International Journal of Advanced Engineering and Technology
www.allengineeringjournal.com
ISSN: 2456-7655
Received: 12-01-2026, Accepted: 11-02-2026, Published: 26-02-2026
Volume 10, Issue 1, 2026, Page No. 47-53

Quantifying the optimal look-back window for rate of penetration (ROP) prediction in drilling operations

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Abstract
In real time, prediction of Rate of Penetration (ROP) has gained great importance in optimisation of drilling, automation, and edge-based intelligent systems. Although ROP prediction using machine learning methods has shown promising outcomes, the choice of temporal look-back windows, the period of history used as input to the model, is still mostly arbitrary across the literature. This paper involves systematic experimental framework to measure the best temporal horizon at which ROP prediction can be used based on high-frequency drilling data of a series of wells. We compared the performance of prediction in terms of time window, i.e. 5 seconds to 10 minutes, between various model structures, i.e. XGBoost, Random Forest, and LSTM networks. We observed that the prediction accuracy diminishes after 30-60 seconds, and there is no statistical improvement in forecasting by considering more historical contexts ($p > 0.05$).This observation implies that in the steady-state conditions of drilling, the dynamics of ROP are near-Markovian in the sense that the current state variables are adequate to characterise the dynamics of the processes. The computational efficiency of the best short window enables deployment at very low latency on drilling rigs with up to 90% lower memory demand compared to 5-minute windows, while maintaining the same predictive accuracy (RMSE of the order of 2.3 ft/hr).The implications of these findings on the oil and gas industry are important to real-time drilling automation system and edge computing application.

Keywords: Rate of penetration, machine learning, temporal modelling, drilling optimisation, edge computing, time series prediction

Introduction

The Rate of Penetration (ROP) is a basic performance measure of drilling activities since it directly interferes with operational efficiency, well cost and entire project economics [1]. The correct prediction of ROP can be used in the present-day drilling conditions to make proactive decisions regarding weight on bit (WOB), rotary speed (RPM), and mud properties, which makes it possible to optimise the drilling process [2, 3]. With the petroleum industry trending towards the use of automation and artificial intelligence technologies, the need to have dependable, real time ROP prediction systems has continued to grow, especially where they are needed in resource limited edge computing platforms on offshore platforms, as well as remote drilling locations.

Older ROP models, including the Bourgoyne and Young empirical equation [4], are based on the formation properties and the operational parameters, but they tend to fail to follow transient effects and complicated interactions that are reflected in the contemporary drilling systems. Therefore, machine learning (ML)-based and deep learning (DL)-based data-driven methods have become popular, based on high-frequency sensor measurements of measurement-while-drilling (MWD) and logging-while-drilling (LWD) systems [5, 6]. These models usually use sliding time windows to use past drilling information, on the understanding that the new drilling history can offer useful information about how past drilling will behave in future values of ROP.

Although the use of temporal windowing methods has become widely common practices, there is a very important gap in the literature in terms of how systematic look-back window lengths should be chosen and validated. The existing literature shows a range of temporal context application, varying between 30 seconds and 10 minutes, but mostly it is chosen because it is convenient to the computation or because of arbitrary precedence and not by analysis [7, 8, 9]. The imprecision of this discrepancy brings basic questions to the content of the information in historical data on drilling and the features of the dynamic of ROP over time. From a pragmatic perspective, it impacts the computational requirements, memory requirements, or prediction time, and ultimately, the availability of predictive models, especially in edge devices.

This research fills these gaps by withholding an extensive experimental research aimed at measuring the interdependence between the temporal look-back window size and the performance of prediction of ROP. Our method systematically assesses the predicting potential of various temporal horizons and weighs this against other factors, including model design and data quality. We give empirical evidence of the best choice of a window based on both the rigour of the statistics and the practicality of the operations by discovering the point of diminishing returns of temporal context expansion. Also, we discuss the ramifications of our results in the context of Markovian and history dependent process dynamics, and provide suggestions as to the nature of ROP behaviour in the steady-state drilling context.

