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Development of a framework for optimization of reservoir simulation studies

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Abstract

We have developed a framework that distributes multiple reservoir simulations on a cluster of CPUs for fast and efficient process optimization studies. This platform utilizes several commercial reservoir simulators for flow simulations, an experimental design and a Monte Carlo algorithm with a global optimization search engine to identify the optimum combination of reservoir decision factors under uncertainty.

This approach is applied to a well placement design for a field-scale development exercise. The uncertainties considered are in the fault structure, porosity and permeability, PVT, and relative permeabilities. The results indicate that the approach is practical and efficient for performing reservoir optimization studies.

Keywords: Reservoir simulation; Experimental design; Response surface; Optimization algorithm; Sensitivity analysis; Well placement optimization

1. Introduction

In recent years the oil industry has given great importance to reservoir management and reservoir uncertainty analysis. Reservoir simulation studies can play a significant role in the evaluation of different scenarios (i.e. reservoir and fluid property description, etc.) that affect the production forecast and ultimate oil recovery. These scenarios represent probable reservoir configurations, in regards to reservoir properties, which may cover a wide range of possible inputs for the simulations (i.e. input data with uncertainties). 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 experimental design, response surface and Monte Carlo simulation have been used to address the uncertainties (Damsleth et al., 1992; Dejean and Blanc, 1999). However, to the best of our knowledge, this is the first time that experimental design, response surface, and Monte Carlo simulation are combined to efficiently perform a large number of possible simulation scenarios.

Dejean and Blanc (1999) proposed the integration of experimental design, response surface and Monte Carlo methods to optimize the production scheme. They applied their methodology to a field to assess the effects of the uncertainties on oil production. Guyaguler and Horn (2001) addressed the uncertainties associated with well placement optimization problems using a hybrid genetic algorithm along with numerical simulations as the evaluation tool. Narayanan et al. (2003) presented a decision framework which integrates across the E&P value chain and allows the professionals across disciplines to preserve

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and share the interdependent uncertainties. Cullick et al. (2003) proposed a system which integrated reservoir simulation, an economic model, and a Monte Carlo algorithm with a global optimization search algorithm to identify more optimal reservoir planning and management decision alternatives under uncertainties. They claimed that there has not been a single technology that fully integrates rigorous reservoir modeling, flow simulation, and economics within a decision optimization framework and explicitly manages risk. Ozdogan and Horn (2006) used pseudohistory concept to evaluate the time-dependent uncertainty for the process of optimizing the well locations.

2. IRSS: An Integrated Reservoir Simulation System

Integrated Reservoir Simulation System (IRSS) is a combination of software (UT_IRSP, etc.) and hardware (a single Linux based machine or a cluster of Linux based machines) to make engineering related decisions by solving various reservoir engineering problems, in which multiple reservoir simulation studies need to be performed and evaluated, using different methodologies (Zhang, 2005a).

Currently, the reservoir engineering problems that can be solved by IRSS include well location optimization, sensitivity studies to rank the important reservoir parameters, stochastic simulation to gauge the risk, the design and optimization of chemical flooding processes (Zhang et al., 2005b,c) and/or an integrated study that combines all the above.

Working as the heart of IRSS, the software UT_IRSP has utilized three reservoir simulators, two spatial stochastic field generators and two job schedulers for performing distributed and/or parallel computing. The three reservoir simulators are UTCHEM (Datta-Gupta et al., 1986; Delshad et al., 1996; UTCHEM-9.0, Volume I, 2000; UTCHEM-9.0, Volume II, 2000; Delshad et al., 2002), ECLIPSE (Schlumberger, 2003) and VIP (Landmark Graphics Corporation, 2003). The two spatial stochastic field generators are MDM (Yang, 1990) and SGSIM of GSLIB (Deutsch and Journel, 1998). The two job schedulers are Portable Batch System, PBS, (Altair Grid Technologies, LLC, 2004) and Load Sharing Facility, LSF, (Platform™ Computing Corporation, 2003). Seven single stochastic distributions have been implemented in the single stochastic algorithm (SSALG) class of UT_IRSP.

We have used window-based commercial software packages to design, analyze, and optimize the results from the reservoir simulation studies. For experimental design and response surface, Design-Expert (Stat-Ease, Inc., 2003) is used. Crystal Ball (Decisioneering, Inc., 2004, 2001) is used for optimization and Monte Carlo simulation to gauge the uncertainties. Tecplot RS (Tecplot, Inc., 2003, 2004) is used for plotting UTCHEM and ECLIPSE 3D maps and the 3DView of VIP is used for plotting VIP 3D images. Microsoft Excel is used for plotting the well production histories. Surfer (Golden Software, Inc., 1999) can be used for variogram analysis on 3D geostatistical data. Fig. 1 shows the structure and the components of IRSS.

