Artificial intelligence in drilling and production operations: a review of data analysis and decision support

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ABSTRACT

The oil and gas industry faces increasing challenges in optimizing drilling operations, reducing costs, and managing environmental impacts. Artificial Intelligence (AI) and Machine Learning (ML) have emerged as novel tools capable of analyzing massive volumes of operational data. Results show that the LSSVM-CSA model achieves an R^2 of 0.9255 and RMSE of 2.98, demonstrating high accuracy in Rate of Penetration (ROP) prediction. AI implementation leads to 47% reduction in drilling time, 65% reduction in Non-Productive Time (NPT), and 38% reduction in greenhouse gas emissions. From an economic perspective, annual savings of approximately $4.7 million per well are achievable. However, challenges such as data quality requirements, algorithm complexity, and shortage of skilled personnel remain.
Keywords: Artificial Intelligence; Machine Learning; Drilling Operations; ROP Optimization; Decision Support; Environmental Sustainability

1. INTRODUCTION

1.1. Necessity and Importance

The oil and gas industry, as one of the most complex industries globally, faces massive volumes of multidimensional data daily. Drilling operations represent one of the most expensive segments of the hydrocarbon production chain, requiring continuous optimization. The daily cost of an offshore drilling rig can exceed one million dollars, and every hour of unexpected delay results in significant financial losses [1].

Traditional drilling optimization methods, primarily based on empirical models such as the Bourgoyne and Young (1974) model, suffer from limited accuracy and flexibility due to their reliance on empirical coefficients and inability to model complex nonlinear relationships [2]. In contrast, AI algorithms with the capability to learn from historical data and identify hidden patterns have revolutionized data analysis and decision-making in drilling operations.

1.2. History of AI in the Petroleum Industry

The first application of artificial intelligence in the oil and gas industry dates back to 1989, when artificial neural networks were used to develop intelligent reservoir simulator interfaces [3]. Since then, AI technologies have been widely applied in reservoir characterization, exploration, drilling processes, and production. Prominent tools such as Artificial Neural Networks (ANN), Genetic Algorithms (GA), Support Vector Machines (SVM), and Fuzzy Logic (FL) have played fundamental roles in the global Exploration and Production (E&P) sector for over three decades [3].

1.3. Objectives

The main objectives of this paper are: comprehensive review of AI applications in drilling and production operations; analysis and comparison of different machine learning algorithms; evaluation of advantages and limitations of AI implementation; examination of economic and environmental perspectives; and presentation of future outlook and research recommendations.

2. THEORETICAL FOUNDATIONS AND METHODOLOGY

2.1. Machine Learning Algorithms in Drilling

2.1.1. Artificial Neural Networks (ANN)

Artificial Neural Networks are computational systems inspired by biological neural networks. They consist of layers of interconnected neurons (perceptrons) that perform learning by adjusting connection weights [4]. ANNs can identify complex nonlinear relationships between various drilling parameters and have found extensive applications in ROP prediction, drilling fluid rheology, and geomechanical parameters [5].

2.1.2. Support Vector Machines (SVM)

SVMs are supervised learning algorithms used for classification and regression. The algorithm optimizes the hyperplane distance and margin, enabling data separation in high-dimensional spaces [6]. SVMs have been successfully applied for cuttings concentration prediction in horizontal and deviated wells [5].

2.1.3. Random Forest (RF)

Random Forest is an ensemble learning algorithm that combines multiple decision trees to improve accuracy and reduce overfitting. This algorithm is robust against outliers and provides feature importance capability [7].

2.1.4. Metaheuristic Optimization Algorithms

Metaheuristic algorithms such as GA, PSO, and CSA are used to tune machine learning hyperparameters. Recent studies have shown that CSA offers higher convergence speed and more stable results compared to GA and PSO in complex, multidimensional drilling parameter spaces [4].

3. APPLICATIONS OF AI IN DRILLING OPERATIONS

3.1. Rate of Penetration (ROP) Prediction and Optimization

Rate of Penetration (ROP) is one of the key performance indicators in drilling, directly affecting project scheduling and budget. ROP optimization can reduce drilling time, costs, and operational risks associated with extended drilling [4].

