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ADAPTIVE CONTROL OF EXPLORATION DRILLING PARAMETERS BASED ON MACHINE LEARNING TO INCREASING CORE RECOVERY

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АДАПТИВНЕ КЕРУВАННЯ РЕЖИМАМИ РОЗВІДУВАЛЬНОГО БУРІННЯ НА ОСНОВІ МАШИННОГО НАВЧАННЯ ДЛЯ ПІДВИЩЕННЯ ВИХОДУ КЕРНУ

Purpose. The goal is to dynamically adjust drilling parameters (bit axial load and rotation speed) according to predicted risks of core integrity disruption, which improves core quality and the reliability of geological data for critical mineral resource assessment.

The methods. The proposed approach combines high-frequency sensor data collection with predictive machine learning models in a closed-loop control system. Drilling parameters (WOB, RPM, torque, mechanical drilling speed, vibrations) were recorded at 100 Hz. The XGBoost classifier, trained on the labeled time series, predicted the probability of core loss and initiated an automatic safe drilling mode with WOB reduction and RPM adjustment.

Findings. The model achieved an accuracy of 0.92 and a completeness of 0.91, predicting core failure an average of 4.4 seconds before it occurred. Adaptive control increased the average core selection ratio from 83.5% to 94.0%, with the largest effect observed in fractured rocks (from 65% to 88%). This was accompanied by a 12% reduction in mechanical drilling speed (from 4.6 to 4.05 m/h) as the system prioritized core integrity in high-risk areas.

The originality. The dependence of core losses during exploratory drilling on changes in drilling technological parameters (axial load on the bit, rotation frequency, torque, mechanical passage speed and vibrations) and structural features of rocks, in particular heterogeneous and fractured formations, has been established. It has been shown that the use of the proposed system allows to increase the core selection ratio by 10% and significantly reduce its losses in difficult geological conditions.

Practical implementation. The proposed system improves the quality of geological data, reduces the costs of re-drilling intervals with substandard core output, reduces project risks and can be integrated into modern drilling rig control systems as an intelligent tool to support exploratory drilling.

Keywords: *adaptive drilling control, machine learning, core selection, geological exploration drilling, real-time optimization, critical minerals.*

Introduction. The pursuit of critical minerals, essential for modern technologies and the global energy transition, places unprecedented demand on the accuracy and efficiency of mineral exploration. At the heart of this exploration process lies diamond core

drilling, the primary method for retrieving pristine rock samples from the subsurface [1, 2]. These core samples are the fundamental data source for geological interpretation, providing the physical evidence needed to understand mineral deposit geometry, rock fabric, and geotechnical properties [3]. They are indispensable for calculating reliable resource and reserve estimates, which form the basis for multi-million dollar investment decisions in mine development [4, 5]. The quality and completeness of this core, therefore, directly dictate the confidence level of the entire geological model and the economic viability of a project.

A persistent and costly challenge in this domain is core loss – the partial or complete failure to recover a representative rock sample from the drilled interval. Core loss can be broadly categorized into two types. Mechanical core loss occurs due to physical damage within the core barrel or drilling assembly, including core jamming, where fragments block the barrel; core breakage, where the sample fractures into unusable pieces; and core grinding, where the sample is pulverized by excessive vibration or weight [6]. Erosional core loss, or washout, happens when the drilling fluid hydraulically erodes softer or fractured zones within the core barrel, washing away the sample before it reaches the surface. Both types render the recovered material unrepresentative of the in-situ rock, creating significant "unknowns" in the geological record.

The economic consequences of poor core recovery are substantial and far-reaching. Unreliable or incomplete core data introduces uncertainty into geological models, potentially leading to misclassification of resources, flawed mine planning, and ultimately, suboptimal economic outcomes. This often necessitates the expensive and time-consuming process of re-drilling lost intervals or entire holes to acquire the missing information [7]. The resulting project delays and budget overruns amplify financial risk, a problem that is particularly acute for critical mineral deposits, which are often characterized by complex geological structures, heterogeneous rock formations, and brittle minerals that are inherently prone to core loss. In such high-value, high-risk projects, every meter of lost core represents a critical gap in knowledge.

Current drilling practices are ill-equipped to proactively manage this problem. Traditional drilling operations rely on pre-set parameters or manual adjustments made by a drillers based on surface observations and experience [8]. This approach is inherently reactive; problems are typically addressed only after core loss has already occurred, signaled by a drop in penetration rate, a sudden change in torque, or reduced core recovery at the surface [9]. The inherent heterogeneity of rock formations means that constant parameters are almost never optimal, and manual responses are too slow and inconsistent to prevent damage in the critical seconds when a core-loss event is imminent. While technologies like wireline systems and dual-tube drilling have improved core retrieval efficiency, they do not offer intelligent, real-time process control focused on preserving core integrity as the primary objective.

