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Full Length Article

Performance forecasting for polymer flooding in heavy oil reservoirs

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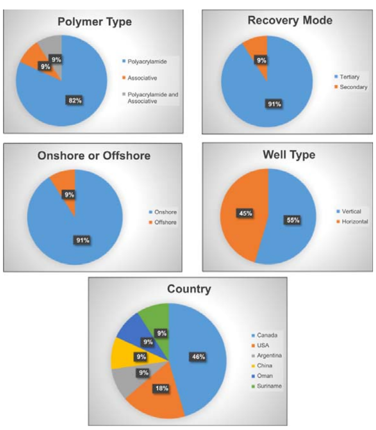
GRAPHICAL ABSTRACT



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ABSTRACT

As a supply for future fuel and energy demand, 95% of the bitumen deposits in North America are expected to become a major source. The Steam Assisted Gravity Drainage (SAGD) provides more efficient recovery of unconventional oil resources, such as heavy oil and bitumen, as compared to the other thermal recovery methods. The drawback associated with SAGD or other thermal methods is that they are economically non-profitable when applied to the deep and thin reservoirs. Environmental concerns related to land, water, and air also hinder the application of the aforementioned methods. These issues have provoked reservoir engineers to employ a remarkable alternate such as polymer flooding recovery technique in heavy oil reservoirs. Quick and practical decision-making process in presence of uncertainty-based reservoir development scenarios is a notable stimuli for reservoir management teams to find substitute modeling techniques for future performance forecasting of heavy oil reservoirs. Cognitive data-driven analytics, including artificial and computational intelligence techniques, statistical analyses, and data-mining practices, offers an attractive alternate especially in presence of high-dimensional data space and predictive modeling of an extremely nonlinear system. This study utilizes an extensive data set from the half-century review of laboratory to field scales polymer flooding in heavy oil reservoirs provided by Saboorian-Jooybari et al. (2015) and (2016). The exploratory data analysis is implemented to construct a comprehensive training data set from polymer flooding experimental and field data, which involves various attributes describing characteristics associated with reservoir heterogeneities and pertinent operating parameters. Demonstrated results imply that this advanced data-driven modeling technique has a great

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potential to be integrated into all reservoir development tools for future performance predictions of the underlying processes.

Nomenclature

Symbols

a	number of nodes on the first hidden layer
b	number of nodes on the second hidden layer
c_p	polymer concentration, ppm
D	reservoir depth, ft
E	vector of ACI-based network errors
F_{sal}	formation water salinity, ppm
H	Hessian matrix
I	identity matrix
J	Jacobian matrix
K	permeability, md
k-folds	number of folds in cross validation method
M	viscosity ratio
M_{wp}	polymer molecular weight
N	total number of assembled data
OF_{obs}	observed objective function
OF_p	predicted objective function
$\overline{OF_{obs}}$	average value of observed objective functions
P	number of training segment samples
PF	pilot pattern factor
Q	number of testing segment samples
R^2	r-squared error
S_p	polymer slug size, number of pore volume
T_r	reservoir temperature, °F
W	weight vector
Ws	well spacing, m
W_{sal}	injection water salinity, ppm

Greek letters

ϕ	porosity, %
μ	oil viscosity, cp
μ_p	polymer solution viscosity, cp
μ_{Tr}	oil viscosity at reservoir temperature, cp
η	training velocity factor
θ	bias vector

Acronyms

ACI	artificial and computational intelligence
ANN	artificial neural network
NN	neural network
API	American petroleum institute
BPN	backpropagation neural network
DLS	damped least-squares
ECA	evolutionary computing algorithms
ES-SAGD	expanding solvent steam assisted gravity drainage
GA	genetic algorithm
GD	gradient decent
GN	Gauss–Newton
IOR	incremental oil recovery, %
LM	Levenberg-Marquardt
OF	objective function
RMSE	root mean squared error
SAGD	steam assisted gravity drainage
SVM	support vector machine
TF	transfer function

1. Introduction

There is now a widespread agreement that the oil and gas resources most easily recovered have already been discovered. Incremental production of oil and gas, at least in North America, largely comes from unconventional resources [1]. Heavy oil and bitumen sources are required to be produced by new technologies to tackle the future needs in energy market. The economical and environmental obstacles according to the application of thermal methods in deep and thin reservoirs are crucial challenges for the oil and gas industry not only in North America, but also in other spots such as Latin America, Middles East, and China. The most costly step in a thermal process like SAGD is the required energy for turning water into steam. This makes such type of recovery processes to be cumbersome in terms of energy supply and usage. Fresh water supply which is an environmental concern is also another example of associated drawbacks with the thermal methods.

One of the most vital techniques for enhancing oil recovery is waterflooding or water injection, which is categorized as a secondary recovery method. Water injection into a reservoir results in a phenomena called voidage replacement in which we intend to deliver pressure support to the reservoir. This is also to drive or displace oil from the reservoir to production wells. Ultimate reservoir dynamic performance and recovery assessment in water flooding process has been extensively studied and evaluated during past few years [2–8]. This method which is the most common practice implemented at the end of primary production have potential problems associated with. These problems include inefficient recovery due to the variable permeability of fluids in the reservoir, unfavorable mobility ratio of the injected water and heavy oil affecting the fluid transport within the porous media, and early water breakthrough, which impedes the production and threatens the surface processing facility. These drawbacks makes the application of waterflooding inefficient when facing a heavy oil reservoir. Considering the issues and challenges related to the application of waterflooding in heavy oil reservoirs, polymer flooding has become a more desirable choice for EOR processes than waterflooding.

Polymer flooding is an enhanced oil recovery method in which vicosified water with polymer is injected into the reservoir. This process involves addition of a small concentration of soluble polymer to the injected water. Poor sweep efficiency during waterflooding results in viscous fingering of the injected fluid in the porous media. Polymer injection improves the sweep efficiency by increasing the viscosity of the injected fluid. The increase in the viscosity of the injected fluid, lowers the mobility ratio of the injected (displacing) fluid to be less than that of the oil phase (displaced) in place. This leads to the maximum sweep efficiency while diminishing any viscous fingering issues and creating a smooth flood front in the reservoir. Horizontal configuration of injection wells in heavy oil reservoirs has increased the chances to inject a big polymer slug size into the reservoir. This advantage of polymer flooding application in heavy oil reservoirs makes it economically more efficient while being environmentally more sound than the other heavy oil recovery techniques, such as SAGD and ES-SAGD [9,10]. Polymer flooding performance evaluation has been widely studied in both experimental [11–29], and detailed numerical simulation contexts [30–37]. Numerical modeling and simulation of polymer flooding recovery performance can be carried out with traditional simulators. The current flow simulators require a huge number of input parameters such as initial saturation and pressure distributions, porosity, permeability, multi-phase flow functions, and well