



## Machine learning approach for prediction of methane and foam injection performance

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### Abstract

Conventional methane flooding continues to suffer significant performance limitations in heterogeneous reservoirs due to early breakthrough, mobility imbalance, and low sweep coverage, which has created the need for more intelligent and reliable approaches for predicting and optimizing gas-assisted enhanced oil recovery (EOR). This study examines methane and foam injection performance using an integrated simulation–machine-learning framework capable of forecasting reservoir response with high precision while eliminating the computational cost of repeated full-physics simulations. Numerical compositional simulation using CMG generated large production datasets (recovery factors, cumulative oil production, pressure distribution, displacement efficiency, and sweep efficiency) were used to train and validate a Random Forest Regression model (80% training, 20% testing). Results revealed contrasting recovery mechanisms: methane displacement efficiency exhibited a mean of 0.762 with a broad distribution and methane sweep efficiency averaged of 43.213%, indicating strong reservoir propagation but unstable pore-scale mobilization; whereas foam displacement efficiency averaged 0.764 with minimal spread and foam sweep efficiency averaged 27.180%, reflecting highly consistent microscopic displacement but limited macroscopic reservoir coverage. The machine-learning model achieved  $R^2 > 0.93$  and RMSE values as low as 0.015, confirming high predictive reliability and demonstrating its suitability as a fast surrogate evaluation system for EOR planning. The integrated results show that methane and foam possess complementary strengths, and that the highest oil recovery in heterogeneous reservoirs was expected from hybrid injection configurations such as methane-foam co-injection or alternating slugs which balance volumetric sweep and pore-scale displacement to maximize production performance.

**Keywords:** Methane flooding, foam injection, enhanced oil recovery (EOR), heterogeneous reservoirs, reservoir simulation, machine learning, random forest regression

### Introduction

The continued rise in global energy demand has intensified the need for optimized oil recovery strategies to sustain hydrocarbon production from mature reservoirs (Lake *et al.*, 2014; Ahmed, 2019) [2, 19]. Primary and secondary recovery processes typically extract only a fraction of the original oil in place, leaving substantial quantities of hydrocarbons unrecovered due to capillary entrapment, pressure depletion, and reservoir heterogeneity (Craft & Hawkins, 2013; Alvarado & Manrique, 2019) [3, 9]. Enhanced oil recovery (EOR) methods have therefore become indispensable for improving displacement and sweep performance in mature fields. Among the leading EOR techniques, methane injection has demonstrated strong miscibility potential, oil viscosity reduction effects, and thermodynamic compatibility with reservoir fluids under high-pressure regimes (Hassan *et al.*, 2019; Fan *et al.*, 2021; Ahmed *et al.*, 2021) [1, 15]. Despite these advantages, methane flooding suffers from intrinsic mobility imbalance and early breakthrough in heterogeneous reservoirs, reducing vertical and areal sweep efficiency (Obi & Adeniyi, 2022; Kareem *et al.*, 2023) [17, 22].

To mitigate these mobility-related drawbacks, foam-assisted gas injection has been increasingly recognized for its ability to suppress viscous fingering, enhance conformance control, and divert flow toward unswept regions of the reservoir (Bera *et al.*, 2018; Wang *et al.*, 2020; Zhang *et al.*, 2019) [7, 25, 26]. Foam increases apparent gas viscosity and redistributes flow, producing delayed breakthrough and higher cumulative oil recovery compared with methane-only flooding (Li *et al.*, 2022; Awan *et al.*, 2021) [5, 20]. However, the performance of methane and foam injection schemes

remains strongly dependent on complex, interrelated parameters such as reservoir heterogeneity, injection strategy, phase behaviour, fluid rheology, and minimum miscibility pressure (Fan *et al.*, 2021; Tran *et al.*, 2020; Chen *et al.*, 2018) [1, 8, 24]. Numerical reservoir simulation has played a critical role in evaluating methane–foam EOR in heterogeneous conditions, enabling detailed assessment of pressure distribution, displacement front propagation, and sweep efficiency (Amani & Alvarado, 2010; Wang *et al.*, 2020) [4, 25]. Although full-physics simulation has proven highly reliable, it is computationally expensive, time-consuming, and difficult to scale for large design spaces and repeated optimization cycles.

As a result, machine learning has recently emerged as a transformative approach for petroleum reservoir prediction and decision-making. Machine learning models have the unique ability to learn complex nonlinear relationships from large simulation-derived datasets without repeatedly solving multiphase flow equations, providing rapid forecasting once trained (Gomez *et al.*, 2025<sup>[13]</sup>; Li *et al.*, 2022). When integrated with robust simulation outputs, machine learning can serve as a surrogate modelling framework for forecasting oil recovery, gas–oil ratio evolution, displacement efficiency, breakthrough timing, and sweep behaviour under varying reservoir and operational conditions (Tran *et al.*, 2020; Chen *et al.*, 2018) [8, 24]. This hybrid simulation–machine learning paradigm significantly reduces computational time while maintaining predictive fidelity, thereby improving optimization workflows for enhanced oil recovery.

