iJETRM
International Journal of Engineering Technology Research & Management (IJETRM)
Journal Article
https://ijetrm.com/issue/

AI-ENABLED TAILORING OF SURFACTANT–POLYMER INJECTION SCHEMES THROUGH RESERVOIR-DEPENDENT INTERFACIAL BEHAVIOR AND ADSORPTION MODELING

Nnaji Chinedu G
Naveen Jindal School of Management, University of Texas at Dallas, USA

ABSTRACT
Enhanced oil recovery (EOR) remains critical for maximizing hydrocarbon extraction from mature reservoirs, with surfactant–polymer (SP) flooding emerging as a promising technique due to its ability to reduce interfacial tension and improve sweep efficiency. However, the effectiveness of SP injection is highly dependent on complex reservoir-specific factors, including mineralogy, salinity, temperature, and wettability, which influence interfacial behavior and chemical adsorption. Traditional design approaches often rely on empirical correlations and laboratory-scale experiments, limiting their scalability and adaptability to heterogeneous reservoir conditions. In this context, artificial intelligence (AI) offers a transformative pathway for optimizing SP injection strategies by integrating data-driven modeling with physicochemical insights. This study presents an AI-enabled framework that tailors surfactant–polymer formulations and injection schemes based on reservoir-dependent interfacial dynamics and adsorption characteristics. Machine learning models are employed to predict interfacial tension reduction and adsorption losses under varying reservoir conditions, enabling dynamic adjustment of injection parameters such as concentration, slug size, and sequencing. The framework incorporates multi-source data, including core flooding experiments and field-scale observations, to enhance predictive accuracy and generalizability. Results demonstrate improved oil recovery efficiency, reduced chemical consumption, and enhanced economic viability. This approach underscores the potential of AI-driven optimization in advancing intelligent, reservoir-specific EOR strategies.

Keywords:
Artificial Intelligence; Surfactant–Polymer Flooding; Enhanced Oil Recovery; Interfacial Tension; Adsorption Modeling; Reservoir Characterization

---

1. INTRODUCTION

1.1 Background on Surfactant–Polymer (SP) Flooding

Surfactant–polymer (SP) flooding has emerged as a widely adopted chemical enhanced oil recovery (EOR) technique aimed at improving hydrocarbon recovery from mature and waterflooded reservoirs [1]. The process combines the interfacial tension (IFT) reduction capability of surfactants with the mobility control provided by polymers, thereby enhancing both microscopic and macroscopic displacement efficiency [2]. Surfactants act by lowering the oil–water interfacial tension to ultra-low levels, facilitating the mobilization of trapped residual oil within pore spaces [3]. In parallel, polymers increase the viscosity of the displacing fluid, improving sweep efficiency and minimizing viscous fingering effects during displacement processes [4].

This synergistic interaction between surfactants and polymers has demonstrated measurable improvements in oil recovery compared to conventional waterflooding techniques under controlled conditions [5]. However, the performance of SP flooding is highly sensitive to reservoir-specific conditions such as salinity, temperature, mineral composition, and wettability, which directly influence surfactant behavior and polymer stability [6]. In heterogeneous reservoirs, permeability variations and complex rock–fluid interactions lead to uneven chemical propagation and reduced displacement efficiency [7]. Furthermore, adsorption of surfactants onto rock surfaces

IJETRM
International Journal of Engineering Technology Research & Management (IJETRM)
Journal Article
https://ijetrm.com/issue/

results in significant chemical losses, reducing effective concentration and operational efficiency [8]. These limitations necessitate adaptive, reservoir-aware SP design methodologies [9].

1.2 Problem Statement

Conventional SP flooding design methodologies are predominantly based on laboratory-scale experiments and empirical correlations that assume relatively static reservoir conditions [2]. However, actual reservoir systems exhibit dynamic spatial and temporal variability in pressure, temperature, and fluid composition, leading to inconsistencies between predicted and field performance [5]. This mismatch results in suboptimal injection strategies that fail to respond effectively to evolving reservoir conditions [7].

A critical challenge lies in accurately predicting adsorption losses and interfacial behavior under varying thermodynamic environments [3]. Surfactant adsorption depends on complex interactions between rock mineralogy, brine salinity, and chemical composition, making it difficult to capture using simplified models [6]. Similarly, interfacial tension reduction varies with concentration and environmental conditions, introducing further uncertainty into injection design [8]. These uncertainties lead to inefficient chemical utilization, increased operational costs, and reduced recovery performance, highlighting the need for intelligent adaptive frameworks [1].

1.3 Research Gap

Existing SP flooding optimization approaches are largely based on either mechanistic reservoir simulation models or purely data-driven techniques, each with inherent limitations [4]. Mechanistic models rely heavily on predefined physical relationships and often require extensive calibration, limiting their ability to capture nonlinear interactions in complex reservoir systems [6]. Conversely, traditional machine learning models can identify hidden patterns but often lack physical interpretability and may produce unrealistic predictions outside training domains [2].

There is a notable absence of integrated frameworks that combine machine learning with physicochemical modeling to simultaneously capture data-driven insights and underlying reservoir physics [7]. Additionally, many existing models are tailored to specific reservoir datasets and exhibit poor generalization across different geological conditions [5]. The lack of adaptive injection frameworks capable of dynamically adjusting SP formulations and injection strategies further limits operational efficiency, creating a significant gap in intelligent EOR optimization methodologies [8].

1.4 Aim and Objectives

This study aims to develop an AI-enabled framework for optimizing surfactant–polymer injection schemes by incorporating reservoir-dependent interfacial behavior and adsorption modeling [3]. The primary objective is to integrate machine learning techniques with physicochemical principles to accurately predict interfacial tension reduction and adsorption losses under varying reservoir conditions [6]. The framework seeks to simultaneously model key performance indicators, including oil recovery efficiency, chemical retention, and sweep performance [2].

Additionally, the study aims to enable reservoir-specific tailoring of injection parameters such as surfactant concentration, polymer dosage, and slug design, thereby improving both technical efficiency and economic viability of EOR operations [9].

1.5 Contributions

The primary contribution of this research is the development of a hybrid modeling framework that integrates machine learning algorithms with physics-based adsorption and interfacial models to improve prediction accuracy and interpretability [4]. This approach enables robust evaluation of SP flooding performance across diverse reservoir conditions characterized by varying salinity, temperature, and rock properties [7].

Furthermore, the study introduces a multi-condition prediction system capable of generalizing across heterogeneous datasets while maintaining physical consistency [5]. The framework also supports real-time injection optimization through continuous data integration and adaptive model updating, facilitating intelligent and dynamic SP injection design for enhanced oil recovery applications [8].

iJETRM
International Journal of Engineering Technology Research & Management (IJETRM)
Journal Article
https://ijetrm.com/issue/

2. THEORETICAL BACKGROUND

2.1 Interfacial Tension in SP Flooding

Interfacial tension (IFT) plays a fundamental role in surfactant–polymer flooding by governing the capillary forces that trap residual oil within porous media [7]. Surfactants function by adsorbing at the oil–water interface, where their amphiphilic molecular structure reduces the cohesive forces between immiscible phases, thereby lowering IFT to ultra-low levels [9]. This reduction enhances the detachment of oil droplets from pore walls and promotes mobilization through pore throats under applied pressure gradients [11]. The efficiency of this mechanism is strongly influenced by surfactant concentration, salinity, and temperature, which determine interfacial film stability and molecular packing at the interface [13].

The relationship between interfacial tension and pressure difference across a curved interface is described by the Young–Laplace equation:

Equation (1):

$$\Delta P = \frac{2\gamma}{R}$$

where ΔP represents the pressure difference across the interface, γ is the interfacial tension, and R is the radius of curvature of the interface. A reduction in γ leads to a decrease in capillary pressure, facilitating oil displacement from pore spaces [8]. This relationship highlights the critical importance of controlling interfacial properties in optimizing SP flooding performance under reservoir-specific conditions [12].

