

Artificial Intelligence–Driven Optimization of Low Salinity Water–Surfactant Flooding for Enhanced Oil Recovery

Dr. Rimi Bordoloi

Ph.D., Department of Petroleum Technology, Dibrugarh University

Abstract

Low Salinity Water–Surfactant Flooding (LSWF) is an advanced hybrid enhanced oil recovery (EOR) technique that combines wettability alteration induced by low salinity water injection with interfacial tension reduction provided by surfactants. While laboratory and pilot studies demonstrate significant incremental recovery, field implementation remains challenging due to reservoir heterogeneity, complex rock–fluid interactions, chemical adsorption, and operational uncertainties. Artificial Intelligence (AI) and Machine Learning (ML) offer powerful data-driven approaches capable of improving reservoir screening, optimizing injection chemistry, predicting performance, and enabling real-time adaptive control. This paper reviews the integration of AI/ML techniques into LSWF design and field implementation workflows. Applications include reservoir suitability prediction, surrogate reservoir modelling, surfactant and salinity optimization, sensitivity analysis, and real-time process control. AI-enabled optimization can enhance recovery efficiency, reduce chemical consumption, minimize operational risks, and improve economic viability. Challenges related to data availability, model generalization, and digital integration are also discussed. The study highlights the potential of AI-assisted chemical EOR to transform field-scale recovery strategies in mature reservoirs.

Keywords: Hybrid, Incremental, Rock-Fluid Interactions, Reservoir Modelling.

1. Introduction

Global energy demand and declining production from mature reservoirs necessitate improved recovery methods that are both cost-effective and environmentally responsible. Low Salinity Water Injection (LSWI) has gained attention as a promising EOR technique due to its ability to alter wettability and improve microscopic displacement efficiency. When combined with surfactant flooding, the hybrid Low Salinity Water–Surfactant Flooding (LSWF) process enhances oil mobilization by simultaneously reducing interfacial tension (IFT) and modifying rock–fluid interaction. Despite encouraging laboratory and pilot results, field deployment of LSWF is complex. Reservoir heterogeneity, chemical adsorption, scaling risks, and uncertainties in injection chemistry design limit consistent performance. Recent advances in Artificial Intelligence (AI) and Machine Learning (ML) provide new opportunities to address these challenges through data-driven optimization and predictive analytics. This paper presents a comprehensive overview of AI-enabled approaches for improving the efficiency and reliability of LSWF in field applications.

2. Mechanisms of Low Salinity Water–Surfactant Flooding

The effectiveness of LSWF arises from multiple coupled mechanisms:

2.1 Wettability Alteration

Low salinity brine modifies surface charge interactions between crude oil, brine, and rock minerals, shifting wettability toward more water-wet conditions.

2.2 Electrical Double Layer Expansion

Reduction in ionic strength expands the electrical double layer, weakening the adhesion between oil and rock surfaces.

2.3 Multicomponent Ion Exchange (MIE)

Exchange of divalent cations (Ca^{2+} , Mg^{2+}) with clay surfaces alters surface chemistry, promoting oil detachment.

2.4 Interfacial Tension Reduction

Surfactants reduce oil–water interfacial tension, increasing capillary number and mobilizing trapped oil.

2.5 Mobility and Sweep Efficiency Improvement

Optimized injection chemistry improves microscopic displacement while enhancing macroscopic sweep efficiency.

3. Challenges in Field Implementation

3.1 Reservoir Heterogeneity

Variations in permeability and mineralogy cause uneven sweep and early breakthrough.

3.2 Chemical Adsorption and Retention

Surfactant loss due to adsorption onto rock surfaces reduces economic efficiency.

3.3 Formation Damage and Fines Migration

Low salinity water can induce clay swelling and fines mobilization, impairing permeability.

3.4 Scaling and Compatibility Issues

Brine mixing may cause precipitation and scaling, affecting injectivity and production.

3.5 Operational Complexity

Optimizing salinity gradients, surfactant concentration, and injection scheduling requires extensive experimentation and simulation.

4. Role of Artificial Intelligence and Machine Learning

AI and ML techniques can model nonlinear reservoir processes, extract insights from large datasets, and optimize operational parameters.

4.1 Reservoir Screening and Candidate Selection

Supervised ML models can predict LSWF suitability using reservoir mineralogy, fluid properties, and salinity data.

4.2 Prediction of Oil Recovery Performance

Artificial Neural Networks (ANN), Random Forest, and Support Vector Machines can forecast recovery factors based on injection parameters and reservoir characteristics.

4.3 Optimization of Injection Chemistry

Machine learning optimization techniques can determine optimal:

- salinity gradients
- ionic composition

- surfactant concentration
- slug size and sequencing

4.4 Surrogate Reservoir Modelling

Deep learning surrogate models replicate reservoir simulation results with significantly reduced computational time, enabling rapid scenario evaluation.

4.5 Sensitivity Analysis and Feature Importance

Tree-based ML algorithms identify dominant parameters controlling recovery efficiency and chemical utilization.

4.6 Real-Time Monitoring and Adaptive Control

Reinforcement learning and predictive analytics enable dynamic adjustment of injection parameters using real-time field data.

5. AI-Driven Workflow for Field Implementation

5.1 Data Acquisition

- Core flood and laboratory data
- Petrophysical and geological data
- Formation water composition
- Production and injection history
- Real-time surveillance measurements

5.2 Data Preprocessing and Feature Engineering

Important engineered variables include ionic strength, divalent ion ratios, salinity gradients, wettability indices, and mobility ratio.

5.3 Model Development

- Supervised learning → performance prediction
- Unsupervised learning → reservoir clustering
- Optimization algorithms → chemical design
- Reinforcement learning → adaptive injection control

5.4 Model Validation

Validation is performed through history matching, pilot testing, and blind prediction evaluation.

5.5 Field Deployment

AI dashboards provide decision support for chemical dosing, injectivity management, and early detection of scaling or formation damage.

6. Operational Benefits

6.1 Improved Recovery Efficiency

Optimized injection chemistry improves displacement and sweep efficiency.

6.2 Reduced Chemical Consumption

AI optimization minimizes surfactant adsorption and chemical loss.

6.3 Risk Mitigation

Predictive models help prevent injectivity decline, scaling, and formation damage.

6.4 Enhanced Economic Performance

Improved recovery with optimized chemical use enhances project feasibility.

7. Challenges and Limitations

- Limited availability of high-quality field datasets
- Need for reservoir-specific model calibration
- Integration challenges with legacy digital infrastructure
- Requirement for multidisciplinary expertise

8. Future Scope of Research

Future developments may include:

- Digital twin reservoirs for chemical EOR optimization
- Explainable AI for mechanistic interpretation
- Integration with smart surfactants and nanofluids

Autonomous injection control systems.

9. Conclusion

Low Salinity Water–Surfactant Flooding represents a promising hybrid EOR method capable of enhancing oil recovery while reducing environmental impact. The integration of Artificial Intelligence and Machine Learning into LSWF design and operation enables intelligent reservoir screening, optimized chemical injection strategies, predictive performance modelling, and real-time adaptive control. AI-driven workflows can significantly enhance recovery efficiency, reduce operational risks, and improve economic viability. As digital oilfield technologies evolve, AI-assisted chemical EOR is poised to become a key component of future reservoir management strategies.

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