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Discerning In Situ Performance of an EOR Agent in the Midst of Geological Uncertainty

S.A. Fatemi* (Delft University of Technology), J.D. Jansen (Delft University of Technology) & W.R. Rossen (Delft University of Technology)

SUMMARY

An enhanced-oil-recovery pilot test has multiple goals, among them to verify the properties of the EOR agent in situ. Given the complexity of EOR processes and the inherent uncertainty in the reservoir description, it is a challenge to discern the properties of the EOR agent in situ. We present a simple case study to illustrate this challenge: a polymer EOR process in a 2D layer-cake reservoir. The intended polymer design value is 21 cp in situ but we allow it might be ¼ that intended in the simulations. We test whether the signals of this difference at injection and production wells would be statistically significant in the midst of the geological uncertainty. We compare the deviation caused by loss of polymer viscosity to the scatter caused by the geological uncertainty at the 95% confidence level. Among the signals considered, the rate of rise in injection pressure with polymer injection and maximum injection pressure in the injector give the most reliable indications of whether a polymer viscosity was maintained in situ. Arrival time of the oil bank, minimum oil cut before oil bank arrival and polymer breakthrough time also give a statistically significant indication.

Introduction

An EOR pilot test has multiple goals, among them to demonstrate oil recovery, verify the properties of the EOR agent in situ, and provide the information needed for scale-up to an economic process. The first goal concerns whether the process achieves its overall objectives (oil recovery) in the given formation. Whether or not the first goal is reached, it is important to assess the process by the second criterion. This is important because a process that did not achieve the desired objectives in the given formation might be successful in another field if it demonstrates that it achieves its technical objectives. For example, the technical criteria for success for an EOR agent in situ could low interfacial tension (IFT) or low residual oil saturation for a surfactant process, a given mobility for a polymer process, etc. In a field pilot, one must determine the technical success of an EOR agent in the midst of geological uncertainty in the reservoir description.
Previous research has examined uncertainty in the EOR process performance or uncertainty in the geological description, but not the two together. Studies on uncertainty in EOR process performance include Alkhatib and King (2014) and Brown and Smith (1984), both examining surfactant-flooding processes. There have also been studies on the effect of geological heterogeneities and their uncertainty on how an EOR process performs. Heterogeneity and geological factors have different impacts on the various EOR processes, including polymer and alkaline-surfactant-polymer, thermal and gas-injection (miscible and immiscible) EOR. Studies of the effects of geological heterogeneity and uncertainty include Soleimani et al. (2011), Rashid, et al. (2012), Kumar (1990), Popov et al. (2013)

In this paper we investigate the impact of both sources of uncertainty together: a statistical approach to discern the performance of the EOR agent in situ in the midst of geological uncertainty.

In this study, we present a simple case study to illustrate the issues involved: a polymer EOR process implemented in a 2D layer-cake reservoir. The polymer is intended to have a viscosity of 21 cp in situ. Then, we allow that the polymer process might fail in situ and viscosity could be ¼ that intended. This failure could be the result of mechanical degradation in surface facilities or on entering the perforations, faulty translation from laboratory-measured properties to properties in situ, faulty characterization of resident reservoir brine, or biological or chemical degradation of polymer. Several of these adverse events would give different polymer properties in different regions of the reservoir. For simplicity, in this initial study we assume that throughout the reservoir polymer viscosity is less than that intended. We test whether the signals of this failure at the injection and production wells would be statistically significant in the midst of the geological uncertainty in the reservoir description. For a population of reservoirs representing geological uncertainty, we compare the deviation caused by loss of polymer viscosity to the scatter caused by the geological uncertainty at the 95% confidence level. Various signals are monitored to see which are most reliable indications of whether a polymer viscosity was maintained in situ. For this initial case study the separate effects of adsorption, mixing with different brines in situ, residual resistance factor, polymer degradation, shear-rate dependence (non-Newtonian behaviour), permeability reduction and temperature have been ignored, except as they are represented indirectly in the loss of polymer viscosity.

Case Study Description

Reservoir Model and Dimensions. Table 1 presents the model dimensions and properties of the case study. The five-layer rectangular reservoir is shown in Figure 1. Polymer-flood simulations were run with one injector and one producer. The producer bottom-hole pressure (BHP) is kept at 70 bars while the injector's BHP can go as high as 150 bars. Polymer viscosity reduces injectivity, but unintended fracturing near the wellbore during polymer injection can increase injectivity. The extent of this unintended fracturing may not be known (Seright et al. 2009). For simplicity, we account for an uncertain extent of injectivity improvement due to fracturing by allowing the injector BHP in the simulation to be greater than what one would expect to be applied in a polymer EOR process.