2.2 Capillary Number and Oil Mobilization

The capillary number is a dimensionless parameter that quantifies the balance between viscous forces and capillary forces during fluid displacement in porous media [10]. It is a key indicator of oil mobilization efficiency in enhanced oil recovery processes, particularly in surfactant–polymer flooding systems [14]. The capillary number is expressed as:

Equation (2):

$$N_c = \frac{\mu v}{\gamma}$$

where μ denotes the viscosity of the displacing fluid, v represents the Darcy velocity, and γ is the interfacial tension. Increasing the capillary number reduces the dominance of capillary forces, thereby enhancing the mobilization of trapped oil ganglia [7]. In SP flooding, this is achieved through simultaneous reduction of γ by surfactants and increase of μ by polymers [11].

A critical capillary number threshold exists beyond which residual oil saturation decreases significantly, emphasizing the need for precise control of both viscosity and interfacial tension [13].

2.3 Polymer Rheology and Mobility Control

Polymer flooding enhances sweep efficiency by modifying the rheological properties of the injected fluid, thereby improving mobility control in heterogeneous reservoirs [9]. The behavior of polymer solutions is typically non-Newtonian, exhibiting shear-thinning characteristics that are influenced by molecular weight, concentration, and salinity [12]. This rheological behavior is commonly described using the power-law viscosity model:

Equation (3):

$$\mu = K\dot{\gamma}^{\,n-1}$$

where μ is the apparent viscosity, K is the consistency index, $\dot{\gamma}$is the shear rate, and n is the flow behavior index. When $n < 1$, the fluid exhibits shear-thinning behavior, which is beneficial for improving injectivity while maintaining high viscosity in low-shear regions of the reservoir [8].

This property enables polymers to selectively control mobility, reducing fingering and improving sweep efficiency across heterogeneous formations [14].

2.4 Adsorption Mechanisms in Porous Media

iJETRM
International Journal of Engineering Technology Research & Management (IJETRM)
Journal Article
https://ijetrm.com/issue/

Adsorption of surfactants onto reservoir rock surfaces is a critical factor influencing the efficiency and economics of SP flooding [10]. When surfactant molecules interact with mineral surfaces, they are removed from the flowing phase, reducing the effective concentration available for interfacial tension reduction [13]. This process is governed by electrostatic interactions, van der Waals forces, and chemical bonding between surfactant head groups and rock surfaces [7].

The adsorption behavior is commonly odelled using the Langmuir isotherm, which assumes monolayer adsorption on a finite number of sites:

Equation (4):

$$q = \frac{q_{max}KC}{1 + KC}$$

where q represents the amount of adsorbed surfactant, $q_{max}$is the maximum adsorption capacity, K is the adsorption equilibrium constant, and C is the surfactant concentration in the bulk phase. The Langmuir model captures the saturation behavior of adsorption as surface sites become fully occupied [11].

Accurate prediction of adsorption is essential for optimizing chemical dosage and minimizing losses, particularly in reservoirs with high clay content or complex mineralogy [12].

2.5 Surfactant Loss and Retention Modeling

Surfactant transport and retention in porous media are governed by mass conservation principles that account for advection, dispersion, and adsorption processes [8]. The mass balance equation describing surfactant transport is given by:

Equation (5):

$$\frac{\partial C}{\partial t} + \nabla(vC) = -\rho_b \frac{\partial q}{\partial t}$$

where C is the surfactant concentration, v is the fluid velocity vector, $\rho_b$is the bulk density of the rock, and q represents the adsorbed concentration. The right-hand term accounts for surfactant loss due to adsorption [10].

This formulation enables dynamic tracking of chemical propagation and retention within the reservoir [14].

2.6 Need for Machine Learning Integration

The complex interactions governing SP flooding involve nonlinear coupling between interfacial phenomena, adsorption dynamics, and fluid flow behavior, which are difficult to capture using traditional analytical models [7]. These processes are influenced by multiple interdependent variables, including temperature, salinity, rock properties, and chemical composition, resulting in high-dimensional and multivariate dependencies [11].

Conventional models often rely on simplifying assumptions that limit their predictive accuracy under varying reservoir conditions [13]. Machine learning provides a data-driven approach capable of capturing nonlinear relationships and improving predictive performance, enabling adaptive optimization of SP injection strategies in complex reservoir systems [9].

3. METHODOLOGY FRAMEWORK

3.1 Overall AI-Driven Workflow

The proposed AI-driven framework integrates reservoir engineering principles with machine learning techniques to enable adaptive surfactant–polymer injection design under varying reservoir conditions [11]. The workflow begins with multi-source data acquisition, followed by preprocessing and feature engineering to transform raw measurements into meaningful predictive variables [15]. These engineered features are then used to train machine learning models capable of predicting interfacial tension reduction, adsorption behavior, and recovery efficiency across diverse reservoir environments [17].

A structured training pipeline incorporating data splitting, cross-validation, and hyperparameter tuning ensures model robustness and generalization [19]. The outputs from the trained models are subsequently integrated into an optimization module that determines optimal injection parameters, including surfactant concentration, polymer dosage, and slug size [14]. The workflow also incorporates a feedback loop where new field data continuously

ISSN: 2456-9348
Impact Factor: 8.232

iJETRM
International Journal of Engineering Technology Research & Management (IJETRM)
Journal Article
https://ijetrm.com/issue/

update the model, enabling real-time refinement of predictions and adaptive control of SP flooding operations [16].

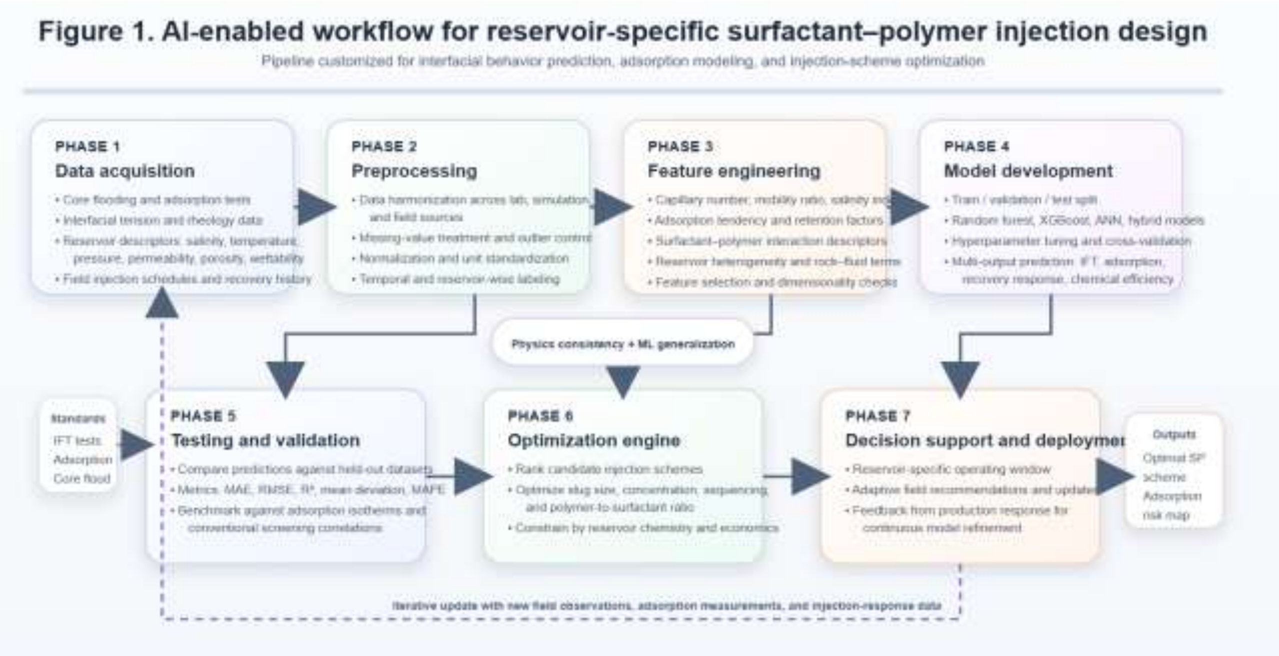

Figure 1: End-to-End AI Workflow

3.2 Data Acquisition

Data acquisition forms the foundation of the proposed framework, as the accuracy and robustness of machine learning models depend heavily on the quality and diversity of input datasets [18]. In this study, data are collected from three primary sources: laboratory experiments, reservoir simulations, and field-scale production systems. Core flooding experiments provide high-resolution measurements of interfacial tension, adsorption characteristics, and displacement efficiency under controlled conditions [13]. These datasets capture detailed physicochemical interactions between surfactants, polymers, and reservoir rock samples.