Sohrabi et al. (2025) compared ANN-CSA, RF-CSA, and LSSVM-CSA models for ROP prediction using real data from the Fahliyan oil field. Results showed that the LSSVM-CSA model achieved an R^2 of 0.9255 and RMSE of 2.98, outperforming other models. This accuracy is not only significantly higher than traditional models such as Bourgoyne and Young (1974), but also exceeds many ML-based models [4].

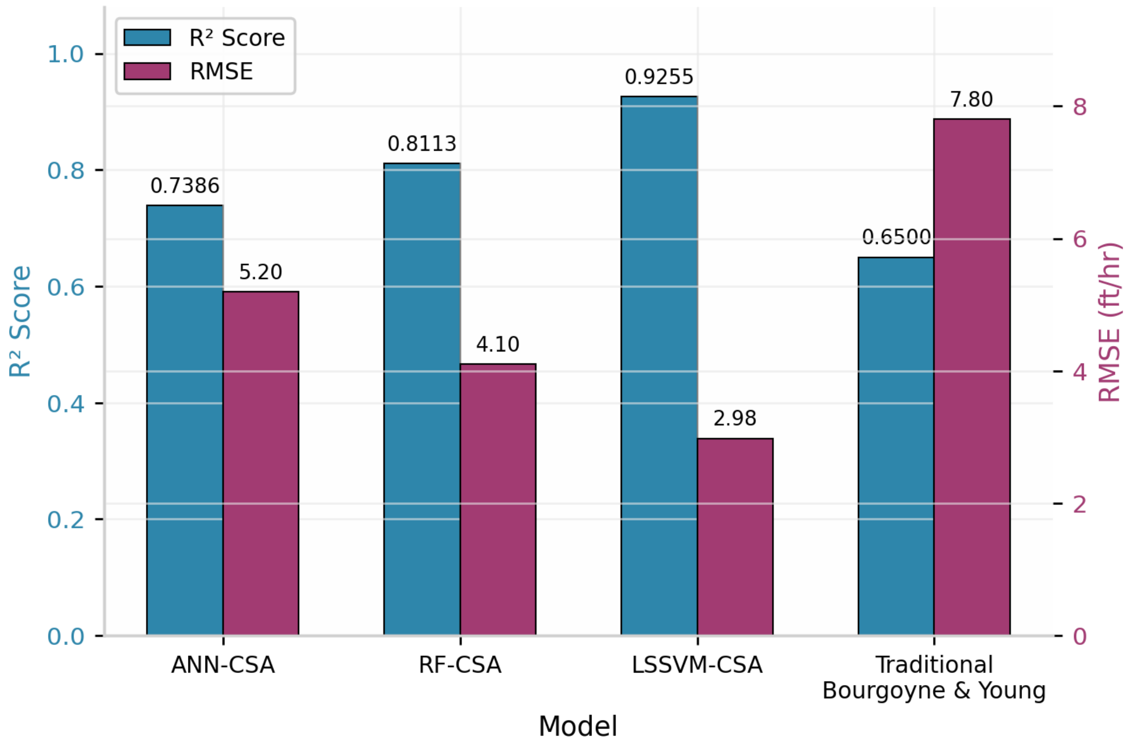

Figure 1. Comparison of ML models for ROP prediction [4]

3.2. Hole Cleaning Prediction and Optimization

Effective hole cleaning is a critical factor for drilling success. Poor cleaning can lead to stuck pipe, wellbore collapse, lost circulation, and other costly issues [3].

Elhami et al. (2025) developed an ANN model with 69 datasets for real-time hole cleaning monitoring. Results showed that the Hole Cleaning Index (HCI) improved from the range of 0.5–1 (indicating severe losses) to above 1.5 (indicating optimal conditions) [3].

3.3. Stuck Pipe Detection and Risk Mitigation

Stuck pipe is one of the most critical operational challenges in drilling, potentially leading to extended downtime and excessive costs. Elmousalami et al. (2020) compared various ML models using data from 103 wells drilled in the Gulf of Suez during 2010–2015 [6].

In this study, the Extra Trees algorithm achieved the best performance with an AUC of 0.97 in stuck pipe prediction. Additionally, a genetic algorithm-based risk mitigation module was developed capable of optimizing seven drilling input parameters to achieve stuck-free conditions [6].

