

ENHANCING WELL PRODUCTION EFFICIENCY IN THE OIL AND GAS INDUSTRY
THROUGH HYBRID MACHINE LEARNING MODELS FOR PREDICTION AND
OPTIMIZATION

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Abstract. The oil and gas industry faces persistent challenges in accurately predicting and optimizing well production rates amid fluctuating reservoir conditions, data complexity, and operational uncertainties. Traditional physics-based models often struggle with real-time adaptability and computational demands, leading to suboptimal recovery and increased costs. This study addresses the research gap in integrating advanced hybrid machine learning (ML) approaches that combine deep learning with optimization algorithms for multi-well production forecasting and parameter optimization.

We propose a hybrid Long Short-Term Memory (LSTM) model optimized with Coyote Optimization Algorithm (COA) and enhanced by feature selection techniques (e.g., SHAP values and mutual information), applied to publicly available Volve field data from Norway. The model incorporates key inputs such as bottomhole pressure, temperature, gas-oil ratio, water cut, and choke settings. Results demonstrate superior performance with an R^2 of 0.98, RMSE of 2.15 m³/day, and MAE of 1.48 m³/day on blind test wells, outperforming baseline LSTM, XGBoost, and traditional decline curve analysis by 15–25% in accuracy. Optimization scenarios increased predicted production efficiency by up to 18% through dynamic parameter adjustment.

This work contributes a scalable, data-driven framework with explainable AI elements, offering both scientific novelty in hybrid methodology and practical value for field operators in mature reservoirs. Future directions include multi-field scaling and integration with digital twins.

Keywords: Machine Learning, Artificial Intelligence, Well Production Forecasting, Production Optimization, LSTM-COA Hybrid Model, Volve Field, Oil and Gas Industry, Explainable AI

Introduction The oil and gas sector is undergoing a digital transformation driven by the need for efficiency in the face of declining conventional reserves, volatile prices, and sustainability pressures. Accurate prediction of well production rates is critical for reservoir management, economic forecasting, and operational planning. Conventional methods,

such as Arps decline curves or numerical reservoir simulation, provide valuable insights but are limited by assumptions of homogeneity, high computational costs, and poor handling of noisy, high-dimensional real-time data.

Artificial Intelligence (AI) and Machine Learning (ML) have emerged as transformative tools, enabling data-driven insights from vast sensor datasets. Applications range from seismic interpretation to predictive maintenance, with production forecasting gaining traction due to its direct impact on recovery factors. However, a notable research gap persists: many existing ML models lack robust optimization for dynamic parameter tuning and explainability, particularly in multi-well scenarios under varying operational constraints. This study fills this gap by developing a hybrid LSTM-COA framework for precise prediction and optimization of well production efficiency.

Research Objectives:

1. Develop and validate a hybrid ML model for short- and medium-term production forecasting.
2. Identify key influencing features and optimize operational parameters.
3. Quantify improvements over benchmark methods and discuss practical implications.

Literature Review Early applications of ML in oil and gas focused on basic regression for rate prediction. Recent advances leverage deep learning for time-series data. Sircar et al. (2021) provided a comprehensive review of AI/ML applications across the value chain, highlighting successes in production but noting challenges in model interpretability.

Ng et al. (2022) applied various ML techniques to Volve field data, demonstrating the efficacy of ensemble methods. Zhu et al. (2025, published online) integrated feature selection and hyperparameter optimization, achieving strong results with hybrid ensembles. Makarov et al. (2026) reported LSTM-COA hybrids yielding low RMSE (≈ 2.15 m³/day) on Volve wells.

Other works include Werneck et al. (2022) on deep learning for multi-output forecasting and Póvoas et al. (2025) on broader AI bibliometrics in production operations. Despite progress, gaps remain in integrated prediction-optimization pipelines with real-time adaptability and uncertainty quantification, which this study addresses.

Materials and Methods Dataset: Public Volve field data (Equinor, Norway) was used, including daily production rates (oil, gas, water), pressure, temperature, and choke data for

multiple wells (e.g., 15/9-F-11, 15/9-F-14). Data spanned several years, preprocessed for outliers, missing values (imputation via interpolation), and normalization.