3. Framework implementation

The framework is designed using the object-oriented concept and is written in C++. Ideally, it works on a

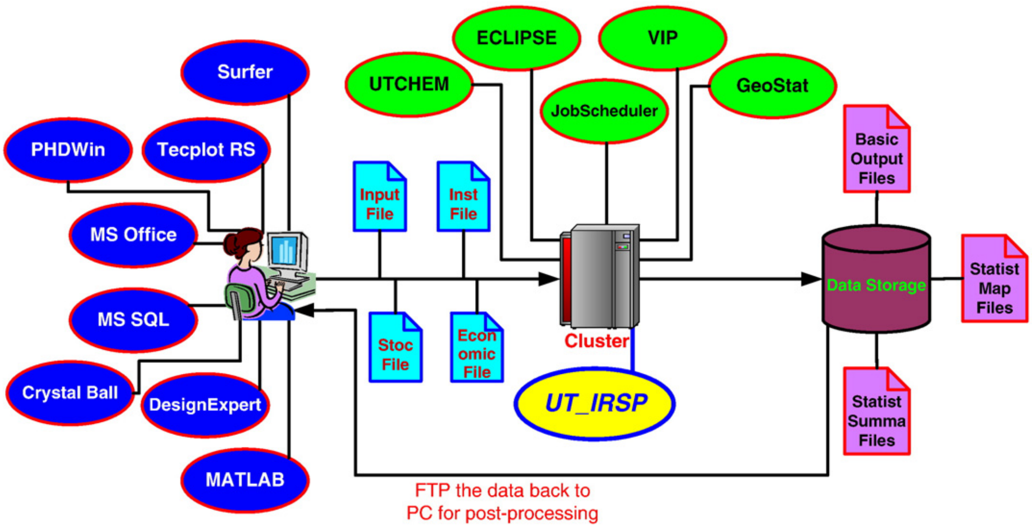

Fig. 1. IRSS — Integrated Reservoir Simulation System.

cluster of computers with LINUX as the operating system. The framework can be divided into three modules. Fig. 2 shows the UML class diagram of the framework.

- Main program works as the frontend to the framework. Once the framework is launched, the user needs to provide the study name and select the numerical model of interest.
- Pre-processing group contains ten classes. This section of the code reads the instruction and/or stochastic files first. Multiple simulation input files are then generated automatically according to the user's specifications. All of the simulation jobs are then submitted to the processors either as a sequential (one simulation at a time), distributed (multiple simulations to a cluster of PCs) or parallel mode. The simulation output files are then saved hierarchically on a storage device. The instruction file contains the following data (1) the number of the simulations, (2) the run number, (3) the execution mode as sequential, distributed or parallel, and (4) the factors that are under investigation and as how these factors are varied for each simulation. The stochastic input file is also needed to generate the single or spatial stochastic fields from the distributions. Sequential Gaussian (sgsim) model from GSLIB is one of the two geostatistical modules available in the framework.
- Post-processing module contains eight classes. The output of the simulations will be collected and summarized either for further data manipulation or graphical presentations.

4. Experimental design and response surface methodology

Design of Experiment (DOE) is a method to select simulations to maximize the information gained from each simulation and to evaluate statistically the significance

