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PREDICTION OF WATER-FLOODING PERFORMANCE IN CORE SCALE: COMPARISON OF NUMERICAL SIMULATOR, NEURAL NETWORK AND CORRELATION

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ABSTRACT

A sensitivity analysis was performed on different parameters affecting recovery factor of water-flooding. A correlation was developed for estimation of the water-flood performance in core scale and constant injection rate experiments. The correlation was based on more than 230 numerical simulator runs for a wide range of porosity, permeability, viscosity ratio and pore size distribution in long core. Also, a neural network for prediction of water-flood recovery factor was created. The results show that the proposed correlation is reliable in a full range of parameters where the neural network fails to estimate water-flood performance in some intervals. The correlation may be used in reverse direction, if the recovery factor is known; the pore size distribution index can be estimated.

KEYWORDS

Water-flooding; correlation; neural networks; numerical simulator; enhanced oil recovery (EOR)

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1. INTRODUCTION

The identification of promising LSE projects requires specific laboratory tests, followed by pilot tests of increasing scale (**Morrow and Buckley, 2011**). In the past, empirical correlations for prediction of water-flood performance were investigated by statistical study of water-flood performances. Guthrie and Greenberger studied oil recovery by water drive empirically to reservoir rock and fluid properties (**Guthrie and Greenberger, 1955**). They studied 73 sandstone reservoirs that had a water drive or that had solution gas drive combined with a water drive. The actual production data were available for these reservoirs. The oil recovery was related to the permeability, porosity, oil viscosity, formation thickness, connate water saturation, depth, oil reservoir volume factor, area, and well spacing. The correlation shown below fits so well that in 50 percent of the time the recovery factor was within 6.2 percent of the reported value, and in 75 percent of the time it was within 9.0 percent.

$$E_R = 0.2719 \log(k) + 0.25569 S_{wi} - 0.1355 \log(\mu_o) - 1.5380 \phi - 0.0003488h + 0.11403 \quad (1)$$

In this correlation, E_R is the fractional recovery efficiency, k is the absolute permeability, S_{wi} is the initial water saturation, ϕ is the porosity, h is the formation thickness and μ_o is the oil viscosity. This equation implies that the water drive recovery efficiency is lower in reservoirs of higher porosity.

Schauer presented an empirical method for predicting the water-flood behavior of Illinois Basin water-floods. This method is based on the past performance of five floods (**Schauer, 1957**). A plot was constructed showing the percentage fill-up at first signs of an oil production response as a function of the Lorenz coefficient. As the Lorenz coefficient increased—that is, with reservoirs of increased non uniformity—the oil production response occurred at a lower percentage of fill-up. Other plots showing the injectivity decline in function of time were also obtained from field performance history.

The API sub-committee on Recovery Efficiency, headed by J. J. Arps, presented a statistical study of recovery efficiency (**Arps et al., 1967**) based on a statistical analysis of data from 312 reservoirs.

They developed correlations for water drive recovery from sandstone and sand reservoirs, and for solution gas drive recoveries from sandstones, sands, and carbonates. The water drive recovery, as a percentage of the original oil in place, is:

$$E_R = 54.898 \left[\frac{\phi(1-S_{wi})}{B_{oi}} \right]^{0.0422} \left[\frac{K \cdot \mu_w}{\mu_o} \right]^{0.0770} (S_{wi})^{-0.1903} \left(\frac{P_i}{P_a} \right)^{-0.2159} \quad (2)$$

In this correlation, E_R is the recovery factor, ϕ is the porosity, μ_o is the oil viscosity, μ_w is the water viscosity, K is the absolute permeability, S_{wi} is the initial water saturation, P_i is the initial pressure, P_a is the pressure at depletion (abandonment pressure) and B_{oi} is the formation volume factor.

This correlation for water-flood recovery is expressed as a logarithmic-type equation. The correlation coefficient for the equation is 0.958, which by its closeness to 1.000 shows a very good fit of the data. This correlation developed from a water drive reservoir performance data has limited usefulness for water-flooding projects. Other correlations for estimating water-flood performance have been developed from histories of floods in Oklahoma (**Bush and Helander, 1968**) and the Denver Basin in Colorado and Nebraska (**Wayhan et al., 1970**). The usefulness of this type of correlation is generally limited to reservoirs in the particular geographical area being studied. **Mai and Kantzas (2009)** predicted the recovery from a heavy oil waterflood. They observed the significance of capillary pressure, flow rate, and oil viscosity. Several researchers (**Li et al., 2002; Reis and Cil, 1993**) have observed that the recovery for fixed volumes of water increases in a manner that is proportional to the square root of injection time. This implies that the imbibition rate or oil production rate should be high at first and, then, should decrease with time.

In this study, a correlation is proposed for predicting water-flooding performance on a laboratory scale (core scale). Such correlation can be used for the validation of water-flood experiments in core scale and the estimation of the recovery factor before performing experiment. If the recovery factor is known, the pore size distribution index (λ) can be estimated from correlation.