Concurrently, the drilling industry has seen a surge in the application of automation and machine learning, but with a distinct focus elsewhere. Significant research has been dedicated to optimizing the rate of penetration (ROP) to reduce drilling time and cost [10, 11]. Other studies have successfully employed machine learning for predictive maintenance of drill bits and downhole tools, forecasting failures based on vibration and

operational data [12]. Further work has focused on using real-time drilling data to identify rock types and formation boundaries [13, 14]. Despite these advances, a clear and critical research gap remains: the application of intelligent systems to preserve the quality of the geological sample itself. The objective function for optimization has, to date, been speed or equipment life, not the integrity of the core.

Therefore, the purpose of this study is to develop and experimentally validate an adaptive control system that leverages machine learning to minimize core loss in real-time during exploration drilling. The core hypothesis is that by learning the subtle, dynamic signatures in drilling parameters that precede core failure, a machine learning model can provide a predictive capability that enables a closed-loop control system to take preemptive action. The specific objectives of this research are to: (a) identify and quantify the key drilling parameters and their dynamic signatures that correlate with the onset of core loss events; (b) develop and train a supervised machine learning model to accurately predict imminent core loss based on real-time sensor data; (c) design and implement a closed-loop control algorithm that integrates the model's predictions to automatically adjust drilling parameters (such as weight on bit and rotational speed) to avert core damage; and (d) experimentally validate the effectiveness of the complete system in improving core recovery rates within a controlled drilling environment that simulates the heterogeneous rock conditions typical of critical mineral deposits.

Research methods. This study employs a multi-stage methodology encompassing the definition of core concepts, the design of a controlled experimental setup, the development of a machine learning model for predictive analysis, the integration of this model into a closed-loop adaptive control system, and the establishment of clear criteria for assessing the system's performance [15]. The overarching goal is to create and validate a framework that transitions drilling control from a reactive to a predictive paradigm, with the explicit objective of preserving core integrity.

A fundamental understanding of drilling mechanics is essential for interpreting the data and designing the control system. The primary parameters monitored and controlled in rotary drilling include Weight on Bit (WOB), which is the force applied to the drill bit, typically measured in kilonewtons (kN); Rotational Speed (RPM), the speed at which the drill string and bit rotate; Torque, the rotational force required to turn the bit, measured in newton-meters (Nm); and the Rate of Penetration (ROP), the speed at which the drill bit advances into the formation, usually expressed in meters per hour (m/hr) [16]. Additional parameters include the Mud Flow Rate, the volume of drilling fluid pumped per unit time, and Differential Pressure, the change in pressure across the downhole motor or drilling system, which is often indicative of the resistance encountered at the bit.

The mechanisms of core loss are directly linked to the interaction of these parameters with the rock fabric. For instance, applying excessive WOB in a fractured or highly interbedded rock formation can cause the core sample to buckle, jam within the inner tube of the core barrel, or grind against the barrel walls as it enters, leading to mechanical core loss [17]. Conversely, an excessively high mud flow rate in a soft or friable zone can erode the core sample before it is safely retrieved, resulting in erosional core loss or washout. The dynamic signatures of these events, such as a sudden spike in torque followed by a drop in ROP, are the precursors that an intelligent system must learn to recognize.

To capture these complex temporal dependencies, machine learning models suited for time-series analysis are required. Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) networks, are powerful tools for this purpose due to their inherent architecture, which includes memory cells capable of learning long-term dependencies in sequential data. Alternatively, tree-based ensemble methods like XGBoost can be highly effective when combined with robust feature engineering. In this approach, the raw time-series data is transformed by creating sliding windows of historical data points, and statistical features (e.g., mean, variance, rate of change) are computed for each window to serve as inputs to the model.

To generate the necessary high-frequency data under controlled conditions, a fully-instrumented laboratory-scale drilling rig will be employed. This rig is designed to simulate the mechanical responses of full-scale drilling operations. It is equipped with a variable-speed top drive, a hydraulic thrust system for precise WOB control, and a fluid circulation system. The rig is interfaced with a high-speed data acquisition system that records WOB, RPM, Torque, and ROP at a frequency of 100 Hz. Additionally, tri-axial accelerometers mounted near the bit sub provide high-frequency vibration data, capturing axial and torsional oscillations that are critical indicators of downhole conditions.

The drilling experiments will be conducted on a suite of manufactured rock samples designed to replicate the heterogeneous nature of critical mineral ores. These samples will include homogeneous blocks of granite and sandstone as baselines, as well as heterogeneous samples constructed by interbedding materials of contrasting strength, such as weak sandstone layers within a stronger matrix, and by introducing artificial fractures and voids. This controlled complexity is vital for training a model that is robust to real-world geological variability.

The creation of a high-quality labeled dataset is paramount. The experimental procedure will involve drilling under various parameter combinations, with the specific intent of inducing core loss. The exact moment of core failure – defined as a sudden audible or vibrational change, a sharp drop in ROP with no corresponding change in parameters, or confirmation of a jammed barrel upon inspection – will be precisely timestamped. For every such event, the time-series data from the preceding period, for example the 10 seconds prior to the failure, will be extracted and labeled as a "pre-failure" or high-risk class. An equivalent amount of data from stable drilling intervals, where core recovery was successful and the rock appeared competent, will be labeled as "normal" or low-risk. This process yields a binary classification dataset.