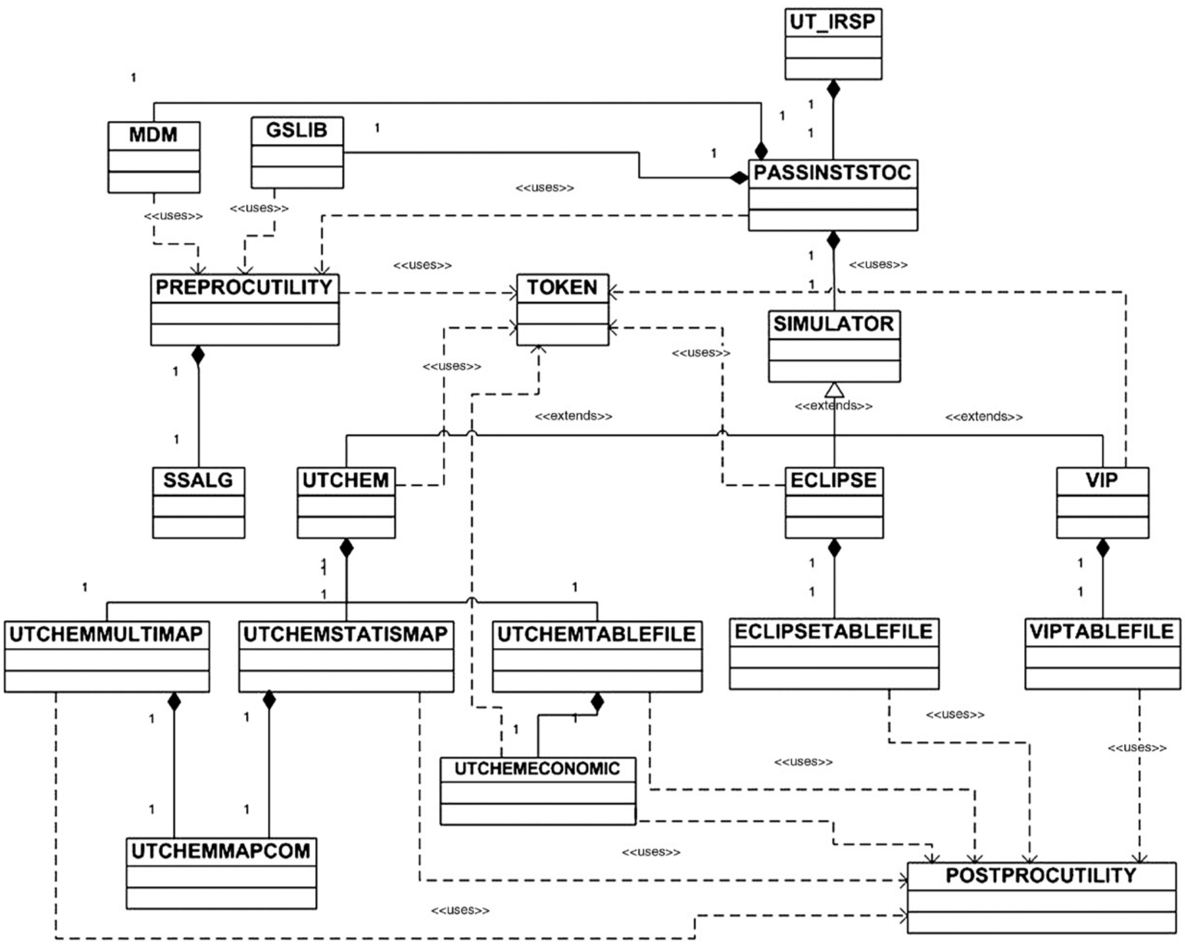

Fig. 2. UML class diagram for framework — UT_IRSP.

of the different factors. An experimental design study 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, often called operating region. The components of the operating region include objectives, requirements, state parameters (with or without uncertainty), decision variables, and constraints. An objective is the statement of the goal, and requirements can be imposed. State parameters are those that cannot be controlled and most of the time has uncertainties associated with them. They can be discrete or continuous. Discrete parameters are also referred to as "scenarios". Decision variables are those that are controllable and are usually choices available to the decision-maker. Constraints are boundary conditions, which restrict values available for the decision variables.

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 (1) identifying the variables that influence the responses (screening) and (2) 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.

In order to compute the regression model, the process has to be sampled over the operating region through experimentation. Design of Experiment is the use of mathematical and statistical methods to determine the number and the location of the experiments in order to get most information at the lowest experimental cost.

We will not describe the detailed mathematical and statistical theories behind response surface and experimental design. More details can be found in a related literature by Myers and Montgomery (1995). A flowchart showing the integration of Design of Experiment and Response Surface in the framework is given in Fig. 3. A commercial software package, Design-Expert from Stat-Ease, Inc., is used for performing experimental design analysis.

The steps to perform RSM and DOE in conjunction with our framework are listed as the following:

- Select the response and identify the settings for the state parameters and decision variables.
- Select the corresponding method of DOE according to the study objective.
- Include the experimental plan from DOE in the instruction and/or stochastic and/or economic file.
- Run the numerical simulations using the framework.