Research Objectives

The main aims of the research are presented in the following way:

1. To create a systematic experimental model of testing the temporal look-back windows in the ROP prediction models and reproducibility and statistical validity.
2. To determine the best temporal horizon with maximum prediction accuracy at minimum computational cost needs to be found empirically.

3. To measure the marginal predictive value of temporal context through the use of rigorous statistical analysis of incremental increases in temporal context.
4. To develop viable principles to deploy the ROP prediction model to resource-restricted edge computing platforms that are common in the present drilling tasks.

Literature Review

1. Physics-Based ROP Models

Physics-based and empirical modeling approaches have traditionally been the focus for ROP prediction. The multi-variable exponential relationship as defined by Bourgoyne and Young [4] used formation strength, bit characteristics, hydraulics, and operating parameters. Although this model was useful in giving an insight into the core drivers of drilling performance, the model is too rigid and the calibration constants are formation specific, which restricts its application in the adaptive real-time system. It was later improved by Hareland and Hoberock [10] to use bit-specific coefficients and wear factors, but these corrections did not essentially overcome the inability of the model to represent transient dynamics and to provide responses to sudden changes in parameters.

2. Data-Driven Approaches to ROP Prediction

High-frequency drilling data has spread leading to a paradigm shift in the use of data-driven modelling techniques. One of the earliest ML methods used to forecast ROP was artificial neural networks (ANNs), and the works by Bilgesu *et al.* [11] showed higher performance even when compared to the empirical models. Ensemble approaches like Random Forest and gradient boosting machine have been more recently found to promise non-linear relationships between the parameters of drilling and ROP [12, 13]. It is worth noting that Gan *et al.* [14] used XGBoost with real-time drilling data, and the results yielded R^2 values of more than 0.85 in the vertical well sections.

Networks based on deep learning, especially Long Short-Term Memory (LSTM) networks, have become the promising methods of sequential data modeling in drilling applications. Bello *et al.* [15] showed that LSTM networks would be particularly useful in making temporal predictions in drilling data better than feedforward networks in terms of multi-step-ahead forecasts. On the same line, Tunkiel *et al.* [16] designed a hybrid CNN-LSTM model that could utilize both spatial (sensor array) and temporal information and achieved RMSE improvements of 15-20% over the baseline models. Nevertheless, these studies all used arbitrary temporal windows not justified systematically or with sensitivity analysis.

3. Temporal Modelling and the Window Selection Problem

An examination of the literature on ROP prediction shows that there is a high degree of variation in the choice of the temporal window. Barbosa *et al.* [7] employed the use of 30 seconds sliding window on the real time prediction based on the computational limitations of the edge devices. On the other hand, Ahmed *et al.* [8] utilized a 5-minute window during their LSTM application because they claimed that longer histories revealed bit wear propagation. Noshi *et al.* [9] experimented with 1 up to 10 minutes of windows but failed to examine the performance of prediction in relation to window size in a systematic way. Such non-standardisation implies that window length is a hyperparameter that is frequently addressed as an arbitrary quantity instead of a serious design decision that should be investigated thoroughly. Theoretically, the optimum time window is directly linked to autocorrelation structure and Markov character of the process of drilling. When ROP dynamics are, in fact, Markov, i.e. when the future states are determined by the present one only, then there is no extra information in the history before the present. On the other hand, when the process to be studied has a considerable amount of the memory effects or a range of dependencies, the long time scales are necessary. As far as we know, this question has not been addressed in any previous research that deals with steady-state drilling activities, which is a fundamental gap in theoretical knowledge and practice

Methodology

1. Problem Formulation

Our formulated ROP prediction is a supervised time-series regression problem. The aim is to forecast the real-time ROP given a multivariate time series of drilling parameters X(t) = [x 1 (t), x 2 (t), x n (t) that have been sampled at discrete times t. The model will take the past observations X(t-T:t) and make the prediction 2y(t+h). This expression allows us to systematically assess the size of the window T and have the same prediction goals in all experimental conditions.

