AI Driven Forecast Error Assessment models for drilling in oil and Gas

Abstract

"Accurate forecasting is a significant part of the drilling process in the oil and gas industry as a whole." Geological formation uncertainties in addition to drilling process parameters, are causing various issues in terms of cost overruns, non-productive time, and safety issues, necessitating more accurate forecast methods in the process. In addition to this, conventional methods in terms of forecasting are unable to meet the mark in accurately estimating the drilling process's nonlinear relationships, causing issues in forecasts as a prominent feature in them. Nowadays, recent advances in AI technologies introduced numerous other options to accurately predict the forecast error in addition to accuracy in the context of drilling processes in the oil-gas industry as a whole, placing a high emphasis on "Forecast error assessment using AI-driven models" as a core part of a respective workflow in the context of drilling processes in the oil-gas industry. In the context of recent advances in AI technologies, "artificial neural networks," "ensemble machine learning," "deep learning," as a major part of AI-driven forecast error assessment models in the context of drilling processes in the oil-gas industry, are analyzed to understand the respective benefits of employing respective error estimation methods to accurately assess forecast error in respective process parameters, thereby reducing the forecast error to a certain extent in the context of respective drilling process parameters. "The results demonstrate how significantly the test demonstrated AI-driven error assessment models perform in comparison to conventional methods," leading to an understanding of employing respective error estimation in reducing forecast error to a certain extent in the context of respective drilling process parameters in the context of "Forecast error assessment using AI-driven models" in respective processes within the oil-gas industry as a whole as a major part of the respective workflow in the context of drilling processes in the oil-gas industry as a whole.

Keywords: Artificial Intelligence, Drilling Forecasting, Error Assessment, Oil and Gas Engineering, Machine Learning, Predictive Analytics

Introduction

The process of well drilling forms the central part of oil and gas exploration activities, while the process of drilling in itself constitutes the hardest stage in oil exploration. The parameters that form part of the oil well drilling rate forecast include the rate of penetration, the time consumed in the process of drilling, the torque, the pressure, and the mechanical specific energy. The accuracy of the process has significant importance in efficient management, planning, and risk management in oil well drilling. The reliability of oil well drilling forecasts has become an issue of serious concern in recent times, especially in the process of oil well exploration targeted at complex reservoirs.

The presence of inherent uncertainty related to drilling environments is one of the primary hurdles in achieving greater accuracy within forecasts. This is because these underground formations have a strong level of spatial heterogeneity and anisotropy. In fact, there is a great level of unpredictability when related to aeromechanics. While a certain level of understanding related to such underground formations is developed through geological and geophysical pre-drilling information, these are invariably approximated and cannot directly address localized variations that arise. In many cases, unforeseen lithology's and abnormal pressure regions arise, and this also indirectly adds to forecasting errors.Hence, the final layer of added complexity in the forecast for drilling operations arises in relation to the gamut of operational variability. This is because of the repercussions of numerous parameters influencing the drilling process in interconnected ways; for instance, there is the effect of the drilling fluids themselves, the type of bit being used in the drilling process, the weight of the equipment on the bit, its speed of turning in the action of rotary drilling, as well as the role of decision-making processes in general. An alteration of policy in the process of drilling also invalidates a forecast partially or totally; this is because of the effect of cumulative error.They are usually based on physics models, empirical models, and statistical models using regression. For example, each of these models provides a level of explanation and basis in terms of understanding and applying the engineering method. However, often in complex and rapidly changing conditions, their effectiveness in terms of predictions usually deteriorates. For example, with physics models, calibration is very expensive, and there are often basic suppositions and assumptions that are not valid under various and different kinds of formations. Also, empirical models are considered very inexpensive in terms of computation. However, empirical models are only based on patterns in historical data, and there are clear suppositions regarding and on their capability and ability to really make a generalization with respect to operational scenarios. Therefore, forecast errors are considered a residual. The uncertainty of forecasts in the drilling processes has considerable economic and safety-based implications. The lack of quantification of forecast errors may lead to suboptimal decisions, such as suboptimal decisions in choosing bits, suboptimal decisions in optimizing well parameters, and delays in handling abnormal behavior. Additionally, this uncertainty from the early stages of forecasting will subsequently influence subsequent planning activities, such as well design, casing, and completion programs. The incompatibility of assessing and explaining forecast errors diminishes the efficiency of a monitoring system as well as a decision-support system in a real-time environment.Recent advancements in the area of artificial intelligence create new possibilities to deal with the aforementioned problems using data-driven modeling approaches. Unlike traditional methods employed in such models, it has the ability to learn nonlinear relationships based on large quantities of obtained operational data. Nonetheless, the bulk of the existing related work centers on how the accuracy of such predictions could be improved without paying heed to the underlying characteristics and mechanisms related to the prediction. Forecast error assessment presents key insights to facilitate the understanding of the aforementioned areas.