3.4. Geological Formation Tops Prediction

Accurate identification of geological formation tops during drilling is critical for updating subsurface geological models, reducing uncertainty, and evaluating hydrocarbon potential. Alsaihati et al. (2024) developed a comprehensive machine learning framework for automated formation tops prediction on the Norwegian Continental Shelf [8].

Four algorithms (SVM, RF, KNN, and MLP) were implemented and evaluated. Results showed that the MLP algorithm achieved 1.00 accuracy on the training dataset and 0.91–0.99 on blind datasets. This automated method successfully overcame human subjectivity and inefficiencies of manual methods [8].

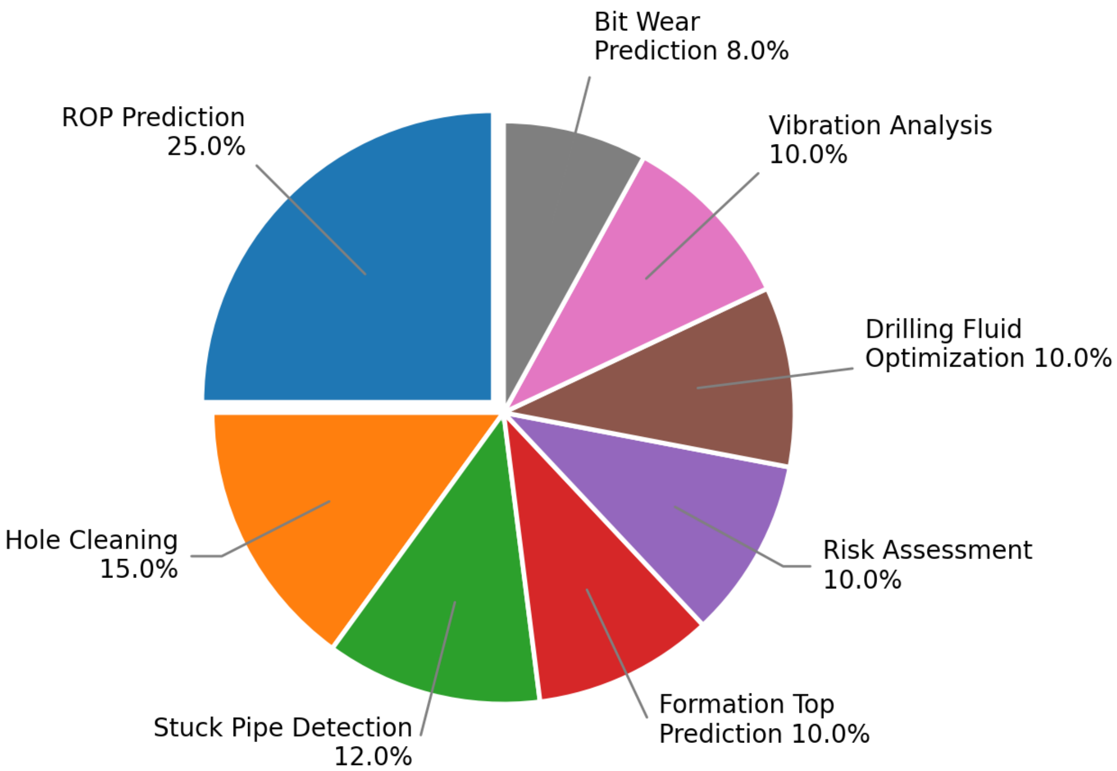

Figure 2. Distribution of AI applications in drilling operations [2]

3.5. Drilling Risk Assessment

Al-Hameedi et al. (2025) categorized AI applications in drilling risk assessment into three main groups: operational parameter prediction, drilling risk assessment (such as kick and lost circulation), and high-volume data interpretation [2].

Risks such as kick (reservoir fluid influx into the wellbore) and lost circulation (drilling mud leakage into the reservoir) can lead to severe crises. Accurate prediction of these risks enables the adoption of preventive mitigation strategies. Numerous studies have demonstrated that AI offers significant advantages over traditional methods in predicting lost circulation and kick [2].