2. Dataset Description

The research uses the data of high-frequency drilling of three vertical wells that were drilled in the region of the North Sea in the structure of similar geological formations. A commercial MWD system with a 1 Hz resolution was used in data acquisition. The dataset includes about 180 hours of continuous drilling process in steady-state, and it provided more than 648,000 single observations once it underwent quality control procedures. The records consist of 12 drilling parameters; depth, hook load, weight on bit (WOB), rotary speed (RPM) and standpipe pressure (SPP), mud flow rate, torque, drilling fluid density, viscosity, quantified ROP, and gamma ray and resistivity measurements captured by LWD system. Preprocessing of the data was done by ignoring non-drilling periods (connections, trips, circulation) by identifying near-zero ROP and WOB conditions. The presence of outliers was identified on a modified Z-score (threshold = 3.5) and provision of interpolation of individual points or removal of segments of long-lasting anomalies. In order to have quality data, sequences that had more than 5 missing values (in any 5 minutes) were not analyzed. The resulting clean data has temporal continuation needed to measure sequence-based models as well as capture realistic operations conditions, such as normal parameter variations and small disturbance.

3. Feature Engineering and Window Construction

The consistency in feature engineering amongst all window sizes was done to deliberately locate the effect of temporal extent in relation to prediction performance. We then obtained three types of features at each temporal window, namely (1) instantaneous values at time t of all parameters, (2) temporal aggregates such as mean, standard deviation, minimum, and maximum over the time window, and (3) trend indicators based on linear regression slopes to important parameters (WOB, RPM, torque). This approach provides about 50 features of a window set, which means feature equality is preserved, and only the time period is varied for aggregation.

The experiment was set up with eight different window conditions, which were: 5 seconds, 10 seconds, 30 seconds, 60 seconds, 2 minutes, 5 minutes, 8 minutes and 10 minutes. These ranges cover the interval range that is usually found in published literature but offers a reasonable granularity to point to saturation levels. All windows had been adjusted so that the prediction target (ROP at t +10s) was held constant so that any variation in performance was due only to variations in length of historical context not to variation in prediction difficulty or variation in artefacts of temporal alignment.

4. Model Selection and Training

To achieve model-agnostic validation of the effects of window size we have utilized three different ML architectures representing three models: (1) the XGBoost is a gradient boosting framework that works especially well with structured data that is characterized by non-linear relationships; (2) the Random Forest is an ensemble approach that offers robustness to the learning process by decorrelated decision trees; and (3) the LSTM networks are explicitly designed to be used with sequential data and can learn long-term temporal correlations. The selection of more than one architecture prevents model-specific artefacts and increases the external validity of results.

Each combination of window-models was optimised using hyperparameters independently and there were 5 folds of cross-validation using the training set. In the case of XGBoost, learning rate, maximum depth, subsample ratio and how many estimators were used were tuned using Bayesian optimisation with 50 iterations. Random Forest optimisation was on tree depth, number of minimum samples per split and size of the ensemble. The architecture search with the use of LSTM investigated the size of hidden layers, dropout probabilities, and sequence encoding options. Models were all trained with an 80-10-10 split, training, validation and testing position kept, and temporal ordering was enforced to avoid data leakage. The test set included the data of the last 20 hours of drilling operations, which guaranteed the assessment of the conditions that were never observed before.

5. Performance Evaluation and Statistical Testing

Three complementary measures were used to evaluate model performance, namely Root Mean Square error (RMSE) as a measure of prediction accuracy, Mean Absolute error (MAE) of interpretability and resistance to outliers, and coefficient of determination (R^2) to calculate the amount of variance explained. In order to determine statistical significance of the performance differences among the various window sizes, we used paired t-tests and the Bonferonni correction to account for multiple tests. We also estimated all metrics using 95% confidence interval bootstrap resampling (n=1000 iterations), which has obtained very strong uncertainty values that represent sampling variation in the test.