The raw sensor data first undergoes a rigorous pre-processing phase. This involves noise filtering, synchronization of all data streams based on their timestamps, and handling of any missing values. Subsequently, a feature engineering process is applied to create derived variables that often have stronger correlations with downhole conditions than raw measurements. A key engineered feature is Mechanical Specific Energy (MSE), a measure of the energy required to remove a unit volume of rock, which is calculated as:

$$MSE = \frac{2\pi \cdot RPM \cdot Torque}{Area_{bit} \cdot ROP} + \frac{WOB}{Area_{bit}}. \quad (1)$$

Other critical features include the rate of change of *WOB* and torque, the *WOB/ROP* ratio, and the standard deviation of high-frequency vibration signals over short windows. The data is then segmented using a sliding window approach. For LSTM models, each window of sequential data points becomes a single input sample. For XGBoost, statistical summaries of the features within each window are computed and used as inputs.

Two primary modeling approaches will be developed and compared. The first is an LSTM network designed to directly learn the temporal patterns preceding a failure. The second is an XGBoost classifier trained on the feature-engineered windows. The model's output for each input window will be a continuous "core loss probability" score between 0 and 1. The complete dataset will be partitioned into three distinct sets: a training set (70% of the data) used to teach the model, a validation set (15%) used to tune hyperparameters and prevent overfitting, and a held-out test set (15%) used for the final, unbiased evaluation of model performance. Model performance will be assessed using standard classification metrics, including Precision (the proportion of predicted high-risk events that were actual failures), Recall (the proportion of actual failures that were correctly predicted), and the F1-score (the harmonic mean of precision and recall). Critically, the model's prediction lead time – the average time between its high-risk alert and the actual failure event – will also be quantified.

The core of this research is the closed-loop control system that integrates the predictive model. The architecture is designed such that real-time sensor data streams continuously feed into the trained machine learning model. The model evaluates the incoming data and outputs its core loss probability score. This score serves as the primary input to the control logic, effectively acting as a "risk meter" for the drilling process.

The control logic is designed with a hierarchical, safety-first approach. The primary objective is to maintain core integrity. A threshold for the core loss probability score will be established based on validation set performance. Under normal conditions, when the probability is below the threshold, the control system permits the rig to operate in a mode that prioritizes ROP, following a pre-defined parameter set for efficient drilling. However, if the model's output exceeds the established risk threshold, the system initiates a pre-programmed "safe mode" protocol.

This protocol is designed to immediately alleviate stress on the core sample. A typical response might involve a controlled reduction in Weight on Bit by a predetermined percentage, such as 30%, while simultaneously making a minor adjustment to the Rotational Speed. The exact parameter adjustments are based on expert knowledge and analysis of the conditions that led to core loss during the data acquisition phase. A Proportional-Integral-Derivative (PID) controller can be used to manage these setpoint changes smoothly. The control law for a PID controller is defined as:

$$u(t) = K_p e(t) + K_i \int_0^t e(\tau) d\tau + K_d \frac{de(t)}{dt}, \quad (2)$$

where $u(t)$ is the control signal sent to the actuators (e.g., to reduce *WOB*), $e(t)$ is the error between the current and desired state, and K_p , K_i and K_d are tuned constants. This integrated approach ensures a rapid, automated, and precise response to mitigate the risk of core loss.

The performance of the complete adaptive control system will be evaluated against three primary criteria. The most important metric is the Core Recovery Rate, defined as:

$$\text{Core Recovery Rate} = \left(\frac{\text{Length of recovered core}}{\text{Length of drilled interval}} \right) \times 100, \% \quad (3)$$

This will be calculated for intervals drilled with the adaptive control system active and compared directly against baseline intervals drilled in the same rock types using conventional, constant-parameter methods. A statistically significant improvement in this rate will be the primary indicator of success.

Secondly, a Core Quality Index will be developed to provide a qualitative assessment of the core's condition. This index will be a composite score based on factors such as the number of naturally induced versus drilling-induced fractures per meter, the presence of grinding or abrasion marks on the core surface, and the overall cylindrical integrity of the sample. This assessment will be performed by a trained geologist to provide an expert, independent evaluation of core quality.

Finally, the impact on Drilling Efficiency will be assessed by monitoring the average ROP. The analysis will compare the baseline ROP against the average ROP achieved during adaptive control. This is crucial to understand the trade-off between maximizing core preservation and maintaining drilling speed, and to quantify the net operational impact of the system. The prediction accuracy metrics defined in section 2.3 will also be recalculated during these closed-loop tests to validate the model's performance in a live control environment.

The results and discussion. The experimental program yielded a comprehensive dataset that enabled the identification of core loss precursors, the development of a high-performance predictive model, and the validation of the adaptive control system. This section presents the key findings from each phase of the research, followed by a critical discussion of the challenges, limitations, and broader implications of the proposed approach.

Analysis of the high-frequency sensor data from the controlled drilling experiments revealed distinct and repeatable signatures that preceded core loss events. By comparing time-series data from stable drilling intervals with those immediately preceding core jamming or breakage, several key precursors were identified. The most significant indicator was a characteristic coupling of a rapid increase in torque with a simultaneous and sudden deceleration in the rate of penetration. This signature was consistently observed across different rock types and is interpreted as the moment when the core sample begins to bind or jam within the inner tube of the core barrel. As the core becomes stuck, the rotational friction increases, causing the torque spike, while the resistance to axial advancement halts progress, causing the ROP to drop, often to near zero, despite constant or even increasing weight on bit.