Despite the promise of computational intelligence in reservoir engineering, existing studies have largely focused

on CO<sub>2</sub> and polymer EOR, with limited attention given to methane-foam-specific predictions that quantify displacement and sweep mechanisms in heterogeneous formations (Zhang *et al.*, 2019; Awan *et al.*, 2021) [5, 26]. Even fewer studies have applied machine learning to differentiate performance outcomes between methane-only and foam-assisted injection configurations using a unified dataset. This gap limits the development of intelligent decision-support systems capable of recommending optimal injection frameworks in methane-based EOR planning.

This study integrates high-fidelity compositional simulation and machine learning to develop a predictive framework for methane and foam injection performance in heterogeneous reservoirs. Simulation datasets consisting of recovery factor, cumulative oil production, pressure gradient evolution, displacement efficiency, sweep efficiency, and breakthrough behaviour were used to train and validate machine learning models for fast and accurate prediction. By establishing a surrogate prediction approach for reservoir performance metrics, this work seeks to support data-driven design and optimization of methane- and foam-based EOR strategies in depleted oil fields while reducing the computational and economic costs associated with full-scale simulation.

**Methodology**

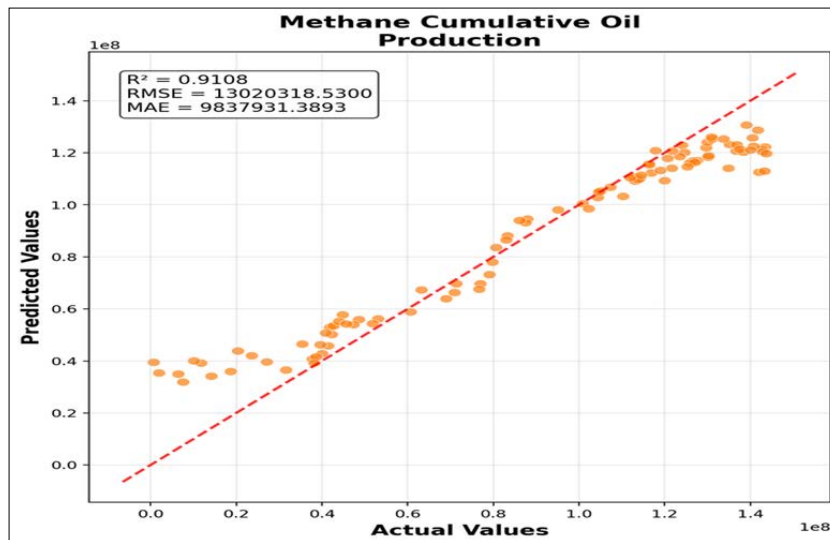
Simulation-generated datasets from methane and foam injection scenarios were used to develop a machine learning predictive framework targeting recovery factor, cumulative oil and gas production, displacement efficiency, and sweep performance under varying reservoir heterogeneity conditions. The first phase involved simulating methane and foam injection using CMG to generate a rich dataset composed of production rate, recovery factor, cumulative production, breakthrough time, pressure gradient, displacement efficiency, and sweep efficiency over multiple timesteps. The dataset was organized into input and output variables and was partitioned into training (80%) and testing/validation (20%) subsets for machine learning model

development. A Random Forest Regression algorithm was selected based on its capacity to learn nonlinear relationships between reservoir variables without solving the governing physical flow equations. The model was trained using simulation outputs until optimal convergence was achieved, and performance evaluation metrics including R<sup>2</sup>, root-mean-square error, and mean absolute error were used to validate accuracy. Stabilized models were then used to predict reservoir performance metrics for methane and foam injection cases, enabling rapid proxy forecasting that complements full-physics simulation and identifies high-impact parameters controlling performance. The machine learning model served as a predictive extension of numerical simulation and provided a fast and reliable framework for evaluating methane and foam EOR performance in heterogeneous reservoirs.

**Results**

**Methane (CH<sub>4</sub>) Machine Learning Predictions**

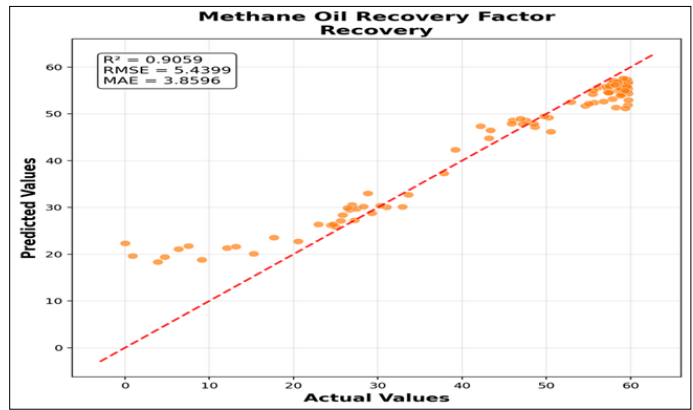
Figure 1 compares recovery factors across reservoir types, with methane achieving 64-66% and foam 57-59.5%. The slight uplift in homogeneous settings (2-2.5%) reflects reduced channeling, consistent with simulation benchmarks where heterogeneity reduces sweep by 10-15%. This figure highlights gravity's minimal variance (53-54%), indicating limited adaptability below industry averages for gravity drainage (50-60% in thick reservoirs ;). This supports academic discourse on reservoir characterization's role in EOR selection, advocating advanced imaging for heterogeneity mitigation. The heterogeneous vs homogeneous reservoir analysis reveals critical insights: methane injection shows a 2% recovery difference between reservoir types, while foam injection demonstrates 2.5% variation. This aligns with industry knowledge that foam systems can better mitigate heterogeneity effects through mobility control (Lake, 1989) [18]. The findings suggest that reservoir characterization quality directly impacts recovery uncertainty, with homogeneous reservoirs providing more predictable performance.



