Iranian Journal of Oil & Gas Science and Technology, Vol. 1 (2012), No. 1, pp. 43-54
http://ijogst.put.ac.ir

Prediction of Nitrogen Injection Performance in Conventional Reservoirs Using the Correlation Developed by the Incorporation of Experimental Design Techniques and Reservoir Simulation

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Abstract

Enhanced oil recovery using nitrogen injection is a commonly applied method for pressure maintenance in conventional reservoirs. Numerical simulations can be practiced for the prediction of a reservoir performance in the course of injection process; however, a detailed simulation might take up enormous computer processing time. In such cases, a simple statistical model may be a good approach to the preliminary prediction of the process without any application of numerical simulation. In the current work, seven rock/fluid reservoir properties are considered as screening parameters and those parameters having the most considerable effect on the process are determined using the combination of experimental design techniques and reservoir simulations. Therefore, the statistical significance of the main effects and interactions of screening parameters are analyzed utilizing statistical inference approaches. Finally, the influential parameters are employed to create a simple statistical model which allows the preliminary prediction of nitrogen injection in terms of a recovery factor without resorting to numerical simulations.

Keywords: Nitrogen Injection, Experimental Design, Reservoir Simulation, Hypothesis Testing, Recovery Factor

1. Introduction

Screening analysis is a methodology applied either to select viable processes for a set of conditions or to determine the dominant parameters in a particular mechanism. In petroleum engineering, screening is the first step before applying an enhanced oil recovery method to any reservoirs. The study normally consists of a complete study of oil properties and reservoir characteristics. Most of the oil companies have their own technical screening for enhanced oil recovery (Alkafeef and Zaid, 2009). In such cases, a reservoir rock and properties are usually compared with those of successful EOR experiences to choose a promising method among others. Screening criteria for different enhanced oil recovery techniques have been comprehensively studied in the literature (Haynes et al., 1976; Bailey et al., 1984; Taber et al., 1997). Some examples of different EOR methods in the United States carbonate oil reservoirs are reviewed in reference (Manrique et al., 2007). Conventional and advanced screening methods for evaluating the applicability of EOR processes to a particular field are also discussed elsewhere (Manrique and Pereira, 2007). Commercial analytical tools and the direct comparison of reservoir properties to international field experiences are classified as conventional techniques,

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whereas an advanced approach includes artificial intelligence. The screening studies performed by Alkafeef and Zaid (2009) and Alvarado et al. (2002) are the examples of a conventional and advanced approach, respectively.

After being introduced to the petroleum engineering in the early 90's, the design of experiment (DOE) has been widely used to filter the main parameters in EOR techniques (Egeland et al., 1992; Damsleth et al., 1992; Eide et al., 1994; Larsen et al., 1994). The application of designed numerical simulations and response surfaces to screening, uncertainty analysis, forecasting, and optimization in the predevelopment study of a reservoir in Gulf of Mexico is demonstrated and, afterwards, the analysis of variance (ANOVA) is used to determine the most effective parameters (White and Royer, 2003). Some investigators applied a standard design of experiment such as Plackett-Burman or factorial design to examine the parameters (Li and Friedmann, 2005; Parada et al., 2005; Liu et al., 2008; Adepoju et al., 2009). Sector or reservoir geological models were utilized in this approach and the simulation results (e.g., net present value, oil production rate, cumulative production, etc.) were analyzed by Pareto chart. Vanegas Prada and Cunha (2008) used experimental design techniques to develop a response surface correlation for the estimation of steam assisted gravity drainage (SAGD) performance. Before proposing their quadratic model, they studied the most effective parameters by fitting the net present value (NPV) to a linear regression model. The parameters with coefficients having the most statistical significance were selected as the most influential parameters. Moreover, they emphasized the great significance of a reasonable range for each parameter in the design of experiments (Amudo et al., 2009; Taber et al., 1997). They showed that the incorrect ranges could cause the Pareto chart to be wrongly interpreted in the screening process. Moradi et al. (2010) determined some important parameters in immiscible nitrogen injection in a conventional reservoir model. They analyzed the results by hypothesis test and demonstrated the output graphically using Pareto chart.

