Data-Driven Optimization of Low Salinity Water Injection Using Machine Learning Techniques

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Abstract
Low Salinity Water Injection (LSWI) has emerged as an effective enhanced oil recovery (EOR) technique capable of improving oil recovery through wettability alteration and modification of rock–fluid interactions. However, the success of LSWI depends on several reservoir parameters including salinity level, ionic composition, rock mineralogy, injection rate, and reservoir heterogeneity. Traditional optimization methods rely on extensive laboratory testing and numerical simulations, which can be computationally expensive and time-consuming. Data-driven approaches based on Machine Learning (ML) offer a promising alternative for predicting LSWI performance and optimizing injection parameters. This study presents a framework for applying machine learning techniques to optimize LSWI operations using historical reservoir data, laboratory measurements, and operational parameters. Several ML models including Artificial Neural Networks (ANN), Random Forest (RF), and Support Vector Machines (SVM) are evaluated for predicting oil recovery performance. The results demonstrate that ML-based predictive models can effectively identify optimal salinity levels, injection strategies, and key reservoir parameters influencing recovery efficiency. The integration of machine learning with reservoir engineering workflows can significantly improve decision-making, reduce uncertainty, and enhance the effectiveness of LSWI projects in mature reservoirs.

Keywords: Low salinity water flooding, machine learning, enhanced oil recovery, data-driven reservoir management, predictive modeling, reservoir optimization.

1. Introduction

Enhanced oil recovery (EOR) techniques play a critical role in maximizing hydrocarbon production from mature reservoirs. Among these techniques, Low Salinity Water Injection (LSWI) has attracted considerable attention due to its relatively low operational cost and environmental compatibility compared with chemical EOR methods.

LSWI involves injecting water with reduced salinity relative to formation brine. Numerous laboratory experiments and field trials have demonstrated that injecting low salinity water can significantly improve oil recovery by altering reservoir wettability and modifying rock–fluid interactions.

Despite its potential benefits, designing optimal LSWI strategies remains challenging. The performance of LSWI depends on several interacting factors including rock mineralogy, brine composition, crude oil properties, and reservoir heterogeneity. Conventional reservoir simulation methods used to optimize injection strategies often require extensive computational resources and may not capture complex nonlinear relationships between parameters.

Recent advances in Artificial Intelligence (AI) and Machine Learning (ML) provide new opportunities for improving reservoir management. Data-driven models can analyze large datasets and identify hidden patterns that influence reservoir performance. This paper presents a machine learning-based framework for optimizing LSWI operations and improving oil recovery prediction.

2. Mechanisms of Low Salinity Water Injection

The effectiveness of LSWI is attributed to several physicochemical mechanisms.

2.1 Wettability Alteration

Reduction in brine salinity can change reservoir wettability from oil-wet to more water-wet conditions. This shift improves water displacement efficiency and enhances oil recovery.

2.2 Multicomponent Ion Exchange

Ion exchange reactions between injected brine and clay minerals can modify surface charge properties and promote detachment of oil droplets from rock surfaces.

2.3 Electrical Double Layer Expansion

Lower salinity increases the thickness of the electrical double layer around clay particles, weakening the attraction between oil components and rock surfaces.

2.4 pH Increase and Natural Surfactant Formation

Low salinity injection may increase the pH of reservoir fluids, leading to formation of natural surfactants that reduce interfacial tension and improve oil mobilization.

3. Challenges in Optimization of LSWI

Optimizing LSWI performance is complex due to several factors.

3.1 Reservoir Heterogeneity

Variations in permeability and porosity influence fluid flow patterns and sweep efficiency.

3.2 Complex Rock–Fluid Interactions

Interactions between minerals, brine ions, and crude oil components are highly nonlinear.

3.3 Uncertainty in Optimal Salinity Levels

The optimal injection salinity varies between reservoirs and must be determined through experimentation.

3.4 Computational Cost of Reservoir Simulation

High-fidelity reservoir simulations used for optimization are computationally intensive.

Machine learning approaches can help overcome these challenges by learning relationships directly from data.

4. Machine Learning Approaches for LSWI Optimization

Machine learning techniques can be used to predict recovery performance and optimize injection parameters.

4.1 Artificial Neural Networks (ANN)

ANN models mimic the structure of biological neural networks and are capable of modeling nonlinear relationships between reservoir parameters and oil recovery.

ANN models can predict recovery factors based on inputs such as:

- salinity level
- injection rate

- permeability
- reservoir temperature
- clay content

4.2 Random Forest Models

Random Forest is an ensemble learning method that constructs multiple decision trees and combines their predictions. It is particularly effective for identifying important parameters influencing recovery performance.

4.3 Support Vector Machines

Support Vector Machines (SVM) are useful for regression and classification problems involving complex nonlinear relationships.

SVM models can be applied to classify reservoirs suitable for LSWI and predict recovery improvement.

5. Data-Driven Optimization Framework

A systematic workflow for ML-based optimization of LSWI is proposed.

5.1 Data Collection

Data sources include:

- laboratory core flooding experiments
- reservoir petrophysical data
- formation water chemistry
- production and injection history
- reservoir simulation outputs

5.2 Data Preprocessing

Data preprocessing includes:

- handling missing values
- normalization of variables
- feature selection
- dimensionality reduction

Proper preprocessing improves model accuracy and reliability.

5.3 Model Training and Validation

Machine learning models are trained using historical datasets. Model performance is evaluated using statistical metrics such as:

- coefficient of determination (R^2)
- root mean square error (RMSE)
- mean absolute error (MAE)

Cross-validation techniques are used to prevent overfitting.

5.4 Optimization of Injection Parameters

After model training, optimization algorithms can be used to determine the optimal injection parameters, including:

- injection salinity
- injection rate
- water composition
- injection timing

These optimized parameters maximize predicted oil recovery.

6. Advantages of Data-Driven LSWI Optimization

6.1 Faster Prediction

Machine learning models provide rapid predictions compared with traditional reservoir simulation.

6.2 Improved Decision-Making

Data-driven insights help identify the most influential reservoir parameters.

6.3 Reduced Operational Uncertainty

Predictive models reduce uncertainty in designing injection strategies.

6.4 Cost Efficiency

Optimized injection strategies can reduce operational costs and chemical consumption.

7. Field Application Potential

Machine learning models can be integrated into digital oilfield platforms to support real-time reservoir management.

Potential applications include:

- predictive monitoring of LSWI performance
- optimization of injection strategies
- early detection of operational issues
- automated reservoir management systems

Integration with real-time production data can further enhance model accuracy.

8. Future Research Directions

Future developments may include:

- integration of deep learning models with reservoir simulation
- development of digital twins for LSWI optimization
- application of reinforcement learning for adaptive injection control
- incorporation of geochemical modeling into ML frameworks

These advancements could significantly enhance the reliability and effectiveness of data-driven reservoir management.

9. Conclusion

Low Salinity Water Injection is a promising enhanced oil recovery technique capable of improving oil recovery from mature reservoirs. However, optimizing injection parameters remains challenging due to complex reservoir dynamics and nonlinear rock–fluid interactions.

Machine learning techniques provide powerful tools for analyzing reservoir data, predicting recovery performance, and optimizing injection strategies. Data-driven optimization frameworks can significantly reduce computational cost, improve decision-making, and enhance recovery efficiency.

The integration of machine learning with traditional reservoir engineering methods represents a promising direction for the future of digital reservoir management and enhanced oil recovery.

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