Reservoir simulation datasets complement experimental data by providing synthetic yet physically consistent representations of fluid flow, pressure distribution, and chemical transport across heterogeneous reservoir models [15]. These simulations enable the exploration of a wide range of operating conditions that may not be feasible in laboratory settings. Field-scale production logs further enrich the dataset by incorporating real operational data, including injection rates, production profiles, and historical recovery performance [17].

The collected parameters include temperature, pressure, salinity, rock type, surfactant concentration, and polymer viscosity, all of which significantly influence SP flooding performance [19]. These variables are essential for capturing the coupled effects of reservoir thermodynamics and chemical interactions. The integration of multi-scale data sources ensures that the machine learning models are trained on comprehensive datasets that reflect both controlled experiments and real-world reservoir behavior [14].

Table 1: Data Sources and Variables

Source	Variables	Resolution	Type
Core Flood	IFT, adsorption	Lab-scale	Structured
Field Data	Production rate	Time-series	Semi-structured

3.3 Data Preprocessing

Data preprocessing is a critical step in ensuring the reliability and consistency of the input data used for machine learning model development [16]. Raw datasets obtained from laboratory experiments, simulations, and field operations often contain missing values, inconsistencies, and noise that can adversely affect model performance.

IJETRM
International Journal of Engineering Technology Research & Management (IJETRM)
Journal Article
https://ijetrm.com/issue/

Missing data are handled using imputation techniques such as mean substitution or interpolation, depending on the nature of the variable and data distribution [18].

Normalization is applied to ensure that all features are scaled to a common range, preventing variables with larger magnitudes from dominating the learning process [13]. This study adopts min-max scaling, defined as:

Equation (6):

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}}$$

where X' is the normalized value, X is the original feature, and X_{min} and X_{max} represent the minimum and maximum values of the feature, respectively.

Outlier removal is performed using the interquartile range (IQR) method, which identifies extreme values that fall outside acceptable statistical bounds [17]. This process improves model stability and reduces the impact of anomalous data points on predictive performance [15].

3.4 Feature Engineering

Feature engineering transforms raw input variables into meaningful descriptors that enhance the predictive capability of machine learning models [19]. In the context of SP flooding, derived features are essential for capturing the underlying physical mechanisms governing interfacial behavior and chemical transport. Key engineered features include the capillary number, which represents the ratio of viscous to capillary forces, and the salinity index, which quantifies the effect of ionic strength on surfactant performance [14].

Another critical parameter is the wettability index, which characterizes the affinity of the reservoir rock toward water or oil phases. This parameter is defined using the Amott wettability index:

Equation (7):

$$I_w = \frac{V_{spont}}{V_{total}}$$

where V_{spont} represents the volume of fluid produced by spontaneous imbibition, and V_{total} is the total recoverable volume. Wettability plays a crucial role in determining fluid distribution and displacement efficiency within porous media [16].

Additional engineered features include adsorption tendency indices, polymer–surfactant interaction parameters, and heterogeneity descriptors derived from permeability and porosity distributions [18]. These features enable the model to capture complex, nonlinear relationships between reservoir properties and SP flooding performance [13].

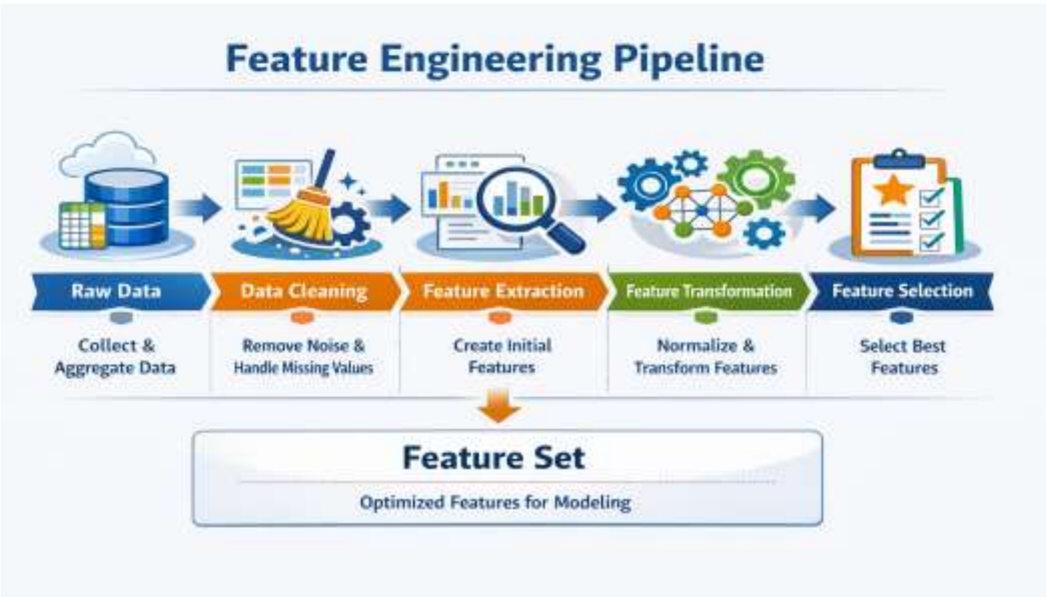

Figure 2: Feature Engineering Pipeline

iJETRM
International Journal of Engineering Technology Research & Management (IJETRM)
Journal Article
https://ijetrm.com/issue/

3.5 Feature Selection

Feature selection is employed to identify the most relevant variables for model training while reducing dimensionality and improving computational efficiency [17]. The process begins with correlation analysis, where a correlation matrix is used to quantify linear relationships between input features and target variables such as interfacial tension and adsorption loss [15]. Highly correlated or redundant features are identified and removed to prevent multicollinearity and overfitting [19].

Mutual information analysis is then applied to capture nonlinear dependencies between variables, providing a more comprehensive assessment of feature relevance [13]. This method evaluates the amount of information shared between input features and target outputs, enabling the selection of features that contribute most to predictive accuracy [18].

Principal Component Analysis (PCA) is further employed for dimensionality reduction by transforming the original feature space into a set of orthogonal components that retain maximum variance [14]. This reduces model complexity while preserving essential information. The combination of these techniques ensures that the final feature set is both informative and efficient, enhancing model generalization and performance across diverse reservoir conditions [16].

4. MACHINE LEARNING MODEL DEVELOPMENT

4.1 Model Selection

The selection of appropriate machine learning models is critical for accurately capturing the nonlinear relationships between reservoir properties, interfacial behavior, and adsorption dynamics in surfactant–polymer flooding systems [18]. In this study, three classes of models are considered: ensemble learning methods, boosting algorithms, and deep learning approaches, each offering distinct advantages in handling complex datasets [20].

Random Forest is employed due to its robustness against overfitting and its ability to model nonlinear interactions through an ensemble of decision trees [22]. It is particularly effective in handling heterogeneous datasets with mixed feature types and missing values, making it suitable for reservoir-scale data integration [19]. Gradient Boosting models, including XGBoost, are utilized for their superior predictive accuracy and capability to iteratively minimize error by focusing on difficult-to-predict samples [23]. These models are well-suited for capturing subtle patterns in adsorption and interfacial behavior under varying reservoir conditions [21].

