Uncertainty Analysis of a Fractured Reservoir's Performance: A Case Study

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Résumé — **Analyse d'incertitudes des performances d'un réservoir fracturé : étude de cas** — Ces dernières années, l'industrie du pétrole a accordé une grande importance à la gestion et à l'analyse d'incertitudes des réservoirs. Le développement d'une méthode permettant de modéliser et de quantifier les incertitudes au cours des études de simulation de réservoir d'une façon efficace et pratique est clairement souhaitable. Des approches différentes telles que la méthodologie des surfaces de réponse (RSM ; *Response Surface Methodology*) et la simulation de Monte-Carlo ont été utilisées pour évaluer les incertitudes.

Au sein de cet article, la méthode de surface de réponse est utilisée pour appréhender les paramètres les plus influents sur les changements en termes de chute de pression et de facteur de récupération, en ce qui concerne leurs niveaux pratiques d'incertitudes au cours du développement d'un modèle de réservoir fracturé. La présente approche est utilisée pour amplifier les paramètres significatifs et développer une équation substitutive compatible et plus réaliste en vue de la prévision de la récupération d'huile à partir d'un réservoir fracturé faiblement perméable typique. Le modèle substitutif permet à l'analyse de Monte-Carlo de déterminer les sensibilités et la quantification de l'incidence de l'incertitude sur les prévisions de production.

Les résultats indiquent que la récupération d'huile est plus sensible à la pression de l'aquifère, à la perméabilité de fracture et à la hauteur de bloc. De plus, toutefois, l'interaction entre d'autres paramètres tels que la taille de matrice, la perméabilité de fracture et le volume d'aquifère a montré un certain degré d'importance au cours de cette analyse. L'analyse de Monte-Carlo prévoit un domaine de grande ampleur de récupération d'huile pour l'exploitation de ce champ.

Abstract — *Uncertainty Analysis of a Fractured Reservoir's Performances: A Case Study* — *In recent years, the oil industry has given great importance to reservoir management and reservoir uncertainty analysis. The development of a method that can model and quantify uncertainties in reservoir simulation studies in an efficient and practical way is clearly desirable. Different approaches such as Response Surface Methodology (RSM) and Monte-Carlo simulation have been used to address the uncertainties.*

In this paper, response surface method is used to realize the most influential parameters on pressure drop and recovery factor changes, regarding their practical levels of uncertainties during the development of fractured reservoir model. The present approach is performed to magnify the significant parameters and developing compatible and more realistic proxy equation for forecasting oil recovery from a typical low permeable fractured reservoir. The proxy model allows Monte-Carlo analysis to determine sensitivities and the quantification of the impact of uncertainty on production forecasts.

Results indicate that the oil recovery is more sensitive to aquifer strength, fracture permeability and block height. In addition, however the interaction between other parameters, such as matrix size, fracture permeability and aquifer volume, showed a degree of importance during this analysis. Monte-Carlo analysis forecasts wide range of oil recovery for this field development.

INTRODUCTION

However, evaluation of petroleum field has become a much more accurate process because of high technology; many Iranian fractured carbonate reservoirs are characterized by significant and wide range of uncertainties, due to their high level of sub-surface heterogeneities. All these uncertainties finally lead to a complex reservoir model; therefore extension of the model (pressure and recovery factor of the field after a certain period of time) to a wide range of time produces unacceptable results. To reduce these uncertainties, petroleum industries require a framework consisting of evaluating sensitivities and estimating impact of uncertainties on the field performance [1, 2, 12].

Experimental design, specially response surface methods and Monte-Carlo analysis, provide such a framework by arranging simulation models to maximize the information gained from each simulation, and to evaluate statistically the significance of different factors [11].

In last decades, petroleum industry has widely used experimental design methods to reduce different kinds of uncertainties during field developments. Peng and Gupta have gathered a data bank of the similar projects till 2004 [3]. This is especially important in financial evaluation of the projects. However, it is necessary to look at the full distribution of Net Present Value (NPV) for an individual asset, not just its expected value. Recent economic theory in Decision and Risk Analysis require more information than an average or expected NPV [4].

In this paper, uncertainties relating to one of Iranian fractured reservoir has been investigated and quantified. These uncertainties mostly come from unknown fracture network, aquifer volume and oil relative permeability. After illustrating the practical ranges of uncertainties for each reservoir parameter, mentioned above, it could be possible to define these ranges in three levels, means: low, base and high. Using reservoir simulation a 3D model could be designed using base values of uncertain parameters. Then RSM provides a suitable selection of 3D simulations, corresponding to known three level patterns. This leads to realize the effective parameters with most powerful effect on the responses; recovery and pressure, in addition, to develop proxy equations for the responses, which are then used to constrain the range of uncertainty in the response by Monte-Carlo simulations.

Sources of Uncertainties in Reservoir Engineering

Sources of uncertainties in this field are almost infinite and are anywhere within the reservoir modeling workflow, and could be classified as follows, as illustrated in Figure 1:
- static model (outcrops and regional studies, well log analysis and seismic acquisition);
- up-scaling (coarsening for highly heterogeneous and/or de-structured media);
- fluid flow modeling (relative permeability curves, well productivity, PVT or the solver);
- production data integration (measured well-production data);
- production scheme development and economic evaluation (optimization of the number of production wells, their location and architecture, injection schemes as well as some surface facilities) [1].