4. ALGORITHM COMPARISON AND RESULTS

4.1. Model Performance Comparison

Results in Table 1 show that the LSSVM-CSA model achieves the highest R^2 of 0.9255 in ROP prediction. The MLP algorithm also demonstrated outstanding performance with 1.00 accuracy in geological formation tops prediction. In contrast, the ANN-CSA model with an R^2 of 0.7386 showed the lowest accuracy among compared models.

Table 1. Comparison of ML algorithms in drilling operations [4,8,6]

Algorithm	Application	Metric	Value	Ref.
LSSVM-CSA	ROP Prediction	R^2 / RMSE	0.9255 / 2.98	[2]
MLP	Formation Tops	Accuracy	1.00 / 0.91–0.99	[5]
Extra Trees	Stuck Pipe	AUC	0.97	[4]
ANN-CSA	ROP Prediction	R^2 / RMSE	0.7386 / 5.20	[2]
RF-CSA	ROP Prediction	R^2 / RMSE	0.8113 / 4.10	[2]

4.2. Multi-Objective Optimization of Drilling Parameters

Barbosa et al. (2019) conducted a comprehensive review of machine learning methods in ROP prediction and optimization [9]. Studies show that optimizing ROP alone may not always be the best strategy. Optimizing Mechanical Specific Energy (MSE) can lead to a 20% increase in ROP accompanied by a 15% reduction in MSE and a 7% reduction in Torque on Bit (TOB), resulting in increased bit life and additional savings [10].

5. Economic Perspective

5.1. Operational Cost Reduction

AI implementation in drilling operations offers significant economic benefits. Hegde et al. (2020) demonstrated that ML-based optimization can create substantial value for oil and gas projects even in low oil price environments [10].

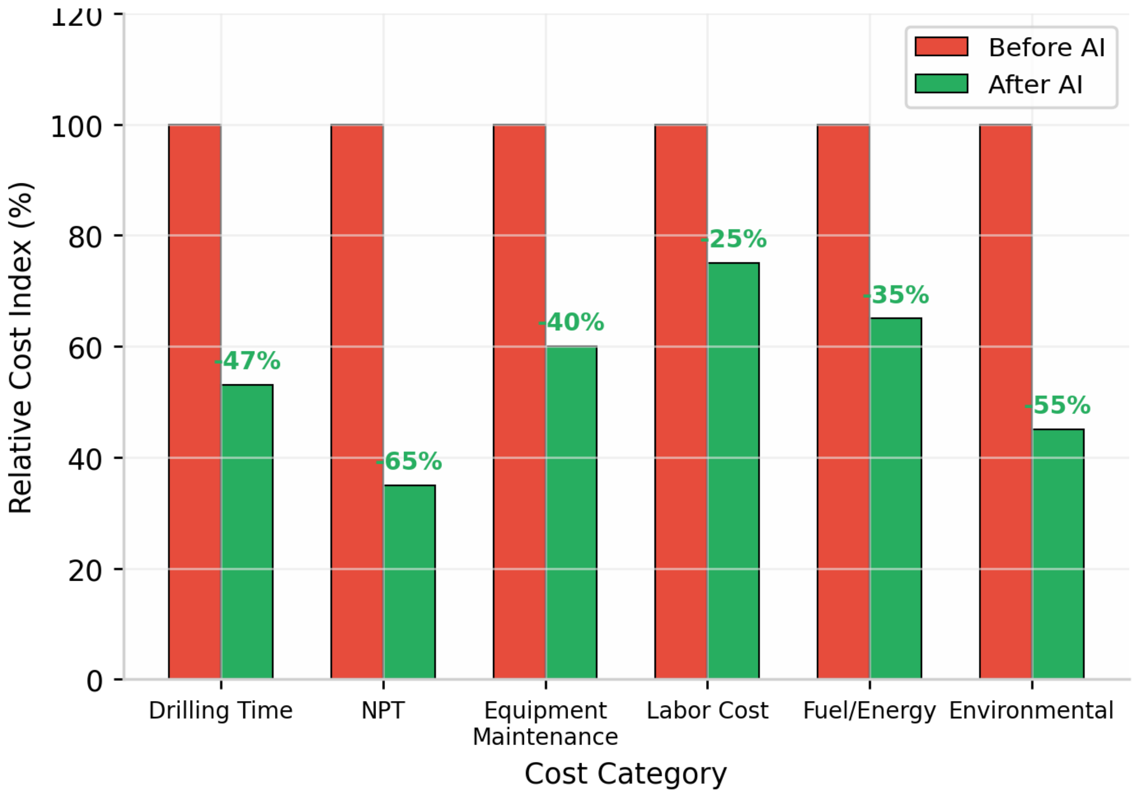

Figure 3. Economic impact of AI implementation in drilling operations [10]