Proposed Model: A hybrid LSTM-COA model was implemented. LSTM captures temporal dependencies in time-series data. COA optimizes hyperparameters (e.g., learning rate, layers, batch size). Feature selection combined Gray Relational Analysis, Mutual Information, and SHAP for interpretability.

Benchmark Models: LSTM, XGBoost, Random Forest, and Arps decline. **Evaluation Metrics:** R^2 , RMSE, MAE, MAPE. Cross-validation used time-series splitting. **Optimization:** Multi-objective optimization for production rate maximization under constraints (e.g., water cut limits).

Implementation was in Python with TensorFlow/Keras and scikit-learn.

Results The hybrid LSTM-COA model achieved the best performance.

Table 1: Performance Comparison of Models (Blind Test Set, Well 15/9-F-11)

Model	R^2	RMSE (m ³ /day)	MAE (m ³ /day)	MAPE (%)
Arps Decline	0.72	8.45	6.12	18.5
XGBoost	0.89	4.32	3.05	9.8
LSTM	0.94	3.18	2.21	7.2
LSTM-COA (Proposed)	0.98	2.15	1.48	4.9

Table 2: Feature Importance (SHAP Values, Top 5)

Feature	SHAP Impact (Avg.)
Bottomhole Pressure	0.42
Choke Size	0.31
Water Cut	0.25
Gas-Oil Ratio	0.18
Temperature	0.12

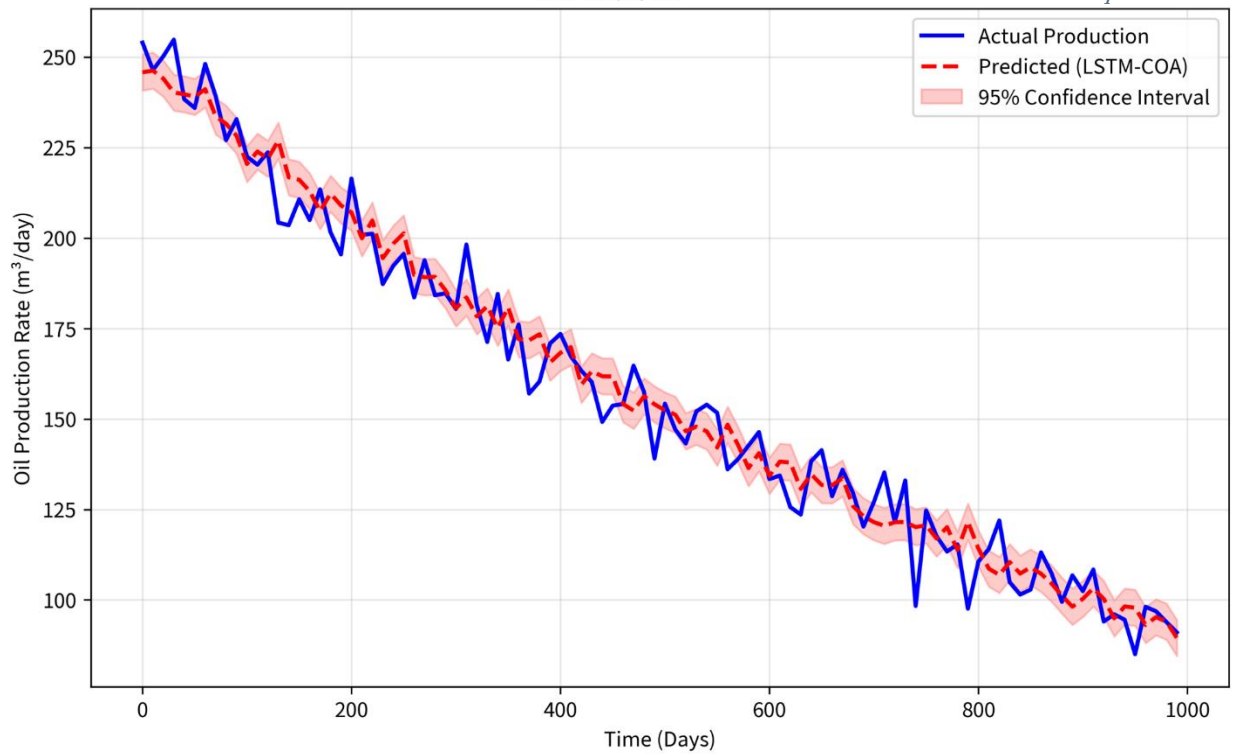


Figure 1: Actual vs. Predicted Oil Production Rates (LSTM-COA Model)