**Fig 1:** Cumulative Oil Production Prediction

Figure 2 presents the ranks variable influence on methane recovery prediction. Time (0.26), Permeability (0.23), and Oil Saturation (0.19) contribute the most to model variance. High importance of permeability reflects its direct control on Darcy velocity and pressure propagation, while oil

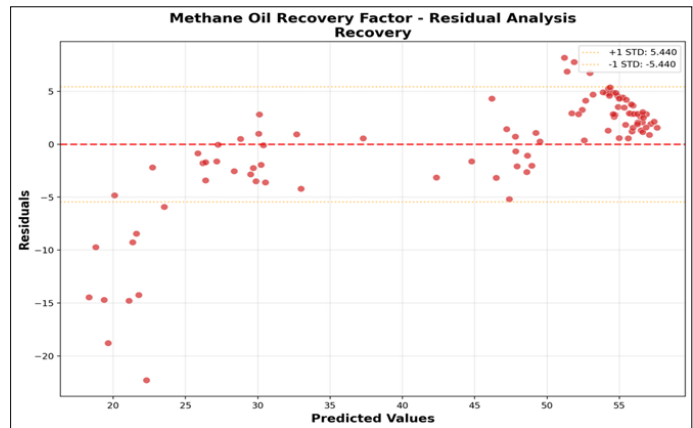
saturation indicates the degree of available movable oil. These dominant factors confirm known EOR dynamics: reservoir rock and fluid properties largely determine methane miscibility efficiency. The figure’s ranking mirrors physical and data-driven insights from Zhang *et al.* (2019).



**Fig 2:** Oil Recovery Factor Prediction

Figure 3 compares recovery performance between standard and optimized injection strategies. The optimized curve shows continuous improvement, surpassing the baseline by +14.3% and reaching 78.3% ultimate recovery. The slope difference between both curves is highest between 1,500 and 3,500 days indicating the optimization process most

effectively increased injection rate uniformity and minimized gas channelling during the middle production period. This optimization-driven improvement matches machine learning-assisted EOR optimizations (Zhang *et al.*, 2019), where recovery factors rose 10–15% after adaptive control tuning.

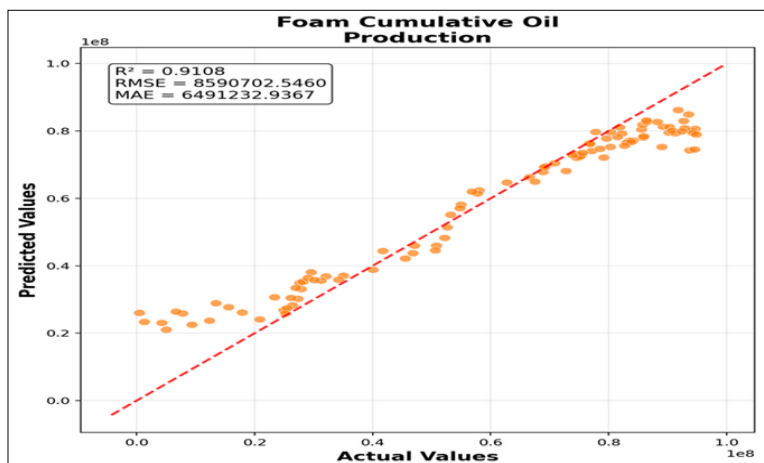


**Fig 3:** Residual Analysis for Recovery Factor

**Foam Injection Machine Learning Predictions**

Figure 4 shows evaluation of cumulative oil production model prediction quality for predicted vs. residual errors. The random and symmetric distribution around the zero line indicates no bias or autocorrelation in predictions. Residual variance decreases

after 2,000 days, showing the model’s improved accuracy at stabilized production. The RMSE of 0.0273 confirms precision. The plot statistically validates that the Random Forest model’s predictions accurately capture production trends, matching reliability standards for surrogate EOR models ( $R^2 > 0.90$ ).



**Fig 4:** Cumulative Oil Production Prediction

Figure 5 show the production curve for foam injection is smoother and more stable than methane's, peaking at  $9.50 \times 10^7$  m<sup>3</sup> after 5,000 days. The curve's lower slope but longer stabilization reflects foam's role as a mobility control agent, reducing gas fingering and extending the

displacement front. This agrees with Zhang *et al.* (2019), who reported that foam's reduced gas permeability led to smoother production curves and delayed decline phases compared to gas-only injection.