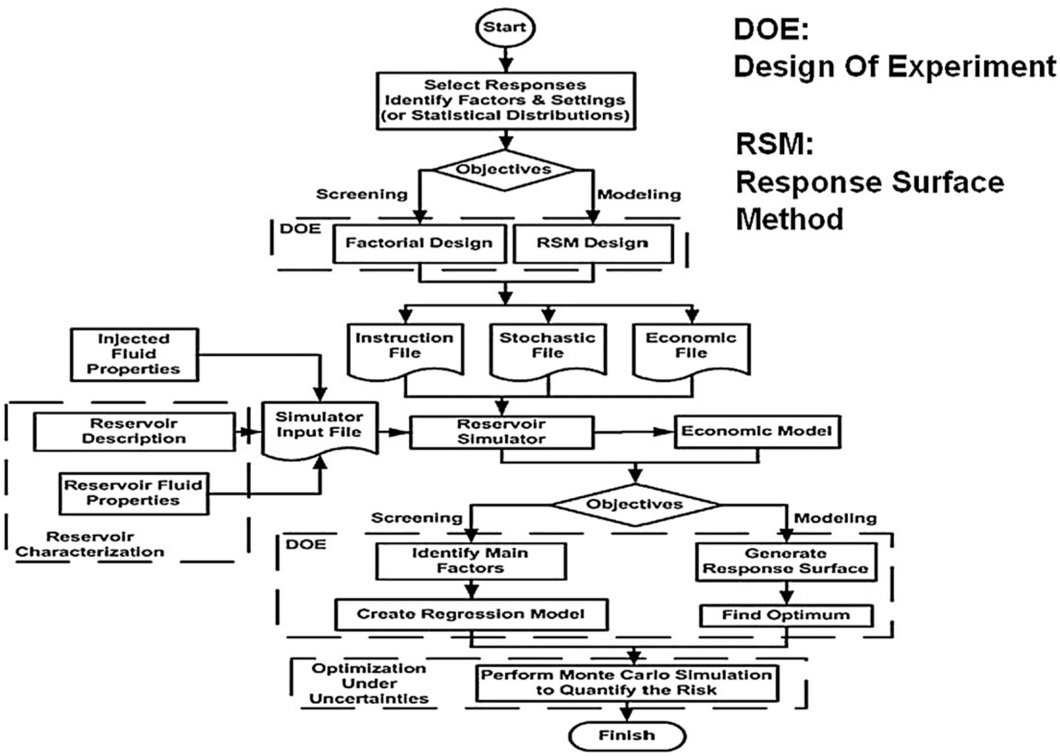

Fig. 3. Flowchart of experimental design and optimization.

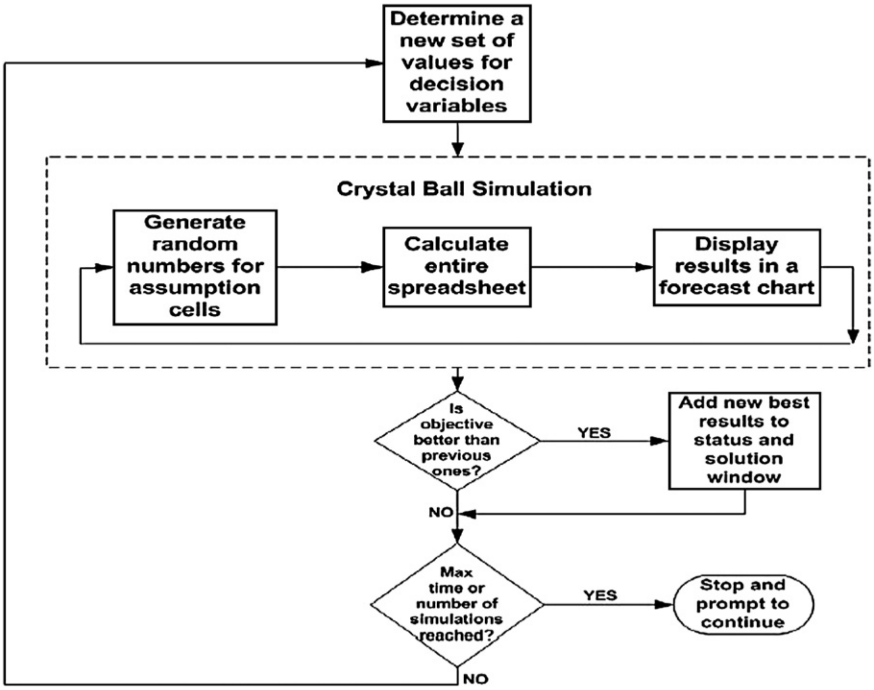

Fig. 4. Flowchart of OptQuest.

- Export the results of the response to DOE and perform statistical analysis.
- Use the response model results to screen the factors and/or to perform further optimization as discussed in the next section.