Classification of Uncertainties

As described above, reservoir evaluation and optimization require handling a very complex modeling on which many
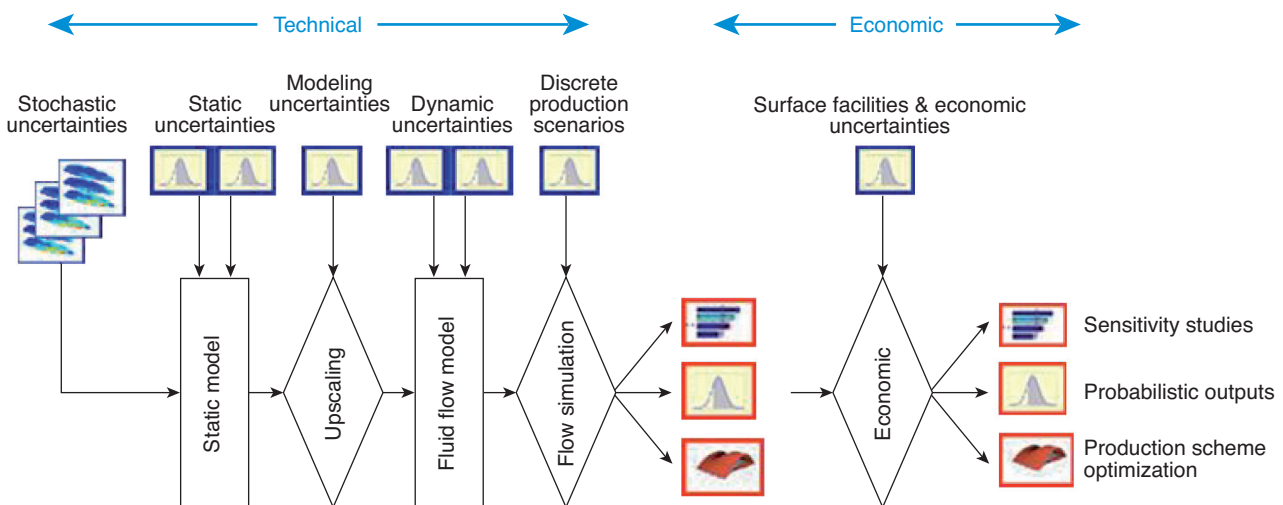

Figure 1

Sources of uncertainties in reservoir modeling workflow [1].

uncertainties remain. It is therefore very important to apply the right methodology to face each uncertainty in order to take the right decision in a risk-prone environment. Three different statistical behaviors can be used to classify the uncertainties:

– deterministic (continues parameters such as: mean facies permeability, porosity, matrix block size, etc.);
– discrete (depositional scenarios or fault conductivity, aquifer size, etc.);
– stochastic (infinity of equiprobable structural maps, fracture maps, geostatistical realizations, history matched models, etc.) [1].

1 RESERVOIR MODEL AND UNCERTAINTY DESCRIPTION

In reservoir engineering, it is necessary to handle any kind of uncertainties (deterministic, discrete, stochastic, etc.) while keeping the consistency of the modeling workflow.

In this study, it is desired to quantify the uncertainties in oil recovery factor and reservoir pressure drop after a certain period of production time (30 years); therefore, for the first step, it is necessary to find the most influential factors. In next step, the amount of their effect should be quantified via a proxy equation. It is possible to do some sensitive analysis, but it could just identify the uncertainties due to main effects, not the ones which come from interactions of different factors. Therefore, using experimental design analysis are the best methodology for this purpose, and then Monte-Carlo analysis should be used to evaluate the impact of uncertainty on production forecasts. The procedure has been schematized in Figure 2.

The studied field in this work is one of Iranian oil fields located in south part of Zagros. Static model of this field (including the grids, permeability and porosity maps, location of faults and wells) was prepared previously, But in order to construct a dynamic model it is necessary to convert the grid network to a fractured one (means matrix block size and fracture permeability should be known) and then it is crucial to assume a suitable set of relative permeability curves and a proper aquifer volume connected to the reservoir. To do this, commercial compositional modeling software is used *(Fig. 3)*. Detail of the reservoir description is as followed.

Reservoir Geology and Structure
The field has 29×10^6 square meters of structural closure within the Water/Oil Contact (WOC) at 2 464 m tvdss, giving a maximum field gross oil column of 432 m. The structure of the field is shown in Figure 4. The field anticline is an onshore structure, lying immediately to the east of a big fault. Seismic profiles indicate a high relief anticlinal structure plunging to the northwest and southeast. The four-way dip closure is about 12 488 by 6 437 meters, at Asmari level which is the main producing reservoir in the studied field.