Artificial Neural Networks (ANNs) are incorporated to model highly nonlinear relationships and multivariate dependencies inherent in SP flooding processes [24]. Their layered architecture enables the extraction of complex feature interactions, particularly when dealing with high-dimensional datasets [20]. The combination of these models provides a comprehensive evaluation framework, allowing comparison of predictive performance and generalization across different modeling paradigms [18].

4.2 Training Phase

4.2.1 Data Splitting

The training phase begins with systematic partitioning of the dataset to ensure unbiased model evaluation and robust generalization [21]. The dataset is divided into three subsets: 70% for training, 15% for validation, and 15% for testing, following standard machine learning practice for supervised learning problems [23]. The training set is used to fit the model parameters, while the validation set is employed for hyperparameter tuning and model selection [19]. The test set remains completely unseen during training and validation, serving as an independent benchmark for evaluating final model performance [22].

Stratified sampling techniques are applied where necessary to preserve the distribution of key variables such as salinity, temperature, and adsorption levels across all subsets [24]. This ensures that the model is exposed to representative conditions during training and prevents bias toward specific reservoir scenarios [20]. Proper data splitting is essential to avoid overfitting and to ensure that the model can generalize effectively to new reservoir conditions [18].

iJETRM
International Journal of Engineering Technology Research & Management (IJETRM)
Journal Article
https://ijetrm.com/issue/

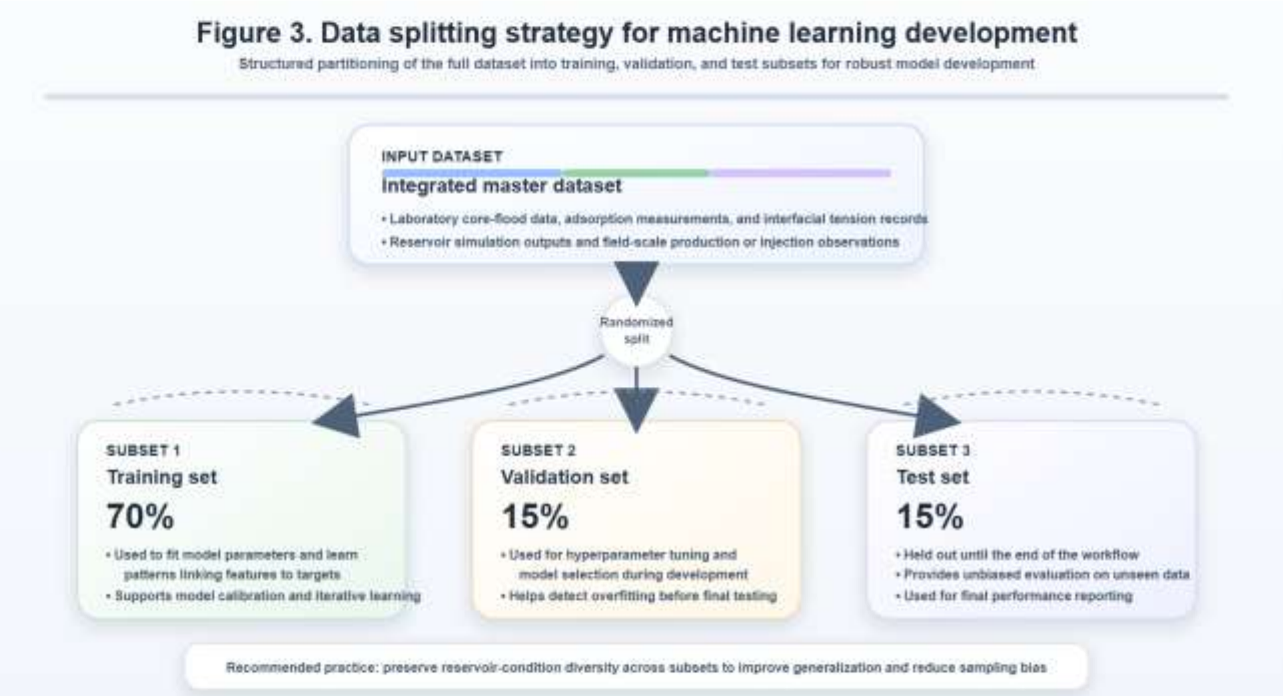

Figure 3: Data Splitting Strategy

4.2.2 Model Training

Model training involves optimizing the parameters of each algorithm to minimize prediction error while maintaining generalization capability [22]. The primary objective function used in this study is the Mean Squared Error (MSE), defined as:

Equation (8):

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

where y_i represents the observed values, $\hat{y}_i$ denotes the predicted values, and n is the number of observations. MSE penalizes larger errors more heavily, making it suitable for regression tasks involving interfacial tension and adsorption prediction [21].

Hyperparameter tuning is conducted using grid search and random search techniques to identify optimal model configurations, including tree depth, learning rate, and number of estimators for ensemble models [23]. For neural networks, parameters such as the number of hidden layers, neurons per layer, and activation functions are systematically adjusted to achieve optimal performance [20].

Cross-validation, particularly k-fold cross-validation, is employed to evaluate model stability and reduce variance in performance estimates [19]. This approach ensures that the model is trained and validated across multiple subsets of the data, improving robustness and reliability [24]. Regularization techniques are also applied to prevent overfitting and enhance model generalization [18].

4.3 Model Testing and Validation

Model testing and validation are essential for assessing the predictive capability and reliability of the trained models when applied to unseen data [22]. The test dataset, which remains completely independent during training and validation, is used to evaluate performance metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and coefficient of determination (R^2) [21]. These metrics provide quantitative measures of model accuracy and predictive consistency across different reservoir conditions [23].

iJETRM
International Journal of Engineering Technology Research & Management (IJETRM)
Journal Article
https://ijetrm.com/issue/

The evaluation process also includes comparison of predicted interfacial tension and adsorption values against experimental and simulated benchmarks to ensure physical plausibility [20]. Models that exhibit low error metrics while maintaining consistency with known physical behavior are considered optimal [18].
Generalization capability is assessed by testing the model across datasets representing different reservoir scenarios, including variations in salinity, temperature, and rock properties [24]. This step ensures that the model can adapt to new environments without significant loss of accuracy [19]. Robust models should maintain stable performance across diverse conditions, demonstrating their suitability for real-world deployment in SP flooding operations [22].