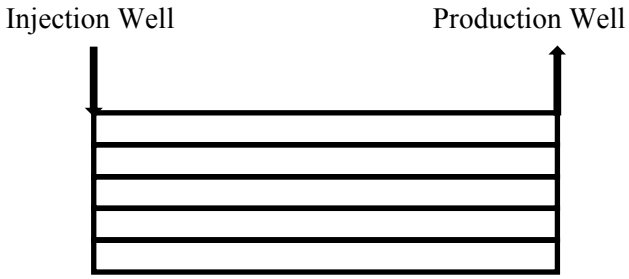


Figure 1 *The case study: a five-layer rectangular reservoir with one producer and one injector.*

Table 1 *Reservoir dimensions.*

Description	Quantities	Units
Total Grid Numbers (NX, NY, NZ)	25 × 1 × 5	
Grid Size (Δx, Δy, Δz)	6.4 × 1 × 6.4	m
Total Dimensions	160 × 1 × 32	m
Porosity (φ)	0.3	

Injection and reservoir fluid properties. Table 2 presents the reservoir and injected fluid properties used here. Water, oil and polymer-slug viscosity were kept constant in the simulations.

Table 2 *Case-study reservoir and injection fluid properties.*

Description	Quantities	Units
Water density	1000	kg/m^3
Oil density	900	kg/m^3
Water viscosity	1.00×10^{-3}	Pa s
Oil viscosity	20.00×10^{-3}	Pa s
Water compressibility	1.00×10^{-5}	bar^{-1}
Oil compressibility	1.00×10^{-4}	bar^{-1}
Initial Reservoir Pressure	85	bar

Screening Criteria for Polymer Flood. Several aspects should be of concern when building up a reservoir model to be a candidate for polymer flooding, such as reservoir type, reservoir oil viscosity and reservoir permeability. The petroleum literature has reported a set of criteria for screening oil reservoirs for polymer flooding and their qualitative analyses. In this case study, we assign values to reservoir properties such that they meet the suggested values in the literature for a typical candidate reservoir to undergo polymer flood. Table 3 shows screening criteria for chemical EOR suggested in the literature (Dickson et al., 2010) and the values used for the case study in the simulations.

Table 3 *suggested values for a reservoir candidate to go through a polymer flood process [Dickson* et al.*, 2010].*

	Suggested in Literature	Case Study
In-situ oil viscosity (cp)	10–1000	21
Average permeability, mD	>100 if (10<μ<100cp) >1000 if (100<μ<1000cp)	1000
Reservoir Temperature, ^{0}F	<170	150
Oil Saturation (%)	> 30%	90%
Formation Salinity (ppm)	<3000 if (10<μ<100cp) <1000 if (100<μ<1000cp)	1000

Representation of Uncertainty in Polymer Performance. We represent uncertainty in process performance using different values of polymer viscosity in situ: 5 cp and 21 cp. As mentioned above, for simplicity, various detailed mechanisms of the polymer in situ viscosity are excluded here. In our simulations, we represent the failure to attain the design viscosity in situ by injecting in those simulations the polymer concentration corresponding to 5 cp (200 ppm) instead of that corresponding to 21 cp (600 ppm).

Representation of Geological Uncertainty. Petroleum engineers usually consider permeability heterogeneity the most important source of uncertainty in reservoir performance (Craig et al., 1974). Modeling of permeability heterogeneities is usually based on a stochastic description, and realizations of such models are input parameters to reservoir simulators (Langtangen, 1991). We therefore represent geological uncertainty with a number of realizations reflecting a range of reservoir properties.

In this layer-cake case study, each layer has a different permeability. The distribution of permeability values follows a log-normal distribution. The log normal distribution has often been used to describe the permeability distribution of heterogeneous reservoirs (Dykstra and Parsons, 1950; Jensen et al., 2000; Lake et al., 2014). The degree of heterogeneity of a reservoir is often characterized by the dimensionless Dykstra-Parsons coefficient of permeability variation (V_{dp}). A homogeneous reservoir has a V_{dp} approaching zero, while an extremely heterogeneous reservoir would have a V_{dp} approaching one. A log-normal permeability distribution can be characterized by this coefficient and an average permeability (Craig, 1971; Hirasaki, 1990). To generate the permeability values for the five layers we use the inverse cumulative distribution function (CDF) of the log-normal distribution. Specifically, the permeability values are drawn from the 10%, 30%, 50%, 70% and 90% percentiles of the CDF. We adjust the magnitudes of the values so that all three distributions have the same arithmetic average permeability (k_{avg}). Therefore in single-phase flow injectivity would be the same for all the nine cases. Table 4 shows the permeability values generated for V_{dp} = 0.6, 0.75 and 0.9.