Other notable precursors included a sharp rise in the standard deviation of axial vibrations, indicating the onset of stick-slip or chaotic motion of the drill string, and a rapid increase in the WOB/ROP ratio. In normal drilling, this ratio remains relatively stable for a given rock type. A sudden, exponential increase signals that energy is being dissipated in friction and deformation rather than in rock fracturing at the bit face, a key indicator that the core is being damaged. Figure 1 illustrates a typical 10-second window comparing the normalized parameter signatures for a stable drilling interval and a pre-

failure interval. The stable interval shows smooth, correlated fluctuations in WOB, torque, and ROP. In stark contrast, the pre-failure interval is characterized by the diverging torque and ROP trends, a clear warning signal that would be imperceptible to a human drifter but is readily detectable by an automated system.

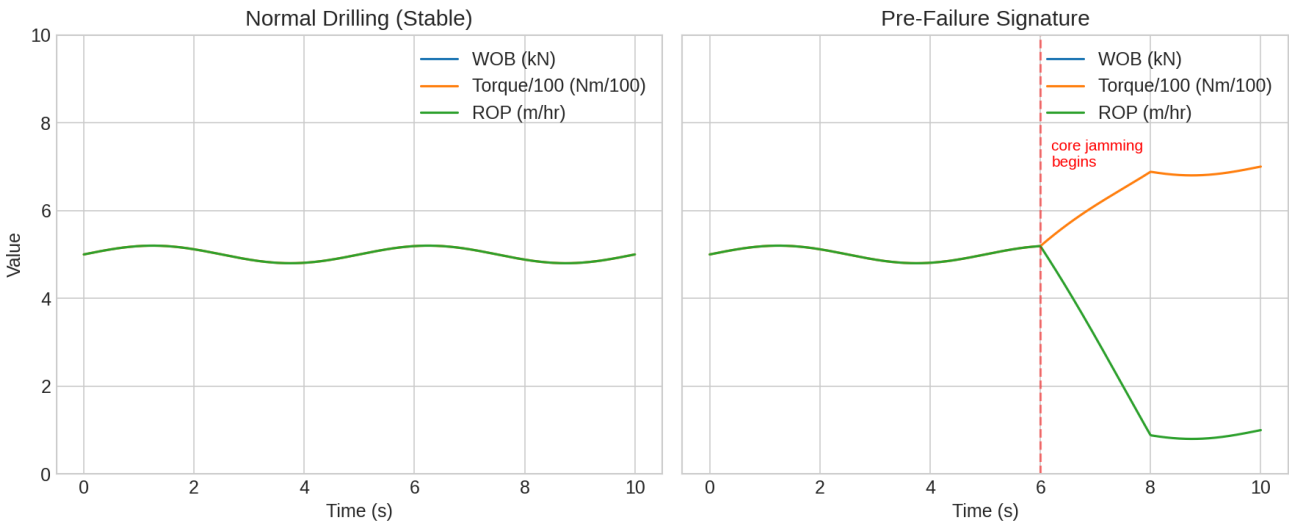


Fig. 1. Drilling Parameter Signatures

Both the LSTM and XGBoost models were successfully trained on the labeled dataset. The XGBoost model, with its extensive feature engineering, marginally outperformed the LSTM in terms of overall accuracy and computational efficiency for this specific application. The final model's performance was evaluated on the held-out test dataset, and the results are disaggregated by rock type in Table 1 to demonstrate its robustness across different geological conditions. The model achieved a weighted average precision of 0.92 and recall of 0.91, translating to an F1-score of 0.91 across all rock types. As expected, performance was highest in homogeneous lithologies where failure mechanisms are more consistent.

Table 1

Machine Learning Model Performance Metrics by Rock Type

Rock Type	Precision	Recall	F1-Score	Avg. Prediction Lead Time (s)
Homogeneous Granite	0.96	0.94	0.95	3.8
Homogeneous Sandstone	0.94	0.95	0.94	4.2
Interbedded (Sand/Shale)	0.91	0.89	0.90	5.1
Artificially Fractured	0.88	0.85	0.86	4.5
Weighted Average	0.92	0.91	0.91	4.4

The slight decrease in precision and recall in the more complex interbedded and fractured samples reflects the inherently higher variability and unpredictability of failure in these challenging formations. Critically, the model maintained a high level of perfor-

mance even in these complex cases. Perhaps more importantly for real-time control, the model provided an average prediction lead time of 4.4 seconds before the actual core loss event. This means that in 91% of the cases where a failure occurred, the system issued a high-probability alert an average of 4.4 seconds in advance, providing a vital window for preemptive control action. In the context of drilling at 2–5 meters per hour, this lead time translates to several centimeters of advance, ample opportunity for the control system to intervene before irreversible damage is done (fig. 2).