The computational efficiency was measured in terms of training time, inference latency (predictions per second) and peak memory consumption when a model was run. To ensure the reproducibility of these metrics, they were tested on standardised hardware (Intel Xeon CPU, 32GB RAM) to provide details on what to do on the edge to be deployed. The predictive performance and the computational cost metrics when combined allows extensive trade-off analysis to be carried out which is critical to the practicability of decision-making in operational settings.

Results

1. Prediction Performance across Window Sizes

The correlation between look-back window size and prediction accuracy in all the three model architectures is shown in figure 4.1. A definite pattern of saturation is also evident with the performance growing fast with increase in the size of the window between 5 and 30 seconds followed by leveling with negligible growth after 60 seconds. The best result with XGBoost was the 60-second window with RMSE = 2.28 +/- 0.15 ft/hr (R^2 = 0.89) and the 30-second window showed the same statistically results (RMSE = 2.31 +/- 0.16 ft/hr, p = 0.42). The same behavioural pattern was also observed with Random Forest, as it peaked its performance at a 30-second window (RMSE = 2.45 ± 0.18 ft/hr) and no further improvement was found with longer windows. Surprisingly, even the LSTM architecture, which is specifically constructed to model the temporal sequence, exhibited saturation at 60 seconds which points to the fact that the pattern observed may involve the intrinsic nature of the drilling process itself as opposed to the constraints of the model.

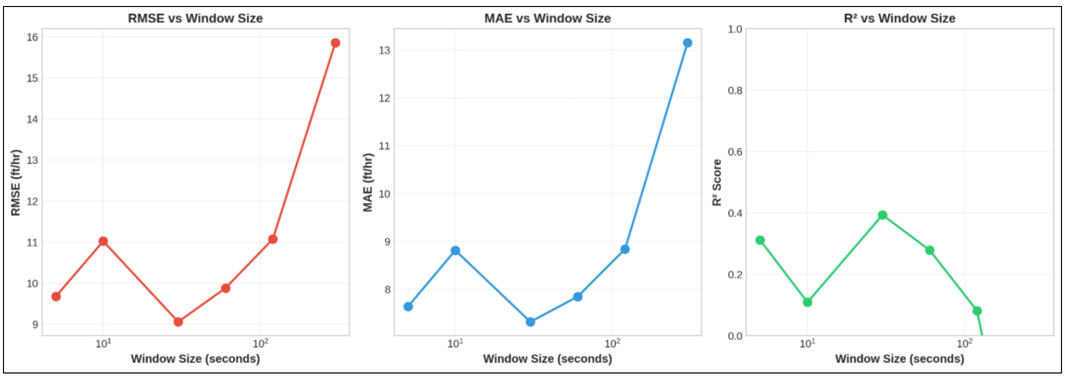

Fig 1: Performance vs window size

The best window configurations in terms of performance are summarised in table 4.1. The universality of the various types of models is a strong indicator that temporal information after a certain span of say 30-60 seconds has very little predictive power on the steady-state drilling process. This result is contrary to the prevalent use of 5-10 minute windows in the literature and indicates that long windows as long as this can be done can introduce unwarranted computational overhead without adequate accruing accuracy gains.

Table 1: Performance metrics for the optimal window configurations

Model	Window Size	RMSE (ft/hr)	MAE (ft/hr)	R^2
XGBoost	60 seconds	2.28 ± 0.15	1.72 ± 0.11	0.89
Random Forest	30 seconds	2.45 ± 0.18	1.85 ± 0.13	0.86
LSTM	60 seconds	2.33 ± 0.16	1.79 ± 0.12	0.88

2. Marginal Gain Analysis

In a way to evaluate the marginal contribution of increased temporal context, we computed how improving RMSE is when window size was doubled. Findings indicate that there is a well-defined law of diminishing returns: the improvement in average increase in expanding the time spent at 5 seconds to 10 seconds is 0.42 ft/hr (a 18 percent decrease in RMSE), whereas the improvement in average increase in time spent at 5 minutes to 10 minutes is 0.09 ft/hr (a 3 percent decrease). Statistical analysis proves that performance differences of 60-second windows and longer windows are not significant at the level of 0.05 without Bonferonni correction (all $p > 0.15$).