In the present study, seven rock/fluid reservoir properties are selected as screening parameters, and the dominant parameters having the most influential effect on the performance of nitrogen injection projects are obtained by the combination of simulation and statistical science. Fractional factorial design, which is the most commonly used method in the design of experiments, is employed to characterize several simulation models to be run by a commercial simulator. Subsequently, the obtained oil recovery factors from various scenarios, which are computed by the simulator, are examined by static inference approaches. Finally, a model is developed for the assessment of the performance of nitrogen injection using a toolbox of MATLAB.

2. Methodology overview

2.1. Simulation model descriptions

As shown in Figure 1, a sector model is constructed to screen the parameters influencing the performance of nitrogen injection. The reservoir is assumed to be homogenous and anisotropic. No aquifer and initial gas cap zones are considered in the model.

The model is 609.6 m (2000 ft) in length and 304.8 m (1000 ft) in width and consists of three layers. The production well produces at a constant production rate whereas the injection well is controlled by a constant bottom-hole pressure constraint. A gas to oil ratio (GOR) of 50 Mscf/stb is used as a constraint for stopping the simulation runs of the production well. The initial reservoir pressure is considered to be equal to 31.0264×10^6 Pa (4500 psi) at the crest of the sector. The reservoir properties are shown in Table 1.

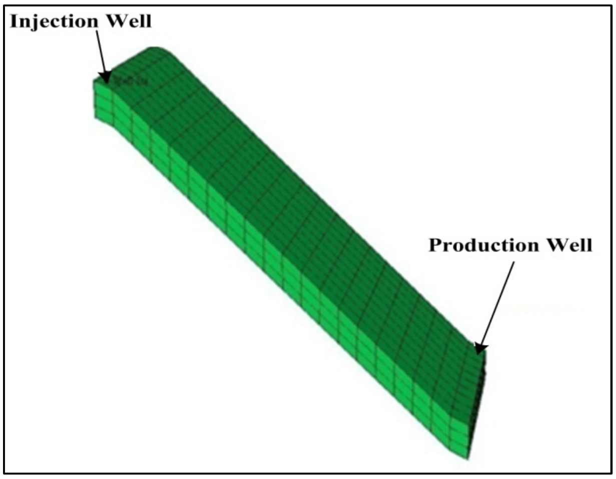

Figure 1
A schematic representation of sector model

Table 1
Summary of the reservoir properties

Property	Value or Equivalent
S_{or}	0.15
S_{gc}	0.02
Rate of production (Q)	200 STB/D
ϕ	0.15
Equation of State (EOS)	Peng-Robinson
k_v/k_h	0.10

2.2. Parameters of study

Screening parameters (Table 2) in a nitrogen injection process are collected from literature based on conventional screening experiments and other similar works by combining DOE with reservoir simulations. Reservoir thickness (h), absolute horizontal permeability (k_h), connate water saturation (S_{wc}), threshold capillary pressure (P_{ct}), pore size distribution parameter (λ), oil viscosity (μ_0) and reservoir dip are regarded as the parameters investigated for screening purposes. S_{wc}, λ, and P_{ct} are used to calculate relative permeability and capillary pressure curves, which is based upon the Brooks and Corey equations. These equations are applied since their adjusting parameters allow us to check how the curvature and endpoints of the relative permeability curves will affect the injection performance. These equations are as follows (Corey, 1954):

$$k_{r,nwt} = \left[1 - S_{wt}^{*}\right]^{2}\left[1 - \left(S_{wt}^{*}\right)^{\frac{2+\lambda}{\lambda}}\right] \tag{1}$$

$$k_{rwt} = \left(S_{wt}^{*}\right)^{\frac{2+3\lambda}{\lambda}} \tag{2}$$

where,

$$S_{wt}^{*} = \frac{S_w - S_{wc}}{1 - S_{wc}} \tag{3}$$

also, k_{rwt} is wetting phase relative permeability, $k_{r,\ nwt}$ stands for non-wetting phase relative permeability, and λrepresents pore size distribution parameter.