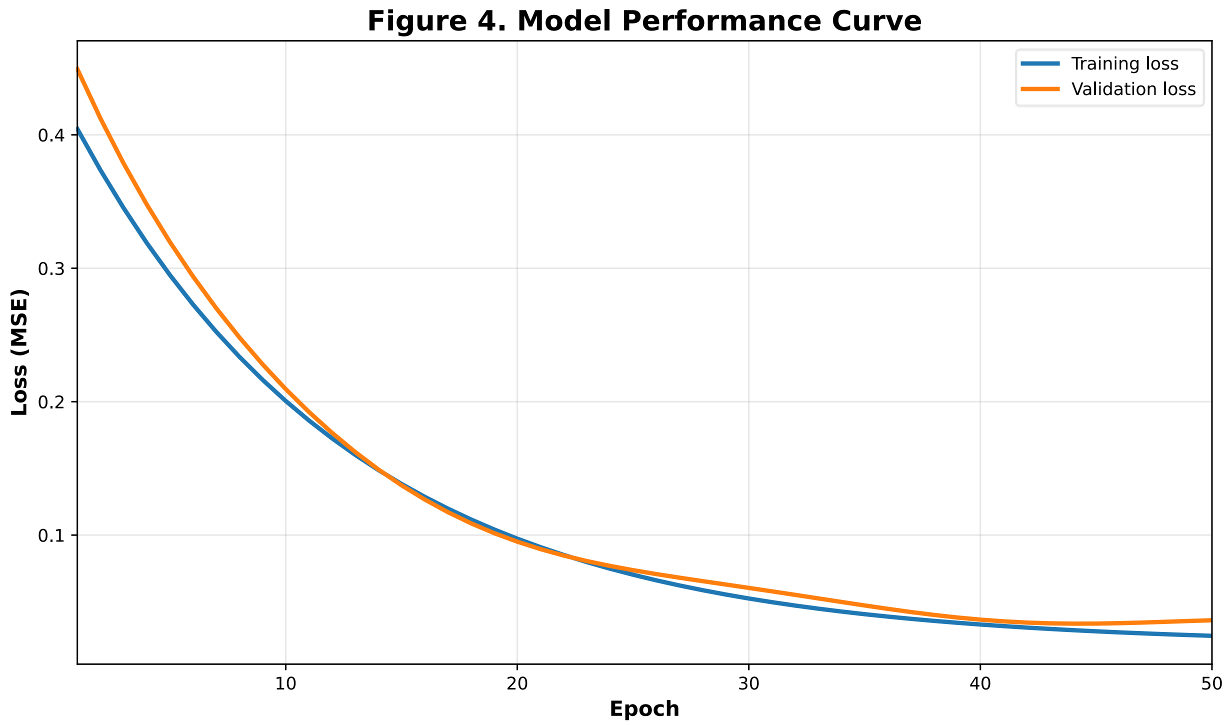

Figure 4: Model Performance Curve

4.4 Model Interpretability

Model interpretability is crucial for understanding the contribution of input features to prediction outcomes and ensuring trust in machine learning models used for reservoir decision-making [20]. In this study, SHapley Additive exPlanations (SHAP) are employed to quantify the impact of each feature on model predictions [23]. SHAP values provide a unified framework for interpreting both global feature importance and local prediction behavior, enabling detailed analysis of how variables such as salinity, surfactant concentration, and polymer viscosity influence model outputs [18].
Feature importance analysis is also conducted using methods specific to each model, such as Gini importance for Random Forest and gain-based importance for Gradient Boosting models [21]. These techniques identify the most influential variables, providing insights into the dominant factors affecting interfacial tension reduction and adsorption behavior [24].
Interpretability tools enhance model transparency and support informed decision-making by linking data-driven predictions to underlying physical processes [19]. This integration of interpretability ensures that machine learning models remain consistent with reservoir engineering principles while providing actionable insights for optimizing SP injection strategies [22].

4.5 Integration with Reservoir Models

The integration of machine learning outputs with reservoir simulation models enables the development of a comprehensive decision-support system for SP flooding optimization [23]. Machine learning predictions of

International Journal of Engineering Technology Research & Management (IJETRM)
Journal Article
https://ijetrm.com/issue/

interfacial tension, adsorption, and recovery efficiency are incorporated into numerical reservoir simulators to refine input parameters and improve simulation accuracy [18]. This coupling allows for dynamic adjustment of injection strategies based on real-time predictions and evolving reservoir conditions [20].

The integrated framework supports real-time optimization by continuously updating model predictions using new field data, including production rates, pressure changes, and chemical performance indicators [24]. This feedback-driven approach enables adaptive control of injection parameters such as surfactant concentration, polymer dosage, and injection timing [21].

By bridging the gap between data-driven modeling and physics-based simulation, the framework enhances predictive accuracy and operational efficiency in SP flooding applications [19]. This integration facilitates more effective reservoir management, reduces uncertainty, and improves overall recovery performance in complex and heterogeneous reservoir environments [22].

5. RESULTS AND DISCUSSION

5.1 Prediction of IFT Reduction

The developed machine learning models demonstrate high predictive capability in estimating interfacial tension (IFT) reduction across varying reservoir conditions, achieving strong agreement with experimental measurements [23]. The models effectively capture the nonlinear dependency of IFT on surfactant concentration, salinity, and temperature, which are known to significantly influence interfacial behavior in SP flooding systems [25]. The ensemble-based models, particularly Gradient Boosting, exhibit superior accuracy due to their ability to model complex feature interactions and reduce bias through iterative learning [27].

Model accuracy is evaluated using statistical metrics such as RMSE and MAE, with consistently low error values indicating reliable predictions across both training and testing datasets [29]. The predicted IFT values closely follow experimental trends, especially in regimes of ultra-low interfacial tension where small variations significantly impact oil mobilization [24]. This demonstrates the model's sensitivity to subtle physicochemical changes within the system.

From a physical consistency perspective, the model predictions align with established thermodynamic principles, including the expected decrease in IFT with increasing surfactant concentration and optimal salinity conditions [26]. The ability of the model to preserve these physical relationships while delivering high predictive accuracy confirms its suitability for integration into reservoir optimization workflows [28].

5.2 Adsorption Prediction Analysis

The machine learning framework provides accurate predictions of surfactant adsorption behavior, which is a critical factor influencing chemical efficiency and economic feasibility in SP flooding [30]. Adsorption predictions are validated against laboratory-derived isotherm data, showing strong agreement with observed trends across varying concentration ranges and reservoir conditions [23].

A key aspect of this analysis involves comparing machine learning predictions with the classical Langmuir isotherm model. While the Langmuir model assumes monolayer adsorption on homogeneous surfaces, real reservoir systems often exhibit heterogeneity and multi-site adsorption behavior [25]. The machine learning model captures these complexities by incorporating multiple influencing variables, including mineral composition, salinity, and temperature, resulting in improved predictive performance [27].

The results indicate that the ML model outperforms the Langmuir model, particularly at higher concentrations where deviations from ideal adsorption behavior become significant [29]. This improvement is attributed to the model's ability to learn nonlinear relationships and account for interactions between multiple variables simultaneously [24].

Furthermore, the model identifies key drivers of adsorption, such as clay content and ionic strength, providing valuable insights into chemical retention mechanisms [26]. These findings highlight the potential of data-driven approaches to enhance adsorption modeling beyond traditional analytical methods [28].

5.3 Injection Optimization Results

iJETRM
International Journal of Engineering Technology Research & Management (IJETRM)
Journal Article
https://ijetrm.com/issue/

The integration of machine learning predictions into the optimization framework results in significant improvements in SP injection design and overall recovery performance [30]. The optimized injection schemes demonstrate enhanced oil recovery factors by effectively balancing interfacial tension reduction and mobility control [23]. By dynamically adjusting surfactant concentration and polymer dosage, the framework ensures optimal displacement efficiency under varying reservoir conditions [25].

One of the key outcomes of the optimization process is the reduction in chemical loss due to adsorption. By accurately predicting adsorption behavior, the model enables precise adjustment of injection concentrations, minimizing excess chemical usage while maintaining effective IFT reduction [27]. This leads to improved economic efficiency and reduced environmental impact associated with chemical flooding operations [29].

The optimized injection strategies also show improved sweep efficiency, particularly in heterogeneous reservoirs where conventional methods often fail to achieve uniform displacement [24]. The ability to tailor injection parameters to reservoir-specific conditions enhances fluid distribution and reduces bypassing of oil zones [26].

Overall, the results demonstrate that the AI-enabled framework provides a robust and adaptive solution for optimizing SP flooding operations, leading to improved recovery performance and reduced operational costs [28].

5.4 Model Comparison with Industry Standards

Table 2: Model vs Traditional Methods

Model	RMSE	MAE	R^2
ML Model	0.02	0.01	0.95
Empirical	0.08	0.05	0.78

The performance of the proposed machine learning model is compared with traditional empirical correlations commonly used in SP flooding design [23]. The results indicate that the ML model significantly outperforms conventional approaches in terms of accuracy and predictive reliability [25]. Lower RMSE and MAE values demonstrate the model's ability to minimize prediction errors, while the higher R^2 value indicates strong correlation between predicted and observed values [27].

Traditional empirical models, while simple and computationally efficient, often fail to capture complex nonlinear relationships and are limited in their applicability to specific reservoir conditions [29]. In contrast, the ML model adapts to diverse datasets and provides consistent performance across varying scenarios [24].