Table 4 *Generated layer permeability values for V_{dp} = 0.6, 0.75 and 0.9; k_{avg} = 1000 mD in all cases.*

	Generated Permeability Values [mD]		
Percentile	V_{dp} = 0.6	V_{dp} = 0.75	V_{dp} = 0.9
0.1	218	84	9
0.3	444	244	53
0.5	726	511	189
0.7	1189	1067	664
0.9	2423	3093	4086

We assume three spatial distributions of permeability: specifically, from top to bottom, high permeability to low permeability, low permeability to high permeability, and a distribution with the lowest permeability in the middle. Figure 2 shows schematically how layer permeabilities are ordered. Three Dykstra Parsons coefficients and three spatial arrangements of layers give nine different

geological representations, to be used in simulations with two different polymer-flood viscosities in situ.

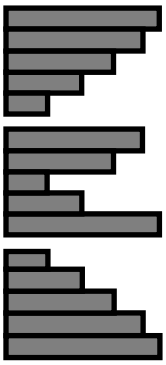


Figure 2 *Schematic of spatial ordering of layer permeabilities.*

Development Scenario and Procedure. We run the polymer-flood simulations using Shell's in-house simulator MoReS (Van Doren et al. 2011). In each simulation, ten years of water injection are followed by twenty years of polymer-slug injection. A production/injection profile for one case is shown in Figure 3.