The motivation behind this research stems from the necessity to develop an organized method that aids in confronting forecast uncertainties during the process of drilling. The subject matter will concentrate on improving the reliability of forecasts made through AI-driven error assessment in place of mere prediction. The implementation of error assessment models will play a significant role in the efficient identification of risky situations, the recalculation of the model, and improving the overall process of making informed decisions. The process of resolving forecast uncertainties via error analysis based on AI will play an imperative role in making the process of oil and gas exploration even more efficient via drilling.

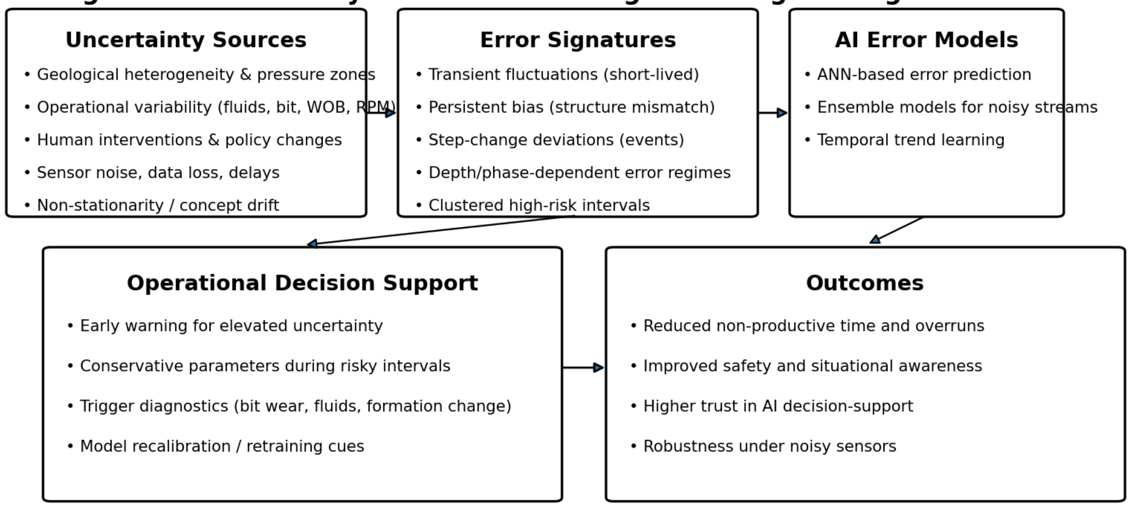
Background and Literature Review

2.1 Drilling Forecasting and Its Engineering Context

The application of forecasting in drilling engineering has also demonstrated significance as a primary element in optimization and risk management through solving various planning requirements associated with specific well construction characteristics. The most dominant oil well construction characteristics or variables associated with drillers during a drilling process include the rate of penetration achieved in directional wells, time spent in digging wells, applied torque or drill pipe drag forces in specific wells or drill strings, and downhole well pressures experienced during different drilling stages. (An analytical model for quantitative evaluation of friction drag in directional sliding drilling, 2025)Traditional models of drilling forecasts have primarily relied upon other elements, such as specific physics formulations or correlations of field experiences in oil well digging or construction challenges. (A review of mathematical modelling approaches to tackling wellbore instability in shale formations, 2021) Such characteristics in oil well digging or construction challenges have significantly impacted or dominated early optimization in oil well digging or construction challenges; however, their reliability in ensuring accurate or satisfactory well digging or construction has also been threatened because of their complexity in recent circumstances. (Iriogbe et al., 2024) Presently, drilling activities often pose a threat of confronting drilling formations with heterogeneities, well trajectory, and high-pressure, high-temperature conditions. (Kumar &Sahoo, 2025) It has often proved challenging and less successful in achieving desirable results through a deterministic model, even under well-calibrated conditions. (Hotvedt et al., 2020) Besides, empirical models are generally less successful in solving drilling activities despite being computationally less demanding, mainly on the grounds of basic assumptions. (Elmo & Adams, 2025) As a result, there are high chances of data deviations from regular drilling activities. (Data-driven prediction of rate of penetration (ROP) in drilling operations using advanced machine learning models, 2025)

