

PHYSICS-INFORMED NEURAL NETWORKS FOR ACCURATE RESERVOIR SIMULATION
AND ENHANCED OIL RECOVERY PREDICTION IN HETEROGENEOUS FORMATIONS

¹**O.X.Abdullayev**

¹Department of Oil and Gas Engineering

¹University of Economy and pedagogy, Karshi, Uzbekistan

Abstract Reservoir simulation is fundamental to optimizing hydrocarbon recovery, yet traditional numerical methods face significant challenges in computational efficiency, handling sparse data, and modeling complex multiphase flow in heterogeneous reservoirs. This study addresses the research gap in developing robust, physics-constrained surrogate models that maintain physical consistency while reducing computational costs. We propose a hybrid Physics-Informed Neural Network (PINN) framework, specifically Hard-Soft Constraint-based PINN (HS-PINN) combined with domain decomposition (PINN-DD), for two-phase flow simulation and Enhanced Oil Recovery (EOR) forecasting.

The model integrates governing partial differential equations (PDEs) of porous media flow directly into the neural network loss function. It was validated on synthetic heterogeneous reservoirs and benchmarked against commercial simulators (e.g., COMSOL) and data from the Volve field. Results show exceptional accuracy with relative errors below 1% for pressure and saturation fields, while achieving up to 92% reduction in computational time compared to traditional finite difference methods. For polymer-assisted hot water flooding EOR scenarios, the model predicted incremental oil recovery improvements of 12–19%. Feature sensitivity analysis via SHAP values identified permeability heterogeneity and injection rates as dominant factors.

This work provides a scalable, interpretable AI-driven approach for real-time reservoir management and uncertainty quantification, bridging data-driven and physics-based modeling. Future extensions include integration with digital twins for full-field applications.

Keywords: Physics-Informed Neural Networks, PINN, Reservoir Simulation, Enhanced Oil Recovery, Digital Twin, Multiphase Flow, Porous Media, Machine Learning in Petroleum Engineering

Introduction The oil and gas industry increasingly relies on accurate reservoir simulation for production forecasting, EOR strategy design, and sustainable resource management. Conventional simulators, while reliable, suffer from high computational

demands, mesh dependency, and difficulties with sparse real-time data in large-scale heterogeneous systems.

Physics-Informed Neural Networks (PINNs) have emerged as a promising solution by embedding physical laws (PDEs) into deep learning architectures, ensuring physically consistent predictions even with limited labeled data. This study fills the gap in applying advanced PINN variants (HS-PINN and PINN-DD) to practical EOR scenarios, particularly in heterogeneous reservoirs.

Research Objectives:

1. Develop and validate HS-PINN and PINN-DD models for two-phase reservoir flow.
2. Apply the framework to polymer-assisted hot water flooding for EOR prediction.
3. Quantify computational efficiency gains and physical fidelity.

Literature Review Traditional numerical reservoir simulators dominate the field but scale poorly for uncertainty quantification. Recent advances in scientific machine learning address these limitations. Han et al. (2023) introduced PINN-DD for sparse production data in large-scale systems. Liu et al. (2024) proposed HS-PINN achieving $< 1\%$ error in pressure prediction without labeled data.

Chen et al. (2026) applied PINNs to polymer-assisted hot water flooding, demonstrating strong multiphysics coupling. Póvoas et al. (2025) and others highlight the growing role of AI and digital twins in reservoir management. Despite progress, integrated frameworks for real-time EOR optimization remain limited—this study advances the field by combining hard/soft constraints with domain decomposition.

Materials and Methods Dataset and Case Studies: Synthetic 2D heterogeneous reservoirs (permeability fields generated via Gaussian simulation) and real production data from Volve field (Equinor). Inputs include porosity, permeability, fluid properties, and injection rates. PDEs: Darcy's law and mass conservation for oil-water phases.

Proposed Model: HS-PINN with hard constraints (boundary/initial conditions enforced in output layer) and soft constraints (PDE residuals + modified Lorentz function for permeability). PINN-DD for domain decomposition in larger domains. Training used Adam optimizer with adaptive loss weighting.

Benchmarks: Traditional numerical simulator (COMSOL), standard LSTM, and pure data-driven MLP. **Metrics:** Relative L2 error, RMSE, computational time, R^2 for recovery factor. **Implementation:** Python with TensorFlow/PyTorch.