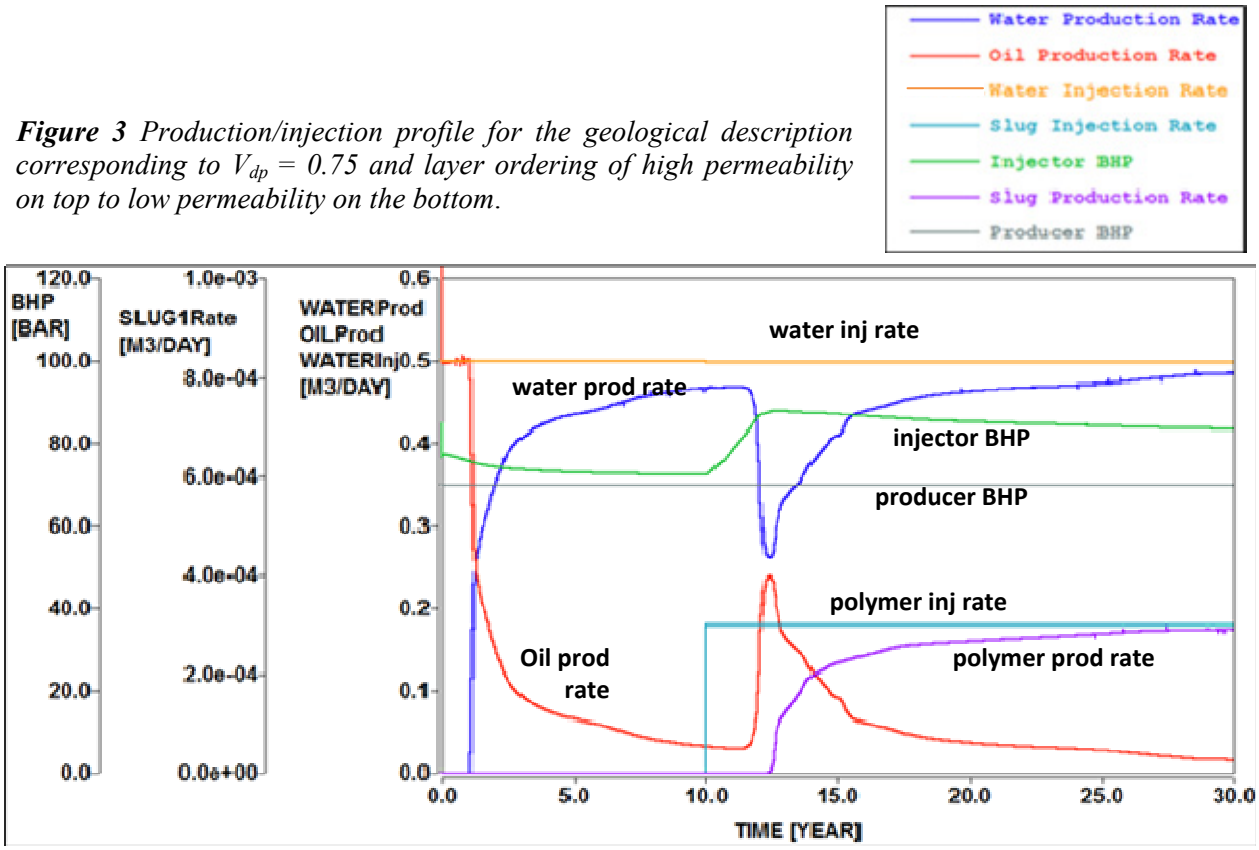


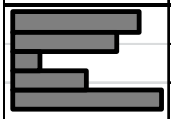
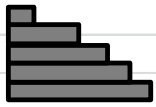
Figure 3 *Production/injection profile for the geological description corresponding to V_{dp} = 0.75 and layer ordering of high permeability on top to low permeability on the bottom.*

As shown in Figure 3, water is injected for 10 years, and it breaks through early into the waterflood phase. A polymer slug is then injected and causes a rise in injection pressure and, later, incremental oil recovery reflected in the rise in oil production shown in the red line. There are a number of possible polymer-flood signals to study:

- Polymer breakthrough time, years (Polymer BT)
- Change in p_{inj} from year 10 to year 11, bars (Slope p_{inj})
- Minimum oil cut (Min. oil cut)
- Time of initial increase in oil production rate, years (Oil Bank Arrival)
- Max injection pressure, bars (Max p_{inj})
- Cumulative oil production at end of simulation, m^3 (End Cumoil)

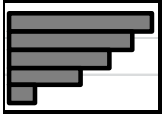
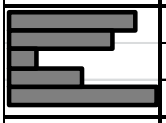
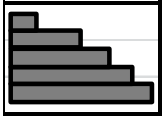
We allow that the polymer process might fail in situ and viscosity could be ¼ that intended. Comparing the signals listed above for a polymer viscosity in situ of 21 cp to those for a viscosity of 5 cp, we test whether the signals of this difference at injection and production wells would be statistically significant at the 95% confidence level in the midst of the geological uncertainty, represented by the nine reservoir descriptions.
Specifically, we calculate the 95% confidence interval for each signal for the nine geological cases with 21 cp polymer viscosity. The results are shown in Table 5.

Table 5 *Signal values calculated for the nine geological cases with 21 cp polymer viscosity, with upper and lower bounds of the 95% confidence interval for each signal.*

Perm. Distribution	V_{dp}	Slope p_{inj}	Polymer BT [year]	Oil Bank Arrival Time [year]	Min. Oil Cut	Max p_{inj} [bar]	End Cumoil [m^3]
	**0.9**	27.85	11.7	11.08	0.05	116	528.66
	0.75	18.75	12.2	11.42	0.06	117	704.39
	0.6	15.33	13	11.92	0.06	119	773.14
	**0.9**	44.00	11.1	10.08	0.04	114	560.84
	0.75	27.51	12	10.08	0.05	112	707.61
	0.6	16.66	12.8	10.17	0.06	116	766.86
	**0.9**	36.56	11.3	10.50	0.03	118	506.96
	0.75	21.34	12	10.83	0.04	115	692.13
	0.6	16.27	12.6	11.08	0.05	113	765.49
CI +		32.61	12.58	11.29	0.06	117.32	749.16
CI -		17.23	11.58	10.30	0.04	113.79	585.53

For each reservoir description we then ask if the given signal with 5 cp polymer viscosity lies outside that confidence interval. If the answer is yes, then the failure of polymer in situ is discernible at the 95% confidence level in the midst of geological uncertainty. Table 6 shows the signal values for the cases with an in situ viscosity of 5 cp. Next to the column with this value, a second column compares the individual signal value to the confidence interval for results with 21 cp viscosity from Table 5. If the signal value falls outside the 95% confidence interval of the whole population, the adjacent column shows a Y (meaning the signal can be distinguished in the midst of geological uncertainty) and otherwise an N (meaning the signal cannot be distinguished from geological uncertainty at the 95% confidence level).