For capillary pressure curve, one may obtain:

$$P_c = P_{ct} S_{wt}^{*\ -1/\lambda} \quad (4)$$

where, P_c and P_{ct} are capillary pressure (psi) and threshold capillary pressure (psi) respectively.

Table 2
Variation ranges of the screening parameters

Parameters	**Unit**	**Min. (-1)**	**Max. (+1)**
Thickness (h)	ft	180	1000
Absolute horizontal permeability (k_h)	mD	35	500
Connate water saturation (S_{wc})	fraction	0.1	0.4
Threshold capillary pressure (P_{ct})	psi	0.75	2
Pore size distribution parameter (λ)	dimensionless	1.5	6
Oil viscosity (μ_0)	cP	0.74	3.1
Reservoir dip	degree	5	40

Two different oil samples are considered to study the effect of oil viscosity (μ_0). The fluid properties of the samples are shown in Table 3.

Table 3
Characteristics of oil samples

Parameters	**Unit**	**Light Oil**	**Heavy Oil**
Molecular weight of C_{7+} (MW C_{7+})	lbm/lbmol	181.48	302.51
Specific gravity of C_{7+} (SG C_{7+})	fraction	0.885	0.939
Bubble point pressure (P_b)	psi	1879.69	1637.48
API	degree	30.82	20.14
Gas to oil ratio (GOR)	scf/stb	601	307
Oil viscosity at initial pressure (μ_0)	cP	0.74	3.1
Reservoir temperature	°F	200	220

2.3. Design of experiments (DOE)

Experimental design is a statistical technique that allows obtaining maximum information on a process at a minimum cost. This method is used to determine the space variation of the results due to the variations in the input parameters of a given process. Generally, experimental design techniques define either the appropriate runs or the combination of input parameters to be used during experiments for the purpose of maximizing the information according to the established objectives (Perada et al., 2005).

Two-level fractional factorial design is a common technique for screening analyses (Montgomery, 2001; NIST/SEMATECH, 2006). Although three and mixed levels of this design have been mentioned, they have received little attention due to the required number of experiments and the complexity of analysis (Hinkelmann and Kempthorne, 2008). In two-level designs, each parameter takes minimum and maximum levels which are usually -1 and +1 respectively. If there are k factors, 2^kdifferent cases exist for all possible combinations. Fractional factorial design selects an adequate fraction of these combinations to reduce the number of runs, albeit at the expense of confounding. Confounding means that the estimated value of a particular effect comes from both that effect itself and contamination from higher order interactions. More details about fractional design can be found elsewhere (Box et al., 2005; NIST/SEMATECH, 2006; Montgomery, 2001; Lazic, 2004; Moradi et al., 2010).

Thirty two (32) simulation experiments were proposed by the fractional factorial design to screen the mentioned parameters. The variation ranges of the screening parameters and the matrix design of the simulations are given in Tables 2 and 4 respectively. The range of the parameters is determined so that most of conventional fields would lie within the criteria of the investigation. However, limitations on simulation runs for all cases are included; in other words, the ranges should be managed so that one can run the entire designed table without any inconsistency during the simulation. All the simulation experiments run by the reservoir engineering simulator were regarded as a response surface. The corresponding oil recovery factors were calculated until reaching the limiting GOR of 50 Mscf/stb.

In this work, screening analysis is applied to determine dominating parameters, which are then used with the experimental design method and regression techniques to create a statistically significant correlation.