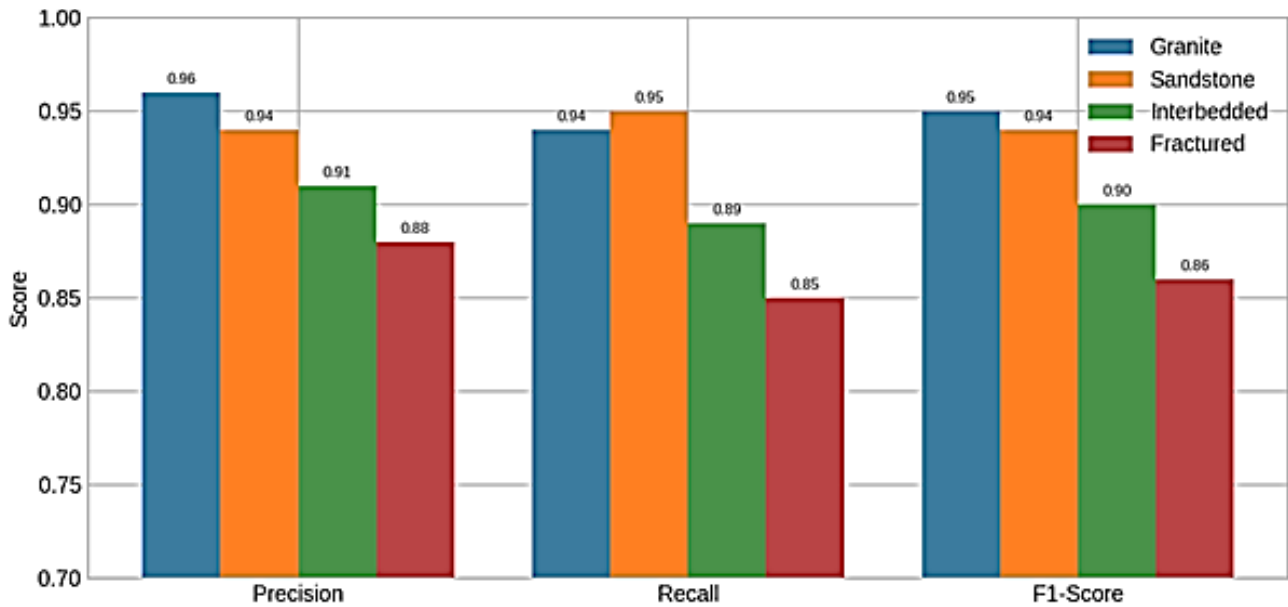


Fig. 2. Model Performance Metrics

Following the successful development and offline testing of the predictive model, the complete closed-loop adaptive control system was implemented and tested on the drilling rig. The system's performance was evaluated by comparing core recovery rates and drilling efficiency against a baseline of conventional, constant-parameter drilling in the same set of rock samples. The results of these validation experiments are summarized in table 2.

Table 2
Comparison of Core Recovery Rates: Conventional vs. Adaptive ML-Controlled Drilling

Rock Type	Conventional Drilling Core Recovery (%)	Adaptive ML Control Core Recovery (%)	Improvement (%)	Average ROP (m/hr) – Conventional	Average ROP (m/hr) – Adaptive
Homogeneous Granite	97	99	+2	4.2	4.0
Homogeneous Sandstone	94	98	+4	5.8	5.3
Interbedded (Sand/Shale)	78	91	+13	4.9	4.1
Artificially Fractured	65	88	+23	3.5	2.8
Overall Average	83.5	94.0	+10.5	4.6	4.05

The results demonstrate a clear and substantial improvement in core recovery with the implementation of the adaptive control system. The overall average core recovery increased from 83.5% with conventional methods to 94.0% with ML-based adaptive control, a relative improvement of over 12%. The most dramatic gains were observed in the most challenging geological conditions. In the artificially fractured samples, designed to simulate a complex critical mineral deposit, core recovery surged from 65% to 88%, an absolute improvement of 23 percentage points. This is a highly significant result, as these are precisely the types of formations where core loss is most prevalent and most detrimental to resource evaluation. In interbedded sequences, recovery improved from 78% to 91%, demonstrating the system's ability to adapt to rapidly changing rock strength (fig. 3).