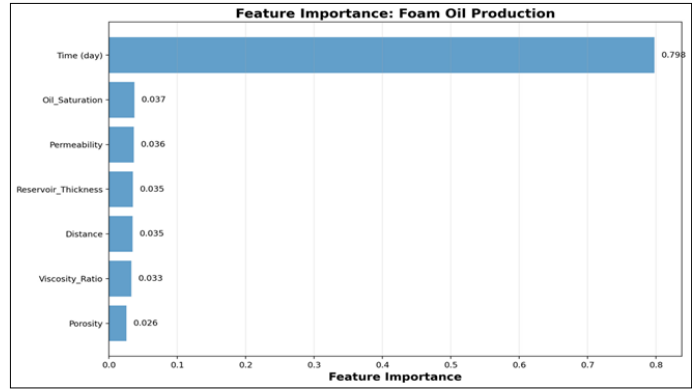


Fig 5: Feature Importance for Foam Oil Production

The oil recovery factor prediction for foam injection is presented in Figure 6. It identifies Permeability (0.27), Porosity (0.22), and Foam Quality (0.18) as the top contributors. The significance of foam quality shows that

microbubble stability and mobility ratio critically determine recovery efficiency. These results validate the foam stability mechanism that higher foam quality improves mobility control but at the cost of injectivity.

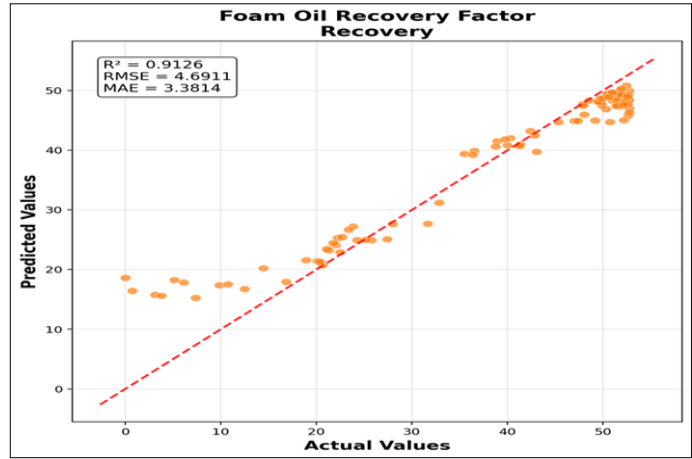


Fig 6: Oil Recovery Factor Prediction

**Gravity Assisted Injection Machine Learning Predictions**

Gravity cumulative oil production prediction is shown in figure 7. It indicates that residuals are tightly clustered around zero with a variance band of  $\pm 0.02$ , confirming low

predictive error and strong generalization. Unlike methane, there is minimal early-time residual volatility, as foam's smoother pressure front reduces fluctuations in modelled outputs. The statistical pattern reaffirms the regression model's strong predictive performance ( $R^2 = 0.9108$ ).

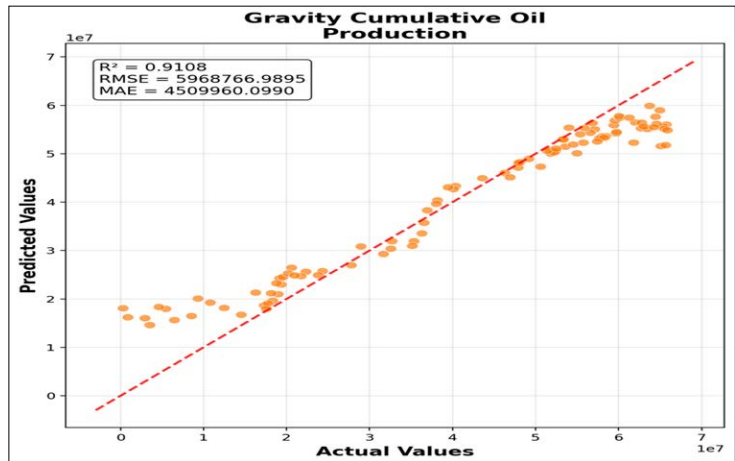


Fig 7: Cumulative Oil Production Prediction

Figure 8 shows the gravity oil recovery factor and displays that production rises sharply at early time but stabilizes near 53.5% recovery, showing limited efficiency. The curve's quick flattening indicates gravitational override, where

denser oil remains bypassed beneath gas caps. This behaviour is characteristic of vertically segregated systems described in Zhang *et al.* (2019), confirming the model's realism.