The productive zone of the field consists of 16 layers and average matrix porosity is around 7%. Gross thickness is 432 m with average Net To Gross (NTG) of nearly 0.8. Permeability values measured on core plugs were used to determine the matrix permeability. Lower parts of Asmari formation contain mostly water with limited oil saturation that are acting as an aquifer; these layers were assumed as an analytical aquifer in the model as it takes less run time and easier analyses. Therefore, the analytical aquifer properties were chosen in a way to describe the numerical aquifer behavior precisely.
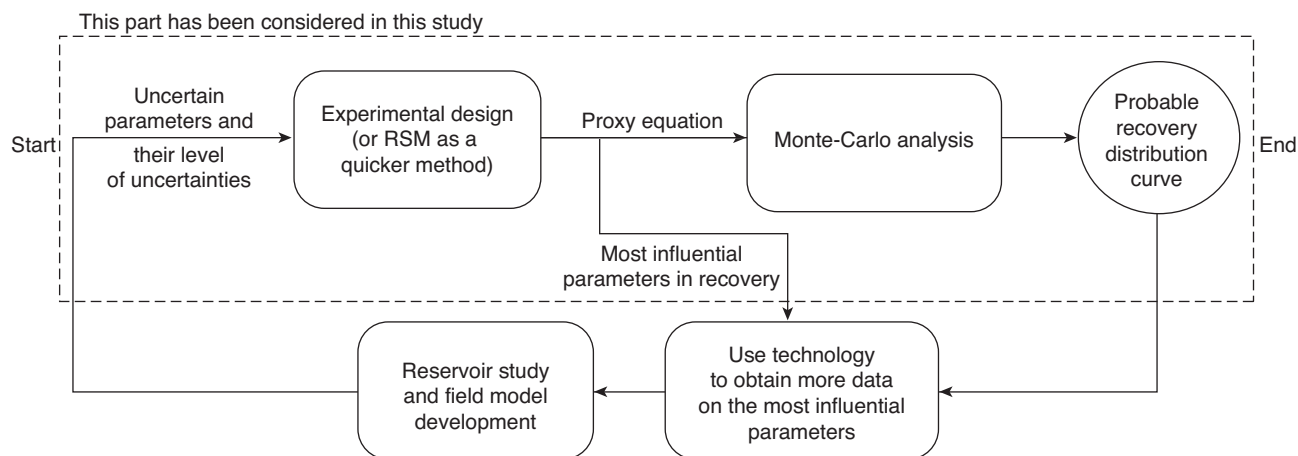

Figure 2

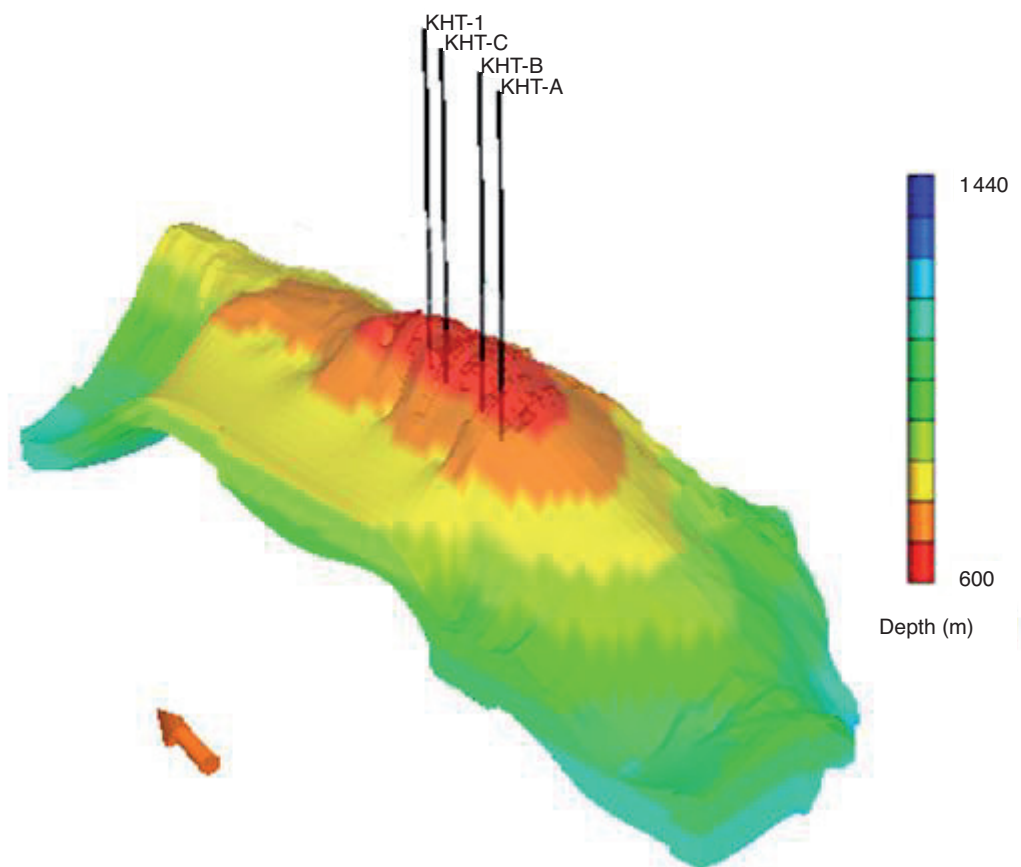Schematic of the study procedure for analyzing reservoir uncertainties.

Figure 3

Schematic of the field modeled in compositional simulation software.

The best wells locations were determined by considering field structure and reservoir properties. Figure 3 also shows the location of 4 wells that were proposed in Master Development Plan (MDP) for initial production strategy.