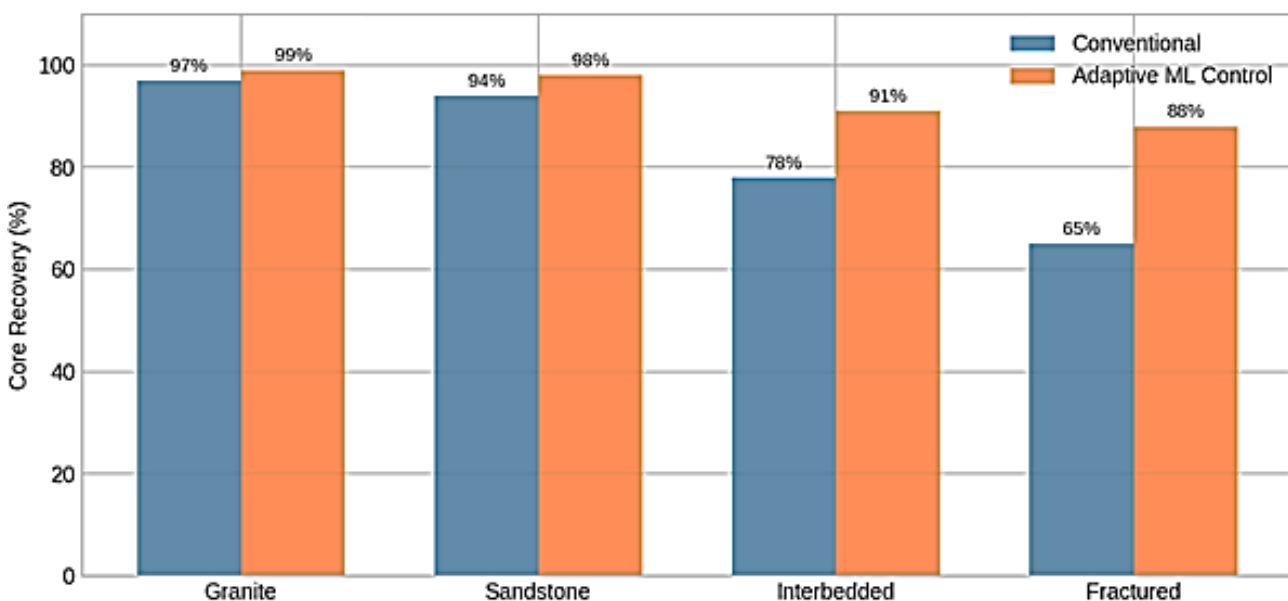


Fig. 3. Core Recovery Comparison

The efficiency analysis reveals the expected trade-off between core preservation and drilling speed. The adaptive system, by its very design, prioritizes core integrity when a risk is detected, which necessarily involves reducing the aggressiveness of the drilling parameters. This resulted in a 12% reduction in overall average ROP, from 4.6 m/hr to 4.05 m/hr. However, the magnitude of this reduction was not uniform. In competent, homogeneous rock where the risk was low, the system allowed ROP to remain near baseline levels. The ROP decrease was most pronounced in the fractured zones, where the system frequently intervened to avert core loss. Figure 4 illustrates this dynamic over a 30-minute drilling interval in an interbedded sample. The figure plots ROP alongside the model's core loss probability score. Periods of stable, low-risk drilling show high ROP. As the drill bit encounters a weaker, fracture-prone zone, the probability score spikes, triggering the "safe mode" protocol. ROP drops sharply as WOB is reduced, the core is successfully retrieved without loss, and as the risk subsides, the system allows ROP to increase again. This adaptive behavior validates the core concept of the research: dynamically trading marginal ROP for substantial gains in core quality.

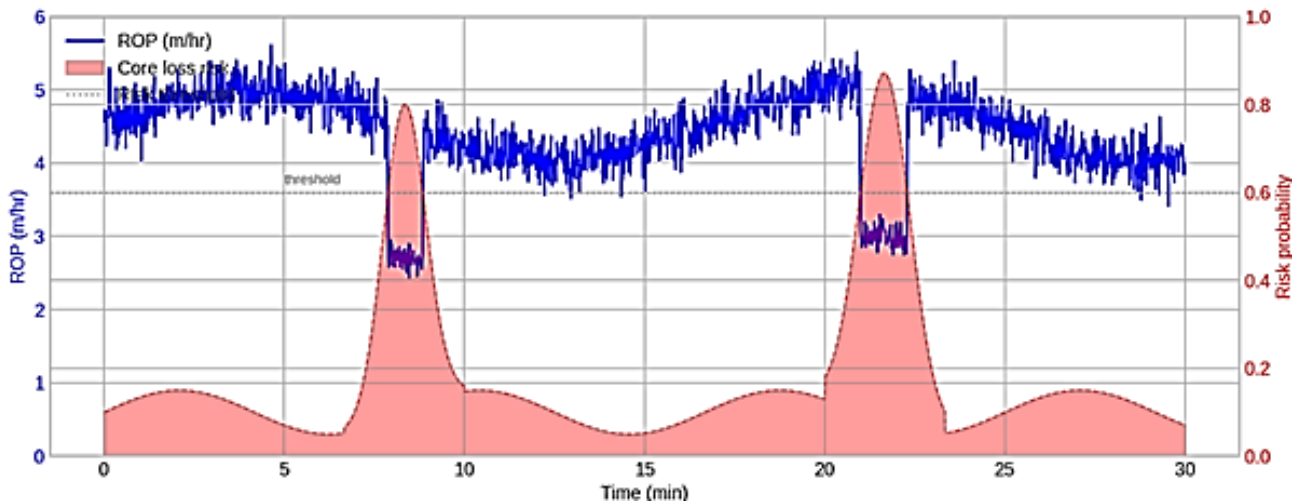


Fig. 4. ROP vs. Risk Probability Over Time

While the experimental results are highly encouraging, several challenges and limitations must be acknowledged and addressed before technology can be considered for widespread commercial deployment.