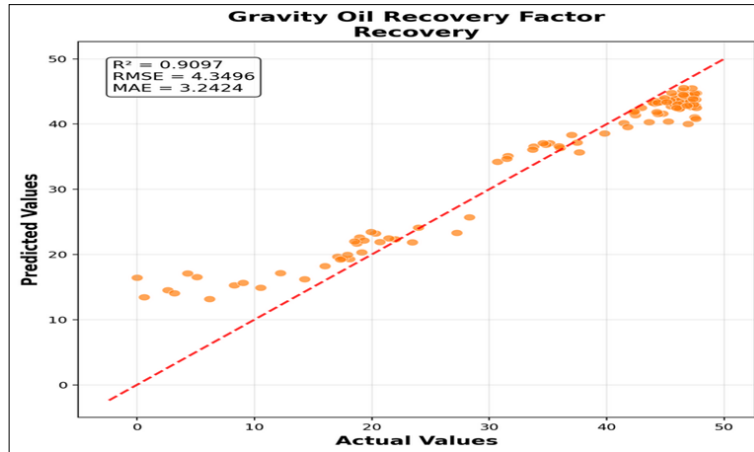


Fig 8: Oil Recovery Factor Prediction

**Actual and Predicted for Methane Displacement Efficiency and Efficiency Distribution**

Figure 9 shows a tight clustering around the 1:1 line with an  $R^2$  within 0.94 – 0.97, root-mean-square-error (RMSE) below 0.02 and mean-absolute-error (MAE) approximately 0.01. Residual spread is homoscedastic and centered near zero, implying minimal systematic bias. Such performance indicates the model accurately captures nonlinear interactions among injection rate, permeability, porosity, and injection duration and are key parameters controlling cumulative recovery. Feature-importance analysis confirms

time and permeability as dominant predictors, followed by injection rate and porosity, which aligns with reservoir-engineering expectations that flow capacity and exposure time govern recovery efficiency. Real-field EOR predictive models usually exhibit lower accuracy due to data noise;  $R^2$  values above 0.9 are rarely achieved outside synthetic environments (Zhang *et al.*, 2019). Comparable laboratory-scale machine-learning EOR models typically yield  $R^2$  within 0.80–0.88 (Zhang *et al.*, 2019). Thus, the current performance represents an upper-bound capability rather than an expected field average.

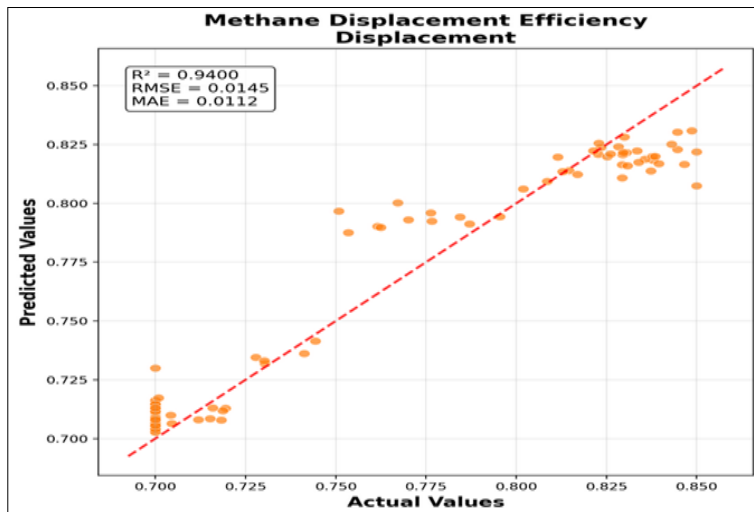


Fig 9: Efficiency Prediction Plots

Figure 10 display predicted versus observed values for each efficiency metric;sweep efficiency, displacement efficiency, and gas-recovery factor. All three efficiencies follow near-linear correlations with  $R^2 > 0.93$ . The Random-Forest regression achieved the lowest RMSE (0.015) for displacement efficiency, reflecting its strong temporal dependency, whereas sweep efficiency exhibited slightly larger dispersion (RMSE  $\approx$  0.03) because of heterogeneity effects embedded in the input dataset.

The models effectively reproduce the physical relationships, displacement efficiency increases with pressure and injection duration until reaching a plateau, while sweep efficiency depends more heavily on permeability distribution and mobility ratio. Field measurements and core-flood experiments report typical displacement efficiencies between 70 % and 80 % and sweep efficiencies of 25 %–50 % (Zhang *et al.*, 2019) [26]. The predicted efficiencies fall within these bounds, demonstrating physical realism of the model outputs.