Table 6 *Discerning the process with 5 cp polymer viscosity from the case with 21 cp polymer viscosity.*

Perm. Distribution	V_{dp}	Slope p_{inj}		Polymer BT [year]		Oil Bank Arrival Time [year]		Min. oil cut		Max p_{inj} [bars]		End Cumoil [m^3]	
	**0.9**	12.17	Y	11.20	Y	10.92	N	0.06	Y	89.91	Y	446.39	Y
	0.75	7.42	Y	11.50	Y	11.42	Y	0.06	Y	90.93	Y	604.87	N
	0.6	5.35	Y	12.50	N	12.00	Y	0.06	Y	91.34	Y	675.24	N
	**0.9**	17.10	Y	10.80	Y	10.08	Y	0.04	Y	89.32	Y	426.29	Y
	0.75	15.70	Y	11.20	Y	10.08	Y	0.06	Y	89.51	Y	595.34	N
	0.6	7.32	Y	11.90	N	10.25	Y	0.06	Y	89.15	Y	662.04	N
	**0.9**	14.73	Y	10.90	Y	10.20	Y	0.03	Y	88.16	Y	381.78	Y
	0.75	7.68	Y	11.35	Y	10.92	N	0.04	N	86.86	Y	539.82	Y
	0.6	5.58	Y	11.85	N	11.08	N	0.05	N	87.74	Y	637.45	N

Of the signals considered, there are two columns with only Y's. One could discern the effect of viscosity with confidence based on the 'max injection pressure' and 'change in p_{inj} from year 10 to

11'. These two signals could discern the failure of the polymer in situ in the midst of geological uncertainty. In both cases, the rise in pressure is less than with the greater polymer viscosity, as expected. In the cases where the difference in polymer breakthrough time and final cumulative oil production was statistically significant, the values were lower than the range of the confidence interval, both also as expected. In contrast, the loss of polymer viscosity in situ could cause either an earlier or later oil bank arrival time than the confidence interval, and the minimum oil cut could be greater or less than the range of the confidence interval. These two signals clearly represent a more complex reservoir response than, for instance, the rise in injection pressure upon injecting a more- or less-viscous fluid.

Summary and Discussion

We present a simple case study illustrating the challenges in discerning the properties of an EOR agent in situ from well data in the midst of geological uncertainty. Among the signals considered, the rate of rise in injection pressure upon polymer injection and maximum pressure in the injection well give the most reliable indications of whether polymer viscosity was maintained in situ. Unfortunately, given the chances of fracturing of the injection well, and the possibly unknown extent of this fracturing, injection pressure may be an unreliable indicator of in situ polymer viscosity. Moreover, various mechanisms not considered here could make polymer viscosity different at the injector than in the rest of the field: non-Newtonian rheology, adsorption, mixing with reservoir brines, chemical or biological degradation, etc. Arrival time of the oil bank, minimum oil cut before the oil bank and polymer breakthrough time give a statistically significant indication of loss of polymer viscosity in situ in some cases.

The range of geological uncertainty assumed here could be viewed as extreme. We assume that injectivity is known but that very little is known about the extent of reservoir heterogeneity, even at the wells. On the other hand, the extent of failure of the polymer in situ, i.e. a loss of viscosity by a factor of 4, could be considered extreme as well. Moreover, we considered a two-well situation whereas in a multi-well setting the effect of viscosity changes may results in different, and possibly weaker, signals in the various wells. Further study should include more realistic geological descriptions and polymer mechanisms and the effect of including more wells. We offer this initial study to illustrate the issues involved in attempting to distinguish EOR process performance in the midst of geological uncertainty.

Acknowledgment

We acknowledge Shell Global Solutions International for their support and permission to publish the work.

References

Alkhatib, A. and King, P. [2014] Uncertainty Quantification of a Chemically Enhanced Oil Recovery Process: Applying the Probabilistic Collocation Method to a Surfactant-Polymer Flood. *Comput Geosci.*, **18**, 77-101, DOI 10.1007/s10596-013-9384-9.

Becerra, R.S., Perez, S. and Soto, D.A. [2013] The Development of a New Methodology to Reduce Uncertainty in Implementing a New EOR Project. IPTC-17017-MS, *International Petroleum Technology Conference*, Beijing, China, ISBN: 978-1-61399-218-0, DOI http://dx.doi.org/10.2523/17017-MS.

Brown, C.E. and Smith, P.J. [1984] The Evaluation of Uncertainty in Surfactant EOR Performance Prediction. SPE-13237-MS, *SPE Annual Technical Conference and Exhibition*, Houston, Texas, ISBN: 978-1-55563-639-5, DOI http://dx.doi.org/10.2118/13237-MS.