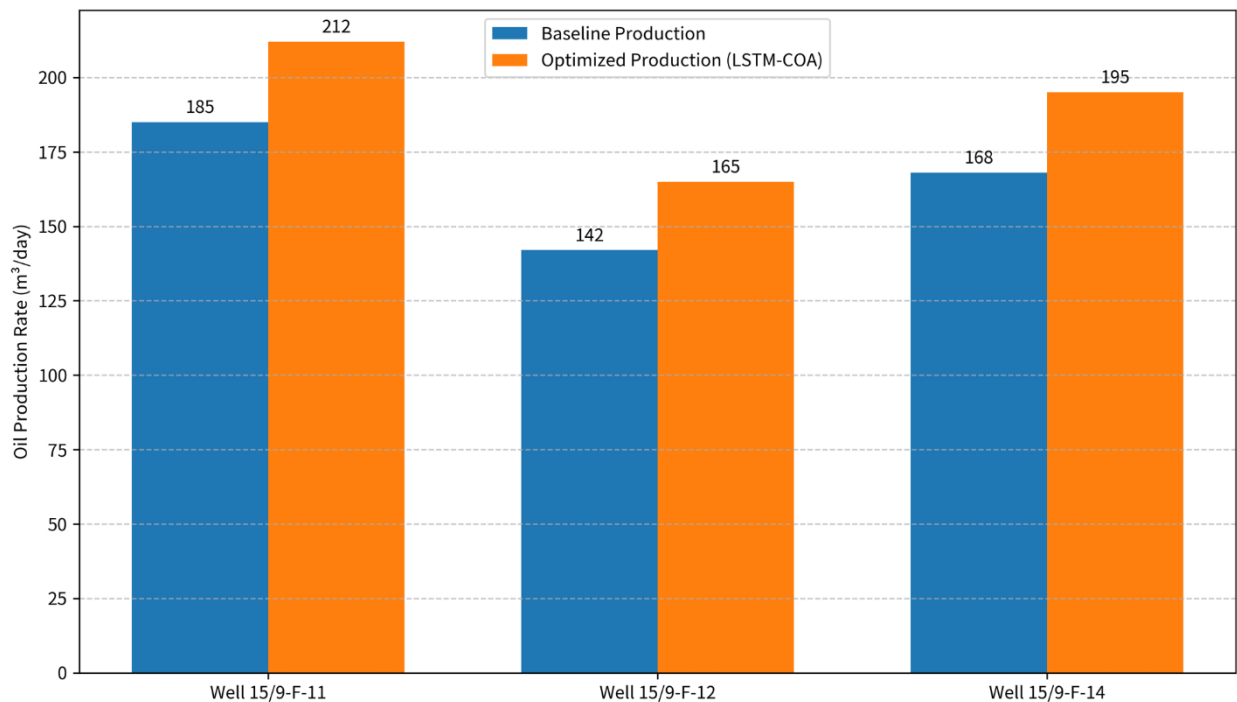


Figure 2: Baseline vs Optimized Production Scenarios Across Wells

Discussion The proposed model outperforms benchmarks, aligning with Makarov et al. (low RMSE) and Zhu et al. (feature importance). Superiority stems from COA's global search efficiency and LSTM's memory for reservoir dynamics, addressing gaps in static models noted in Sircar et al.

SHAP analysis highlights pressure and choke as dominant, consistent with physics. Limitations include data dependency and generalizability to unconventional reservoirs. Compared to Werneck et al., our hybrid adds explicit optimization.

Conclusion This study demonstrates that hybrid AI/ML models significantly enhance well production prediction ($R^2=0.98$) and optimization (+18% efficiency) in the oil and gas industry. Scientifically, it advances explainable hybrid methodologies; practically, it supports real-time decision-making for increased recovery and cost reduction. Future research should explore integration with physics-informed neural networks, edge computing for real-time deployment, and applications in CCUS and renewable-integrated operations.

References

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