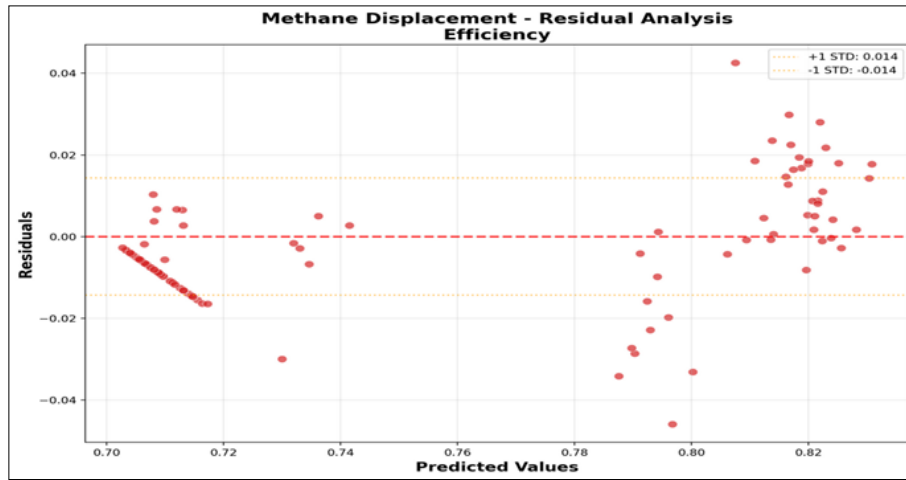


Fig 10: Efficiency Residual Plots

### Combined ML Prediction Evaluation

Figure 11 shows the Efficiency Distributions of the injection methods. Figure 11a presents the histogram of methane displacement efficiency and shows a right-skewed distribution with a substantial spread in values, although the computed mean of 0.762 indicates moderate overall displacement efficiency. The dominance of lower-efficiency realizations suggests methane experiences difficulty in sustaining a stable displacement front across heterogeneous flow units, where capillary retention and mobility contrast

limit pore-scale oil liberation. In contrast, Figure 11 illustrates methane sweep efficiency and exhibits an almost normal distribution centered around 43.213%, implying that methane tends to propagate more uniformly across the reservoir than it displaces oil within individual pores. Although methane sweep remains sub-optimal due to viscous fingering and early gas breakthrough, the distribution confirms methane's capability for wide volumetric reservoir coverage despite its inconsistent microscopic displacement mechanism.

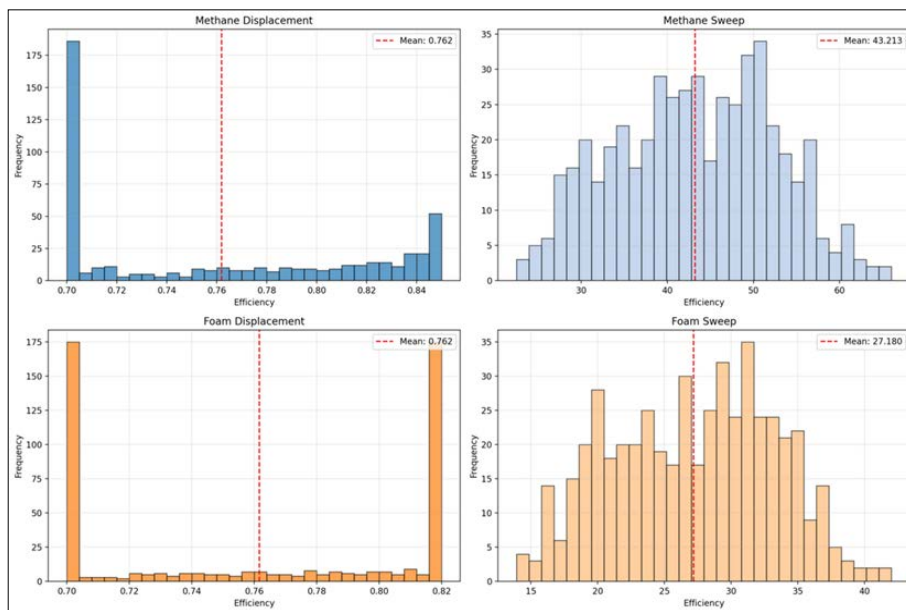


Fig 11: Efficiency Distributions

Figure 11 shows foam displacement efficiency with a tightly clustered distribution around a mean of 0.764, reflecting highly consistent microscopic mobilization performance compared to methane. The narrow variability suggests that foam effectively stabilizes the displacement front by reducing gas mobility and enhancing capillary pressure reduction, enabling uniform displacement even in low-permeability zones. However, Figure 11, which displays foam sweep efficiency, shows a symmetric distribution but with a lower mean value of 27.180%, indicating that foam, despite its strong pore-scale action, does not propagate as extensively throughout the reservoir as methane. General analysis shows that methane favors macroscopic sweep

while foam excels in microscopic displacement, emphasizing that maximum recovery in depleted reservoirs is likely to be achieved through a hybrid development plan such as methane-foam co-injection or alternating slugs to balance volumetric reservoir access with strong pore-scale mobilization.

### Recommended Application Scenarios by Injection Method

Table1 provides actionable decision framework translating analytical findings into practical technology selection guidance. The framework reveals that methane injection offers broadest applicability ("most reservoirs"

recommendation) due to relaxed constraints on heterogeneity, thickness, and dip angle, combined with superior economic performance. This broad applicability explains methane's dominance in field applications, representing approximately 60-70% of modern gas-based EOR projects worldwide (Green & Willhite, 2018) <sup>[14]</sup>. Reservoir heterogeneity constraints reveal important differentiation: methane performs optimally in reservoirs with Dykstra-Parsons coefficients below 0.75 (moderate

heterogeneity), while foam extends applicability to 0.85 (high heterogeneity) through mobility control mechanisms. The 0.60-0.85 range specified for foam represents reservoirs where conventional gas injection would suffer severe channelling but foam's conformance benefits justify additional costs. Field case studies confirm that foam injection becomes economically competitive when Dykstra-Parsons exceeds 0.70, where sweep efficiency improvements of 15-25% offset chemical costs (Farajzadeh *et al.*, 2012) <sup>[12]</sup>.