The most significant concern is the generalization of the model. The predictive model was trained and tested on data generated from a single, laboratory-scale drilling rig and a specific set of manufactured rock samples. The dynamic signatures of drilling, including vibration modes, resonance frequencies, and the response of the control system, will vary significantly with drill rig scale, power, and stiffness. A model trained on a small laboratory rig may not perform optimally on a full-sized exploration rig with vastly different mechanical characteristics. Similarly, the rock samples, while designed to be heterogeneous, cannot fully replicate the infinite variability of natural geological formations, including variations in in-situ stress, pore pressure, and mineralogy. The model's ability to generalize to unseen geological environments remains an open question and a critical focus for future research. A potential pathway forward is the development of a foundational model pre-trained on a large corpus of drilling data from diverse sources, which can then be fine-tuned for specific rigs and localities.

A second major challenge is the impact of sensor noise and reliability. The high-frequency data streams that enable this technology are susceptible to noise from electromagnetic interference, vibration of sensor mounts, and signal drift. During the experiments, occasional spurious spikes in sensor readings were observed. While the pre-processing filters were effective in a controlled lab setting, a noisy signal in the field could lead to a false positive (unnecessary ROP reduction) or, more worryingly, a false negative (failure to predict an actual event). The robustness of the model and the control system to realistic levels of sensor noise and occasional sensor failure must be rigorously tested. Strategies such as sensor fusion, where information from multiple sensors is combined to validate a reading, and the use of ensemble models that are less sensitive to individual noisy inputs, will be essential for field deployment.

Thirdly, the issue of computational latency is paramount for real-time control. The current system, running on a dedicated workstation with a GPU, processes data and updates the control signal with a latency of approximately 50-100 milliseconds, which is perfectly adequate. However, deploying this on a standard industrial programmable logic controller (PLC) with limited computational power could introduce delays that erode the

valuable prediction lead time. The model architecture may need to be optimized for edge deployment, potentially through techniques like model quantization or pruning, to ensure that the control loop can close quickly enough to be effective.

Finally, the system's performance embodies the fundamental "exploration vs. exploitation" dilemma. The control system must constantly balance the competing objectives of maximizing ROP (exploiting the opportunity to drill quickly) and minimizing core loss (exploring for information safely). The current rule-based logic, which triggers a fixed "safe mode" above a threshold, is a somewhat blunt instrument. It does not learn from the outcome of its interventions. A more sophisticated approach, such as a reinforcement learning agent, could potentially learn an optimal policy that dynamically weighs the expected gain in ROP against the probabilistic risk of core loss, based on the current state and past experience. This would allow for a more nuanced and efficient trade-off, pushing ROP higher when conditions are safe while still reacting decisively to genuine threats, and represents the next frontier in intelligent drilling automation.

Conclusions and prospects for further research. This research successfully achieved its primary objective of developing and experimentally validating a real-time adaptive control system that leverages machine learning to minimize core loss during mineral exploration drilling. The study conclusively demonstrates that by learning the dynamic precursors to core failure from high-frequency sensor data, a predictive model can be integrated into a closed-loop control architecture to automatically adjust drilling parameters and avert sample damage. The key achievements of this work are threefold. First, distinct and quantifiable precursor signatures, most notably the characteristic coupling of a rapid torque increase with a sudden drop in rate of penetration, were identified as reliable indicators of imminent core jamming. Second, a machine learning model, specifically an XGBoost classifier with extensive feature engineering, was developed and achieved a weighted average precision of 0.92 and recall of 0.91 in predicting core loss events, providing an average prediction lead time of 4.4 seconds. Third, and most importantly, the complete adaptive control system was experimentally validated, demonstrating a substantial improvement in core recovery. Across all tested rock types, the system increased the average core recovery from 83.5% with conventional drilling to 94.0% with adaptive control. The most dramatic gains were observed in the most challenging geological conditions, with recovery in artificially fractured samples improving by 23 percentage points, from 65% to 88%. These results provide compelling evidence that an intelligent, data-driven approach to drilling control can fundamentally enhance the quality of geological sampling.

The scientific and practical significance of this work extends beyond the immediate improvements in core recovery. From a scientific perspective, this research introduces a novel objective function for drilling automation: core integrity. While previous applications of machine learning in drilling have focused on maximizing rate of penetration or predicting equipment failure, this study pioneers the use of these techniques to preserve the value of the geological sample itself. It establishes a quantitative framework for linking real-time drilling mechanics to the quality of the data product, opening a new avenue for research in precision geosampling and "measurement-while-drilling" applications. Practically, the technology provides a direct and scalable pathway to higher-quality geological data. For the critical minerals sector, where deposits are often complex, heterogeneous, and expensive to evaluate, every meter of high-quality core is invaluable. By reducing core loss, this system can dramatically improve the accuracy of geological in-

terpretation, geomechanical characterization, and resource and reserve estimation. This, in turn, reduces project risk, minimizes the need for costly re-drilling, and supports more informed and confident investment decisions. Technology embodies a shift from reactive problem-solving to proactive quality assurance in the exploration value chain.

