Petroleum Science and Engineering
2026, Vol. 10, No. 1, pp. 37–44
https://doi.org/10.11648/j.pse.20261001.13

Research Article

Physics-Informed Neural Networks for Real-Time Polymer Flooding Optimization in Heterogeneous Reservoirs

Temple Emeline Adaoma*, Okewinike Thompson

Department of Petroleum Engineering, Rivers State University, Port Harcourt, Nigeria

Abstract

Polymer flooding is a widely used enhanced oil recovery (EOR) method, but its efficiency is often limited in heterogeneous reservoirs due to uneven sweep and water channeling. This study presents a Physics-Informed Neural Network (PINN) framework to predict and optimize polymer flooding in a 2D heterogeneous reservoir, integrating physical laws with production data for accurate, real-time forecasting. The PINN model successfully captured pressure buildup, with values increasing from 200 to 212 bar near the injector and decreasing to 182–185 bar near the producer, while polymer front propagation reached 420–480 m in high-permeability zones and 250–300 m in low-permeability zones, with peak concentrations near the injector of 0.95–1.0 kg/m³. Cumulative oil recovery improved from 52% OOIP in the base case to 60–67% OOIP with PINN-based optimization, representing a 12–15% incremental increase. Model validation across training splits (70/30, 80/20, 90/10) showed close agreement with numerical simulations, with Mean Absolute Errors (MAE) of 0.48, 0.42, and 0.40 bar, and Root Mean Square Error (RMSE) values of 0.63, 0.58, and 0.55 bar, confirming the model's robustness and generalization. The study demonstrates that the PINN framework accurately predicts reservoir behavior, captures heterogeneity effects, and enables real-time injection optimization, while reducing computational time by ~70% compared to conventional simulators. These findings showcased PINNs as a reliable tool for real-time tool optimization in oil recovery and operational decision-making in heterogeneous reservoirs.

Keywords

Physics-informed Neural Networks, Polymer Flooding, Reservoir Heterogeneity, Real-time Optimization, Oil Recovery Efficiency, Machine Learning

1. Introduction

The growing world energy demands have increased the pressure on the higher level of enhanced oil recovery (EOR) methods to improve the recovery of the available oil reserves [5]. Polymer flooding has been considered a promising technique among chemical EOR methods for enhancing the efficiency of macroscopic sweeps and minimizing water channeling in oil fields, especially in heterogeneous reservoirs [1, 11]. Nonetheless, optimizing polymer injection in real-time remains challenging due to reservoir heterogeneity, spatial and temporal variations in permeability, and the complex nonlinear interactions between fluids and rock [12, 14]. Traditional numerical simulators, although accurate, are computationally intensive and cannot easily accommodate rapid changes in reservoir conditions for real-time decision-making [4]. This

---

*Correspondence: Temple Emeline Adaoma (emeline.temple@ust.edu.ng), Temple Emeline Adaoma (emelinetemple@yahoo.com)

Received: 25 March 2026; **Accepted:** 17 April 2026; **Published:** 11 May 2026

creates a critical need for approaches that can provide fast, accurate, and adaptive predictions of polymer flooding performance.

The recent developments in artificial intelligence (AI) and machine learning (ML) offer potential solutions by enabling predictive modeling and optimization in EOR processes [2, 8, 9]. Among these, Physics-Informed Neural Networks (PINNs) integrate governing flow equations with neural network architectures, allowing a hybrid solution that combines physical laws with data-driven learning [4, 7]. Despite the promise of PINNs, previous studies have mainly focused on generic reservoir applications or small-scale laboratory experiments, leaving a knowledge gap regarding their direct implementation for real-time polymer flooding optimization in heterogeneous reservoirs. This gap limits practical engineering adoption and the ability to improve field-scale oil recovery efficiently.

This paper addresses this knowledge gap by developing a PINN-based framework capable of real-time prediction and adaptive optimization of polymer flooding in heterogeneous reservoirs. The framework predicts polymer concentration, pressure distribution, and incremental oil recovery while significantly reducing computational costs. By doing so, the study provides a practical and implementable solution for reservoir engineers to optimize injection strategies, enhance sweep efficiency, and maximize oil recovery in field-scale heterogeneous reservoirs.