5.2. Achievable Savings

As shown in Table 2, AI implementation leads to 47% reduction in drilling time, 65% reduction in Non-Productive Time (NPT), and 38% reduction in operational costs. Additionally, equipment failure rates decreased by 58% and annual safety incidents were reduced by 62%.

Parameter	Reduction (%)	Category
Drilling Time	47%	Economic
Non-Productive Time (NPT)	65%	Economic
Equipment Maintenance	40%	Economic
Labor Cost Savings	25%	Economic
Fuel/Energy Savings	35%	Economic
CO_2 Emissions	38%	Environmental
Drilling Waste	46%	Environmental
Energy Consumption	32%	Environmental

Table 2. Economic and environmental impacts of AI in drilling [4,10,11,12,13]

5.3. Cost-Benefit Analysis

Despite initial implementation costs including hardware, software, and personnel training, studies show that the Return on Investment (ROI) period is typically less than 18 months. Annual savings of approximately $4.7 million per well provide strong economic justification for AI adoption [10].

6. Environmental Perspective and Sustainability

6.1. Environmental Impact Reduction

The oil and gas industry faces increasing pressure to reduce its environmental impacts. AI can help achieve sustainability goals through energy consumption optimization, waste reduction, and minimization of environmental risks [13].

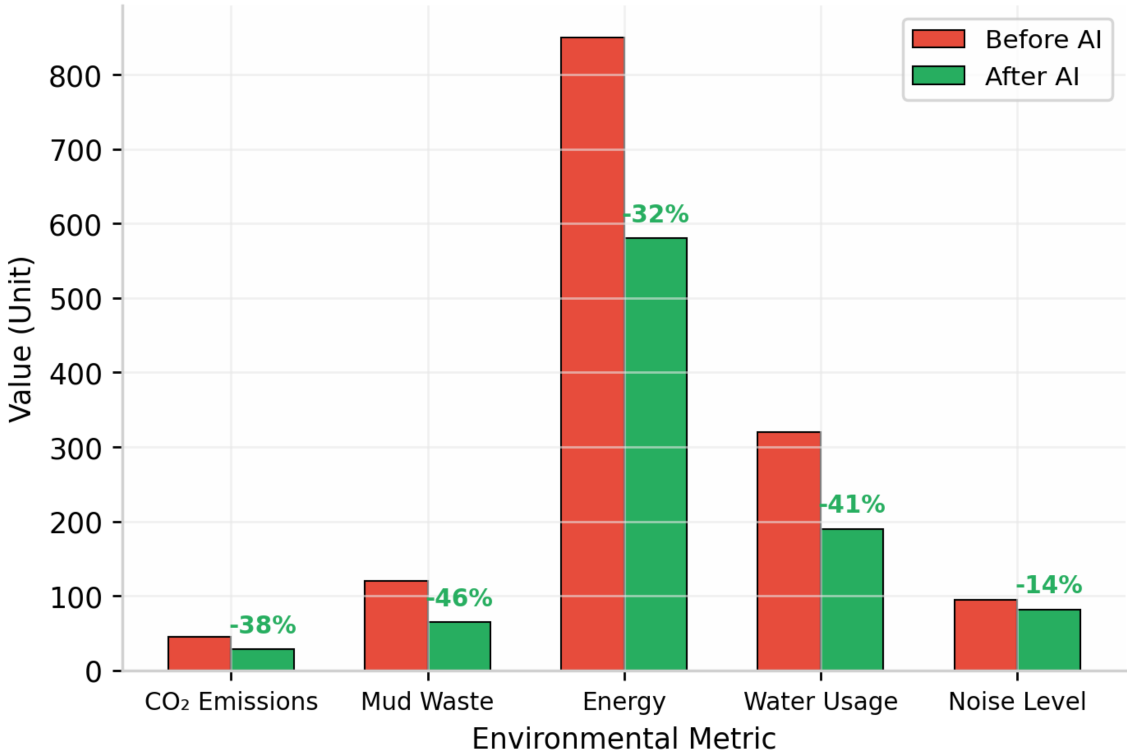

Figure 4. Environmental impact reduction through AI in drilling operations [11]