Table 1. Parameters used in runs.

Parameter	Value
Porosity	0.05-0.45
Permeability (md)	0.1-500
Pore size distribution index (λ)	0.5-20
Viscosity ratio	0.01-10
Initial water saturation	0-0.45
Core length (cm)	150
Core diameter (cm)	3.81
Number of runs	>230

Artificial neural networks have been used successfully to model reservoir behavior under water injection (Nikraves et al, 1996). Therefore, a neural network predictor was created to estimate the recovery factor and to validate the correlation. Then, the results of the correlation, the neural network, and the numerical simulator were compared.

2. METHODOLOGY

2.1 Data set

Data sets used for developing the correlation and the training neural network are from more than 230 runs of the numerical simulator for wide range of permeability, porosity, initial saturation, pore size distribution index, and viscosity ratio in long core. The ranges of the used parameters are shown in Table 1.

2.2 SCAL data

The water-flood performance is related to the SCAL data; thus, the water-flood recovery is strongly dependent on the shape of the imbibition capillary pressure curves. To include SCAL data in the correlation, the pore size distribution index (λ) was used by Burdine in its correlation (Burdine, 1953) to integrate both relative permeability and capillary pressure effect in a single parameter (λ):

$$K_{rw} = K_{rw}^0 (S_w^*)^{\frac{2+\lambda}{\lambda}} \quad (3)$$

$$K_{ro} = K_{ro}^0 (1 - S_w^*)^2 \left(1 - (1 - S_w^*)^{\frac{2+\lambda}{\lambda}} \right) \quad (4)$$

$$P_c = P_{cd} (S_w^*)^{\frac{-1}{\lambda}} \quad \text{For } P_{cd} > 0 \quad (5)$$

$$P_c = -1 + (S_w^*)^{\frac{-1}{\lambda}} \quad \text{For } P_{cd} = 0 \quad (6)$$

$$S_w^* = \frac{S_w - S_{wi}}{1 - S_{wi}} \quad (7)$$

In these equations, K_{ro} is the oil relative permeability, K_{ro}^0 is the oil relative permeability at irreducible water saturation, K_{rw} is the water relative permeability, K_{rw}^0 is the water relative permeability at residual oil saturation, P_c is the capillary pressure, P_{cd} is the displacement (Threshold) capillary pressure, P_i is the initial reservoir pressure, S_w^* is the normalized water saturation, S_{wi} is the initial water saturation and λ is the pore size distribution index. Li and Horne (2006) have shown that the capillary pressure is expected to decrease for rocks with higher permeability, since permeability is related to the average pore size in the rock.

Figures 1 and 2 show the effects of pore size distribution index (λ) on capillary pressure and on oil-water relative permeability, respectively.

Table 2. Neural network properties.

Network Properties	
Network type	Feed-forward network
Training method	Levenberg-Marquardt back propagation
Number of layers	2
Number of neurons	25
Transfer functions	TANSIG(hidden layer)- PURELIN(output layer)

2.3 Neural networks

In order to find relationship between the input (rock and fluid properties) and output data (recovery factor of water-flooding) driven from numerical simulator, a more powerful method than traditional modeling is necessary. Neural Network is an efficient algorithm to approximate any function with finite number of discontinuities by learning the relationships between input and output vectors (Hagan and Demuth, 1996; Biglin, 2004). In this study, Neural Network is used for validation of the proposed correlation. The properties of the created network are mentioned in Table 2. Training, validation and testing of neural network was done with more than 230 data sets. The input data is the matrix of 5x234 and the target data is the matrix of 1x234 recovery factors.

3. RESULTS AND DISCUSSION

3.1 Sensitivity analysis

In order to study the effects of each rock and fluid property on the recovery factor, sensitivity analyses were done on porosity, pore size distribution index, initial water saturation, and viscosity ratio. Also, the effect of permeability was investigated, but in the studied cases, core scale water-flooding with constant injection rate, it affects the differential pressure but has practically no effect on the recovery factor.

Figure 1. Effect of pore size distribution on capillary pressure.

Figure 3. Effect of pore size distribution on the recovery factor.

Figure 2. Effect of pore size distribution on relative permeability.

Figure 4. Effect of porosity on the recovery factor.

3.1.1 Pore size distribution

Sensitivity analysis was done on pore size distribution index (λ). The small λ values indicate a very large distribution of pore size, while very large λ values indicate uniformity of pore size. Results in Figure 3 shows that the recovery factor reduced with the increase of λ . It means that uniform pore size distribution has lower recovery factor. Also, results show that a decreasing viscosity ratio increases the effect of λ on oil recovery factor. Higher λ causes a higher water relative permeability, a lower oil relative permeability, and a lower capillary pressure. The latter delays imbibition phenomena in the water-flood process.

