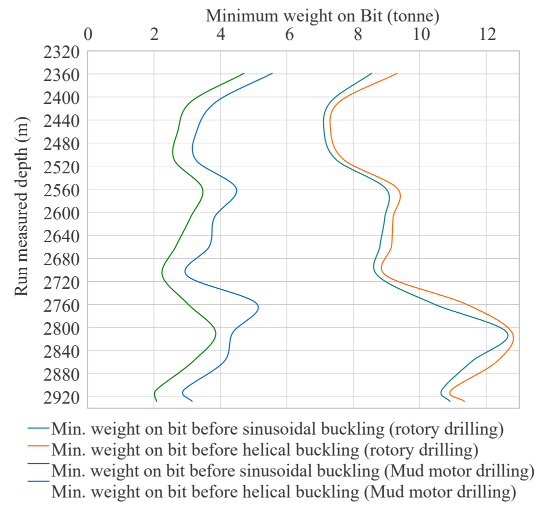

Fig. 6. Weight on bit vs MD from Wellplan (aktobe120)

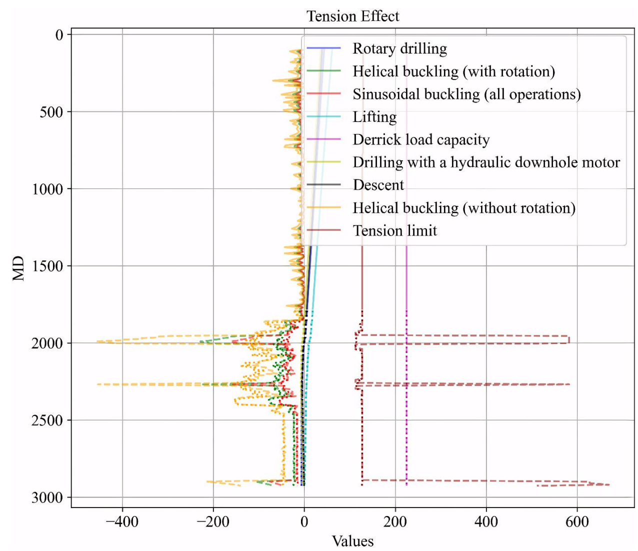

Fig. 7. Effective tension (ton) vs MD from ML results (aktobe120)

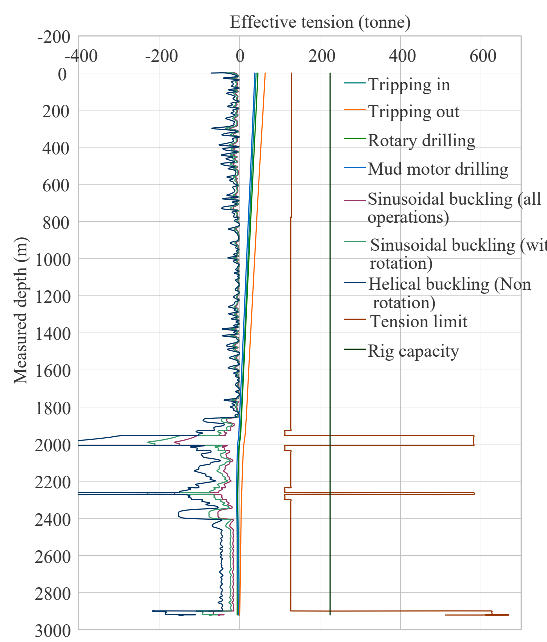

Fig. 8. Effective tension (ton) vs MD from WellPlan results (aktobe120)

According to these graphs, it is also possible to see an almost perfect correspondence between the output data of the trained model and the results of calculations by the world-renowned Wellplan software.

5. 2. Validation of neural network accuracy

The results of the model – predictions with errors (wMAPE) were entered into the following Table 1. This table presents 25 predicted mechanical and operational characteristics of the drill string and drilling equipment that affect drilling efficiency, equipment safety, drill string stability and the safety of the drilling process. Managing these parameters allows operators to optimize the drilling process, minimize equipment wear and prevent emergency situations, including stuck pipes.