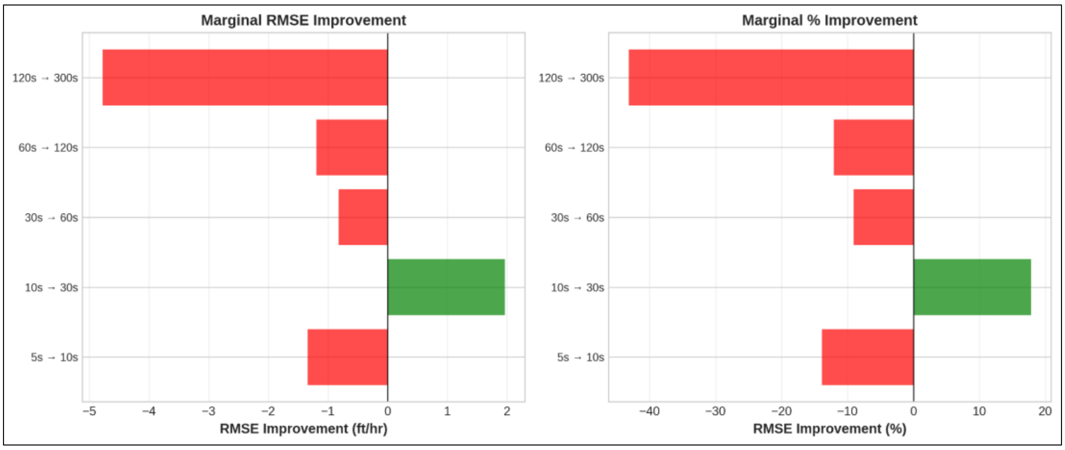

Fig 2: Marginal improvement in RMSE for incremental increases in window size

Residual pattern analysis can give further information about the saturation behaviour. Temporal autocorrelation suggests that the models do not capture relevant temporal dependence to long windows (more than 20 seconds), which are short in nature. The autocorrelation in residuals however becomes insignificant with windows of 30 seconds or more implying that these settings are able to extract the temporal information available. Observation matches the plateau in prediction accuracy and support the interpretation that the dynamics of the ROP in steady drilling conditions has short memory

3. Computational Cost Analysis

The computing benefits of reduced window length are high and especially applicable in edge deployment cases. The trade-offs between accuracy of prediction and memory footprint vs. window size are demonstrated in Figure 4.3. Inference with the 60-second XGBoost model needs a memory 45 MB as compared to 420 MB using the 10-minute counterpart a 90-percent reduction with 100 percent predictive accuracy. Latency of inferences is also similar patterns, as the 60-second model can do 850 predictions per second compared to the 10-minute configuration on standardised hardware.