Chen, Q., Gerritsen, M.G. and Kovscek, A.R. [2008] Effects of Reservoir Heterogeneities on the Steam-Assisted Gravity-Drainage Process. SPE-109873-PA, *SPE Reservoir Evaluation & Engineering*, **11**(5), 921-932, DOI http://dx.doi.org/10.2118/109873-PA.

Craig, F.Jr. [1971] The Reservoir Engineering Aspects of Waterflooding. *SPE Monograph Henry L. Doherty Series*, **3**, 62-68.

Dykstra, H. and Parsons, R.L. [1950] The Prediction of oil Recovery by Water Flood. *Secondary Recovery of Oil in the United States,2nd Edition.* API, New York, 160-174.

Hirasaki, G.J. [1990] Properties of log-normal permeability distribution for stratified reservoirs. *SPE-13416-MS.*

Jensen, J.R., Lake, L.W., Corbett, M.W., Goggin, D.V. [2000] *Statistics for Petroleum Engineers and Geoscientists.* Elsevier Science B.V., Second Edition, 2000.

Kumar, M. [1992] Interwell Heterogeneity Representation and Its Effect on Steamflood Performance. SPE-24932-MS, *SPE Annual Technical Conference and Exhibition*, Washington, D.C., ISBN: 978-1-55563-500-8, DOI http://dx.doi.org/10.2118/24932-MS.

Lake, L.W., Johns, R.T., Pope, G.A. and Rossen, W.R. [2014] *Fundamentals of Enhanced Oil Recovery*. Society of Petroleum Engineers, Richardson, TX.

Langtangen, H.P. [1991] Sensitivity analysis of an enhanced oil recovery process. *Applied Mathematical Modelling*, **15**(9), 467-474, DOI: 10.1016/0307-904X(91)90036-O.

Popov, Y., Spasennykh, M., Miklashevskiy, D., Parshin, A.V., Stenin, V., Chertenkov, M., Novikov, S. and Tarelko, N. [2010] Thermal Properties of Formations From Core Analysis: Evolution in Measurement Methods, Equipment, and Experimental Data in Relation to Thermal EOR. *Canadian Unconventional Resources and International Petroleum Conference*, Calgary, Alberta, Canada, SPE-137639-MS, DOI http://dx.doi.org/10.2118/137639-MS.

Rashid, B., Muggeridge, A., Bal, A.L. and Williams, G.J. [2012] Quantifying the Impact of Permeability Heterogeneity on Secondary-Recovery Performance. SPE-135125-PA, *SPE J*, **17**(2), 455-468, DOI http://dx.doi.org/10.2118/135125-PA.

Saleh, L.D., Wei, M. and Bai, B. [2014] Data Analysis and Novel Screening Criteria for Polymer Flooding Based on a Comprehensive Database. SPE169093MS, *SPE Reservoir Evaluation & Engineering*, **17**(1), 15-25, DOI http://dx.doi.org/10.2118/168220-PA.

Seright, S.R., Seheult, J.M., Talashek, T. [2009] Injectivity Characteristics of EOR Polymers. SPE-115142-PA, *SPE Reservoir Evaluation & Engineering*, **12**(5), 783-792, DOI http://dx.doi.org/10.2118/115142-PA.

Soleimani, A., Penney, R.K., Hegazy, O., Bingah, W., Sulliman, A.E. and Tewari, R.D. [2011] Impact of Fluvial Geological Characteristics on EOR Screening of a Large Heavy Oil Field. SPE-143650-MS, *SPE Enhanced Oil Recovery Conference*, Kuala Lumpur, Malaysia, ISBN 978-1-61399-135-0, DOI http://dx.doi.org/10.2118/143650-MS.

Van Doren, J., Douma S.G., Kraaijevanger, J.F.B.M. and De Zwart, A.H. [2011] Adjoint-based Optimization of Polymer Flooding. SPE-144024-MS *SPE Enhanced Oil Recovery Conference*, Kuala Lumpur, Malaysia, DOI http://dx.doi.org/10.2118/144024-MS.

Wang, W. and Gupta, A. [1999] Effects of the Strategies of Geological Modelling and Simulation On Scale-up. *PETSOC-99-39, Annual Technical Meeting*, Calgary, Alberta ISBN 978-1-61399-104-6, DOI http://dx.doi.org/10.2118/99-39.