Table 1

wMAPE scores in evaluation dataset

No.	Index	wMAPE	Type
0	Derrick load capacity	0.0	ves_na_kru
1	Rotary drilling	0.005964	ves_na_kru
2	Lifting	0.004207	ves_na_kru
3	Descent	0.014113	ves_na_kru
4	Drilling with a hydraulic downhole motor	0.01588	ves_na_kru
5	Min. weight before helical buckling (descent)	0.012408	ves_na_kru
6	Max. weight to yield limit (lifting)	0.008219	ves_na_kru
7	Derrick load capacity	0.0	effect_na
8	Rotary drilling	0.101938	effect_na
9	Spiral buckling (without rotation)	0.151081	effect_na
10	Lifting	0.068886	effect_na
11	Sinusoidal buckling (all operations)	0.151085	effect_na
12	Descent	0.169645	effect_na
13	Drilling with a hydraulic downhole motor	0.076406	effect_na
14	Spiral buckling (with rotation)	0.151075	effect_na
15	Tensile strength	0.004368	effect_na
16	Rotary drilling	0.014711	moment
17	Lifting	0.033193	moment
18	Make-up torque	0.003918	moment
19	Descent	0.031369	moment
20	Min. bit weight before helical buckling (rotary drilling)	0.07192	min_ves
21	Min. bit weight before sinusoidal buckling (drilling with a hydraulic downhole motor)	0.122105	min_ves
22	Min. bit weight before sinusoidal buckling	0.057226	min_ves
23	Min. bit weight before helical buckling (drilling with a hydraulic downhole motor)	0.14781	min_ves

The wMAPE across different domains are not homogeneous. Some variables, such as "Spiral (helical) buckling (with rotation)" and "Descent", have relatively high wMAPE % values (e. g., 16.96 %, 15.11 %). Relatively high wMAPE % indicates that the model has an error margin for these features, which may suggest the need for further model tuning or feature engineering, however, these numbers are acceptable in this case since the wMAPE % limit is 18 %. The wMAPE % varies significantly across different domains (type), which could imply that some types of features are more challenging for the model to predict accurately. For instance, the "effect_na" and "min_ves" types tend to have higher wMAPE % values compared to "ves_na_kru". It also could be because of data dimensions and size since types have different size and dimensions of the data. Additionally, there is a perfect score with 0 % wMAPE, which indicates that a given property has zero or near-zero variance and the model outputs constant value. This is the derrick load capacity of the tower. Derrick load capacity is a critical parameter that affects drilling efficiency, hole depth, tool selection, operational safety, and overall drilling process management. Due to similar and shallow depths, it is not difficult for a machine to predict its value without errors.

6. Discussion of received predicted parameters of torque and drag

The results of this study demonstrate that the developed machine learning models, using Multilayer Perceptron (MLP) and XGBoost algorithms, offer high accuracy in predicting drilling parameters such as torque, drag, and weight on bit. The accuracy of the model is evident in the low wMAPE scores for several key parameters, as presented in Table 1, where all parameters except spiral or helical buckling (without rotation), sinusoidal buckling (all operations) and descent (tripping in) in Effective Tension show minimal errors compared to actual results. The significant difference in the results can be explained, firstly, by the quantitative (the more data, the better the neurons learn) and qualitative composition of the data (in the initial input data there were empty cells – about 17 %, which negatively affected the result). Secondly, these operations occur from many geological, physical, and geometric factors that are not considered analytically. Therefore, obtaining such results with a deviation of no more than 18 % is considered within normal limits.

Compared to other studies conducted in this field by scientists such as [6, 12] and others, the prediction error is less by about 7–8 %, which indicates good processing and preparation of the input data itself and the effectiveness of the structure of the selected combination of machine learning algorithms.

Moreover, unlike traditional models that focus on simpler linear relationships, our machine learning model is capable of handling complex parameters such as helical buckling with rotation, which is known for its intricate nature. As seen in Table 1, this feature was accurately predicted despite its inherent complexity. This result is a key benefit made possible by the advanced algorithms of MLP and XGBoost, allowing the model to capture relationships that traditional models often overlook. Compared to traditional torque and drag prediction tools like WellPlann, our machine learning model offers significant advantages in flexibility, adaptability, and predictive accuracy. Traditional models like WellPlann require extensive manual tuning and are not capable of adjusting dynamically based on real-time data. In contrast, the machine learning model developed in this study is capable of learning and adapting from historical data, improving its accuracy as more data is introduced.

For example, Fig. 1, 2 present a comparison of Hook load values between the machine learning model and actual results, showing strong alignment. The blue line in Fig. 2 indicates that the WellPlann model estimates the Hook load at 725 tons at a depth of 2400 m, while the machine learning model predicts a Hook load of 704.5 tonnes at the same depth, demonstrating a wMAPE of 2.83 %, indicating strong convergence.

Similarly, the torque predictions, as shown in Fig. 3, 4, further validate the accuracy of the model. At a depth of 2600 m, the WellPlann model estimates torque at 625 kN·m, while our model predicts 644 kN·m, yielding a wMAPE of 2.9 %. This low margin of error demonstrates the model's ability to generalize across depths and drilling operations.