2.4. Statistical analysis of main effects

The main effect of any factors can be determined by (Moradi et al., 2010):

Main effect=(Average recovery factor when the parameter takes maximum level) -(Average recovery factor when the parameter takes minimum level) (5)

The main effects of different parameters are given in Table 5. For example, the main effect of k_h is equal to 12.64, denoting that increasing k_h from 35 mD to 500mD causes recovery factor to increase by approximately 12.64%. The statistical significance of this figure cannot be understood unless the related variance is available. We resolve this issue by calculating parameter effects in paired experiments. For each parameter, the experiments are selected one by one and a conjugate is found for the selection. The paired experiments should be as similar as possible from all the factors, but the particular parameter of interest, viewpoints. If the design of experiments is balanced, the pairing can be made with no problem. Generally, the difference in recovery factors of corresponding experiments in a pair is the sum of two or more effects (Moradi et al., 2010). For example, in order to estimate the thickness effect in the paired experiments of 17 and 1, one may write:

$$(\text{Recovery factor})_{17}-(\text{Recovery factor})_{1} = \text{Thickness effect-Viscosity effect} \quad (6)$$

where, the subscripts denote experiment number from Table 4. Here, the viscosity effect is introduced into Equation (6) because experiments 17 and 1 are different not only in thickness, but also in viscosity. If the viscosity effect is estimated by its main effect, the thickness effect in Equation (6) can then be calculated. For the other parameters, one may consider suitable corresponding experiments by pairing and replacing the extra introduced effects with their main effects and then calculating the effect of the desired parameter. Thus, for N simulation experiments, each parameter will have $N/2$ members as effect data (Moradi et al., 2010). Effect data for parameters are presented in Table 5.

Table 4
Matrix of runs to perform screening analysis

Exp. No.	h	k_h	S_{wc}	P_{ct}	λ	μ_0	dip	Exp. No.	h	k_h	S_{wc}	P_{ct}	λ	μ_0	dip
1	1-	1-	1-	1-	1-	1	1	17	1	1-	1-	1-	1-	1-	1
2	1-	1-	1-	1-	1	1	1-	18	1	1-	1-	1-	1	1-	1-
3	1-	1-	1-	1	1-	1-	1-	19	1	1-	1-	1	1-	1	1-
4	1-	1-	1-	1	1	1-	1	20	1	1-	1-	1	1	1	1
5	1-	1-	1	1-	1-	1-	1-	21	1	1-	1	1-	1-	1	1-
6	1-	1-	1	1-	1	1-	1	22	1	1-	1	1-	1	1	1
7	1-	1-	1	1	1-	1	1	23	1	1-	1	1	1-	1-	1
8	1-	1-	1	1	1	1	1-	24	1	1-	1	1	1	1-	1-
9	1-	1	1-	1-	1-	1-	1-	25	1	1	1-	1-	1-	1	1-
10	1-	1	1-	1-	1	1-	1	26	1	1	1-	1-	1	1	1
11	1-	1	1-	1	1-	1	1	27	1	1	1-	1	1-	1-	1
12	1-	1	1-	1	1	1	1-	28	1	1	1-	1	1	1-	1-
13	1-	1	1	1-	1-	1	1	29	1	1	1	1-	1-	1-	1
14	1-	1	1	1-	1	1	1-	30	1	1	1	1-	1	1-	1-
15	1-	1	1	1	1-	1-	1-	31	1	1	1	1	1-	1	1-
16	1-	1	1	1	1	1-	1	32	1	1	1	1	1	1	1

The statistical significance of main effects can be evaluated by hypothesis testing which is a standard method of statistical inference (Larsen, and Marx, 2006; Wonnacott, and Wonnacott, 1969). In this method, two opposite hypothesis are considered. In the first consideration, null hypothesis, it is assumed that the actual effect of a parameter is negligible (i.e. zero) and the reported value for main effect is due to the chance or any other reason except the role of the parameter itself. The alternative hypothesis assumes that the nonzero main effect demonstrates the real effect of a parameter. Apparently, if one of them is accepted, the other one is rejected. The credibility of the null hypothesis can be determined by calculating the P-value which describes how much it is probable that the null hypothesis is true (Moradi et al., 2010; Wonnacott, and Wonnacott, 1969).