Fluid Properties and Equation of State
The available Pressure/Volume/Temperature (PVT) data indicate the presence of oil with average 36°API and viscosity 5.72 cp. At initial reservoir conditions (29.8 MPa and 94°C), average Gas Oil Ratio (GOR) and oil formation volume factor vary between 71 to 125 std.m^3/m^3 and 1.1 to 1.5 res. m^3/std.m^3 in that order, and bubble point pressure is 12.9 MPa. The salinity and viscosity of formation water are 160 000 and 0.50 respectively. Compositional analyses of reservoir fluid indicate that it mostly consists of 24% C1 and 46% of C7 + fractions.

The irreducible water and gas saturation and residual oil saturation with respect to water and gas were set as follows by using available data: S_{wr} = 0.15, S_{gr} = 0.01, S_{orw} = 0.25, S_{org} = 0.3.

The solution GOR at the saturation pressure and reservoir temperature is about 106.8 m^3/m^3. The cubic Peng-Robinson EOS model was tuned by adjusting the critical temperature, critical pressure, acentric factor, volume shift and binary interaction parameters of non-hydrocarbons to match all PVT data and laboratory tests. The critical pressure and temperature of oil are about 10.3 MPa and 399°C.

According to the field MDP a production scheme for 30 years with a plateau rate of 4 769.6 m^3/D and recovery factor of 22% (where the aquifer volume is equal to the oil volume) were considered as the base case development scheme *(Fig. 4)*.

Primary Sensitivity analysis, using simulation results, show that six factors listed in Table 1 have the most important effect on production, while they have different levels of uncertainties. The upper and lower limits for the selected parameters are chosen based on vicinity fractured oil reservoirs located on the same fields.
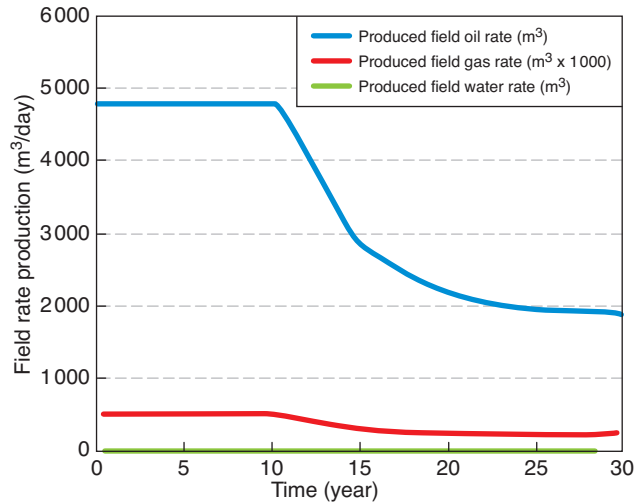
Figure 4

Base case production performance.

TABLE 1

Uncertainty levels of the most effective parameters

		Low	Base	High
A	Matrix block size (m)	1.52	3.05	4.57
B	Effective fracture permeability (md)[1]	10	23	36
C	Vertical matrix permeability/Horizontal matrix permeability	0.1	0.2	0.3
D	Aquifer size/IOIP[2]	0	1	2
E	Water relative permeability	0.25	0.375	0.5
F	Oil relative permeability	0.168	0.284	0.4

[1] Fracture permeability times its porosity.
[2] Initial Oil In Place.

2 EXPERIMENTAL DESIGN AND RESPONSE SURFACE METHODOLOGY

Design Of Experiment (DOE) is used to generate response surfaces that identify the various factors that cause changes in the responses and also predict these variations in a simple mathematical form. The purpose of Response Surface Methodology (RSM) is to approximate a process over a region of interest. Engineers define objectives of the process called responses as the output and the settings for the state parameters and decision variables as input. RSM provides tools for:

– identifying the variables that influence the responses (screening) and;
– building regression models relating the responses to the strategic variables (modeling).

The final models are used to make predictions of the process over the domain [2].

Design of experiments is the application of statistical methods to determine the number and level of the variables in order to get most information at the lowest experimental runs. More details can be found in a related literature [5].

Experimental design methods were first studied in the oil/gas industry back in 1960s and 1970s, but were mainly applied in physical experiments. Most of the studies focus on the production performance (*e.g.* ultimate recovery) as the output response.

To select efficient designs for subsurface reservoir uncertainty studies, many design matrices ranging from 2 to ≤ 16 variables with more than 3 levels, and up to 100 s of design runs have been studied, and they include: Placket-Burman, 2k-p fractional factorial designs, 3k-p fractional factorial designs, 2k and/or 3k full factorial, Central Composite, Box-Behnken, mixed 2- and 3-level full factorial, D-optimal, and other modified designs [3].

Expert opinion and knowledge about the experiments are very important to have a good understanding about independent effects and aliased one due to the limited degree of freedom in the design runs and therefore this could help to selection of a good method. Narayanan *et al*. (1999) [6], Chewaroungroaj *et al*. (2000) [7], White *et al*. (2001) [8], Risso *et al*. (2007) [9] and Rai *et al*. (2009) [10] have chosen Box-Behnken method to investigate the ultimate oil recovery of the field.

In this study, oil recovery factor and pressure decline are considered as response, and decision variables are presented in Table 1. Box-Behnken is chosen as the method of DOE, because primary investigations showed that factorial design could not provide any extra information in comparison with Box-Behnken, which reduces the number of experiments beneficially (note that this design would consist of $3^6 = 729$ if the method of full factorial was performed), see Table 2.