2.2 Sources of Forecasting Challenges in Drilling Operations

Figure 2 – Uncertainty Sources → Error Signals → Engineering Actions



Connects drilling uncertainties to observable error patterns and proactive operational controls.

There are several forecasting challenges in drilling operations. These challenges arise from different sources of uncertainty that tend to interact. Currently, geological uncertainty constitutes the greatest forecasting problem in drilling and carries more weight than other factors. (Maguire et al., 2024) For instance, geological formations tend to exhibit nonlinear behavior that might not arise from models. Additionally, even within a certain formation, unexpected abrupt variations often emerge that might result in a failure of forecasting models. (Hussein et al., 2024, pp. 15-25) However, operational uncertainty adds an extra layer of complexity to the issue within the context of a predictive model approach. Drilling process performance not only varies due to a number of parameters that one controls, but also due to several parameters that one cannot control. Apart from that, there exists an added (Damarla& Zhu, 2025)complexity due to human intervention, which otherwise impacts the process of drilling as per real-time observations and thereby invalidates an otherwise pre-drilled plan. Similarly, uncertainties like sensor noise, data loss, and delays affect real-time sensor data accuracy.

Another challenge to be faced from an implemental standpoint is the inherent nonlinear and evolving characteristic of drilling processes. Not only is the mechanical interaction between drilling parameters nonlinear and time-dependent as depth is increased, but evaluating the performance is difficult and challenging due to the inability of traditional methods to cope dynamically and evasively as required while tackling the flow and onrush of time. (Nguyen et al., 2024)

2.3 Application of Artificial Intelligence in Drilling Engineering

High-frequency drilling data has been increasingly made available. This has helped the adoption of new artificial intelligence methods in drilling engineering. (Application of artificial intelligence to predict rock strength and drilling efficiency using in-cutter sensing data and vibration modes, 2024) AI is deemed useful for nonlinear systems with a large dimensionality where a physical relationship is difficult to explicitly define. (Learning high-dimensional ionic model dynamics using Fourier Neural Operators, 2025) AI has been utilized in drilling engineering with initial applications including the improved prediction of the rate of penetration and drilling time employing artificial neural networks. These are seen as having superior prediction capabilities compared to traditional methods. (Khan, 2025) Later studies have extended the application of this field of AI to also include ensemble learning algorithms. Ensemble learning algorithms rely on random forests and boosting algorithms. This is aimed at increasing robustness. Another recent addition is the application of deep learning to effectively model temporal dependencies in the drilling data. This is a major step towards better modeling of sequential behavior. (Delgado-Panadero et al., 2024) Another important application of AI techniques in drilling processes is in detecting drilling anomalies, estimating bit wear conditions, and drilling optimization. This again confirms the versatility of AI techniques in dealing with different types of issues in various branches of engineering in drilling processes. (Al-Fakih et al., 2024) Nonetheless, most of the research on AI in drilling processes focuses on the overall accuracy of predictions with reference to performance criteria as measured by error statistics.

2.4 Limitations of Existing AI-Based Forecasting Studies

Despite the success of various AI models in achieving reliable predictions in drilling, various drawbacks exist in the current literature. One of them lies in understanding the lack of interpretability of various artificial intelligence models, which could act as a barrier in accepting various AI tools in practice, as engineers require reliable forecasts as well as understanding pertaining to model behavior in variousconditions. While black box models are accurate, they can be limited in terms of explaining why forecast deviations are occurring.Another limitation is the narrow focus on performance optimization and its accuracy, without adequate emphasis on and sensitivity analyses of forecast uncertainty and error behavior. Typically, models use performance metrics to assess the accuracy of point predictions but disregard uncertainty and error behavior. (Damarla& Zhu, 2025) This limitation is critical in drilling operations. Moreover, in most studies of artificial intelligence systems in specific fields of interest, their models are trained and operated over stationary data sets. (Artificial Intelligence Index Report 2025, 2025) At other times, in real-world drilling systems, understanding their behavior means recognizing them as non-stationary systems corresponding to what is known as 'concept drift.' (Tziouvaras et al., 2025) It is no surprise then that their performance is not up to par in many real-time applications, resulting in unforeseen forecast errors. (Muhammad et al., 2024)