Building upon the foundational achievements of this study, several promising avenues for further research are identified to advance this technology toward commercial deployment and to expand its capabilities. The first and most critical step is the execution of comprehensive field trials. While the laboratory results are robust, the transition from a controlled environment to a real-world exploration campaign is non-trivial. Field trials on active drilling projects are essential to validate the system's performance under true operational conditions, which include variable rig dynamics, a wider range of unpredictable geological formations, diurnal temperature fluctuations, dust, vibration, and the logistical constraints of a remote exploration camp. Such trials would provide invaluable data on the model's generalizability, the robustness of the hardware and software, and the practical integration of the system into existing drilling workflows, ultimately de-risking the technology for industry adoption.

A second critical direction is the integration of the control system with real-time Geology While Drilling (GWD) data. The current model relies solely on drilling mechanics and vibration data, which are indirect indicators of rock properties. By incorporating direct mineralogical or geochemical data from technologies such as real-time X-ray fluorescence (XRF) or infrared spectroscopy of drill cuttings, the model's understanding of the subsurface would be profoundly enhanced. For example, knowing that the drill bit has just entered a zone of soft, clay-rich alteration products would allow the model to anticipate a high risk of washout or erosion and preemptively adjust the mud flow rate, even before the mechanical signatures of core loss begin to appear. This fusion of mechanical and compositional data would create a far more powerful and predictive system, capable of adapting to changing rock properties with unprecedented precision.

Third, the control logic itself can be substantially improved through the adoption of more advanced control algorithms. The current rule-based system, while effective, is fundamentally reactive to the model's risk score. A more sophisticated approach would involve the use of reinforcement learning (RL). An RL agent could be trained to interact directly with the drilling environment, learning an optimal control policy through trial and error. The agent's objective would be to maximize a cumulative reward function that balances multiple goals, such as core recovery and ROP. Over time, the RL agent would learn nuanced strategies, such as how aggressively to reduce WOB for a given level of risk, or how to modulate parameters to navigate a tricky formation without triggering a full "safe mode" shutdown, potentially achieving better efficiency than a rule-based system.

Finally, the framework should be extended to true multi-objective optimization. The current system's primary goal is core preservation, with ROP optimization as a secondary consideration when risk is low. However, in commercial drilling operation, multiple objectives compete for priority, including ROP, bit wear, drill string fatigue, and fuel consumption, in addition to core recovery. Future research should focus on developing a system that can simultaneously optimize for these competing objectives, providing the driller or mine planner with a flexible interface to set priorities. For instance, during a critical phase of in-fill drilling for resource estimation, the operator could assign a high weight to core recovery. Conversely, during a less critical step-out drilling campaign,

they might prioritize ROP to cover more ground quickly. This would create a truly intelligent and versatile co-pilot for the drilling rig, capable of adapting its behavior to the strategic goals of the exploration program, thereby maximizing both the quality of the data and the efficiency of its acquisition.

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АНОТАЦІЯ

Мета. Метою є динамічне регулювання параметрів буріння (осьового навантаження на долото та частоти обертання) відповідно до прогнозованих ризиків порушення цілісності керна, що підвищує якість кернавого матеріалу та достовірність геологічних даних для оцінювання ресурсів критичної мінеральної сировини.

Методика. Запропонований підхід поєднує високочастотний збір даних сенсорів із прогнозними моделями машинного навчання в системі керування із замкненим контуром. Параметри буріння (WOB, RPM, крутний момент, швидкість механічного буріння, вібрації) реєструвалися з частотою 100 Гц. Класифікатор XGBoost, навчений на розмічених часових рядах, прогнозував імовірність втрати керна та ініціював автоматичний безпечний режим буріння зі зменшенням WOB і коригуванням RPM.

Результати. Модель досягла точності 0,92 та повноти 0,91, прогножуючи руйнування керна в середньому за 4,4 секунди до його виникнення. Адаптивне керування підвищило середній коефіцієнт відбору керна з 83,5 % до 94,0 %, причому найбільший ефект спостерігався у тріщинуватих породах (з 65 % до 88 %). Це супроводжувалося зменшенням механічної швидкості буріння на 12 % (з 4,6 до 4,05 м/год), оскільки система надавала пріоритет збереженню цілісності керна в зонах підвищеного ризику.

Наукова новизна. Встановлено залежність втрат керна під час розвідувального буріння від зміни технологічних параметрів буріння (осьового навантаження на долото, частоти обертання, крутного моменту, швидкості механічного проходження та вібрацій) і структурних особливостей порід, зокрема неоднорідних та тріщинуватих формацій. Показано, що застосування запропонованої системи дозволяє підвищити коефіцієнт відбору керна на 10% та суттєво зменшити його втрати у складних геологічних умовах.

Практична значимість. Запропонована система підвищує якість геологічних даних, зменшує витрати на повторне перебування інтервалів з некондиційним виходом керну, знижує проєктні ризики та може бути інтегрована в сучасні системи керування буровими установками як інтелектуальний інструмент підтримки розвідувального буріння.

Ключові слова: адаптивне керування бурінням, машинне навчання, відбір керна, геологорозвідувальне буріння, оптимізація в реальному часі, критична мінеральна сировина.

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