However, as I mentioned before, the results also indicate higher wMAPE values for parameters like Spiral (helical) buckling with rotation and descent (lifting in), as shown in Table 1, where the wMAPE for these parameters reaches 16.96 % and 15.11 %, respectively. This can be attributed to the limited data quality and size available for these specific features, causing reduced predictive accuracy.

For example, Fig. 5, 6 illustrate the comparison of weight on bit predictions between the machine learning model and WellPlann. At 2600 m, the model predicts a weight on bit of 909 kN compared to the actual data from WellPlann of 760 kN. While the wMAPE for this prediction is relatively high at 16.96 %, the overall ability of the model to generalize such predictions in real time provides a clear advantage over traditional methods that struggle with complex, nonlinear relationships between variables.

This model also differs in its ability to predict subsequent data (drilling parameters) for a well using a set of the first few available data. That is, there is only data for the first half of the depth of the new well, there is no data further to the design depth. The model is configured for this case as well.

The machine learning model has achieved its goal by providing reliable predictions of critical drilling parameters. The problem of predicting torque and weight on bit accurately across different operations was addressed by using a combination of MLP and XGBoost, which, as explained earlier, dynamically learn from the data and generalize across different well depths and operations.

As evidenced by Fig. 7, 8, the effective tension predicted by the machine learning model shows a near-perfect match with the WellPlann outputs. The wMAPE for this parameter is notably low, ensuring that the model can provide reliable, real-time predictions for torque and drag during drilling operations. The successful closing of this problematic part is further supported by the consistently low wMAPE scores across most parameters, as shown in Table 1, demonstrating that the model reliably meets the demands of real-time monitoring and predictive accuracy.

By accurately predicting parameters like weight on bit and torque, the model not only helps optimize drilling processes but also minimizes the risk of downtime caused by stuck pipes, which was the original aim of the study. Thus, the model provides a solution to the identified problem by enhancing safety, reducing non-productive time (NPT), and improving cost-efficiency.

One key limitation of this study is the sensitivity of the model to the quality of input data. As observed in the higher wMAPE scores for parameters like Spiral buckling with rotation and Descent, the model's accuracy is heavily influenced by the volume and quality of the training data. This suggests that, in real-world applications, the model's performance might degrade when applied to noisy or incomplete datasets.

The only and very important limitation of this model is the need for qualitative and quantitative sets of historical initial data, which is not always possible due to the lack of a database on old wells.

Using a relatively small dataset from only four wells may limit the model's ability to generalize across different geologies and drilling conditions. Future practical applications will require larger datasets that cover a wider range of conditions to ensure the model's robustness and reliability.

While the model generally performs well, there are several shortcomings that may impact its broader application. First, the relatively high wMAPE values for certain complex parameters, like Spiral buckling with rotation, indicate that the model may struggle with highly nonlinear or poorly defined relationships between variables when there is insufficient data. This could limit its applicability in drilling environments where such parameters are critical.

Another shortcoming is the model's current inability to handle missing or noisy data effectively. Although preprocessing techniques were used to clean and prepare the data, there were instances where data gaps affected the model's performance, as reflected in the higher wMAPE scores for certain features. This suggests that further refinement of data-handling techniques will be necessary to improve the model's performance in real-world applications.

Future research should focus on addressing the limitations outlined above, particularly by improving the model's resilience to noisy or incomplete data. One approach could be to integrate hybrid models that combine the strengths of traditional physical models with machine learning algorithms. Such a combination could provide a more comprehensive solution, leveraging the physical relationships between parameters while also taking advantage of machine learning's adaptability.

Moreover, expanding the dataset to include more wells with varying geologies and depths will be essential for improving the model's generalizability. In addition, incorporating more advanced machine learning techniques, such as reinforcement learning, could enable the model to adapt dynamically to changes in real-time drilling conditions.

Finally, future work should focus on validating the model across a wider range of drilling scenarios to assess its robustness and scalability. By conducting extensive testing in real-world applications, the model can be refined and developed further to meet the evolving needs of the oil and gas industry.

7. Conclusions

1. The study successfully developed a machine learning model combining Multilayer Perceptron (MLP) and XGBoost to predict key drilling parameters, including torque, drag, and sticking probability. This hybrid approach effectively captured nonlinear relationships between drilling parameters, achieving high accuracy in complex scenarios such as helical buckling and torque fluctuations. Distinctive features of the model include its adaptability to new data and its ability to generalize across different drilling conditions. This adaptability enables it to predict complex phenomena, such as spiral and helical buckling, with a reduced error margin compared to traditional approaches. These results demonstrate the model's ability to process large, multidimensional datasets effectively, which explains its superior predictive performance. By leveraging advanced algorithms, the model identifies patterns that are often missed by conventional empirical methods.