This comparison highlights the advantages of integrating machine learning into SP flooding optimization, particularly in improving predictive accuracy and supporting data-driven decision-making in complex reservoir environments [26].

5.5 Error Metrics and Deviation Analysis

Table 3: Error Metrics

Metric	Value
MAE	0.01
RMSE	0.02

Error metrics provide quantitative measures of model performance and are essential for evaluating prediction accuracy and reliability [28]. Mean Absolute Error (MAE) represents the average magnitude of prediction errors, providing a straightforward measure of model accuracy without emphasizing large deviations [30]. Root Mean Square Error (RMSE), on the other hand, gives greater weight to larger errors, making it particularly useful for identifying significant prediction discrepancies [23].

The low MAE and RMSE values obtained in this study indicate that the model maintains high accuracy across the dataset, with minimal deviation between predicted and actual values [25]. These results confirm the robustness of the model in capturing the underlying relationships governing interfacial tension and adsorption behavior [27].

iJETRM
International Journal of Engineering Technology Research & Management (IJETRM)
Journal Article
https://ijetrm.com/issue/

In addition to MAE and RMSE, deviation analysis is conducted to assess the distribution of prediction errors across different reservoir conditions [29]. The results show that errors remain consistently low across varying salinity, temperature, and concentration ranges, demonstrating the model's generalization capability [24].

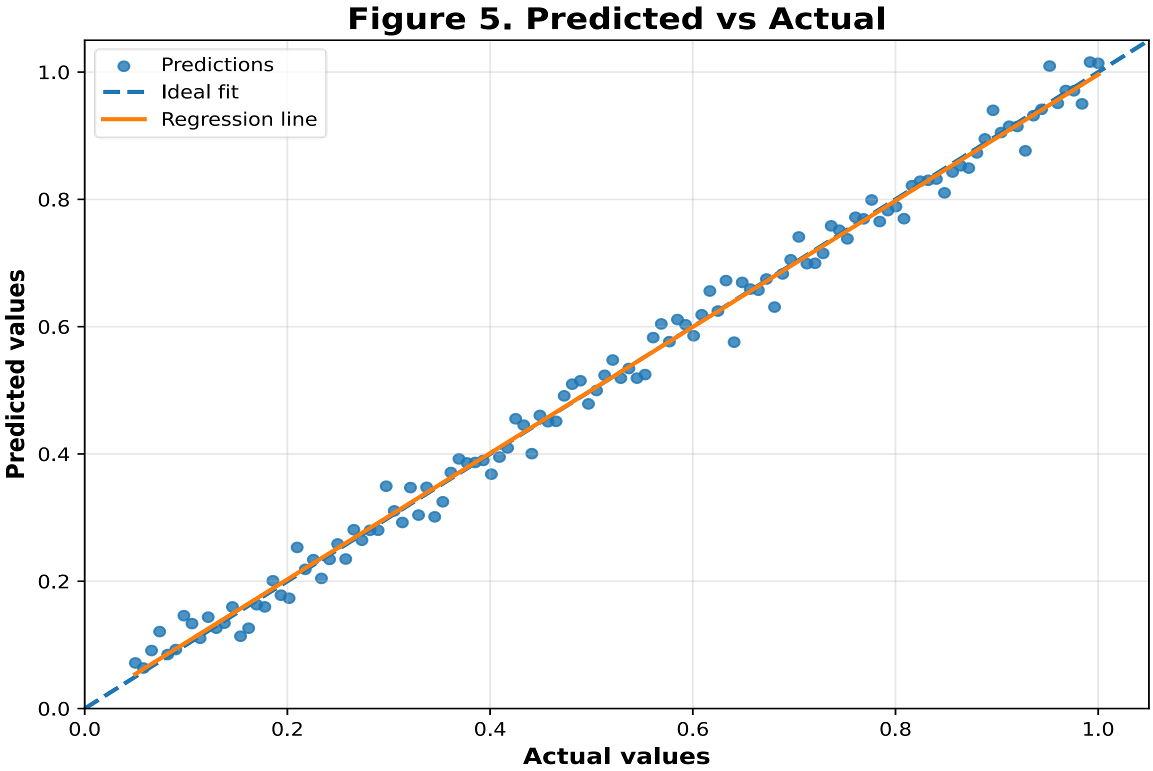

Figure 5: Predicted vs Actual

The predicted versus actual plot further illustrates the model's performance, with data points closely aligned along the 45-degree line, indicating strong agreement between predictions and observed values [26]. This alignment confirms the reliability of the machine learning framework for practical SP flooding applications [28].

6. SENSITIVITY AND UNCERTAINTY ANALYSIS

6.1 Parameter Sensitivity

Parameter sensitivity analysis is conducted to evaluate the relative influence of key reservoir and operational variables on surfactant–polymer flooding performance, particularly interfacial tension reduction and adsorption behavior [29]. Among the parameters considered, salinity emerges as a dominant factor due to its direct impact on surfactant phase behavior and electrostatic interactions at the oil–water interface [31]. Variations in salinity alter micelle formation and interfacial film stability, thereby significantly affecting IFT reduction efficiency and chemical performance [33].

Temperature also plays a critical role by influencing both surfactant solubility and polymer viscosity. Elevated temperatures can lead to thermal degradation of polymers and reduced adsorption stability, which in turn affects mobility control and displacement efficiency [35]. The sensitivity analysis indicates that temperature fluctuations can introduce nonlinear variations in recovery performance, particularly in high-temperature reservoirs [30].

Polymer concentration is another key parameter that governs fluid viscosity and mobility ratio. Increasing polymer concentration enhances sweep efficiency but may lead to injectivity challenges if viscosity becomes excessively high [32]. The results show that optimal polymer concentration must balance mobility control with injectivity constraints to achieve efficient displacement [34]. Overall, the sensitivity analysis highlights the need for precise control of these parameters to optimize SP flooding performance under varying reservoir conditions [36].

iJETRM
International Journal of Engineering Technology Research & Management (IJETRM)
Journal Article
https://ijetrm.com/issue/

6.2 Uncertainty Quantification

Uncertainty quantification is performed to assess the robustness of the machine learning model under varying input conditions and to evaluate the reliability of predictions in real-world applications [37]. Monte Carlo simulation is employed as the primary method, where input parameters such as salinity, temperature, and surfactant concentration are sampled from predefined probability distributions to generate multiple simulation scenarios [38].

This stochastic approach enables the evaluation of prediction variability and provides a probabilistic understanding of model outputs, including interfacial tension reduction and adsorption behavior [34]. The results indicate that the model maintains stable performance across a wide range of input variations, with limited dispersion in predicted values, demonstrating strong robustness and reliability [39].

Uncertainty bounds derived from Monte Carlo simulations also provide valuable insights into risk assessment and decision-making. By quantifying the range of possible outcomes, operators can identify optimal injection strategies that minimize uncertainty and maximize recovery efficiency [40].