Box-Behnken experimental designs for Response Surface Methodology, devised by George E. P. Box and Donald Behnken in 1960 *(Fig. 5)*, could be introduced simply as a design which begins from three factors, is a three level design, can predict the quadratic effect of each factor with less experiments than Central Composite Design (CCD), and would not use the corner points.

Table 2 shows Box-Behnken design for six factors, first column is the standard order of the experiments, next columns show the rotation of levels for different factors introduced in Table 1 and overall 49 experiments is suggested for the whole analysis.

3 RESULTS AND DISCUSSION

Corresponding to the pattern introduced in Table 2, 49 different 3D reservoir models have been prepared and each full field reservoir model run took approximately eigth hours to be completed. The percentage of oil recovery (%) and reservoir
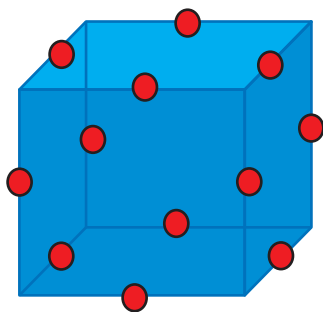
Figure 5

A Box-Behnken design for three factors.

TABLE 2

Box-Behnken design for six uncertain variables

Run	A	B	C	D	E	F	Run	A	B	C	D	E	F
1	-	-	0	-	0	0	26	+	0	0	-	-	0
2	+	-	0	-	0	0	27	-	0	0	+	-	0
3	-	+	0	-	0	0	28	+	0	0	+	-	0
4	+	+	0	-	0	0	29	-	0	0	-	+	0
5	-	-	0	+	0	0	30	+	0	0	-	+	0
6	+	-	0	+	0	0	31	-	0	0	+	+	0
7	-	+	0	+	0	0	32	+	0	0	+	+	0
8	+	+	0	+	0	0	33	0	-	0	0	-	-
9	0	-	-	0	-	0	34	0	+	0	0	-	-
10	0	+	-	0	-	0	35	0	-	0	0	+	-
11	0	-	+	0	-	0	36	0	+	0	0	+	-
12	0	+	+	0	-	0	37	0	-	0	0	-	+
13	0	-	-	0	+	0	38	0	+	0	0	-	+
14	0	+	-	0	+	0	39	0	-	0	0	+	+
15	0	-	+	0	+	0	40	0	+	0	0	+	+
16	0	+	+	0	+	0	41	-	0	-	0	0	-
17	0	0	-	-	0	-	42	+	0	-	0	0	-
18	0	0	+	-	0	-	43	-	0	+	0	0	-
19	0	0	-	+	0	-	44	+	0	+	0	0	-
20	0	0	+	+	0	-	45	-	0	-	0	0	+
21	0	0	-	-	0	+	46	+	0	-	0	0	+
22	0	0	+	-	0	+	47	-	0	+	0	0	+
23	0	0	-	+	0	+	48	+	0	+	0	0	+
24	0	0	+	+	0	+	49	0	0	0	0	0	0
25	-	0	0	-	-	0							

pressure (MPa), at the end of 30 years of natuural depletion, are reported in Table 3.

During Analysis of Variance (ANOVA), the confidence level was considered as 5% while R-square was calculated as 0.9926 and adjusted one as 0.9830, it could be saying that analysis was reliable. For the next step, after elimination of insignificat terms, following equation was obtained in terms of uncoded values:

$$
\begin{aligned}
\% \text{ Recovery} = &+ 18.24206 \\
&- 0.225732 \times \text{Matrix size} \\
&+ 0.33553 \times \text{Fracture perm.} \\
&+ 7.02156 \times \text{Aquifer vol./IOIP} \\
&+ 1.90374 \times K_{ro} \\
&- 1.73502\text{E-}03 \times \text{Matrix size} \times \text{Fracture perm.} \\
&- 0.029375 \times \text{Matrix size} \times \text{Aquifer vol./IOIP} \\
&+ 0.074038 \times \text{Fracture perm.} \times \text{Aquifer vol./IOIP} \\
&+ 0.0929 \times \text{Matrix size}^2 \\
&- 5.05672\text{E-}03 \times \text{Fracture perm.}^2 \\
&- 1.85264 \times \text{Aquifer vol./IOIP}^2
\end{aligned}
$$

Results of analysis of variance showed that "K_v/K_h" (Vertical Permeability/Horizontal Permeability) and "K_{rw}" (Water Relative Permeability) had no significant effect on oil recovery within the proposed range of variations; while the ratio of aquifer volume to IOIP, matrix block size and fracture permeability had important effects. Oil recovery was a week function of oil relative permeability while the reservoir was fractured, because, oil relative permeability was included only in fluid flow equations of matrix, and the whole calculated flux from matrix was considered as a source or sink for fractures fluid flow equations.

Figure 6 shows the dependency of the oil recovery to factors A, B, F and D, within a normalized range of investigation. Zero point is corresponding to the base case properties as shown in this figure.