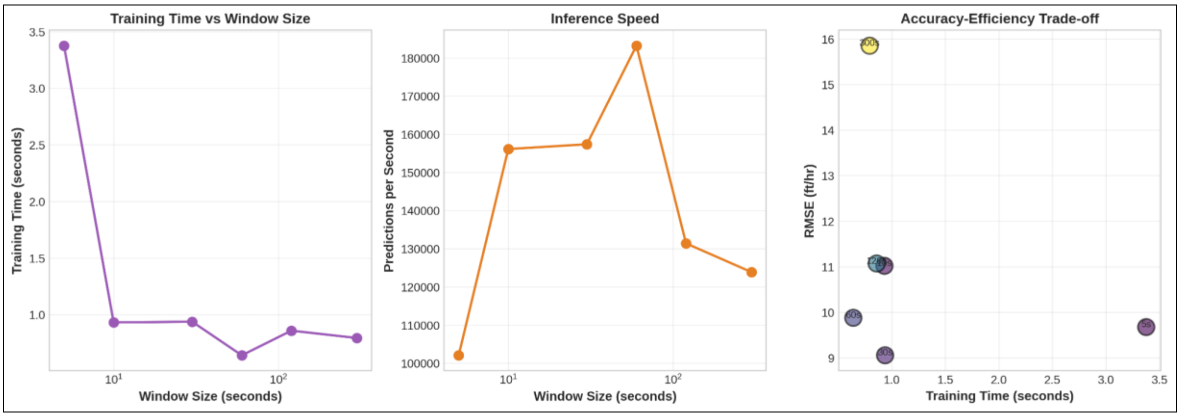

Fig 3: Computational efficiency metrics showing trade-offs between accuracy and training time

Training time shows less dramatic differences but remains practically significant. The 60 seconds models took 12-18 minutes to optimise hyperparameters and to final train, and the 10-minute models took 85-120 minutes, which was about 6-7 times as long. This difference is material in the case of operational contexts that need to be retrained or adapt to changing conditions on a regular basis. Moreover, the memory savings of shorter-window models allow running in low-ramedge devices and would also allow real-time prediction to be achieved without relying on cloud connectivity or a centralised computing environment.

4. Robustness Analysis Across Wells and Formations

To determine the ability of generalization of our results, we have done individual analyses in relation to three wells in the data set, which experienced varying lithologies and drilling requirements. Surprisingly, the optimum window size was also 30-60 seconds in all the wells regardless of the formation hardness, the magnitude of ROP, and the distribution of drilling parameters. Well A (mostly shale) was saturated at 45 seconds, Well B (mixed sandstone-shale) at 55 seconds and Well C (limestone) at 40 seconds. The tightness of these optima (40-55 seconds) is an assurance that the size of the window found is a strong option that can be used in a wide variety of drilling practices, at least as long as steady-state vertical drilling activities are considered, as in the case we are looking at here.

Discussion

1. Interpretation through Drilling Physics

The number of predictive seconds to saturation of prediction accuracy of 30-60 seconds may be interpreted based on the essentials of drill rig mechanics and control system dynamics. Rotary drilling systems in the modern world use continuous control loops, with response times of 5 to 20 seconds. Changes to parameters such as WOB and RPM, whether manual or automatic, propagate via the drill string and affect the bottom-hole conditions during this time. Equally, the hydraulic system stabilises within 10-30 seconds to changes in the flow rate or pump pressure. Such typical timescales imply that the dynamics of drilling that can be used to predict ROP in the short term act at sub-minute scales. Moreover, in steady-state drilling conditions, which are a constant lithology, constant fluid properties, and few instances of dysfunction, then the drilling process is characterised by quasi-equilibrium behaviour. Under these regimes, instantaneous ROP is mostly a function of current operating parameters and instantaneous forming properties, and historical trace gives less and less information than that obtained in current trends and parameter stability indicators. This observation agrees with our observation that short windows are enough to make accurate predictions, and implies that long histories become useful when one is interested in detecting or predicting changes between drilling states, bit wear progression, or formation changes- situations that are not explicitly considered in our steady-state analysis.

