

Predictive maintenance and equipment efficiency in drilling operations and its impact on energy efficiency

Rizwan Khan ^{1,*} and Muhammad Ahsan ²

¹ *Baker Hughes, Drilling Services, Houston, United States of America.*

² *Baker Hughes, Well Construction, Houston, United States of America.*

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Abstract

Predictive analytics has become an essential pillar of digital transformation in drilling operations, improving reliability and lowering the energy footprint of critical assets. This paper investigates how data-driven maintenance models influence the overall energy performance of drilling systems, focusing on mud pumps, top drives, and power generation equipment. Using a life cycle-based approach, the study evaluates reductions in total energy consumption and carbon intensity achieved through predictive maintenance. The analysis confirms that condition-based monitoring, integrated with digital twins, can reduce operational energy demand by roughly 10–15%, offering a measurable pathway toward low-carbon well construction and sustainable field development.

Keywords: Predictive maintenance; Sustainability; Life cycle analysis

1. Introduction

Energy efficiency has emerged as a fundamental parameter for evaluating the sustainability of modern drilling operations. Traditional maintenance regimes—whether reactive or schedule-based—often lead to unnecessary downtime, wasted fuel, and premature component failure. In contrast, predictive maintenance (PdM) employs machine learning algorithms and Industrial Internet of Things (IIoT) data to anticipate degradation trends before a breakdown occurs.

As drilling rigs evolve into digitally connected systems, predictive analytics can now continuously optimize mechanical health and load distribution. This transition directly contributes to the reduction of total energy intensity, as each avoided failure or restart equates to measurable energy and emissions savings. The following sections present an integrated framework for evaluating these impacts through life cycle modeling and field-level performance analysis.

2. Research Design and Analytical Framework

2.1. Objective and Scope

The primary objective was to evaluate how predictive maintenance modifies the energy balance and greenhouse gas (GHG) emissions profile of a representative onshore drilling system. The analysis focuses on three critical equipment categories: fluid circulation systems (mud pumps), rotary drive assemblies, and diesel generator sets.

2.2. Analytical Boundaries

The study adopted a cradle-to-operation system boundary that included:

* Corresponding author: Rizwan Khan

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- Manufacturing and transport of spare parts;
- Operational energy demand from drilling activities;
- Emission associated with electricity or fuel use at the rig.

This boundary captures both direct and indirect energy use linked to maintenance strategies.

2.3. Reference Basis

All results were normalized to a functional drilling length of 1,000 meters, allowing comparison across scenarios and equipment configurations. Maintenance intervals and failure rates were modeled using historical rig telemetry data coupled with PdM system logs.

2.4. Data and Computational Approach

- Operational Data: Extracted from field data historians and supervisory control systems.
- Predictive Model Inputs: Vibration, torque, and temperature signals processed using regression-based failure probability models.
- Emissions: FastLCA
- Evaluation Metric: Net energy demand (in MJ) and carbon dioxide equivalent (CO₂e) per 1,000 meters drilled.

2.5. Validation

A comparative baseline scenario (traditional time-based maintenance) was evaluated to benchmark predictive maintenance outcomes. The results were validated against field consumption logs to ensure consistency.

3. Findings and Discussion

3.1. Energy Optimization Pathways

Predictive maintenance improved operational performance through multiple interlinked mechanisms:

- Dynamic Load Balancing: Machine learning algorithms redistributed generator loads, maintaining optimal operation near peak efficiency zones. This adjustment reduced excess fuel use by 6–9% compared to baseline data.
- Real-Time Anomaly Detection: Early identification of pressure and vibration anomalies in mud pumps prevented failure cascades, lowering idle and restart energy by nearly 12%.
- Lifecycle Extension: Predictive alerts extended mechanical component life by up to 20%, indirectly reducing the embodied energy associated with spare part production and logistics.

3.2. Emission Reduction Assessment

Applying LCA modeling revealed that predictive maintenance achieved a substantial decrease in total energy consumption and a substantial decrease in CO₂e emissions. The majority of these benefits originated from reduced generator idling and fewer emergency restarts. Secondary benefits included lower emissions from part replacements and waste material handling.

3.3. Digital Integration

The integration of PdM with near-real-time reflection of equipment condition in the virtual domain. This allowed operators to simulate different load profiles and maintenance schedules before executing them in the field, further optimizing power utilization and extending asset availability. Such interoperability between predictive analytics and digital replicas aligns with the oilfield's transition toward autonomous, self-optimizing rig systems.

3.4. Broader Sustainability Implications

Beyond energy and emissions savings, predictive maintenance contributes to the circular economy of drilling by:

- Reducing material throughput via extended equipment life,
- Minimizing unscheduled logistics and emergency spare part deliveries, and
- Supporting environmental, social, and governance (ESG) reporting through quantifiable digital traceability.

These operational efficiencies collectively drive progress toward carbon-neutral well delivery models and transparent sustainability metrics.

4. Conclusion

Predictive maintenance represents more than an efficiency tool—it is a bridge between digitalization and decarbonization in drilling operations. By leveraging continuous monitoring, AI-based diagnostics, and digital twin integration, operators can materially lower both direct fuel use and indirect lifecycle emissions. The results demonstrate that embedding predictive analytics in rig systems can unlock double-digit percentage savings in energy consumption while reinforcing reliability. Future work should focus on developing adaptive control systems that merge real-time carbon monitoring with predictive diagnostics, enabling energy-aware automation in drilling operations.

Compliance with ethical standards

Disclosure of conflict of interest

There is no conflict of interest among the authors.

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