The steps of hypothesis testing can be summarized as follows (Larsen et al., 1994):

1. Construct a suitable null hypothesis;

2. Calculate t-value;

$$t = \frac{ME - x_0}{s/\sqrt{n}} \tag{7}$$

where, ME is the reported main effect and s stands for the standard deviation of data; n is the number of effect data and x_0 represents the assumed average value according to null hypothesis, which is equal to zero in this case.

3. Calculate the P-value by student t-distribution;

4. Accept or reject the null hypothesis based on P-value. If the null hypothesis is rejected, alternative one is accepted.

The critical value which is the criterion for accepting or rejecting the null hypothesis is called significance level. If the P-value falls below the significance level, the null hypothesis is rejected.

Conversely, the null hypothesis is accepted when the P-value becomes greater than significance level. The most popular values for this level are 5% and 1% (Moradi et al., 2010). The calculated P-values for the screening parameters are shown in Table 5.

Table 5

Effect data set for screening parameters

Factor	Main Effect	Variance	P-Value (%)	Effect Data
h	5.06	36.19	0.43	{6.18, 1.83, 2.25, 4.83, -9.88, 0.22, 4.62, 6.37, 10.67, 18.6, -0.32, 7.77, 6.89, 7.11, 8.35, 5.85}
k_h	12.64	44.14	1.6×10^{-4}	{10.49, 11.96, 6.97, 14.59, 0.4, 3.58, 22.75, 6.7, 11.19, 17.24, 13.07, 15.61, 20.15, 22.41, 17.81, 8.1}
S_{wc}	-7.66	34.75	0.01	{-5.68, -10.89, -6.13, -12.14, -16.57, -14.19, -8.74, -9.69, -1.53, -10.23, -3.81, 0.61, -4.43, 9.14, -7.17, -14.23}
P_{ct}	0.9	34.75	54.89	{-2.33, 2.38, 1.39, -5.66, 9.81, 7.43, -0.17, -1.12, -5.23, 3.47, 4.75, 9.18, -12.43, 4.13, 2.44, -3.57}
λ	3.25	25.4	2.1	{7.8, 2.05, 4.6, -1.91, 15.89, -0.45, 7.17, -0.16, -2.37, -0.9, 5.15, -0.11, 5.56, -0.68, 0.79, 9.55}
μ_0	-4.19	36.19	1.39	{-3.06, -7.41, -1.38, -3.96, 10.75, 1.09, -4.63, -2.88, -9.8, -17.73, -9.56, -1.47, -2.35, 2.13, 7.48, -4.99}
Reservoir dip	10.12	25.4	8.2×10^{-5}	{12.03, 8.78, 13.49, 4.97, 7.67, 6.2, 3.83, 6.72, 15.75, 14.67, 5.98, 11.32, 7.81, 22.76, 6.2, 13.82}

2.5. Statistical analysis of interactions

Considerable variations in a set of effects may be evidence for two factor interactions. This occurs when a parameter amplifies (or reduces) the effect of another parameter. Interaction effects should be taken into account since a factor may have a small main effect but considerable interactions. Based on sparsity of effects, it is assumed that the higher order interactions, compared to lower order ones, are smaller and thus the higher order interactions are ignored (Moradi et al., 2010; NIST/SEMATECH, 2006).

Therefore, only two-factor interactions are discussed in this paper. Table 4 gives a set of 16 members for the effect data of each parameter. The orthogonality of the design guarantees that eight members of any data set occur at the minimum level of another parameter while the remaining eight members occur at the maximum level of that parameter. The calculation of the interaction between thickness (h) and k_h is shown using an example in Table 6. The minus sign of interaction between two parameters means that increase in level of one parameter decreases the effect of another ones and vice versa.

Statistical inference can be employed again to determine the validity of interactions. In this case, the null hypothesis assumes that the two subsets have the same mean and the reported difference in their averages is not statistically significant. The student t-distribution is then used to calculate the P-value of the null hypothesis. The procedure is quite similar to the one mentioned earlier but with different t- and standard deviation terms (Larsen, and Marx, 2006). The last column in Table 6 reports the P-value for the influence of horizontal permeability level on thickness effect for the above example. Since the P-value is small (P-value< 5%), the null hypothesis can be rejected.