2.5. Forecast Error Assessment and Uncertainty Modeling

Forecast error evaluation methods promote a scientific approach to learning the limitations of the forecast models. Error analysis in various engineering systems traditionally relies on statistical evaluation of error measures, such as mean absolute error and root-mean-square error. (Hodson, 2022, pp. 5481-5487)As far as drilling is considered, the area of AI in error assessment is still not as widely researched. (Artificial Intelligence in the Oil and Gas Industry: Applications, Challenges, and Future Directions, 2026) Studies carried out thus far have not sufficiently addressed the inclusion of error modeling as a part of the forecasting method. (Data-driven prediction of rate of penetration (ROP) in drilling operations using advanced machine learning models, 2025) As can be understood, there are undeniable benefits from assessing the reliability of the predictions performed.

2.6 Research Gap and Motivation

The literature shows an increased use of AI in drilling performance forecasting; however, concerns have been raised regarding uncertainty in this process and the reliability of estimates generated through it. (Damarla& Zhu, 2025) It has been seen that even though the accuracy of estimates has been taken to the next level using AI, not enough attention has been paid to error analysis in this context. (Application of artificial intelligence to predict rock strength and drilling efficiency using in-cutter sensing data and vibration modes, 2024) There is a very obvious need to develop methodologies that go beyond just estimates.This research gap is filled by the specific research on the application of AI technologies in the development of models assessing the forecast error in the case of drilling operations. Thus, the idea here is to apply the realistic data obtained in the course of drilling while using the advanced capabilities of the machine learning approach to improve the understanding of forecast uncertainties. On the other hand, it would be correct to highlight the specific advancements in the field of drilling engineering due to applying the error assessing component in the AI forecasting approach.

Methodology

3.1 Research Framework Overview

The method that has been adopted in the current research study focuses essentially on evaluating forecast errors in drilling processes, as computed through artificial intelligence techniques. While generally, forecast errors are considered as measures of performance in line with traditional concepts, in this framework, errors in forecasts are considered as outcomes that should be examined in detail. Three steps have indeed gone into forming the research framework, as presented below.The overall workflow starts with real-world data preparation for existing drilling operations. This is supplemented with AI model development for forecasting various drilling performance parameters. Errors are thereafter found through forecasting error calculation based on real-world measurements. This error is used to establish measures for further AI model development aimed at addressing AI forecasting deviations.

3.2 Data Preparation and Feature Engineering

Real-time and historical drilling data are the basis of its methodology. Parameters included in its dataset are operational data, i.e., depth, rate of penetration, weight on bit, rotary speed, drilling fluid flow rate, standpipe pressure, and finally, torque. Geological data are included in its dataset, specifically those obtained from formation evaluation and logging data. Data pre-processing requires cleaning of erroneous sensor readings and interpolation of missing values. Smoothing of signal noise, especially from sensors having a high sampling rate, may require the utilization of the moving average method. It should, in this instance, not have a significant effect. Normalization of the input values to the models, specifically those that employ neural network-based technologies, requires consideration. During this phase, there was a need to perform certain engineering to enrich the models. To consider temporal features, temporal elements are added to the input vectors to consider temporal factors during the modelling process, allowing the models to recognize the time-dependent conditions encountered during operations. Lag features are added to consider the short-term dependency between the drilling performance and operational input variables, which is important to consider while analyzing the errors encountered during drilling operations.

3.3 Development of AI-Based Forecasting Models

It should be noted that AI forecasting models are constructed to predict certain key drilling performance indicators; however, due to their potential to approximate complex nonlinear relations, artificial neural networks are utilized as primary forecasting models. In this context, a variety of layers in an artificial network exist, including hidden layers. Apart from neural network models, ensemble machine learning models are used. Their intention here is to attain robustness and generality. Here, many different decision trees operate on different portions of the data. Hyper parameters of the models undergo optimization via cross-validation.