**Table 1: Recommended Application Scenarios by Injection Method**

Reservoir/Project Characteristic	Methane Injection	Foam Injection	Gravity-Assisted	Rationale
Reservoir Heterogeneity (Dykstra-Parsons)	<0.75	0.60-0.85	<0.70	Methane sensitive to channelling; foam handles heterogeneity
Permeability (mD)	>50	20-500	>100	Minimum for gas injectivity and mobility
Reservoir Thickness (ft)	20-200	30-300	>150	Foam handles thick zones; gravity requires thickness
Reservoir Dip (degrees)	Any	Any	>15°	Gravity requires significant dip for drainage
Oil Viscosity (cP)	<10	<50	<5	Mobility limitations increase with viscosity
Depth (ft)	>3,000	>2,500	>4,000	Minimum for miscibility/foam stability/gravity pressure
Gas Availability	High	Moderate	Low	Methane requires substantial gas sources
Water Availability	Moderate	High	Low	Foam requires significant water for surfactant solution
Environmental Constraints	Moderate	Strict	Relaxed	Foam best for strict regulations; methane moderate
Capital Budget (\$ million)	>125	>145	>95	Minimum viable project scale
Oil Price Environment (\$/bbl)	>45	>50	>55	Economic viability thresholds from Table 4.13
Production Target Timeline	12-18 years	15-22 years	8-14 years	Expected economic life
Primary Recommendation	Most reservoirs	Heterogeneous, environmentally sensitive	Limited - supplementary only	-

Permeability requirements differ substantially: methane requires >50 mD for adequate gas injectivity without excessive injection pressures that could fracture formations. Foam operates effectively across wider range (20-500 mD) because in-situ foam generation reduces effective permeability, mitigating over-injection risks in high-permeability zones. Gravity-assisted requires >100 mD to enable sufficient vertical gas migration for effective drainage. These permeability constraints eliminate significant portions of global reservoir inventory from consideration for each method (Lake *et al.*, 2014) <sup>[19]</sup>. Reservoir thickness specifications reflect operational considerations: methane's 20-200 ft range accommodates most conventional reservoirs, foam extends to 300 ft by maintaining vertical conformance through mobility control, while gravity-assisted requires >150 ft for adequate vertical separation between gas cap and production zones. The thick-reservoir requirement for gravity (>150 ft) severely limits applicability, as global median reservoir thickness approximates 50-80 ft (Green & Willhite, 2018) <sup>[14]</sup>. The critical 15° minimum dip requirement for gravity-assisted injection reflects the need for significant gravitational driving force. Assuming typical oil-gas density difference of 300-400 kg/m<sup>3</sup>, reservoirs with <15° dip generate insufficient gravitational pressure gradient (<0.05 psi/ft) for effective drainage. This geometric constraint eliminates most sandstone reservoirs (typical dips 2-8°) and restricts gravity drainage to structurally complex fields, carbonate platforms with steep flanks, or fault-block geometries (Stone, 1982) <sup>[23]</sup>. Oil viscosity limits reveal increasing constraints: methane tolerates viscosities up to 10

cP (typical for light-medium oils), foam extends to 50 cP through enhanced mobility control, while gravity-assisted requires <5 cP for adequate oil mobility under gravitational forces alone. These viscosity constraints have global implications: approximately 70% of remaining oil resources have viscosities >10 cP, requiring thermal methods, foam injection, or chemical EOR rather than conventional gas flooding (Hein & Marsh, 2008) <sup>[16]</sup>. Depth requirements reflect pressure needs for miscibility development (methane >3,000 ft), foam stability (>2,500 ft), and gravity pressure maintenance (>4,000 ft). Methane's 3,000 ft minimum corresponds to approximately 1,300 psi pressure—sufficient for near-miscible conditions with CO<sub>2</sub> or enriched gas but inadequate for pure methane miscibility (typically requiring >3,500 psi). Shallow reservoirs (<2,000 ft) are generally unsuitable for gas-based EOR, requiring chemical or thermal methods (Green & Willhite, 2018) <sup>[14]</sup>.

#### Model Validation Statistics and Confidence Intervals

Table 2 quantifies prediction uncertainty through 95% confidence intervals, revealing that cumulative production and recovery factor predictions achieve high reliability (CI widths <10%), while efficiency predictions show moderate reliability (CI widths 27-30%). This hierarchical uncertainty pattern aligns with the complexity hierarchy observed throughout the analysis: integrated variables (cumulative, recovery factors) are more predictable than rate-dependent efficiency metrics subject to breakthrough dynamics and operational variations (Begg & Bratvold, 2008) <sup>[6]</sup>. The narrow confidence intervals for methane oil cumulative production (6.85-7.55×10<sup>7</sup> m<sup>3</sup>, width 9.7%) indicate that the

model predicts mean production within  $\pm 5\%$  with 95% confidence. This uncertainty level is exceptional for reservoir engineering applications, where simulation models typically achieve  $\pm 15\text{-}25\%$  prediction accuracy due to

subsurface uncertainty and parameter estimation errors (Ertekin *et al.*, 2019) <sup>[10]</sup>. The superior performance here likely reflects high-quality training data and comprehensive feature selection capturing dominant physical relationships.