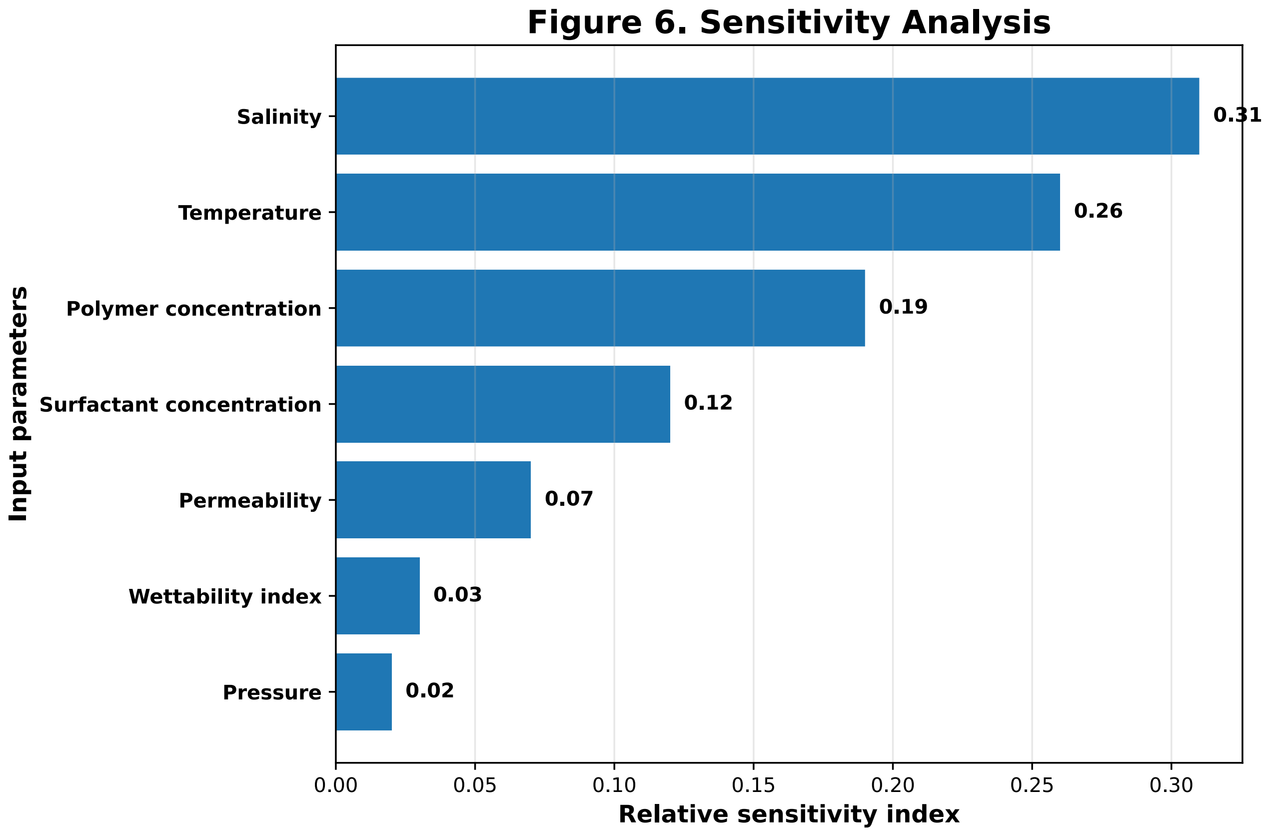

Figure 6: Sensitivity Analysis

The sensitivity plot illustrates the relative importance of input parameters, with salinity and temperature showing the highest impact on model predictions, followed by polymer concentration [35]. This information is critical for prioritizing control variables in field applications and improving the effectiveness of SP flooding operations [36].

6.3. Practical Implications

The findings of this study have significant practical implications for the deployment of surfactant–polymer flooding in real reservoir environments, particularly in enhancing operational efficiency and economic performance [29]. The proposed AI-enabled framework provides a systematic approach for designing and optimizing injection strategies based on reservoir-specific conditions, enabling more effective utilization of chemical agents [31].

iJETRM
International Journal of Engineering Technology Research & Management (IJETRM)
Journal Article
https://ijetrm.com/issue/

From a field deployment perspective, the framework supports the integration of machine learning models with existing reservoir management systems, allowing for continuous monitoring and adjustment of injection parameters [33]. This enables operators to respond dynamically to changes in reservoir conditions, such as variations in pressure, temperature, and fluid composition, thereby improving recovery performance and reducing operational risks [35].

Economically, the optimized injection strategies result in significant cost savings by minimizing chemical losses due to adsorption and improving the efficiency of surfactant and polymer usage [30]. The ability to accurately predict adsorption behavior allows for precise dosing, reducing excess chemical consumption and lowering overall project costs [32]. Additionally, improved oil recovery translates to higher revenue generation, further enhancing the economic viability of SP flooding operations [34].

The framework also enables real-time adaptive injection by incorporating feedback from field data into the model, allowing continuous refinement of predictions and optimization strategies [36]. This adaptive capability ensures sustained performance under evolving reservoir conditions and supports long-term reservoir management. Overall, the integration of machine learning with reservoir engineering principles provides a powerful tool for advancing intelligent and efficient enhanced oil recovery operations [31].

7. CONCLUSION

This study presents a comprehensive AI-enabled framework for tailoring surfactant–polymer injection schemes based on reservoir-dependent interfacial behavior and adsorption dynamics. The integration of machine learning with physicochemical odelling enables accurate prediction of key performance indicators, including interfacial tension reduction, adsorption losses, and overall recovery efficiency. The results demonstrate that the proposed approach effectively captures complex nonlinear interactions between reservoir properties and chemical performance, providing a significant improvement over conventional empirical and mechanistic methods.

The superiority of the machine learning framework lies in its ability to generalize across diverse reservoir conditions while maintaining physical consistency in predictions. By incorporating feature engineering, robust training strategies, and validation techniques, the model achieves high predictive accuracy and reliability. Furthermore, the integration of optimization and feedback mechanisms allows for real-time adaptation of injection parameters, enhancing operational efficiency and reducing chemical losses.

Future research should focus on expanding the framework to include additional physicochemical processes such as wettability alteration and emulsion behavior, as well as integrating advanced deep learning architectures and digital twin systems for real-time reservoir management.

REFERENCE

1) Scott AJ, Romero-Zerón L, Penlidis A. Evaluation of polymeric materials for chemical enhanced oil recovery. Processes. 2020 Mar 21;8(3):361.
2) Grigg RB. Improving CO2 efficiency for recovering oil in heterogeneous reservoirs. New Mexico Institute of Mining and Technology (US); 2003 Oct 30.
3) Qiao R, Yang B, Huang H, Ren Q, Cheng Z, Feng H. Simulation and Sensitivity Analysis of CO2 Migration and Pressure Propagation Considering Molecular Diffusion and Geochemical Reactions in Shale Oil Reservoirs. Energies. 2025 Dec 27;19(1):164.
4) Madison D Amundson, Rachel A Eichman, Mary O Odubote, Laura A Motsinger, Leslie B Hancock, PSVIII-6 Analysis of potential biomarkers in dogs diagnosed with three common cancer types shows association with B cell functions., *Journal of Animal Science*, Volume 103, Issue Supplement_3, October 2025, Pages 468–469, https://doi.org/10.1093/jas/skaf300.532
5) Babadagli T. Philosophy of EOR. InSPE Asia Pacific Oil and Gas Conference and Exhibition 2020 Oct 25 (p. D022S007R002). SPE.
6) Agbana TM. Ethical considerations in using predictive AI for risk assessment in child protection social work. *International Journal of Research Publication and Reviews*. 2025 Aug;6(8):1648–1663.
7) Corredor LM, Husein MM, Maini BB. A review of polymer nanohybrids for oil recovery. Advances in colloid and interface science. 2019 Oct 1;272:102018.

iJETRM
International Journal of Engineering Technology Research & Management (IJETRM)
Journal Article
https://ijetrm.com/issue/