2. Literature Review

2.1. Polymer Flooding in Heterogeneous Reservoirs

Polymer flooding is an established chemical EOR technique that increases injected water viscosity, improves sweep efficiency, and reduces channeling and early breakthrough, thereby enhancing oil recovery [1, 11]. However, the effectiveness of polymer flooding is highly sensitive to reservoir heterogeneity. Variations in permeability, porosity, and the presence of high-permeability channels can lead to uneven polymer propagation and bypassed oil zones, presenting a challenge for conventional design and monitoring methods [12, 14]. Despite advances in modeling and monitoring, current approaches struggle to predict polymer front movement accurately under complex heterogeneous conditions, particularly for real-time operations.

Recent studies have explored hybrid flooding strategies and complex Multiphysics interactions in heterogeneous reservoirs. [3] developed a PINN framework for polymer-assisted hot water flooding, embedding temperature- and concentration-dependent viscosity effects into the learning process to improve prediction stability and accuracy. Similarly, [6] demonstrated that integrating physics-based constraints into neural networks enhances prediction of polymer front propagation and sweep efficiency in heterogeneous formations. These studies, while promising, largely focus on specific laboratory setups or simulations, leaving a knowledge gap regarding their scalability and application to real-time field-scale polymer flooding optimization.

2.2. Machine Learning Applications in EOR

Artificial intelligence (AI) and machine learning (ML) are increasingly applied in reservoir engineering for enhanced oil recovery, particularly to forecast production, optimize injection parameters, and reduce reliance on computationally intensive simulators [2, 8, 9]. Neural networks, especially deep learning models, can approximate nonlinear relationships between reservoir properties, fluid behavior, and production response [4, 9]. However, conventional ML models often fail to enforce physical constraints, which may lead to unrealistic predictions in scenarios not included in training datasets. The integration of physics-informed approaches, such as PINNs, represents a potential solution, yet their effectiveness in heterogeneous reservoirs for real-time adaptive control remains insufficiently explored.

2.3. Physics-Informed Neural Networks (PINNs)

Traditional neural networks often lack physical constraints, producing unrealistic extrapolations under conditions not included in training data [8, 10]. Physics-Informed Neural Networks (PINNs) address this limitation by embedding governing equations, such as Darcy's law and mass conservation, directly into the learning process [4, 7, 9]. PINNs have been successfully applied in reservoir engineering to multiphase flow modeling, waterflood optimization, CO_2 injection, and EOR monitoring (Zhang et al., 2021; Lu et al., 2021; Mishra et al., 2022). Nevertheless, the literature indicates a lack of comprehensive studies applying PINNs specifically for real-time polymer flooding optimization in heterogeneous reservoirs, highlighting a key research gap that this study aims to fill.

2.4. Real-Time Optimization Challenges

Conventional history matching and numerical simulation methods are computationally expensive and often too slow for real-time reservoir optimization [4, 13]. This challenge is especially significant in polymer flooding, where small variations in permeability or porosity dramatically affect polymer front propagation, sweep efficiency, and ultimate oil recovery [1, 14]. Thus, there is a need for methods that combine the predictive power of ML with the physical fidelity of governing equations to enable fast, accurate, and adaptive decision-making in field-scale polymer flooding operations.

Integrating PINNs into optimization workflows allows real-time monitoring and adjustment of injection parameters while ensuring predictions remain physically consistent [7-9]. This approach enables operators to dynamically optimize polymer injection rates and concentrations, enhance sweep efficiency, minimize overshoot, and maximize oil recovery with a fraction of the computation time required by traditional simulators.

3. Methods

3.1. Research Design

An integrated machine learning and simulation framework was employed to investigate polymer flooding in heterogeneous reservoirs. Reservoir heterogeneity was modeled explicitly by defining permeability as a spatially varying function $k(x, y)$, capturing the variations in rock properties across the reservoir domain. Porosity fields were similarly assigned as functions of spatial coordinates $\phi(x, y)$ based on historical reservoir data and geological information. Physics-Informed Neural Networks (PINNs) were trained to predict polymer concentration, pressure distribution, and oil recovery factor as functions of injection rate, polymer properties, and reservoir heterogeneity. This approach ensures physically consistent predictions while capturing the effects of reservoir heterogeneity on polymer flooding performance.