With the same procedure a mathematical relation could be derived for field's pressure variation:

Pressure (MPa) =

$$
\begin{aligned}
&+ 19.0885 \\
&- 0.0106454 \times \text{Matrix size} \\
&- 0.228004 \times \text{Fracture perm.} \\
&+ 1.86572 \times \text{Aquifer vol./IOIP} \\
&- 0.0309448 \times \text{Fracture perm.} \times \text{Aquifer vol./IOIP} \\
&+ 0.00382583 \times \text{Fracture perm.}^2 \\
&- 0.198757 \times \text{Aquifer vol./IOIP}^2
\end{aligned}
$$

Finally, these equations were used in Monte-Carlo simulation technique for further analysis, and to find the range of response uncertainty due to uncertainties exist in main factors and their interactions can be computed in Monte-Carlo analysis.

While no enough information was available for possible distribution of the variables; main factors are introduced with uniform probability functions which have the same extremisms

TABLE 3

Results of compositional simulation used in DOE as response

| Run	Matrix size (m)	Fracture perm. (md)	K_v/K_x	Aquifer vol./IOIP	K_{rw}	K_{ro}	Recovery (%)	Pressure (MPa)
1	1.52	10	0.2	0	0.375	0.3	18	16.7
2	4.57	10	0.2	0	0.375	0.3	16	16.3
3	1.52	36	0.2	0	0.375	0.3	20	15.5
4	4.57	36	0.2	0	0.375	0.3	17	15.4
5	1.52	10	0.2	2	0.375	0.3	25	19.4
6	4.57	10	0.2	2	0.375	0.3	21	18.8
7	1.52	36	0.2	2	0.375	0.3	31	16.6
8	4.57	36	0.2	2	0.375	0.3	25	16.3
9	3.05	10	0.1	1	0.25	0.3	21	18.3
10	3.05	36	0.1	1	0.25	0.3	24	16.0
11	3.05	10	0.3	1	0.25	0.3	21	18.3
12	3.05	36	0.3	1	0.25	0.3	24	16.0
13	3.05	10	0.1	1	0.5	0.3	21	18.3
14	3.05	36	0.1	1	0.5	0.3	24	16.0
15	3.05	10	0.3	1	0.5	0.3	21	18.3
16	3.05	36	0.3	1	0.5	0.3	24	16.0
17	3.05	23	0.1	0	0.375	0.2	17	15.6
18	3.05	23	0.3	0	0.375	0.2	18	15.6
19	3.05	23	0.1	2	0.375	0.2	26	16.9
20	3.05	23	0.3	2	0.375	0.2	25	17.0
21	3.05	23	0.1	0	0.375	0.4	18	15.6
22	3.05	23	0.3	0	0.375	0.4	18	15.6
23	3.05	23	0.1	2	0.375	0.4	26	16.9
24	3.05	23	0.3	2	0.375	0.4	27	16.9
25	1.52	23	0.2	0	0.25	0.3	20	15.7
26	4.57	23	0.2	0	0.25	0.3	17	15.6
27	1.52	23	0.2	2	0.25	0.3	29	17.3
28	4.57	23	0.2	2	0.25	0.3	24	16.8
29	1.52	23	0.2	0	0.5	0.3	20	15.7
30	4.57	23	0.2	0	0.5	0.3	17	15.6
31	1.52	23	0.2	2	0.5	0.3	29	17.3
32	4.57	23	0.2	2	0.5	0.3	24	16.8
33	3.05	10	0.2	1	0.25	0.2	21	18.2
34	3.05	36	0.2	1	0.25	0.2	24	16.0
35	3.05	10	0.2	1	0.5	0.2	21	18.2
36	3.05	36	0.2	1	0.5	0.2	24	16.0
37	3.05	10	0.2	1	0.25	0.4	21	18.3
38	3.05	36	0.2	1	0.25	0.4	25	16.0
39	3.05	10	0.2	1	0.5	0.4	21	18.4
40	3.05	36	0.2	1	0.5	0.4	25	16.0
41	1.52	23	0.1	1	0.375	0.2	27	16.6
42	4.57	23	0.1	1	0.375	0.2	21	16.3
43	1.52	23	0.3	1	0.375	0.2	27	16.6
44	4.57	23	0.3	1	0.375	0.2	22	16.3
45	1.52	23	0.1	1	0.375	0.4	27	16.6
46	4.57	23	0.1	1	0.375	0.4	22	16.2
47	1.52	23	0.3	1	0.375	0.4	27	16.7
48	4.57	23	0.3	1	0.375	0.4	22	16.3
49	3.05	23	0.2	1	0.375	0.3	24	16.4
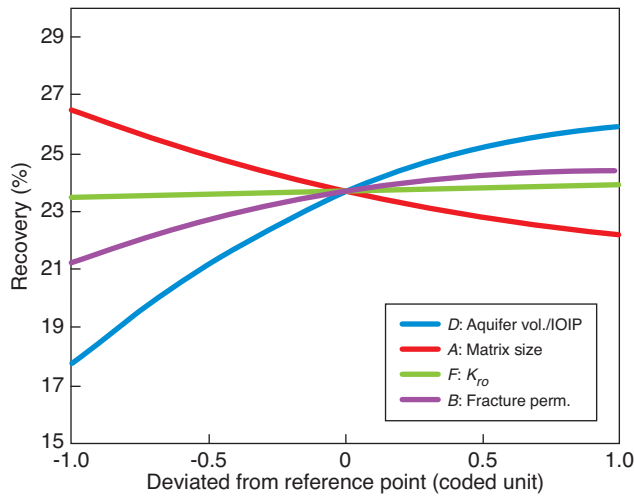
Figure 6