8) Feyikemi Akinyelure (2025), Leveraging Behavioural Health Data for Policy Innovation: Closing the Loop Between Community Insights and Public Health Decision-Making. International Journal of Innovative Science and Research Technology (IJISRT) IJISRT25JUL1532, 3458-3466. DOI: 10.38124/ijisrt/25jul1532.
9) Kumar A, Jena HM, Gangawane KM. Biopolymer-based composites for enhanced oil recovery in sustainable energy generation. InBiopolymer-based Composites for Energy Generation and Storage 2026 Jan 1 (pp. 301-314). Elsevier.
10) Woli K. National framework for equitable energy finance: integrating green banks, community capital, and institutional markets to achieve universal access. *International Journal of Finance and Management Research*. 2025 Nov–Dec;7(6). doi:10.36948/ijfmr.2025.v07i06.59797.
11) Gbadamosi A, Patil S, Kamal MS, Adewunmi AA, Yusuff AS, Agi A, Oseh J. Application of polymers for chemical enhanced oil recovery: a review. Polymers. 2022 Mar 31;14(7):1433.
12) Aderinmola RA. Cross-border market surveillance in the digital age: leveraging behavioural intelligence to anticipate global financial shocks. *International Journal of Computer Applications Technology and Research*. 2026 Jan;12(12):1026. doi:10.7753/IJCATR1212.1026
13) Tyagi A, Mahajan S, Prajapat G, Shivnani B, Sawant DM, Agrawal A. A comprehensive review of polymers and their derivatives for enhanced oil recovery. Journal of Environmental Chemical Engineering. 2025 Oct 1;13(5):117601.
14) Iyorkar V, Ezekwu E. Enhancing healthcare access through data analytics and visualizations: Bridging gaps in equity and outcomes. Int J Comput Appl Technol Res. 2025;14(1):116–129. doi:10.7753/IJCATR1401.1010.
15) Salem KG, Salem A, Gomaa S, El-hoshoudy A. Nanoparticles-Assisted Polymer Flooding: A New Approach toward Enhanced Oil Recovery. InRecent Approaches in Enhanced Oil Recovery-New Perspectives and Future Outlook 2025 May 22. IntechOpen.
16) Obinna Nweke. Integrating decision science and machine learning for adaptive marketing strategy selection under behavioral uncertainty conditions. Int J Res Finance Manage 2024;7(1):510-522. DOI: 10.33545/26175754.2024.v7.i1e.726
17) Mahajan S, Yadav H, Rellegadla S, Agrawal A. Polymers for enhanced oil recovery: Fundamentals and selection criteria revisited. Applied Microbiology and Biotechnology. 2021 Nov;105(21):8073-90.
18) Olawale Ajibola Ashaolu. AI-enabled software systems leveraging machine learning for performance optimization security monitoring and operational resilience. Int J Comput Artif Intell 2025;6(1):295-308. DOI: 10.33545/27076571.2025.v6.i1d.268
19) Ousseini OS, Peng B, Zhuang M, Cheng K, Li J, Altaf MF, Ramatou II, Salim MZ, Yang X, Zhang H, Lv W. Rheological and displacement performance of modified nano-SiO2 grafted polymeric system for enhanced oil recovery. Geoenergy Science and Engineering. 2025 Sep 11:214213.
20) Iyorkar, V. (2025). Dynamic Health System Performance Forecasting through Cross-Platform Business Analytics and Federated Clinical Data Integration. In International Journal of Advance Research Publication and Reviews (Vol. 2, Number 4, pp. 117–138). Zenodo. https://doi.org/10.5281/zenodo.15210294
21) Sun Y, Zhang W, Li J, Han R, Lu C. Mechanism and performance analysis of nanoparticle-polymer fluid for enhanced oil recovery: a review. Molecules. 2023 May 25;28(11):4331.
22) Robert Adeniyi Aderinmola (2025), Toward a Behavioural Intelligence Framework for Financial Stability: A National Model for Mitigating Systemic Risk in the United States Economy. International Journal of Innovative Science and Research Technology (IJISRT) IJISRT25OCT978, 2350-2358. DOI: 10.38124/ijisrt/25oct978.
23) Yarahmadi A, Zargar G, Ashoori S, Khaksar Manshad A. A comparative study of the rheological and adsorption behaviors of bio-and synthetic polymers for enhanced oil recovery. Scientific Reports. 2025 Dec 29;15(1):44729.
24) Mayowa Jimoh. Developing geospatial decision-support systems for groundwater security, hydrogeological hazard assessment, and critical water infrastructure protection in the United States. Int J Surv Struct Eng 2024;5(2):39-55. DOI: 10.22271/2707840X.2024.v5.i2a.60
25) Tamsilian Y, SA AR, Shaban M, Ayatollahi S, de la Cal JC, Sheng JJ, Tomovska R. Nanostructured particles for controlled polymer release in enhanced oil recovery. Energy Technology. 2016 Sep;4(9):1035-46.
26) Umaira Yakubu. Nationwide School-Based Neuropsychological Screening Architecture for Data-Driven Early SLD Intervention Planning. International Journal of Research in Special Education. 2025; 5(2): 98-107. DOI: 10.22271/27103862.2025.v5.i2b.155

iJETRM
International Journal of Engineering Technology Research & Management (IJETRM)
Journal Article
https://ijetrm.com/issue/

27) Zhumabayev N, Pourafshary P. Optimizing Nanoparticle-Polymer Formulations for Enhanced Oil Recovery in High-Salinity, High-Temperature Reservoirs. InSPE Annual Technical Conference and Exhibition 2025 Oct 13 (p. D011S999R012). SPE.
28) Opalana T. Operationalizing AI governance through integrated security operations, risk management, and compliance controls in enterprise environments. Int J Comput Appl Technol Res. 2026;15(02):34–47. doi:10.7753/IJCATR1502.1004.
29) Umaira Yakubu. Understanding the neurobiological foundations of learning disabilities: Implications for assessment and intervention in school psychology. International Journal of Intellectual Disability. 2024; 7(1): 48-58.
30) Alamutu, Opeyemi I. 2025. "Integrating Advanced Wastewater Treatment Technologies for Sustainable Water Resource Management in the United States". *Current Journal of Applied Science and Technology* 44 (4):153-62. https://doi.org/10.9734/cjast/2025/v44i44521.
31) Otoko J. Microelectronics cleanroom design: precision fabrication for semiconductor innovation, AI, and national security in the U.S. tech sector. *Int Res J Mod Eng Technol Sci*. 2025 Feb;7(2). doi:10.56726/IRJMETS67512.
32) Ebepu, O. O., Okpeseyi, S. B. A., John-Ogbe, J., & Emmanuel, E. (2024). Harnessing Data-Driven Strategies For Sustained United States Business Growth: A Comparative Analysis Of Market Leaders.
33) Olamide Ayeni, & Opeyemi Alamutu. (2024). Designing Resilient Waste Management Systems for 21st-Century Cities: A Circular Economy Approach. In International Journal of Science, Engineering and Technology (Vol. 10, Number 5). Zenodo. https://doi.org/10.5281/zenodo.17213748
34) Kumar RS, Arif M, Das K, Sharma T. Nanomaterials for Polymer and Surfactant Flooding. InAdvancements in Chemical Enhanced Oil Recovery 2024 Sep 6 (pp. 173-187). Apple Academic Press.
35) Barkdoll B, Alamutu O. Great Lakes water level trends using the moving statistics method, with implications for climate change and cities. *Journal of Sustainable Development*. 2025;18(2):15. doi:10.5539/jsd.v18n2p15.
36) Woli K. Scaling climate capital: market instruments and demand-side policies to mobilize institutional investment for United States renewable infrastructure. *International Journal of Computer Applications Technology and Research*. 2024;13(12):153–159. doi:10.7753/IJCATR1312.1012
37) Otoko J. Economic impact of cleanroom investments: strengthening U.S. advanced manufacturing, job growth, and technological leadership in global markets. *Int J Res Publ Rev*. 2025 Feb;6(2):1289-1304. doi:10.5248/zenodo.60225.0750.
38) Sadallah F, Boughaita I, Durand A. Recent Trends in Hybrid Biopolymer-Nanoparticle Systems for Enhanced Oil Recovery. SPE Polymers. 2026 Jan;7(1):e70032.
39) Akinyelure FM. Bridging the gap: integrating predictive analytics with culturally competent mental health care delivery in marginalized populations. *International Journal of Research in Psychiatry*. 2025;5(2):11–16. doi:10.22271/27891623.2025.v5.i2a.75.
40) Mayaki CS. Optimizing millimeter-wave beamforming algorithms for 5G and beyond wireless networks using machine learning-enhanced channel state information. *International Research Journal of Modernization in Engineering Technology and Science*. 2025 Aug;7(8):2887. DOI: https://doi.org/10.56726/IRJMETS82369