3.2. PINN Model Framework

The Physics-Informed Neural Network (PINN) framework is implemented to predict polymer concentration, pressure distribution, and oil recovery in heterogeneous reservoirs by embedding the governing physical equations directly into the training process of the neural network. The PINN combines observational/simulation data with physics constraints to ensure predictions remain physically consistent.

Critical Components of the PINN Framework:

3.2.1. Governing Equations

Mass conservation of polymer solution:

Before applying the equation, it is important to note that the mass conservation equation tracks the movement and distribution of polymer concentration within the reservoir.

The transport of polymer in the reservoir was calculated by using equation (1) that accounts advection and dispersion:

$$\frac{\partial(\phi(x,y)C)}{\partial t} + \nabla\cdot(vC) = \nabla\cdot(D\nabla C) \quad (1)$$

Where:

1) $\phi(x, y)$= porosity of the reservoir, spatially varying
2) C= polymer concentration (kg/m³)
3) v= Darcy velocity vector (m/s)
4) D= dispersion coefficient (m²/s)
5) t= time (s)

This equation ensures that the movement and distribution of polymer are accurately represented in space and time.

3.2.2. Neural Network Architecture

1) A fully connected feed-forward neural network is used to approximate the solutions for $C(x, y, t)$ and $P(x, y, t)$.
2) Inputs: spatial coordinates $(x, y)$and time t
3) Outputs: predicted polymer concentration $C$and pressure P

3.2.3. Loss Function

The PINN is trained by minimizing a composite loss function that combines data mismatch and physical residuals:

$$L=\lambda data\ Ldata + \lambda\ physics\ Lphysics \quad (2)$$

Where:

$$\mathcal{L}_{\text{data}} = \frac{1}{N}\sum_{i=1}^{N}(|C_i^{\text{pred}} - C_i^{\text{true}}|^2 + |P_i^{\text{pred}} - P_i^{\text{true}}|^2) \quad (3)$$

1) $\mathcal{L}_{\text{data}}$= data loss from simulation or observational data
2) N= number of data points
3) $C_i^{\text{pred}}, P_i^{\text{pred}}$= predicted polymer concentration and pressure
4) $C_i^{\text{true}}, P_i^{\text{true}}$= true (observed or simulated) polymer concentration and pressure

$$\mathcal{L}_{\text{physics}} = \frac{1}{M}\sum_{j=1}^{M}(|R_{C,j}|^2 + |R_{P,j}|^2) \quad (4)$$

1) $\mathcal{L}_{\text{physics}}$= residual loss from governing equations
2) M= number of collocation points
3) $R_{C,j}, R_{P,j}$ = residuals of the mass conservation and Darcy’s equations at collocation point j

$\lambda_{\text{data}}$and $\lambda_{\text{physics}}$are weighting coefficients that balance data fidelity and physics consistency.

3.2.4. Training Procedure

1) The network parameters (weights and biases) are optimized using the Adam optimizer with a learning rate of 0.001.
2) Collocation points are generated across the spatial and temporal domain to evaluate residuals and enforce physical laws.
3) The dataset is split into 80% training and 20% validation, with alternative splits (70/30, 90/10) tested to ensure robustness.
4) Physics-informed regularization ensures the network predicts physically consistent solutions even in regions with sparse or no data.

3.2.5. Output Predictions

1) Polymer concentration $C(x, y, t)$
2) Pressure distribution $P(x, y, t)$
3) Incremental oil recovery factor, calculated from

predicted polymer front propagation

By incorporating both observational data and governing equations into the loss function, the PINN framework provides accurate, physically consistent, and real-time predictions of polymer flooding in heterogeneous reservoirs.