5. Optimization algorithm

Traditional search methods work well when finding local solutions around a given starting point with model data that are precisely known. These methods fail,

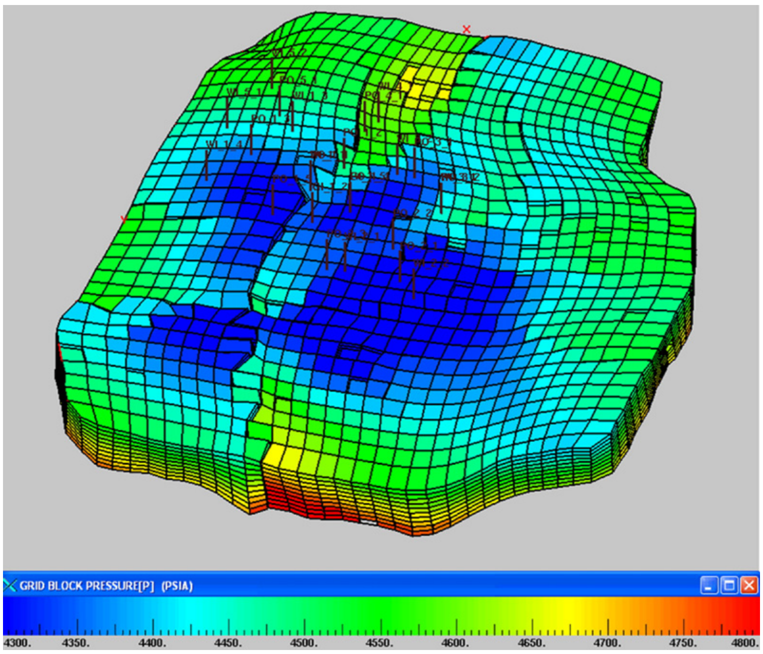

Fig. 5. Initial reservoir pressure distribution.

Table 1
Two-level full factorial design for four uncertain variables

Factor	Name	Actual low	Coded low	Actual high	Coded high
A	Faulting	1	−1	2	+1
B	Variogram	Short	−1	Long	+1
C	PVT	1	−1	2	+1
D	Relperm	1	−1	2	+1

however, when searching for solutions to real world problems that contain significant level of uncertainties. Recent developments in optimization have produced efficient search methods capable of finding optimal solutions to complex problems involving elements of uncertainty.

The optimization algorithm incorporates metaheuristics to guide its search algorithm toward better solutions. The approach uses a form of adaptive memory to store which solutions worked well before and recombines them into new improved solutions. Since this technique does not use the hill-climbing approach of ordinary solvers, it does not get trapped in local solutions, and it does not get thrown off course by noisy (uncertain) model data. Scatter and tabu searches are used to globally search the solution space. Neural network is used as a predictive model to help the system accelerate the search by screening the reference points that are likely to have inferior objective function values. The optimizer is described in detail in April et al. (2003a,b).

OptQuest from OptTek Systems, Inc. is the commercial optimizer that implements the above stated optimization algorithm and has been integrated in Crystal Ball, a risk analysis software package from Decisioneering, Inc. We use Crystal Ball and OptQuest to perform the optimization under uncertainty. Fig. 4 shows the workflow of OptQuest in the Crystal Ball environment.

6. Case study procedure

Our approach is applied to a synthetic reservoir from Landmark Graphics (Narayanan et al., 2003). Two-level-full-factorial design was applied over four uncertain variables to identify their sensitivities. D-optimal design was used to obtain the optimal location for the next producer on each geological realization over a most likely area of the reservoir (determined by engineering judgment and intuition). An exhaustive simulation study (ESS) approach was performed to verify the results from D-optimal design. In order to optimize the well location under all the uncertainties, we performed DOE and RSM analysis over five factors again. Three of them are uncertain factors and two are decision variables, the well location coordinates (x, y). After we calculated the probability for each uncertain scenario, the Crystal Ball model was created according to the response we obtained from the last step. OptQuest was run and the