Forecasts generated by the models are used to train the models. On the other hand, the models are expected to validate the forecasts using the historical information for drilling. In the evaluation of the model performance, the models use standard statistics for performance evaluation. Nevertheless, the statistics are used only as the initial evaluation.

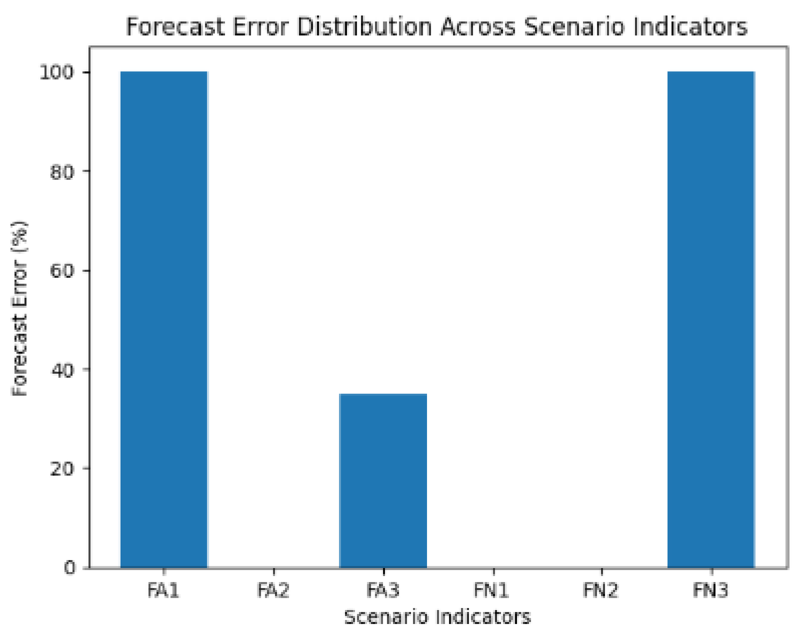
3.4 Forecast Error Computation and Scenario Classification

Forecast error computation in this study is performed using a **scenario-based evaluation logic**, ensuring that forecast accuracy is assessed only under operationally meaningful conditions. Forecast errors are not treated as purely numerical deviations but are interpreted within the interaction between **forecast availability (F)**, **stock availability**, and **actual consumption (C)**.

Each material instance is classified into one of six mutually exclusive scenarios using predefined indicators (FA1–FA3 and FN1–FN3). These indicators ensure that forecast error is not unfairly penalized when consumption does not occur or when inventory constraints prevent execution.

- **FA1:** Forecast exists, stock is available, but no consumption occurs (FE = 100%)
- **FA2:** Forecast exists, stock is not available, and no consumption occurs (FE = 0%)
- **FA3:** Forecast exists, stock is available, and consumption occurs (FE computed using formula)
- **FN1:** No forecast, stock available, no consumption (FE = 0%)
- **FN2:** No forecast, no stock, no consumption (FE = 0%)
- **FN3:** No forecast, stock available, and consumption occurs (FE = 100%)

This classification prevents misleading forecast evaluations and ensures alignment with real operational constraints commonly encountered in drilling supply chains.



3.5 Quarterly Forecast Error Measurement Logic (New – Added)

Forecast Error (FE) is calculated on a **quarterly basis**, consistent with drilling planning cycles and inventory review practices. The methodology evaluates forecast performance for the **last completed quarter**, and historical FE values are retained at the quarterly level for trend analysis.

- **Forecast (F):**
  Forecast quantities are aggregated at the **drilling level** and filtered based on the **current forecast load month**. Only forecastable materials assigned to forecast plants are considered.
- **Consumption (C):**
  Consumption is calculated as the **total material usage during the evaluated quarter**, aggregated across **Drilling Plants** and **Maintain Potential Plants**. MRP planning types are excluded to avoid artificial demand signals.
- **Inventory Reference:**
  Inventory is referenced as the **closing stock of the previous quarter**, representing the opening stock of the evaluated quarter. For example, when calculating FE for Q4, inventory as of **September 30** is used.