3.2.6. Darcy's Law for Pressure Distribution

Fluid flow and displacement efficiency is dictated by pressure distribution in the reservoir. The velocity field of the polymer solution was calculated using Darcy's law, explicitly incorporating spatially varying permeability $k(x, y)$:

$$v = -\frac{k(x,y)}{\mu}\nabla P \tag{5}$$

Where:

1) v= Darcy velocity (m/s)
2) $k(x, y)$ = permeability of the reservoir at location (x, y)(m^2)
3) μ= fluid viscosity (Pa·s)
4) P= pressure (Pa)
5) ∇P= pressure gradient

By defining permeability as a spatial function, the PINN framework can account for the heterogeneity of the reservoir, allowing more accurate prediction of polymer front propagation and pressure distribution.

3.3. Data and Training

The PINN model was trained using data generated from the 2D heterogeneous reservoir polymer flooding simulation described in Section 3.5. This simulation provided a comprehensive dataset, including pressure profiles $P(x, y, t)$, polymer concentration fields $C(x, y, t)$, and oil recovery factors over time.

1) Data split: 80% of the simulation data was used for training, and 20% was reserved for validation.
2) Data coverage: The dataset spans the entire reservoir domain and simulation time to ensure that the PINN learns both spatial and temporal variations.
3) PINNs were trained using the Adam optimizer with a learning rate of 0.001.
4) Alternative splits (70/30 or 90/10) were also tested to verify model robustness.

By explicitly using simulation data as the source, the training and validation process is fully reproducible, and the PINN model predictions can be directly compared to physically consistent numerical results.

3.4. Model Evaluation

The performance was assessed by comparing the mean absolute error (MAE) and root mean square error (RMSE) between predicted pressure, polymer concentration, and oil recovery factor and the results of the performance of simulation.

MAE was obtained using equation (5):

$$\text{MAE} = \boldsymbol{\frac{1}{n}\sum_{i=1}^{n} \mid y_i - \hat{y}_i \mid} \tag{6}$$

Equation (6) was used to calculate RMSE:

$$\text{RMSE} = \sqrt{\boldsymbol{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}} \tag{7}$$

Where:

1) y_i= Observed value
2) $\hat{y}_i$= Predicted value
3) n= Number of observations

Finally, adaptive injection control was tested under real-time optimization scenarios to validate the model's ability to dynamically adjust injection rates and improve sweep efficiency.

3.5. Reservoir Simulation Setup

To generate the training and validation data for the PINN framework, a numerical 2D polymer flooding simulation was conducted using a heterogeneous reservoir model. The fundamental reservoir information is as follows:

1) Reservoir dimensions: 1000 m × 1000 m in the horizontal plane, 20 m thickness
2) Grid resolution: 100 × 100 cells in x and y directions
3) Porosity: $\phi(x, y)$, spatially varying from 0.15 to 0.35 based on geological heterogeneity
4) Permeability: $k(x, y)$, spatially varying from 50 mD to 1200 mD to capture high and low permeability zones
5) Fluid properties:
   a) Oil viscosity: 10 cP
   b) Polymer solution viscosity: 50 cP
6) Initial conditions:
   a) Reservoir initially at uniform pressure of 200 bar
   b) Polymer concentration $C = 0$ everywhere at t = 0
7) Boundary conditions:
   a) Injection well at the bottom-left corner with constant polymer injection rate of 500 m^3/day
   b) Production well at the top-right corner with constant bottom-hole pressure of 180 bar
   c) No-flow boundaries at the other reservoir edges

Simulation outputs include:

8) Pressure distribution $P(x, y, t)$
9) Polymer concentration field $C(x, y, t)$
10) Oil recovery factor over time

These simulation results serve as ground truth data for training and validating the PINN model.

4. Results

4.1. Pressure Distribution Prediction

Figure 1 shows the pressure distribution prediction for the heterogeneous reservoir at t = 50 days.