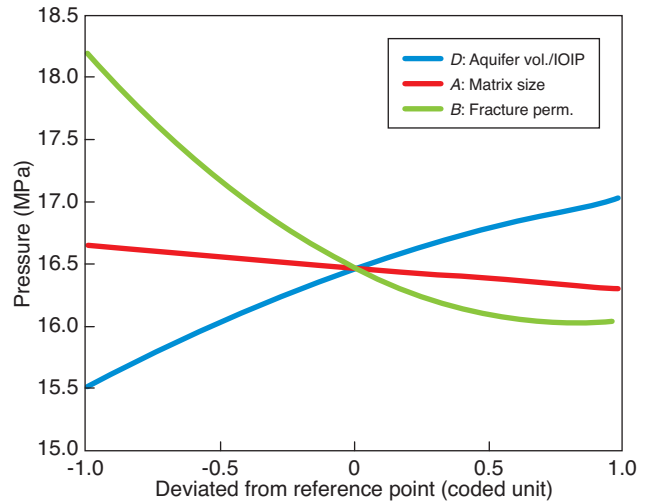Perturbation plot describing the main influential parameters
on recovery.

Figure 7

Perturbation plot describing the main influential parameters
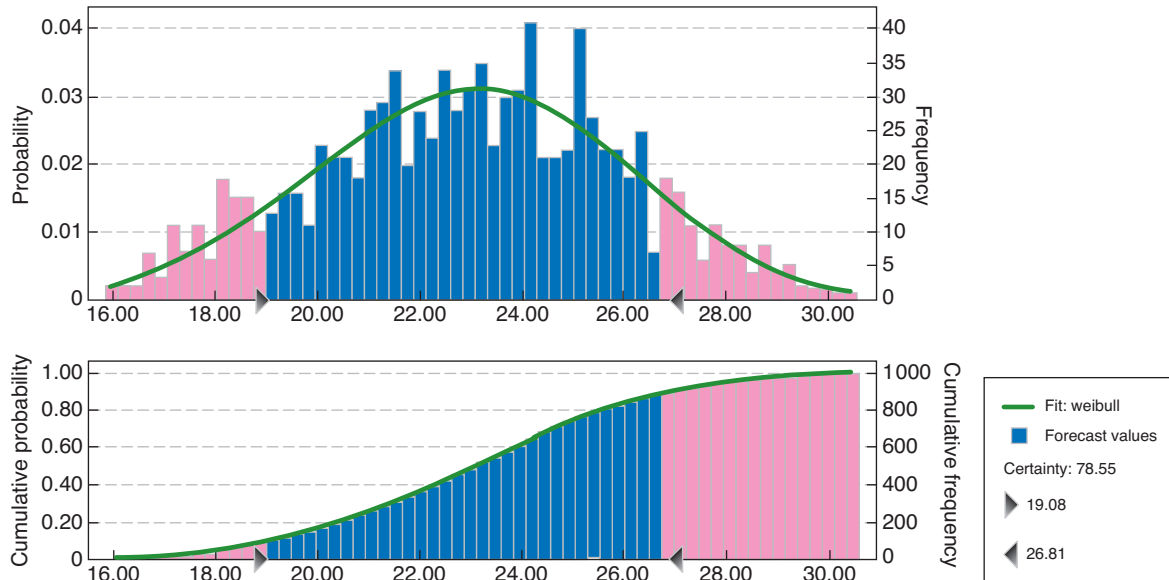on recovery.

Figure 8

Probability distribution for the recovery factor after 30 years.

as in DOE (low and high levels). Software uses values from
their identified intervals in 1 000 trials to produce probability
distribution for "% Recovery" which has been defined with
the equation derived from DOE *(Fig. 7)*.

After fitting a probability curve to the results, it is possible
to find different parameters of probability distribution such as
mean, median, 10th percentile and 90th, etc. *(Fig. 8)*.

Sensitivity chart shown in Figure 9 illustrates importance
of each factor's effect on response in comparison with the
others. For example, in this range of investigation, aquifer
size is the most influential parameter, and matrix block size
and fracture permeability are the two next important factors.
The main concept of this chart is similar to what is shown in
Figure 6, as a perturbation graph.

Effect (%)
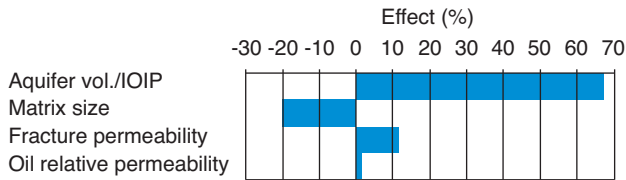
Figure 9

Sensitivity chart for recovery.

From reservoir engineering point of view, Figure 9 mentions that for a reservoir with larger aquifer volume, rate of pressure drop would be lower (as shown in *Fig. 7*), this lets the wells to keep higher pressure for a longer period of time. Therefore, cumulative oil production will increase at the end of 30 years. In addition, for a reservoir with smaller fractured density, which tends to lower fracture permeability, effective permeability of the reservoir decreases and ability of the reservoir for conduction of oil to the well decreases consequently.

Table 4 shows that distribution shown in Figure 8 mean and median is equal to 22.95, and mod is 23.01, which agrees with previous studies on this field.