3.6 Stock Availability and Minimum Forecast Adjustment

Stock availability during the quarter is determined using on-hand inventory logic that reflects both physical and planning constraints:

- **MRP-based materials:**

Inv_ Qty = max (Opening Inventory, Total Quarterly Consumption)

- **Customer-specific materials (lead-time planning):**

Inv_ Qty = max (Opening Inventory, Total Quarterly Consumption) + Supplier Stock

If supplier stock data is unavailable, forecast quantity defaults to inventory quantity to ensure conservative estimation.

To prevent overstatement of forecast error due to excess forecasting beyond physical availability, a **Minimum Forecast (MF)** is applied exclusively for FE computation:

MF = min (Forecast Quantity, Stock Available Quantity)

3.7 Forecast Error Formula and Capping Rule

Forecast Error is computed using a normalized formulation:

$$FE = \left(\frac{|MF - C|}{MF} \right) \times 100$$

If the calculated FE exceeds **100%**, it is capped at **100%** to maintain interpretability and prevent statistical distortion in aggregated results.

3.8 Material Equivalency Group (MEG) and Weighted Forecast Error

To enable meaningful aggregation across heterogeneous materials, forecast errors are first calculated at the **material–MEG (MAT_MEG)** level. Materials with similar functional and consumption behavior are grouped into **Material Equivalency Groups (MEGs)**.

Weighted Forecast Calculation

$$\text{Weighted Forecast} = \frac{\text{Max Value}}{\sum \text{Max Value}}$$

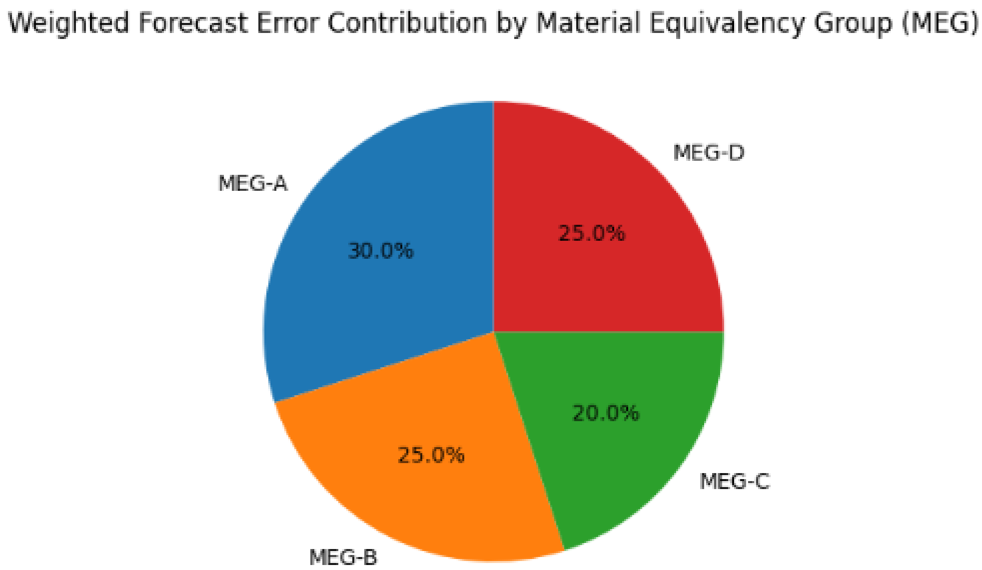
Where:

- **Max Value** = maximum of *(Total Forecast Value, Total Consumption Value)*

Weighted Forecast Error

Weighted FE = Weighted Forecast × FE

Weighted metrics are aggregated from **MAT_MEG** to **Drilling Group (DRGR)** and **Maintain Potential Group (MPGR)** levels, preserving proportional material impact on overall forecast accuracy.



3.9 Integration with AI-Based Error Assessment Models

The AI-driven error assessment models incorporate **scenario indicators, quarterly FE values, MEG classifications, and weighted FE outputs** as learning inputs. Artificial neural networks and ensemble models learn both the magnitude and persistence of forecast deviations, enabling early identification of high-risk drilling intervals.

This integrated approach ensures that error prediction models reflect **operational reality**, inventory constraints, and planning logic, rather than relying solely on statistical deviations.