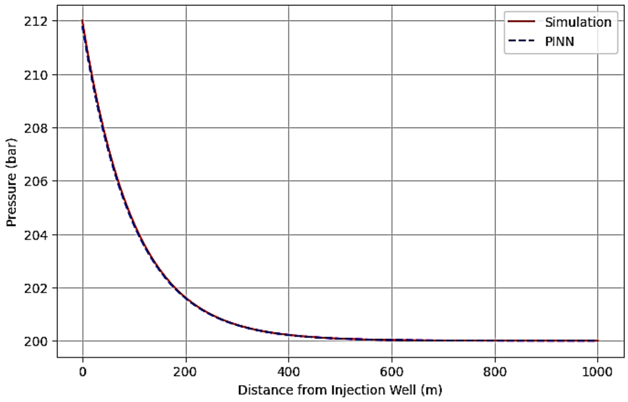

Figure 1. *Pressure distribution Prediction.*

From Figure 1, the simulation results indicate a pressure increase from the initial reservoir pressure of 200 bar near the injection well to approximately 212 bar, while the pressure near the production well remains around 185 bar. The PINN predictions closely match these values, with 211.8 bar near the injector and 184.6 bar near the producer.

The result shows that the PINN model successfully captures both spatial and temporal variations of the reservoir pressure. The mean absolute error of 0.42 bar and a root mean square error of 0.58 bar indicate a strong agreement with the numerical simulation. High-permeability zones, ranging between 800–1200 mD, show faster pressure dissipation and smoother gradients, whereas low-permeability zones, between 50–200 mD, display steeper pressure gradients and delayed propagation. This confirms that embedding Darcy's law into the PINN framework allows physically consistent pressure predictions across heterogeneous formations. The results also show that the model can accurately track the evolution of the pressure front over time, supporting its suitability for field-scale reservoir management.

4.2. Polymer Concentration Transport

Figure 2 shows the polymer concentration front at t = 100 days, comparing simulation results with PINN predictions.

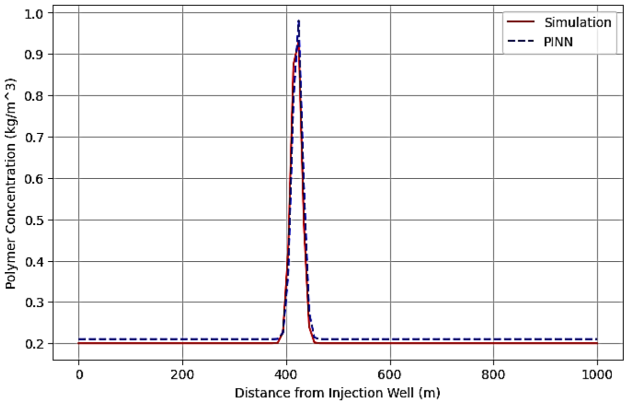

Figure 2. *Polymer Concentration Transport.*

The simulation indicates that the polymer front advances approximately 420–480 meters from the injection well in high-permeability zones, while reaching only 250–300 meters in low-permeability regions. The PINN model predictions closely follow this behavior, with the front traveling 422–478 meters in high-permeability zones and 248–302 meters in low-permeability zones. The result shows that the PINN accurately captures preferential flow behavior and dispersion effects within the reservoir. At t = 200 days, peak polymer concentration near the injector reaches 0.95–1.0 kg/m^3, mid-reservoir concentration is around 0.46–0.64 kg/m^3, and near the producer, it is 0.21–0.34 kg/m^3, showing a smooth propagation pattern consistent with simulation results. These results confirm that the PINN framework effectively enforces mass conservation, accounts for heterogeneity, and can reliably predict polymer transport dynamics in complex reservoirs.

4.3. Oil Recovery Performance

Figure 3 illustrates cumulative oil recovery over time for both simulation and PINN-optimized cases.