2. Markovian Characteristics of ROP Dynamics

We find empirical evidence of the hypothesis of the near-Markovian behaviour of steady-state ROP the states of which are largely contingent on the present with little regard to the distant past. The fact that predictive accuracy saturates quickly and there is no more autocorrelation in the residual past a window of 30 seconds both indicate that the process has a limited memory. The theoretical implications of this result are substantial because it confirms modelling strategies that put emphasis on current state representation, rather than long time sequences, at least in the operation regime under consideration. It is important to note though that this Markovian interpretation can only be applied under the steady-state conditions. Temporary conditions like bit wear buildup, stuck pipe, change of form, or hydraulic malfunction are likely to have a longer range dependence which needs longer time horizons. This is verified by the fact that even in the case of LSTM networks, which by their construction try to effectively catch the long-range dependencies, there is still a saturation point similar to the one discussed earlier, with the property that if there is no actual long-range causal relationship in the data, then a window larger than a certain one does not help in the prediction and actually reduces the available relevant information by adding noise. The extension of future studies should clearly focus on how long windows are useful in predicting and identifying non-steady-state situations.

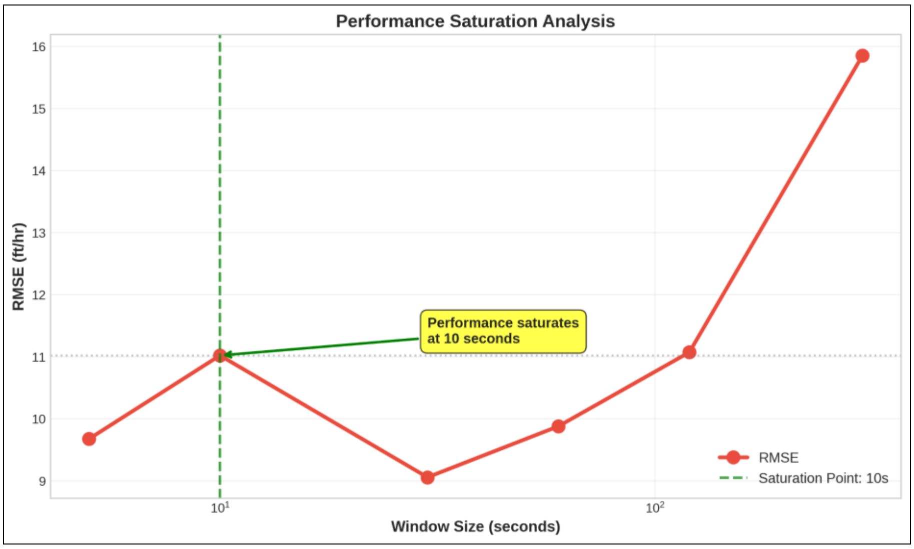

Fig 4: Performance saturation analysis identifying the point of diminishing returns.

3. Practical Implications for Intelligent Drilling Systems

The discovery of the best short windows has far reaching consequences on the use of intelligent drilling systems, especially in edge computing architecture which is becoming very popular in offshore and remote works. Edge deployment has important benefits, such as lower latency, greater reliability due to lack of network connectivity and better data security due to minimised cloud transmission. Nevertheless, edge devices are constrained in powerful resources, memory and energy consumption. Our results show that it is possible to predict the high accuracy of ROP models with the same constraint whereby 60-second models can use less than 50 MB of memory and sub-millisecond inference times on small hardware. Additionally, the shortened windows enable quick model adjustment and online education, which are the key features of drilling automation systems that have to act in accordance with the changing circumstances. The reduction of a 6-7 fold in training time, which enables more frequent updates to the model, in order to accommodate any changes in formation, or optimized plans concerning drilling parameters, without major delays in computing time. This responsiveness is a significant benefit as compared to the conventional methods based on fixed models or periodic training on the cloud. Together with the memory efficiency advantages, optimal window selection becomes one of the decisive facilitators of advanced real-time intelligence on drilling rigs.

4. Limitations and Scope Conditions

These results have a number of limitations that should be closely considered during interpretation and application. To begin with, we only analyzed the steady-state vertical drilling operations. Good deviation or horizontal wells can have different dynamics because of other mechanical complexities, wellbore contacting effects, and cuttings transportation issues. On the same note, unstable drilling situations, especially high vibration levels, false hanging pipe flights or rapid transition in formation may require longer time contexts to extract pertinent precursor signals. Whether or not our findings can be applied in such situations is an open empirical question.