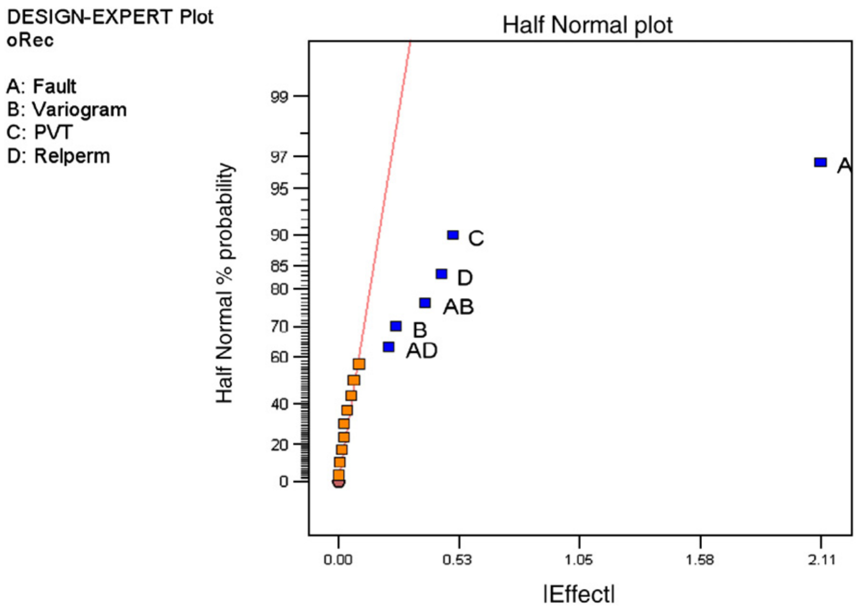

Fig. 6. Sensitivity study from two-level full factorial design.

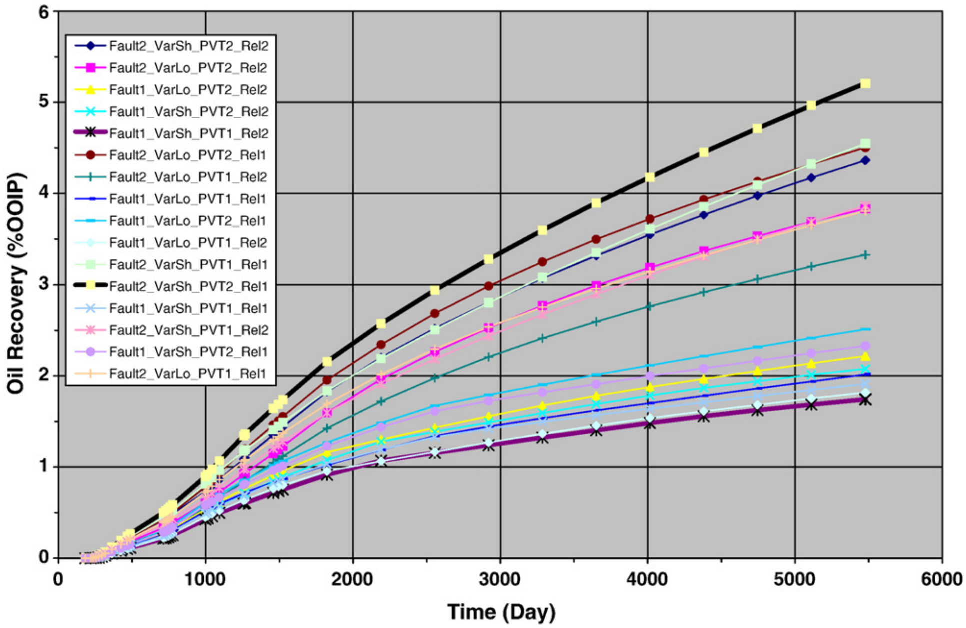

Fig. 7. Oil recovery for 16 simulations from 2-level full factorial.

optimal well location was obtained with all these uncertainties. The risk was then identified.

7. Reservoir model description

The reservoir data is based on an offshore field, covering about 30 square miles, with 3D seismic and several non-producing appraisal wells with petrophysical log suites. The average reservoir thickness is about 450 ft. A conventional interpretation analysis of the seismic and the petrophysical logs identifies faults and horizon surfaces. The best estimates for the fluid contacts from the log suites are 5350 ft subsea for the water–oil contact and 4900 ft subsea for the gas–oil contact. Porosity and permeability at the wells have also been interpreted from the log suites.