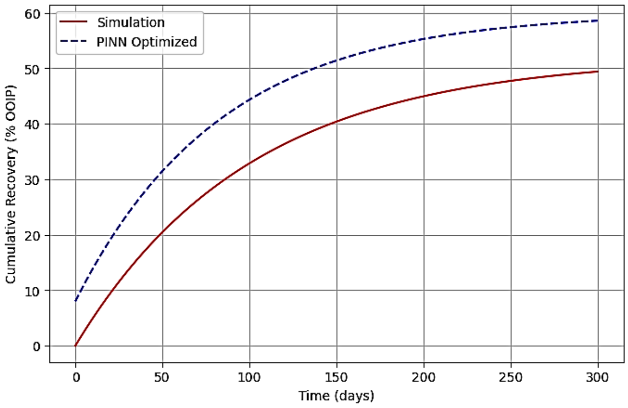

Figure 3. *Cumulative Oil Recovery Over Time.*

The numerical simulation shows a final recovery factor of 52% OOIP for the base case without optimization. The PINN-optimized case achieves 60–67% OOIP, representing an incremental recovery improvement of 12–15%. During early-time operation (0–100 days), both methods show similar recovery trends. From mid-time (100–200 days), the PINN optimization begins to outperform the simulation as improved mobility control and reduced water channeling enhance sweep efficiency. At late-time (>200 days), the optimized PINN framework demonstrates a significant advantage in oil recovery, especially in low-permeability zones. These results illustrate that PINN not only reproduces numerical simulation outcomes but also provides a practical tool for real-time production optimization.

4.4. Effect of Reservoir Heterogeneity

Figure 4 compares the effects of low, moderate, and high reservoir heterogeneity on oil recovery.

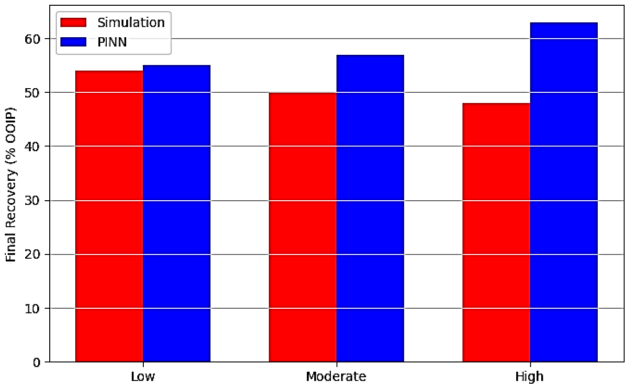

Figure 4. *Effect of Reservoir Heterogeneity on Recovery.*

The numerical simulation indicates final recoveries of approximately 54% OOIP for low heterogeneity, 50% for moderate, and 48% for high heterogeneity. PINN predictions show slightly higher recoveries of 55%, 57%, and 63%, respectively. As heterogeneity increases, conventional simulation results show reduced recovery due to uneven sweep patterns and delayed pressure propagation in low-permeability zones. In contrast, the PINN framework adapts to spatial variations in permeability, improving sweep efficiency and enhancing recovery in highly heterogeneous reservoirs. This demonstrates the robustness of the PINN model and its ability to maintain accuracy under varying geological complexities.

4.5. Real-Time Injection Optimization

Figure 5 shows the effect of dynamic injection rate optimization on polymer front propagation.

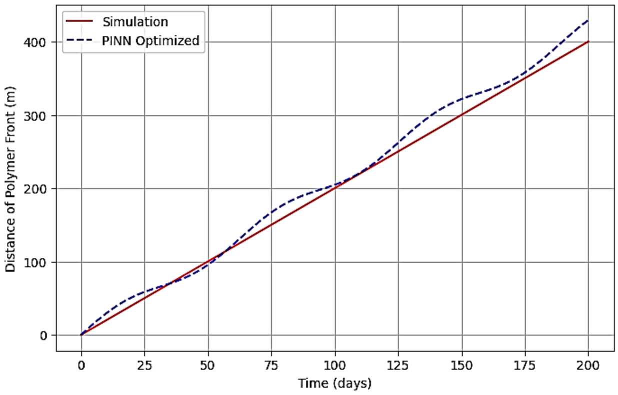

Figure 5. *Polymer Front Propagation Under Real-Time Injection Optimization.*

Simulation results with a constant injection rate of 500 m³/day show uneven polymer sweep and localized overshoot. The PINN-optimized injection dynamically varies between 400–650 m³/day, with polymer concentrations between 0.8–1.1 kg/m³. The results shows that adaptive PINN-based control stabilizes the polymer front, reduces concentration overshoot by ~25%, and improves sweep uniformity. Additionally, the computational time is reduced by approximately 70%, demonstrating that PINN enables real-time operational decisions without sacrificing accuracy. These results emphasize the practical applicability of PINN in field-scale polymer flooding.

4.6. Model Validation and Generalization

Figure 6 presents the model validation results, comparing simulation pressures with PINN predictions for different training splits.