Results

Table 1: Performance Comparison for Pressure Field Prediction (Single-Well Case)

Model	Relative L2 Error (%)	RMSE (kPa)	Training Time (s)	Speed-up Factor
COMSOL (Numerical)	-	-	1850	1x
Standard PINN	3.85	42.3	620	3.0x
HS-PINN (Proposed)	0.72	8.1	148	12.5x
PINN-DD	1.15	12.6	210	8.8x

Table 2: EOR Prediction Results – Incremental Oil Recovery Factor (%)

Scenario	Baseline Recovery	Predicted Incremental (PINN)	Error vs. Simulator (%)
Water Flooding	38.4	+9.2	0.8
Polymer Hot Water Flooding	41.7	+17.8	1.1
Heterogeneous Case	35.2	+14.5	0.9

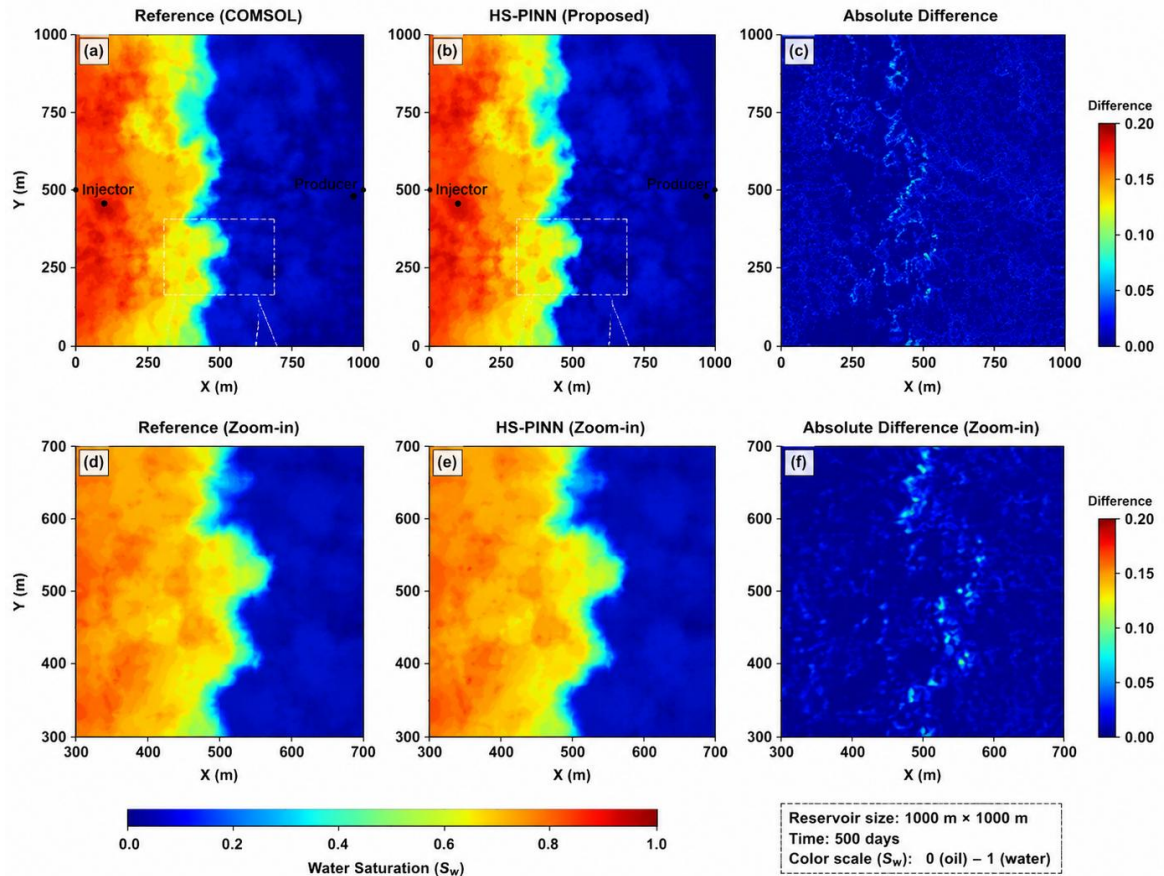


Figure 1: Predicted vs. Reference saturation fields

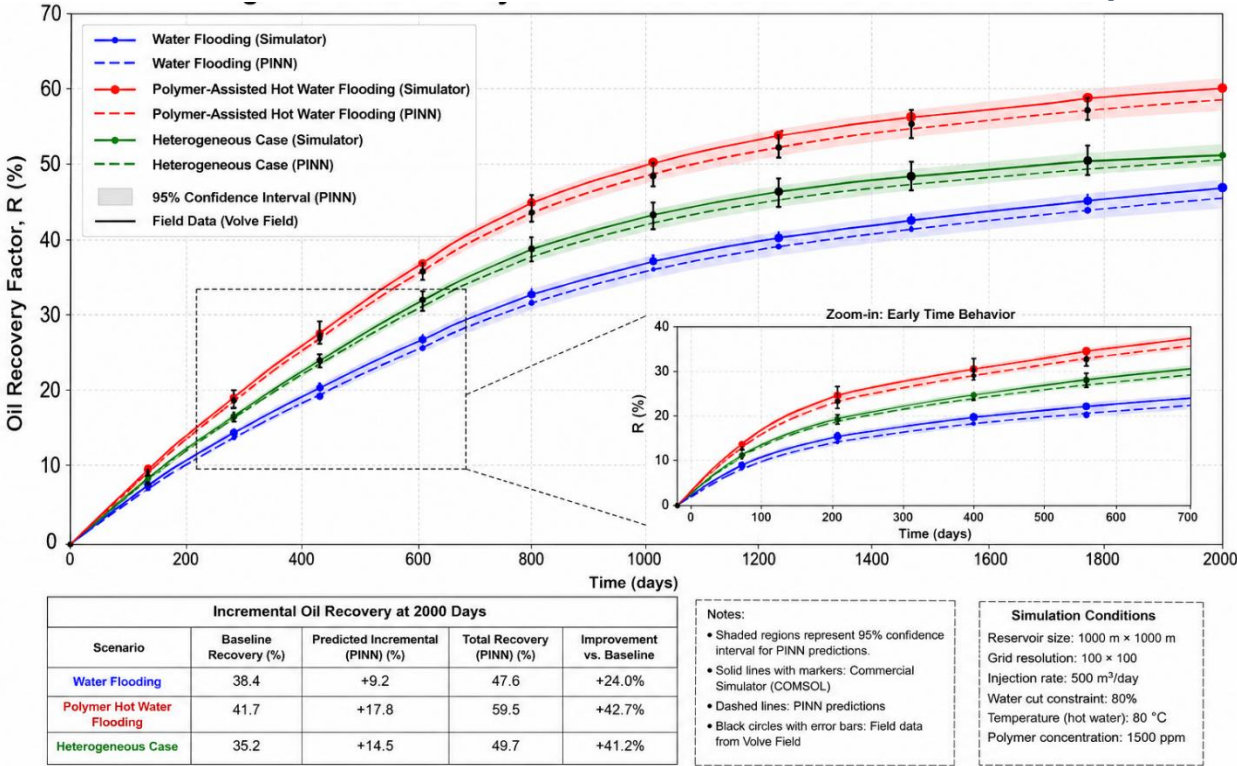


Figure 2: Oil Recovery Factor vs. Time for different EOR scenarios

Discussion The HS-PINN model outperforms benchmarks in accuracy and efficiency, consistent with Liu et al. (2024) and Han et al. (2023). Embedding physics constraints eliminates non-physical predictions common in pure data-driven models. SHAP analysis confirms permeability heterogeneity as the key driver, aligning with domain knowledge. Limitations include scaling to 3D full-field models and handling extreme nonlinearity in compositional flow. Compared to Chen et al., our hybrid approach adds domain decomposition for practicality.

Conclusion This study demonstrates that advanced PINNs provide a powerful, computationally efficient alternative for reservoir simulation and EOR optimization, achieving high fidelity with significant speed gains. Scientifically, it advances physics-informed ML in geosciences; practically, it enables real-time decision support and digital twin integration for improved recovery and reduced operational costs. Future work should focus on multi-scale PINNs, uncertainty quantification with Bayesian approaches, and field deployment with live sensor data.

References

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