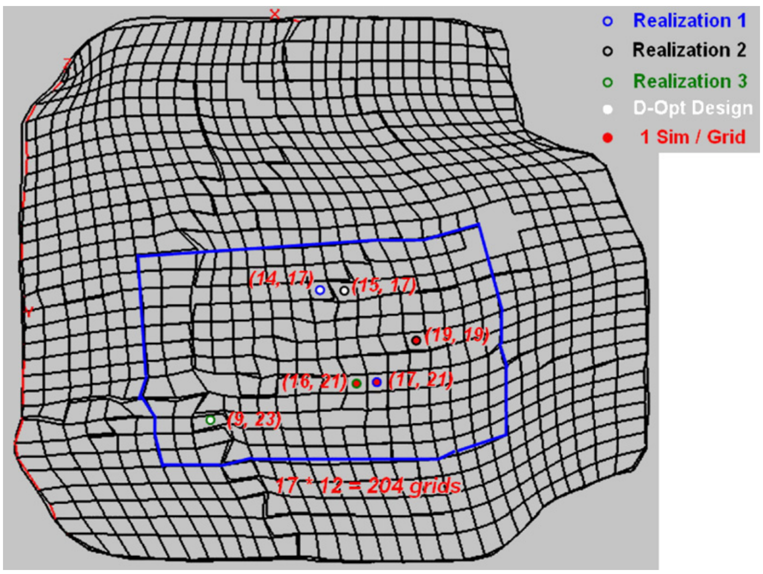

Fig. 8. Well locations for three realizations.

Table 2
Oil recovery comparison before and after the well placement

Faulting1_Long_ WellScenario3_ pvt1_relperm1	Before well placement oil recovery (%OOIP)	After well placement oil recovery (%OOIP)	Incremental percentage (%)
Realization-1	2.0074	3.4599	72.36
Realization-2	1.9361	3.7709	94.77
Realization-3	1.4626	3.118	113.18

There are two reservoir grid definitions corresponding to two faulting scenarios. For "Faulting1", the reservoir model has 9000 gridblocks (30×30×10) and 4840 (22×22×10) gridblocks for "Faulting2". It is a black oil simulation model with two gas injectors, ten water injectors and 12 oil producers. The simulation time is 15 years. Fig. 5 shows the reservoir grid, well locations and the initial reservoir pressure distribution for "Faulting1".

8. Reservoir uncertainty description

Scenarios around the faulting, the degree of correlation with seismic for porosity, the sedimentary correlation length and anisotropy were considered to be the major uncertainties in the subsurface geological model. There were two faulting scenarios, "Faulting1" and "Faulting2". First scenario assumed that many small faults might ultimately control fluid flow. The second scenario had the assumption that only the three major faults would impact the flow. Two variogram scenarios with "short" and "long" correlation lengths and different anisotropy were assumed to recognize uncertainty in the depositional understanding. Three porosity realizations were generated using collocated Gaussian simulation correlated with the seismic data. Permeability distribution was generated as a transform of porosity with a correlation coefficient.

Uncertainties in the fluid contacts, PVT, net to gross volumes, and porosity affect the fluid volumes in the model. Uncertainties in the fluid PVT, fluid contacts, extent to which faults are sealing, permeability and relative permeability were also included as sources of reservoir energy. Two PVT tables, "PVT1" and "PVT2" reflect the uncertainty in oil density and gas in solution. Two sets of relative permeability and capillary pressure tables, "Relperm1" and Relperm2", were considered to model uncertainties in Corey exponents and residual saturations.

9. Sensitivity analysis

A two-level full factorial design was used to investigate the sensitivities of the four uncertain variables. Table 1 shows the ranges for these variables for the numerical experiments. Fig. 6 shows the results after the statistical analysis from these 16 reservoir simulations. We can see that "Faulting" is the most important factor affecting the objective function, the oil recovery in percentage of OOIP. It can be ranked as the first sensitive group. "PVT", "Relperm", the interaction between fault and variogram, variogram, and the interaction between the fault and "Relperm" are also important factors in that order and can be ranked as the second sensitive group. If the traditional one-factor-at-a-time (OFAT) sensitivity analysis approach was taken, the sensitivity of the interactions cannot be identified. If we had money to spend on further identifying the uncertainty, the money should be used on a better characterization of the nature of the faults, "Faulting".

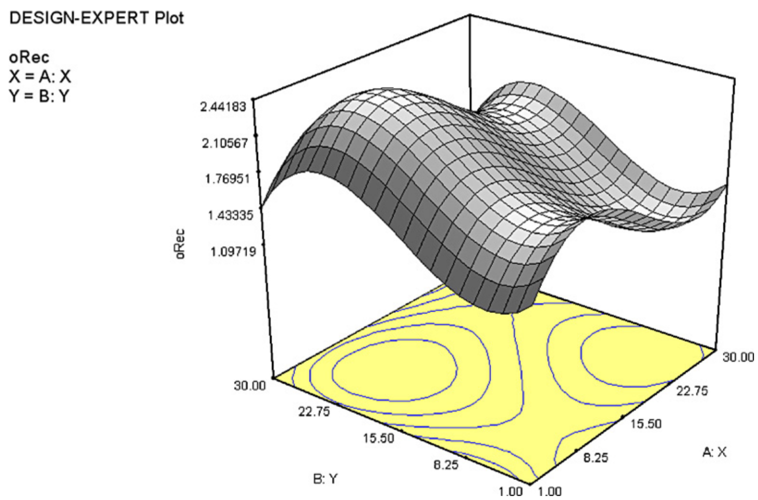

Fig. 9. 3D response surface for additional producer coordinates of realization 3.