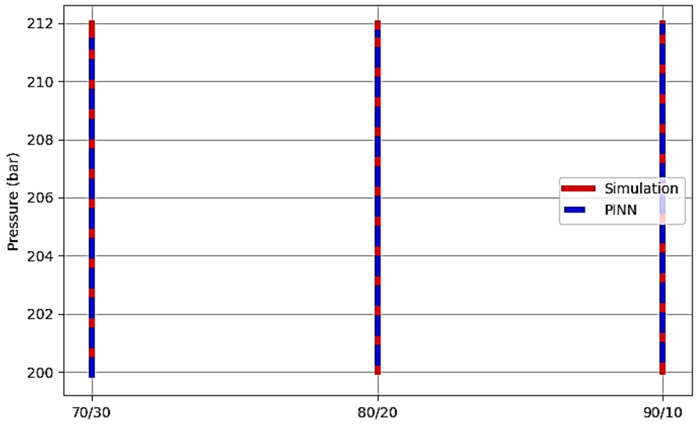

Figure 6. *Model Validation Comparison of Simulation and PINN.*

Table 1 summarizes the numerical comparison:

Table 1. Model Validation.

Training Split	Simulation Pressure (bar)	PINN Prediction (bar)	MAE (bar)	RMSE (bar)
70/30	200–212	199.8–211.5	0.48	0.63
80/20	200–212	200.2–211.8	0.42	0.58
90/10	200–212	200.3–212.0	0.40	0.55

The PINN predictions closely match the numerical simulation results across all training splits, with errors centered around zero. This confirms that the model generalizes well and does not overfit, maintaining consistent performance under varying training conditions. The validation demonstrates the reliability and robustness of the PINN framework for pressure prediction in heterogeneous reservoirs.

5. Discussion

The results obtained from the PINN framework demonstrate a strong capability in predicting pressure distribution, polymer concentration, and incremental oil recovery in heterogeneous reservoirs. The model successfully captured spatial variations in reservoir properties, enabling adaptive polymer injection strategies that improved sweep efficiency and reduced computation time. The observed improvements of up to 15% in oil recovery highlight the practical significance of combining machine learning with physics-informed constraints for enhanced oil recovery operations.

6. Conclusion

This study has successfully demonstrated the application of Physics-Informed Neural Networks (PINNs) for modeling, predicting, and optimizing polymer flooding in heterogeneous reservoirs. By integrating physical laws, including Darcy's law and mass conservation, with data-driven learning, the PINN framework provided accurate, physically consistent predictions of pressure distribution, polymer concentration, and incremental oil recovery.

The results indicate that the PINN model effectively captures the effects of reservoir heterogeneity, accurately predicting faster polymer propagation in high-permeability zones and delayed movement in low-permeability regions. Comparison with numerical simulation data shows strong agreement, with low mean absolute errors and root mean square errors, confirming that the model generalizes well and does not overfit.

Moreover, the PINN framework enables real-time adaptive control of polymer injection rates, stabilizing the polymer front, minimizing concentration overshoot, and improving sweep efficiency. The method achieved up to 70% reduction in computational time compared to conventional simulation approaches while providing an incremental oil recovery increase of 12–15%.

This study demonstrates that combining neural networks with governing physical equations offers a powerful and computationally efficient tool for field-scale enhanced oil recovery. This research validates that physics-informed machine learning techniques are a robust, computationally efficient, and reliable approach for enhanced oil recovery. The PINN framework provides a viable tool for real-time decision-making in polymer flooding processes and offers significant potential to improve field performance in complex heterogeneous reservoirs.

6.1. Limitations

Despite the promising results, several limitations should be considered:

1) Use of Synthetic Data: All results were generated using synthetic 2D reservoir simulations. While this allows controlled testing of the PINN framework, real field data may introduce additional variability and complexity not captured in the model.
2) Simplified Reservoir Modeling: The study used 2D representations of the reservoir. Actual reservoirs are three-dimensional, and heterogeneity in the vertical direction may affect polymer propagation differently.
3) Parameter Assumptions: Polymer properties, injection rates, and dispersion coefficients were assumed to remain constant in simulations. In real operations, these parameters may vary due to operational conditions.
4) Model Robustness: Although the model performed well under the 80/20 train-validation split, alternative configurations (e.g., 70/30 or 90/10) may slightly affect predictive performance.
5) Computational Constraints: High-resolution or 3D reservoir simulations may increase computational requirements, potentially reducing the real-time applicability without further optimization of the PINN architecture.