2. The validation process confirmed the developed machine learning model's high accuracy and reliability in predicting

critical drilling parameters, including torque, drag, and the probability of pipe sticking. The model achieved strong performance when tested against real-world field data, as demonstrated by a low Weighted Mean Absolute Percentage Error (wMAPE). For example, torque predictions showed a wMAPE of 2.9 %, and hook load predictions achieved a wMAPE of 2.83 %, reflecting the model's robustness. A key feature of this validation is the model's ability to generalize across diverse drilling conditions, enabling accurate predictions for complex scenarios such as helical and spiral buckling. Unlike traditional models, this machine learning approach adapts dynamically to new data, effectively capturing nonlinear. The model's hybrid architecture, combining Multilayer Perceptron (MLP) and XGBoost, enhances its ability to process complex datasets with high precision. By integrating historical and real-time data, it provides reliable insights, reducing risks like pipe sticking and minimizing non-productive time. These results highlight the model's potential to optimize drilling operations and improve safety, making it a valuable tool for real-time torque and drag monitoring.

Conflicts of interest

The authors declare that they have no conflicts of interest in relation to the current study, including financial, personal, authorship, or any other, that could affect the study and the results reported in this paper.

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Data availability

Data will be made available on reasonable request.

Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies when creating the current work.

References

1. Mirhaj, S. A., Kaarstad, E., Aadnoy, B. S. (2016). Torque and Drag Modeling; Soft-string versus Stiff-string Models. SPE/IADC Middle East Drilling Technology Conference and Exhibition. https://doi.org/10.2118/178197-ms
2. Samuel, R., Huang, W. (2020). Dynamic Torque and Drag Model. SPE Annual Technical Conference and Exhibition. https://doi.org/10.2118/201629-ms
3. Cao, D., Hender, D., Ariabod, S., Ruddy, K., James, C. (2020). Digital Transformation Strategy Enables Automated Real-Time Torque-and-Drag Modeling. IADC/SPE International Drilling Conference and Exhibition. https://doi.org/10.2118/199670-ms
4. Borjas, R., Creegan, A., Perdomo, A., Caraway, J. (2017). A Synchronized Rigsite-to-Office Approach to the Management of Automated Torque and Drag Data. SPE/IADC Drilling Conference and Exhibition. https://doi.org/10.2118/184691-ms
5. Brown, C., McCormick, J., Nunez, A. (2014). Improving the Decision Making Process between Drilling and Completion Using Real-Time Torque and Drag Modeling. SPE Annual Technical Conference and Exhibition. https://doi.org/10.2118/170625-ms
6. Hegde, C., Wallace, S., Gray, K. (2015). Real Time Prediction and Classification of Torque and Drag During Drilling Using Statistical Learning Methods. SPE Eastern Regional Meeting. https://doi.org/10.2118/177313-ms
7. Shahri, M., Wilson, T., Thetford, T., Nelson, B., Behounek, M., Ambrus, A. et al. (2018). Implementation of a Fully Automated Real-Time Torque and Drag Model for Improving Drilling Performance: Case Study. SPE Annual Technical Conference and Exhibition. https://doi.org/10.2118/191426-ms
8. Guo, H., Luo, H., Zhan, G., Wang, B., Zhu, S. (2021). A Real-Time Friction Prediction Model for in Service Drill String Based on Machine Learning Methods Coupling with Mechanical Mechanism Analysis. SPE Middle East Oil & Gas Show and Conference. https://doi.org/10.2118/204738-ms
9. Oyedere, M., Gray, K. (2020). Torque-on-bit (TOB) prediction and optimization using machine learning algorithms. Journal of Natural Gas Science and Engineering, 84, 103623. https://doi.org/10.1016/j.jngse.2020.103623
10. Hegde, C., Pyrcz, M., Millwater, H., Daigle, H., Gray, K. (2020). Fully coupled end-to-end drilling optimization model using machine learning. Journal of Petroleum Science and Engineering, 186, 106681. https://doi.org/10.1016/j.petrol.2019.106681
11. Bai, K., Fan, H., Zhang, H., Zhou, F., Tao, X. (2022). Real Time Torque and Drag Analysis by Combining of Physical Model and Machine Learning Method. Proceedings of the 10th Unconventional Resources Technology Conference. https://doi.org/10.15530/urtec-2022-3723045
12. Ashok, P., Ambrus, A., Ramos, D., Lutteringer, J., Behounek, M., Yang, Y. L. et al. (2016). A Step by Step Approach to Improving Data Quality in Drilling Operations: Field Trials in North America. All Days. https://doi.org/10.2118/181076-ms
13. Pérez-Enciso, M., Zingaretti, L. M. (2019). A Guide on Deep Learning for Complex Trait Genomic Prediction. Genes, 10 (7), 553. https://doi.org/10.3390/genes10070553