TABLE 4

Distribution function of recovery

Statistics	Values
Trials	1 000
Mean	22.95
Median	22.96
Mode	23.01
Standard deviation	2.96
Variance	8.79
Skewness	– 0.027
Kurtosis	2.48
Coeff. of variability	0.129
Minimum	15.88
Maximum	30.55
Range width	14.67
Mean std. error	0.09

Furthermore, by analyzing the cumulative probability, it could be shown that 10th percentile is 18.9 and 90th is 26.96. This is a quit large range of uncertainty from reservoir engineering point of view, because IOIP of the reservoir is about 1 billion barrels of oil and 8% recovery means 80 million barrels of oil. Therefore, it is necessary to decrease the levels

of uncertainty within the reservoir model using the advantages of high technology. For example, it is important to make sure about the aquifer strength and volume or fracture network properties by using different kinds of logs or drilling more observation wells.

Results for pressure variation prediction are shown in Table 5.

TABLE 5

Distribution function of pressure

Statistics	Forecast values
Trials	2 000
Mean	16.89
Median	16.68
Mode	16.47
Standard deviation	0.81
Variance	0.66
Skewness	0.7347
Kurtosis	2.84
Coeff. of variability	0.0481
Minimum	15.56
Maximum	19.37
Range width	3.81
Mean std. error	0.02

Probability distribution of ultimate reservoir pressure has been shown in Figure 10. Table 5 illustrates that mean of this distribution is equal to 16.89, median 16.68, and mod 16.47.

Cumulative probability shows that P10 is 15.96 and P90 is 18.11.

Sensitivity chart *(Fig. 11)* identifies that which parameter has the biggest effect on pressure, and what is the rank of each parameter regarding to their normalized effect. It could be shown that fracture permeability has the largest negative effect on pressure drop; it means rate of pressure drop would be more in a reservoir with higher fracture permeability, which is a reasonable statement in reservoir engineering. Then, aquifer volume as a supporter has a positive effect on pressure. This implies that, when strong aquifer volume connected to the reservoir, reservoir pressure decreases very gently.

CONCLUSION

This paper demonstrates how Experimental Design could be used in forecasting the probable performance of oil reservoir
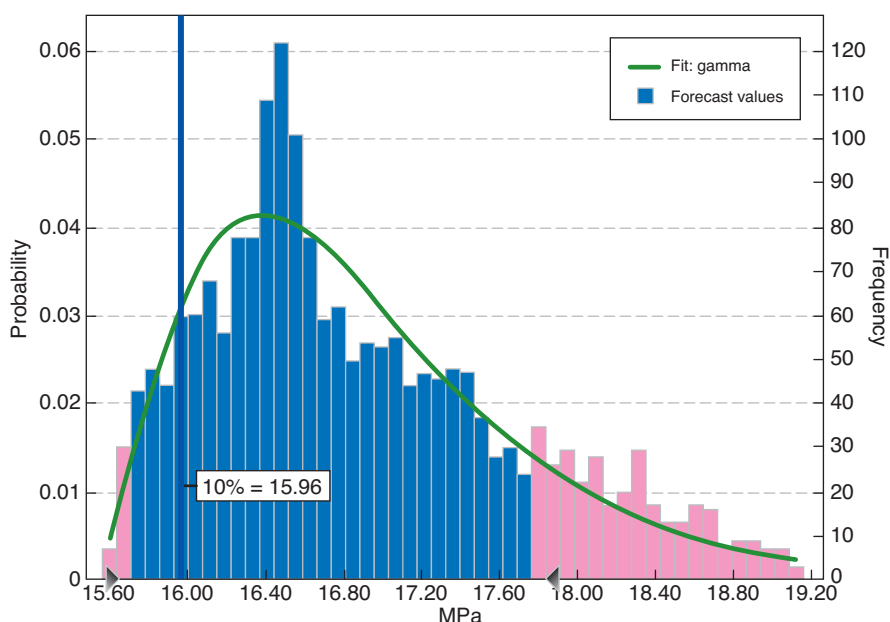
Figure 10

Probability distribution for reservoir pressure after 30 years.
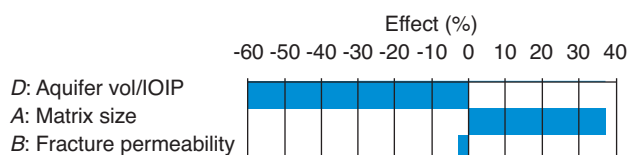

Figure 11

Sensitivity chart for pressure.

during its lifetime. Box-Behnken method was used to find the most influential parameters on pressure and recovery, as well as finding a proxy equation to model the responses. DOE identified that for natural depletion in a fractured reservoir like the one studied in this paper, the most significant parameters were: ratio of aquifer volume to the IOIP, matrix size, and fracture permeability. Furthermore, oil recovery was a week function of oil relative permeability while the reservoir was fractured.

The proxy model allowed the study of the full distribution of oil recovery and reservoir pressure rather than just its expected value, by using the Monte-Carlo analysis. Although, the results show the most probable recovery for this model is about 23% (which is in agreement with previous studies on this field), there is a large difference between 10th percentile probability (18.9) and 90th (26.96). In terms of reservoir engineering, 8% recovery factor, based on IOIP of this field, means 82 million barrels of oil. Therefore, it is necessary to reduce the uncertainty of the model parameters by extended field analysis technologies.

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