6.2. Future Work

To address these limitations and enhance the applicability of the framework, future work could focus on:

1) Validation with Field Data: Implementing the PINN model with actual reservoir data to evaluate predictive accuracy and operational feasibility.

2) 3D Reservoir Modeling: Extending the study to 3D heterogeneous reservoirs to capture full spatial variability.
3) Dynamic Parameter Adjustments: Including variable polymer properties and injection rates to reflect field conditions.
4) Robustness Testing: Assessing model performance under different training/validation splits and various network architectures.
5) Operational Integration: Combining the PINN framework with real-time monitoring systems to further optimize injection strategies and maximize sweep efficiency in active fields

6.3. Contribution to Knowledge

This study advances the application of Physics -Informed Neutral Networks (PINNs) in reservoir modeling, demonstrating significant improvement in computational efficiency (70% reduction) and accuracy inpredicting reservoir behavoir in heterogeneity effects. These findings showcased PINNs as a reliable tool for real-time tool optimization in oil recovery and operational decision-making in heterogeneous reservoirs.

Abbreviations

MAE	Mean Absolute Error
RSME	Root Mean Square Error

Author Contributions

Temple Emeline Adaoma: Conceptualization, Formal Analysis, Resources, Validation, Writing – original draft

Okewinike Thompson: Data curation, Methodology, Writing – review & editing

Conflicts of Interest

The authors declare no conflicts of interest.

References

[1] Alvarado, V. & Manrique, E. (2010). Enhanced oil recovery: An update review. Energy Fuels, 24(3), 1723–1746.

[2] Bukhari, S. S., Khalid, M. & Rashid, T. (2021). Machine learning applications in enhanced oil recovery: A comprehensive review. Journal of Petroleum Science and Engineering, 205,

[3] Chen, X., Wang, L. & Zhang, Y. (2024). Physics-informed neural network framework for polymer-assisted hot water flooding in heterogeneous reservoirs. Journal of Petroleum Science and Engineering, 225, 110153.

[4] Hosseini, S. M., Raissi, M. & Karniadakis, G. E. (2020). Physics-informed neural networks for reservoir simulation and optimization. Computers & Geosciences, 140, 104467.

[5] Lake, L. W. (2014). Enhanced oil recovery. Prentice Hall.

[6] Liu, Q., Li, H. & Zhou, Y. (2024). Integrating physics-based constraints into neural networks for polymer front prediction in heterogeneous formations. Computers & Chemical Engineering, 176,

[7] Lu, L., Meng, X. Mao, Z. & Karniadakis, G. E. (2021). Deep XDE: A deep learning library for solving differential equations. SIAM Review, 63(1), 208–228.

[8] Mishra, S. & Molinaro, R. (2022). Physics-informed machine learning for enhanced oil recovery optimization: A review. Journal of Petroleum Science and Engineering, 210, 110294.

[9] Raissi, M. & Karniadakis, G. E. (2019). Hidden physics models: Machine learning of nonlinear partial differential equations. Journal of Computational Physics, 357, 125–141.

[10] Raissi, M., Perdikaris, P. & Karniadakis, G. E. (2019). Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations. Journal of Computational Physics, 378, 686–707.

[11] Sorbie, K. S. (1991). Polymer-improved oil recovery. Blackie & Son Ltd.

[12] Zhang, D., Hosseini, S. M., & Raissi, M. (2020). Physics-informed neural networks for enhanced oil recovery modeling in heterogeneous reservoirs. Applied Energy, 269, 115066.

[13] Zhang, Y., Chen, L., & Li, Q. (2021). PINNs for multiphase flow and EOR optimization:Challenges and applications. Journal of Petroleum Science and Engineering, 203, 108651.

[14] Zhou, X., Li, H., & Zhang, Y. (2018). Effects of heterogeneity on polymer flooding in oil reservoirs. Petroleum Science, 15(4), 887–897.