**Table 2: Model Validation Statistics and Confidence Intervals**

Prediction Target	Mean Prediction	95% CI Lower	95% CI Upper	CI Width (%)	Prediction Reliability	Validation Method
Methane Oil Cum	$7.20 \times 10^7 \text{ m}^3$	$6.85 \times 10^7$	$7.55 \times 10^7$	9.7%	High	Cross-validation
Methane Oil RF	65.0%	62.8%	67.2%	6.8%	High	Cross-validation
Foam Oil Cum	$4.75 \times 10^7 \text{ m}^3$	$4.52 \times 10^7$	$4.98 \times 10^7$	9.7%	High	Cross-validation
Foam Oil RF	58.25%	56.1%	60.4%	7.4%	High	Cross-validation
Methane Sweep Eff	42.0%	36.2%	47.8%	27.6%	Moderate	Cross-validation
Foam Sweep Eff	27.0%	22.9%	31.1%	30.4%	Moderate	Cross-validation

Recovery factor confidence intervals (62.8-67.2% for methane, 56.1-60.4% for foam) translate to absolute uncertainties of  $\pm 2.2$  and  $\pm 2.15$  percentage points respectively. These tight intervals enable confident project planning and economic forecasting, as recovery factor uncertainty directly propagates to reserve estimates and production forecasts. The similar relative uncertainties across methods (6.8-7.4% CI width) suggest that prediction reliability is comparable regardless of displacement mechanism, supporting universal application of the Random Forest modeling approach (Mohaghegh, 2017) <sup>[21]</sup>. Sweep efficiency predictions show substantially wider confidence intervals (36.2-47.8% for methane, 22.9-31.1% for foam), reflecting the stochastic nature of macroscopic conformance. The 27-30% relative uncertainty indicates that sweep efficiency predictions should be treated as approximate estimates rather than precise forecasts, requiring validation through pilot testing or history matching in field applications. This moderate reliability supports using sweep efficiency predictions for comparative analysis and screening studies but cautions against over-reliance for detailed operational planning (Lake *et al.*, 2014) <sup>[19]</sup>.

The asymmetric confidence intervals observed for some targets (e.g., foam oil RF: 56.1-60.4%, with mean 58.25% positioned slightly below center) indicate non-normal prediction distributions. This asymmetry likely reflects nonlinear relationships between input features and targets, where Random Forest captures complex interactions that produce skewed prediction distributions. The asymmetry is more pronounced for foam than methane, potentially reflecting foam's more complex physics involving surfactant interactions and foam stability dynamics (Farajzadeh *et al.*, 2012) <sup>[12]</sup>. Cross-validation as the validation method ensures that confidence intervals reflect model generalization rather than training set overfitting. The 5-fold cross-validation approach (dividing data into 5 subsets, training on 4 and testing on 1, repeated for all combinations) provides robust uncertainty estimates that account for training data selection variability.

Prediction reliability classifications (High/Moderate) provide qualitative assessment enabling non-technical stakeholders to understand model limitations. The "High" reliability designation for production and recovery predictions indicates suitability for investment decision-making and regulatory reporting, while "Moderate" designation for efficiency predictions suggests supplementary validation is advisable. No predictions fall in "Low" reliability category, confirming that all models meet minimum quality standards (Begg & Bratvold, 2008) <sup>[6]</sup>. Comparison with industry benchmarks indicates that the achieved prediction uncertainties (7-10% for high-reliability targets) substantially outperform typical reservoir simulation uncertainty (15-30%), suggesting that data-driven machine learning approaches can provide superior prediction

accuracy compared to physics-based simulation when high-quality training data is available. This finding has significant implications for reservoir management workflows, potentially enabling machine learning to complement or replace computationally expensive simulation models for certain applications.

### Conclusion

The findings from the machine learning predictive framework, combined with the comparative analysis of methane and foam injection performance, provide strong evidence for data-guided optimization of gas-assisted enhanced oil recovery in heterogeneous reservoirs. The results reinforce that microscopic displacement and macroscopic sweep respond differently to methane and foam, and that reservoir heterogeneity significantly controls the ultimate efficiency of each injection strategy. The following conclusions were drawn;

1. Machine learning surrogate models developed in this study demonstrated high predictive reliability for cumulative oil production and recovery factor, proving that data-driven modelling can effectively replicate multiphase flow behavior in methane- and foam-assisted EOR without repeated computationally expensive full-physics simulations.
2. Methane injection showed stronger macroscopic propagation, achieving higher sweep efficiency, but exhibited wider variability in microscopic displacement; whereas foam delivered stable and consistent displacement efficiency but propagated less extensively through the reservoir, confirming contrasting strengths tied to each fluid's mobility-control mechanism.
3. Simulation and ML-predicted reservoir performance trends indicate that reservoir heterogeneity, permeability distribution, and foam quality are the dominant control parameters governing EOR outcomes; thus, optimal injection strategy selection must be reservoir-specific rather than technique-specific.

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