Results and Case Application

The proposed framework of assessing forecast error through AI was tested for its efficiency using real-life data that pertained to a drilling procedure. The results show that while assessing forecast error, a useful interpretation that would otherwise go unnoticed is possible if a conventional method of assessing accuracy is employed instead. The useful interpretation comes from considering patterns that arise rather than assessing each event in isolation from others.The initial forecasting models were shown to be valid with regard to the general forecast accuracy within the pertinent drilling parameters. It was noted, however, that closer inspection of the resultant residuals showed that the initial forecast result performed differently for different depth intervals and various drilling phases. Consequently, a number of deviations were portrayed within the regions involving a change in formation as well as with regard to the various drilling parameters deliberately modified to alleviate instability.Indeed, the AI-based error assessment models were able to learn the correlations between the operational inputs and the predicted deviations. As such, there were consistent trends demonstrated for the predicted errors that closely aligned with the trends of the respective errors. Unlike traditional approaches of error assessment that relied on statistics, this model demonstrated a better capacity to model non-linear interactions. This made it possible to identify the regimes of elevated uncertainty.An example of a case application, where a drilling steady state is focused upon in detail to highlight the practical utility of the proposed methodology, can be made as follows: In the course of drilling, it has been realized that throughout a certain drilling interval, the proposed model underestimated the rate of penetration as a result of lithological variation. Moreover, the error assessment model has detected a growing trend in errors caused by variation in the torque as well as in the mechanical specific energy, which indicates lower reliability in the accuracy of drilling estimates. Further, a comparative analysis revealed that the ensemble-based error assessment models demonstrated improved robustness compared to the traditional single-neural-network models, especially when dealing with noisy sensor information. Indeed, the use of ensemble models assisted in mitigating the effects of outliers, as the errors were predicted with improved stability. The robustness of the proposed models will be vital, especially when operating in real-time drilling scenarios. The analysis of error trends in time demonstrated that the system deviations within the forecast were not uniformly spread out in time; they were concentrated around some operational events. These events were bit wear, changes in drilling fluid properties, and formation changes. It should be noted that the framework was carried out very accurately, allowing us to distinguish between persistent errors in the system structure and those that were just disturbances in the system.In terms of insights for engineers, this work suggests that forecast error assessment generally helps with situation awareness. This is because forecast error assessment will allow engineers to gain predictive insights towards understanding error magnitudes and error directions, leading to more forward-thinking measures rather than necessarily reacting to these errors.The case application also shows how incorporating error estimation relates to increased confidence in artificial intelligence-based tools applied in decision support systems in oil well drilling. In other words, engineers are given pertinent information concerning prediction or forecast reliability instead of completely trusting the results of various models they use in their oil well drillings.Overall, the outcome validates the hypothesis that the application of the error measure by AI would be able to provide a significant upgrade in the process of performing drilling performance forecasting. Although the case application is based on specific circumstances regarding the project area to be drilled, the methodology has the potential to be applicable across a broad array of drilling scenarios.Nevertheless, the aforementioned results clearly emphasize the necessity of transitioning from accuracy-oriented evaluation to uncertainty-based predictive models in drilling engineering science. Error assessment in artificial intelligence models might represent an advancing step within oil and gas forecasting.

Discussion and Engineering Implications

In particular, the outcome of the current analysis pointed to the important place that the evaluation of AI-based drilling prediction models with respect to specific forecast errors holds in relation to their practical effectiveness. Even though previous studies had emphasized the importance of the accuracy of prediction models for their practical effectiveness, the current analysis pointed to the conclusion that the accuracy of AI-based prediction models was not sufficient for effective decision-making within the complex environment of the drilling system. As mentioned within the topic of the current analysis, errors involving the forecasts of prediction models contained important information related to the operation of the drilling system.One of the most striking findings was that there was a strong context dependency in errors recorded. For instance, there was a marked increase in forecast errors during formation transitions, adjustments in system parameters, and instability. A major problem with these states has often been that they are quite difficult states to model, given their dynamic changes. However, as seen with AI-driven models in assessing errors, there was a clear indication that there was a contextual dependency in changes recorded from deviations in the forecast.As an engineer, this has significant implications from an optimization standpoint for drilling operations as follows:

"With this information, engineers may implement monitoring and control methods that target regimes where forecast uncertainty is high according to the error model. In other words, if forecast uncertainty is predicted to increase during some future interval of operations, conservative drilling parameters may be used during that period, or additional diagnostic tools may enter into the procedure in real-time, as opposed to correcting performance issues only when degradation is noted to have occurred."The addition of error assessment will also increase the trustworthiness of decision-support tools based upon artificial intelligence. One of the challenges in effectively adopting artificial intelligence in controlling a drill is the lack of clarity, which comes as a result of this model of prediction. It becomes more transparent, therefore, as a way of informing a human decision-maker, so that a decision will be well-informed. He does not blindly accept the output of the model.Another key feature is relevant to the adaptability of the models. In drilling operations, there is a phenomenon called concept drift, in which the relationships between the relevant input factors and the preferred performance metric change over time. The indication of the time clustering in the errors is consistent with the behavior of the models, where static models may be increasingly unfit. The AI capabilities for error assessment can be utilized as an alert system for the need to adjust the models.

These results also reinforce the significance of ensemble-based strategies for error evaluation in uncertain operational settings. Drill data typically faces problems due to imprecision in sensor systems, communication problems that cause delays in data transfer, and also due to data incompleteness. Ensemble models showed higher resilience to such disturbances or noise in data transfer, as they presented more stable error predictions. This data needs to showcase more promising performance for actual application in the field.

If seen from a wider angle of the operation of things, the implementation of the AI system for forecast error assessment is actually a part of the efforts regarding the digital transformation of the field of oil and gas. This is so because, as the processes of drilling within this field become progressively more automated, prediction systems have to not just make forecasts but also quantify this error.

Finally, it is also seen that, whereas there is a widespread notion of post-evaluative procedures in forecast error assessment, it is not seen as a post-evaluative step but as a part of drilling analytics generally. This is seen as part of a generalized transformation of better and more realistic uses of AI approaches in drilling engineering.

Conclusions and Future Research

Overall, the purpose of this research has been to identify the usefulness of the AI-driven models in the oil and gas drilling industry. Throughout the reporting components in this document, it has been indicated how the approach to handling forecast deviations as opposed to considering them as part of the residuals, could be more insightful in assessing the reliability of the predictions made in the oil and gas drilling activity in terms of the likelihood of such predictions to occur as per the performance. It has been noted how the errors in the forecasts correlate to the context. Additionally, with the added incorporation of AI-based error assessment, there has been a clear improvement in terms of model interpretability and more engineering confidence in data-driven decision support systems. As discussed in the study, ensemble learning and neural networks were indeed successful in terms of correcting nonlinear error trends and time-dependent behavior, with early indicators of raised uncertainties. (Kim &Durlofsky, 2022) This would thus present the operator with a chance to apply corrective measures prior to deviations in predictions turning into operational issues. Importantly, there has been adaptability and continuous calibration in response to issues of concept drift. (Arostegi et al., 2024)In an engineering context, the research also underscores the importance of considering the estimation of errors in forecasting as part of the overall process of AI-assisted drilling analytics. By incorporating additional models that not only enable forecasting but also provide a degree of uncertainty or reliability of forecasts, it not only enhances the safety, efficiency, and resilience of drilling processes but also promotes a healthy approach to the current digital revolution that the industry finds itself in, as seen through the framework of utilizing cutting-edge approaches in pursuing a real-life problem. (Alyaev et al., 2025)

In that direction, future avenues of work include:

Real-time sensor data streams in error assessment models will improve adaptive forecast response.

A multi-parameter error model will take into account multiple parameters in error assessment, allowing a multidisciplinary analysis that may prove to be useful in advancing the robustness of the forecast model.Offshore or high-pressure-high-temperature drilling will be explored to further establish its universal applicability in heterogeneous drilling environments. Finally, interpretable versions of neural networks or other AI architectures may help improve the model acceptance by drilling engineers in various drilling environments by employing attention mechanisms in error analysis. In this sense, it is worthwhile to note that the use of artificial intelligence in the assessment of forecast errors represents a pivotal improvement in how to approach the optimization of drilling performance models, in which there is a need to properly address uncertainty in forecasts while addressing predictability in models and their use in supporting operations in general. (Artificial Intelligence Approaches to Modeling Equivalent Circulating Density for Improved Drilling Mud Management, 2016, pp. 1530-1539) The findings generated through this specific study pave the way to facilitate implementation and continuing study in instances of data-driven optimization of drilling in general.

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