Table 6

Effect of thickness on recovery factor at different levels of horizontal permeability

	Effect of h on recovery factor at different k_h								Average	Interaction	P-value
k_h=500	6.18	1.83	2.25	4.83	-9.88	-0.22	4.62	6.37	1.99	-3.06	3.66
k_h=35	10.67	18.6	-0.32	7.77	6.89	7.11	8.35	5.85	8.12		

Table 7 shows the values of interactions and their corresponding P-values for the other influential parameters.

Table 7

Evaluation and statistical analysis of interactions

Parameters	Interaction	P-value	Parameters	Interaction	P-value
$k_h \to h$	-3.06	3.66	$\lambda \to S_{wc}$	-2.32	11.92
$S_{wc} \to h$	-1.42	36.26	$\mu_0 \to S_{wc}$	2.61	7.5
$P_{ct} \to h$	-0.09	95.47	$Dip \to S_{wc}$	-1.83	22.81
$\lambda \to h$	1.46	34.89	$k_h \to P_{ct}$	0.56	71.7
$Dip \to h$	-0.75	63.56	$\lambda \to P_{ct}$	1.13	46.53
$h \to k_h$	-3.06	6.58	$P_{ct} \to \lambda$	1.13	39.14
$P_{ct} \to k_h$	0.56	74.79	$k_h \to \mu_0$	2.75	6.45
$\lambda \to k_h$	-0.11	94.81	$Dip \to \mu_0$	1.46	34.89
$\mu_0 \to k_h$	2.75	9.81	$k_h \to Dip$	-2.16	9.1
$Dip \to k_h$	-2.16	20.24	$S_{wc} \to Dip$	-1.83	15.29
$h \to S_{wc}$	-2.32	35.37	$\mu_0 \to Dip$	1.55	22.41
$k_h \to S_{wc}$	-2.86	5.13			

2.6. Statistical model

Determining the most dominant parameters is important to construct the mathematical models for the estimation of recovery factors without the expense of doing simulation. The selection of appropriate parameters for the recovery factor correlation is a common problem which can be solved by means of statistical analyses. Statistical analyses show that five of the introduced parameters are more important in the nitrogen injection process. Based on the effective parameters and 32 recovery factors which are calculated by the simulator software, four models can be proposed for estimating the recovery factor of the nitrogen injection process. These models are obtained using various methods including: (a) linear model, (b) Pure Quadratic model, (c) Interaction model, and (d) Quadratic model. These methods are based on the general equation given below (Box et al., 2005; Chu, 1990; Larsen et al., 1994):

$$F(x) = b_0 + \sum_{i=1}^{n} b_i x_i + \sum_{i<j}^{n} b_{ij} x_i x_j + \sum_{i=1}^{n} b_{ii} x_i^2 \tag{8}$$

The expression includes an independent term (b_0), linear terms (x_i), two-factor interaction terms ($x_i x_j$), quadratic terms (x_i^2), and their respective parameters of the regression model (b_i, b_{ij}, and b_{ii}).

There are two statistic criteria to compare the models numerically. These criteria include mean square error (MSE) and correlation coefficient (R^2). Any model with the values of R^2 close to 1 and a minimum mean square error introduces the best model.

3. Results and discussion

In the previous section, a methodology was developed to screen the parameters involved in the nitrogen injection process based on statistical inference. One may select 5% as the significant level for screening analyses. According to Table 4, the parameters most affecting the recovery factor in the nitrogen injection process include horizontal permeability, reservoir dip, connate water saturation, reservoir thickness, oil viscosity, and pore size distribution, the corresponding P-values of which are less than 5%. Accordingly, these parameters may be considered as the most important factors controlling the mechanism of the nitrogen injection process. Threshold capillary pressure has a minor effect on recovery factor and also corresponds to a P-value much greater than 5%. In this case, the null hypothesis is accepted, which means that this parameter has no significant effect on oil recovery factor as long as it ranges from 0.75 to 2 psi. Table 6 also shows that this parameter does not have any considerable interactions with the other parameters. Therefore, this parameter can be ignored with no considerable errors. Furthermore, the main effects of connate water saturation and oil viscosity are negative; this denotes that increasing these two factors respectively from 0.1 to 0.4 and from 0.74 to 3.1 reduces recovery factor to 7.66 and 4.19 correspondingly.