3.1.2 Porosity

There are two ideas about the effect of porosity on recovery factor. First, the recovery factor decreases with increasing porosity, which is shown in the Guthrie and Greenberger correlation (Eq. 1). Second, the recovery factor is directly proportional to porosity, which was mentioned in the API correlation (Equation 2). The results of sensitivity analysis on porosity with numerical simulators are shown in Figure 4. In different viscosity ratios, the porosity is inversely proportional to the recovery factor.

3.1.3 Viscosity ratio

The viscosity ration is defined as the ratio of water (displacing fluid) viscosity to oil (displaced fluid) viscosity. It is obvious in Darcy and fractional flow equations that higher viscosity ratio improves performance of water-flood. The results of the sensitivity analysis on viscosity ratio in different pore size distribution indices (λ) are shown in Figure 5.

3.1.4 Initial water saturation

In preferentially water-wet rock, the initial water saturation has a negative effect upon the oil relative permeability. Therefore the higher the initial water saturation is, lower the recovery factor will be on water-flooding. This is in line with the results shown in Figure 6, which shows the sensitivity analysis on the amount of initial water saturation. It is important to highlight that the highest recovery factor was achieved with no initial water saturation.

3.2 Correlation

A correlation, based on the four parameters mentioned above, is proposed for the estimation of the recovery factor of water-flooding in core scale under constant water injection rate. The coefficients and powers of parameters were determined using a non-linear regression. The correlation mainly depends on Dimensionless Water-flooding Number (DWN) defined below:

$$DWN = (1 - S_{wi})^{0.25} \cdot \left(\frac{\mu_w}{\mu_o} \right)^{0.0257} \cdot \lambda^{\left(\frac{0.00534}{\left(\frac{\mu_w}{\mu_o} \right)^{0.6}} \right)} \cdot \phi^{-0.0334} \quad (8)$$

Then, the recovery factor was calculated with the following equation or graphically with Figure 7:

$$E_R = 1.744(DWN) - 1 \quad (9)$$

In this correlation, E_R is the recovery factor, DWN is the Dimensionless Water-flooding Number, ϕ is the porosity, μ_o is the oil viscosity, μ_w is the water viscosity, S_{wi} is the initial water saturation and λ is the pore size distribution index.

Figure 5. Effect of viscosity ratio on the recovery factor.

Figure 6. Effect of initial water saturation on recovery factor.

Table 3. Performance of the correlation.

Goodness of fit	Value
SSE	0.2228
R-square	0.9436
Adjusted R-square	0.9432
RMSE	0.03099

Figure 7. Graphical representation of correlation A) Recovery factor estimation and B) Pore size distribution (λ) estimation.

The equation suggests that the recovery factor is directly proportional to the *DWN*. The performance and errors of proposed correlation are shown in Table 3. The R-square of 0.94, being close to 1.00, shows a very good fit of the data.

The correlation may be used in reverse direction. That is, if the water-flood experiment was done and the recovery factor is known, the *DWN* could be calculated. Once the *DWN* is calculated, the pore size distribution index (λ) can be estimated (Figure 7).

3.3 Comparison with neural network

Training, validation and testing of neural network are shown in Figure 8. The outputs of correlation were compared with the results of numerical simulator and neural network.

Figure 8. Training, validation and testing of neural network.

Figure 9 shows the results from the three methods listed above. As observed, in low values of DWN ($DWN < 0.6$), neural network fails to estimate the correct recovery factor. But, in higher values of DWN , neural network predictor is reliable.

Figure 10 compares the correlation and the neural network error at each data point. As shown in Figure 10, neural network error in low values of DWN is between 10 to 35 percent, but error of correlation in this interval is below 17 percent. The average error of correlation and neural network was compared and the difference was small (4.26% error for neural network and 3.98% error for correlation).

Figure 9. Comparison of the calculated recovery factor from numerical simulator, correlation and neural network.

Figure 10. Percentage error of neural network and correlation for each run.

4. CONCLUSIONS

A correlation was proposed for estimation of oil recovery factor in water-flood process in core scale. If the recovery factor was known, pore size distribution index could be predicted by the correlation. Also, the neural network predictor of recovery factor created lacked reliability in some instances, but the proposed correlation was reliable in wide range of input parameters.

NOMENCLATURE

B_{oi}	Initial oil volume formation factor
DWN	Dimensionless Water-flooding Number
E_R	Fractional recovery efficiency
h	Formation thickness
K	Absolute permeability
K_{ro}	Oil relative permeability
K_{ro}^0	Oil relative permeability at irreducible water saturation
K_{rw}	Water relative permeability
K_{rw}^0	Water relative permeability at residual oil saturation
P_a	Abandonment pressure
P_c	Capillary pressure
P_{cd}	Displacement (Threshold) capillary pressure
P_i	Initial reservoir pressure
S_w^*	Normalized water saturation
S_{wi}	Initial water saturation
μ_o	Oil viscosity
μ_w	Water viscosity
ϕ	Porosity
λ	Pore size distribution index

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