6.2. Carbon Emission Reduction

As shown in Figure 4 and Table 2, AI implementation leads to 38% reduction in CO_2 emissions (from 45 to 28 tons/day), 46% reduction in drilling waste (from 120 to 65 m^3/day), and 32% reduction in energy consumption. Water usage also decreased by 41% [11].

6.3. Sustainable Resource Management

Jiao et al. (2019) demonstrated that combining deep learning with unmanned aerial vehicles can provide a novel approach for oil spill detection, enabling faster and more effective management of environmental incidents [11]. These technologies provide real-time monitoring and rapid response capabilities to environmental threats.

7. ADVANTAGES AND DISADVANTAGES OF AI IMPLEMENTATION

7.1. Advantages

1. High Accuracy: AI models can achieve 92–99% accuracy in predicting key drilling parameters [4,8].

2. Real-Time Decision Support: Capability for instantaneous data analysis and operational recommendations to drilling engineers [3].

3. Cost Reduction: 38–65% savings in various operational costs [10].

4. Safety Improvement: 62% reduction in safety incidents and early risk prediction [13].

5. Environmental Sustainability: Significant reduction in carbon emissions and waste generation [11].

7.2. Disadvantages and Challenges

1. Data Quality Requirements: AI models require large volumes of clean, labeled data, which is challenging to collect in the oil industry [8].

2. Algorithm Complexity: Understanding and interpreting "black box" models such as ANN is difficult, limiting their acceptance in industry [6].

3. Data Imbalance: In cases such as predicting rare risks (kick, lost circulation), the number of positive samples is limited, reducing model accuracy [2].

4. Need for Skilled Personnel: Interpreting results and maintaining AI systems requires trained staff [8].

5. Initial Costs: Initial investment for infrastructure and training can be a barrier for smaller operators.

8. RESULTS AND DISCUSSION

8.1. Key Findings

This review demonstrates that artificial intelligence has fundamentally transformed drilling operations. The LSSVM-CSA model with 92.55% accuracy in ROP prediction, MLP with 99–100% accuracy in formation tops prediction, and Extra Trees with 97% accuracy in stuck pipe detection exemplify AI success in this domain.

8.2. Comparison with Traditional Methods

Traditional models such as Bourgoyne and Young (1974) typically achieve 65–75% accuracy [2,4]. In contrast, ML models using advanced optimization algorithms and capable of learning complex patterns achieve 90–99% accuracy.

8.3. Remaining Challenges

Despite significant progress, challenges remain:

• Data Quality: Drilling data often contains missing values, outliers, and noise [8].

• Generalizability: Models trained in one field may perform poorly in another with different geological characteristics.

• Industry Adoption: Resistance to change and lack of trust in autonomous systems are major obstacles.

9. CONCLUSION AND RECOMMENDATIONS

9.1. Conclusion

Artificial intelligence has established itself as a transformative technology in drilling and production operations. The findings of this paper demonstrate that:

1. Hybrid models such as LSSVM-CSA with metaheuristic optimization provide the highest accuracy in predicting drilling parameters.

2. AI implementation can achieve 47% drilling time reduction, 65% NPT reduction, and 38% operational cost savings.

3. From an environmental perspective, 38% CO_2 reduction and 46% drilling waste reduction are achievable.

4. Challenges such as data quality, model complexity, and need for skilled personnel still require attention.

9.2. Future Research Recommendations

1. Development of "white box" models with high interpretability for increased industry adoption.

2. Creation of standardized databases and data sharing between oil companies to improve model quality.

3. Development of integrated Digital Twin systems for real-time simulation of the entire drilling process.

4. Integration of AI with Internet of Things (IoT) and remote sensing technologies for comprehensive operations monitoring.

5. Research in Transfer Learning to improve model generalizability across different geological settings.

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