Table 7 shows the values of interactions and their respective P-values for the parameters. The interactions may have either a significant or insignificant impact on recovery factor, depending on both interaction values and corresponding P-values. According to Table 7, the interaction of k_h-h is the most important one among the others; this interaction is negative. It means that although a reservoir with higher horizontal permeability is possibly a better candidate for nitrogen gas injection, the interactions of reservoir thickness with horizontal permeability may challenge this rule. The terms of k_h-S_{wc}, μ_0-S_{wc}, and k_h-μ_0 have P-values somewhat greater than 5%, but their interaction values can be accepted with a little caution. The rest of the interactions have corresponding P-values greater than 5%; hence, these terms are not useful and their effects on recovery factor are insignificant.

Comparison of the MSE and R^2 values of the four models in Table 8 shows that the best model is interaction model which is in good agreement with the results of the simulation runs. This model consists of one constant term, five linear terms, and 10 two-factor interaction terms, which are depicted in a tabulated form in Table 9.

Table 8
Summary of MSE and R^2 values for the four models

Gas	**Criteria**	**Models**			
		Linear	**Pure Quadratic**	**Quadratic**	**Interaction**
N_2	**MSE**	22.01	81.23	40.79	12.65
	R^2	0.84	0.51	0.87	0.94

Table 9
Correlation coefficients for the interaction model

Terms	Coefficients	Terms	Coefficients
Constant	44.79	$h\times\mu_0$	0.001
h	0.012	$h\times Dip$	-5.212×10^{-5}
k_h	0.043	$k_h\times S_{wc}$	-0.041
S_{wc}	-14.058	$k_h\times\mu_0$	0.005
μ_0	-6.513	$k_h\times Dip$	-2.6×10^{-4}
Dip	0.411	$S_{wc}\times\mu_0$	7.373
$h\times k_h$	-1.61×10^{-5}	$S_{wc}\times Dip$	-0.349
$h\times S_{wc}$	-0.012	$\mu_0\times Dip$	0.035

4. Conclusions

1. The main effects of the rock and fluid properties of seven reservoirs on the performance of nitrogen injection process were investigated by using the combination of experimental design techniques and reservoir simulations.
2. The analysis of the main effects by hypothesis testing revealed that horizontal permeability, reservoir dip, connate water saturation, reservoir thickness, oil viscosity, and pore size distribution parameters have the most effective impact on recovery factor respectively. Threshold capillary pressure has a minor effect on recovery factor.
3. The interaction of the parameters should also be considered in the field screening and mathematical modeling. The results of the statistical analysis showed that k_h-h has the most influential impact on recovery factor in the nitrogen injection process.
4. The interaction model is the best method which can be used to quickly obtain the performance of nitrogen injection processes in terms of recovery factor in conventional reservoirs.

Acknowledgements

The authors would like to thank Computer Modeling Group (CMG) Ltd. for providing the computer programs used in this study, namely Calgary, Version 2009 and a toolbox of MATLAB, Version 2010.

Nomenclature

EOS	: Equation of state
GOR	: Gas oil ratio (scf/stb)
h	: Thickness (ft)
k_h	: Absolute horizontal permeability (mD)
k_v	: Vertical permeability (mD)
MSE	: Mean square error
P_b	: Bubble point pressure (psi)
P_{ct}	: Threshold capillary pressure (psi)
Q	: Rate of production (STB/D)
R^2	: Coefficient correlation
s	: Standard deviation
S_{gc}	: Critical gas saturation
S_{wc}	: Connate water saturation
λ	: Pore Size distribution parameter
μ_0	: Oil viscosity (cP)

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