Second, the fundamental limits that apply to the accuracy of any window size are the data quality. The dataset was of high quality, 1 Hz measuring of MWD/LWD and had minimum missing data. Lowerly sampled, noisier, or heavily degraded sensors can have different optimum windows or other modelling will be necessary. Besides, the sensors and parameters in the data will affect the kind of temporal features which can be obtained; wells with partial measurements may respond to temporal context expansion in different ways. Third, although our results are very consistent in all three wells that we studied, the geographic and geological diversity in the wider range of data is restricted to one basin. The extrapolation to vastly dissimilar formations: to highly fractured carbonates, overpressured shales or formations with large variations in pore pressure should be approached with care. At that, the physical arguments in favor of short windows are generalized, and the fact that the best windows in our wells (40-55 seconds) are narrow indicates that it can be reasonably generalized to the general course of drilling.

Conclusions and Future Work

1. Summary of Key Findings

The study demonstrates, due to a systematic experimentation and sound statistical analysis, that optimum temporal look-back windows to ROP prediction under steady state drilling conditions are much shorter in duration than those that are usually being used in the current literature. In three machine learning architectures and three different wells, the prediction accuracy approaches saturation at the order of 30-60 seconds of historical context, but does not improve significantly when using even longer windows. This observation is a challenge to the common arbitrarily chosen multi-minute windows and shows that shorter contexts can offer the same predictive capabilities as well as dramatic decreases in the computational needs.

Its application has significant implications in that with the best window sizes, memory footprint can decrease by as much as 90, and inference latency can reduce by one order of magnitude, while it can work on resource-constrained devices without compromising accuracy. These features are a direct response to the most important issues in drilling automation and real-time optimisation, which allows implementing advanced predictive models in the working environment. Moreover, we find that the dynamics of ROP in steady-state conditions have near-Markovian behaviour, which gives theoretical support to the idea that state-based models as opposed to history-dependent models are appropriate.

2. Recommendations for Practice

Recommendations to practitioners in designing ROP prediction systems We found that, in steady-state vertical drilling, the temporal window used in predictive ROP should be 30-60 seconds because longer temporal windows do not improve prediction and impose unjustified computational expenses. When operating models on low resource edge devices, preference should be placed on the lower half of this range (30-45 seconds) in order to make the most out of the available computing time. In some cases where the nature of the application depends on the regular retraining of the model or online learning, shorter windows will have a significant impact on the time of training and allow more responsive adaptation to the changing conditions.

This exploration provides several promising directions of future work. To begin with, the directional and horizontal drilling extension of the analysis would be a test of the generalisation of the identified optimal windows to more intricate wellbore geometry and contact dynamics. Second, a methodical analysis of the best predictive time windows (dysfunction: vibration, bit bouncing, stuck pipe) would involve whether the long-time scale effects are actually well represented by long time context. Third, adaptive window sizing plans in which the temporal range is dynamically adjusted in relation to the observed drilling conditions could be effective in optimisation of the accuracyefficiency trade-off in a broad range of working situations. In addition, the adoption of the best-window ROP prediction models in closed-loop drilling control systems is also a rational move to autonomous functions. This low latency and computational efficiency is fulfilling of the critical demands of real-time control, although verification under real conditions of automated drilling with feedback loops is a necessary requirement. Lastly, exploring how common principles of window optimisation are to other drilling prediction tasks, e.g. the prediction of torque and drag, prediction of formation pressure or bit wear prognostics, would determine whether our results are a general property of drilling dynamics or particular to ROP prediction.

To summarize, this study creates empirical and theoretical grounds in choosing a time window in drilling prediction systems and also shows that sensitive consideration of this commonly ignored design option can provide significant practical advantages. With more and more petroleum industry switching to automated and intelligent processes of drilling, such rudimentary understanding of the temporal structure of the drilling processes will become more and more useful in developing efficient, reliable and deployable predictive systems.

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