Table 3
96 D-optimal design for uncertain variables

Factor	Name	Units	Type	−Actual	+Actual	−Coded	+Coded
A	*X*	Grid Block	Continuous	14	21	−1	+1
B	*Y*	Grid Block	Continuous	17	24	−1	+1
C	Variogram		Discrete	Faulting1 Short_1	Faulting1 Long_3	−1	+1
D	PVT		Discrete	pvt1	pvt2	−1	+1
E	Relperm		Discrete	relperm1	relperm2	−1	+1

Fig. 7 shows the cumulative oil recovery versus time for 16 reservoir simulations of two-level full factorial design. Simulation Number 12 results the maximum oil recovery while Simulation Number 5 results the minimum oil recovery. The simulations using “Faulting2”, the three major faults controlling the fluids flow, had higher oil recovery than the simulations with “Faulting1”.

10. Verification of D-optimal design

We choose the “Faulting1”, “Long” variogram, “PVT1”, “Relperm1” for the D-Optimal design. Since there are three realizations for porosity and permeability, we used D-optimal design to find the optimal location for the next producer under each realization.

In order to define the design space, we first examined the initial oil saturation distribution. There was a lot of oil initially located in the southern part of the reservoir. However, the wells were mainly drilled in the northern part. Then we checked the *kh* map of the reservoir. There is no obvious indication of sweetest spots (locations that have the highest *kh* values). Therefore, a 17 by 12 gridblock-area (within the blue polygon of Fig. 8) to the south was considered as the design space. Three sets of D-optimal design were performed and the optimal well location for each set was found using the internal optimization routine of Design-Expert over the three response surfaces obtained. Then the exhausted simulation studies (ESS) on the design space were performed to verify the results from RSM. From Fig. 8 we can see that the well locations obtained from RSM and ESS are not that far apart. Again, RSM can provide reasonable results for the design and optimization of the reservoir development. The approach that we are proposing here is the following:

- Using RSM designs to reduce the search area of the next producer.
- Using ESS approach to find the best well location within the reduced area.

Table 2 shows the oil recovery enhancement after the well placement for three realizations. The incremental oil recovery is very significant. The total oil production

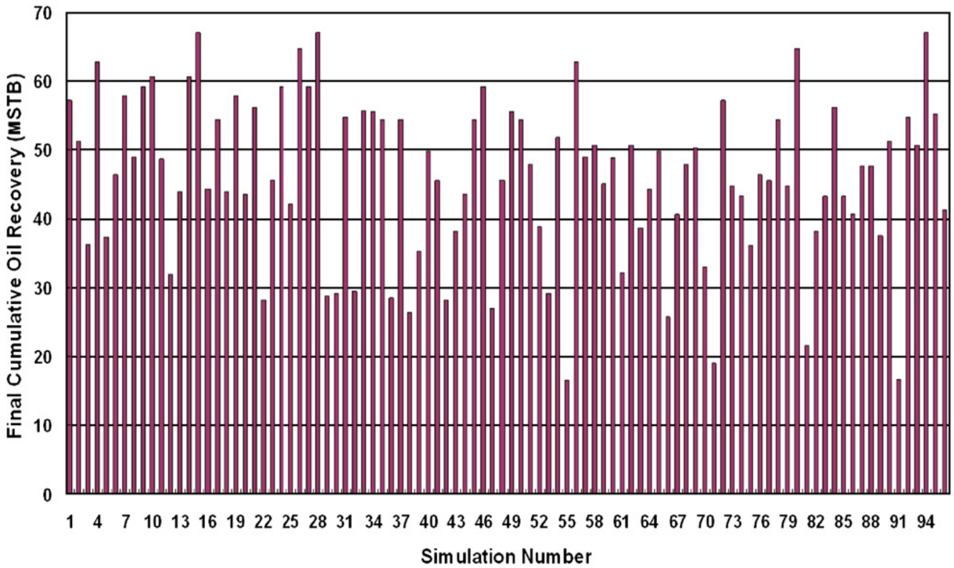

Fig. 10. Final cumulative oil recovery for 96 D-optimal design.

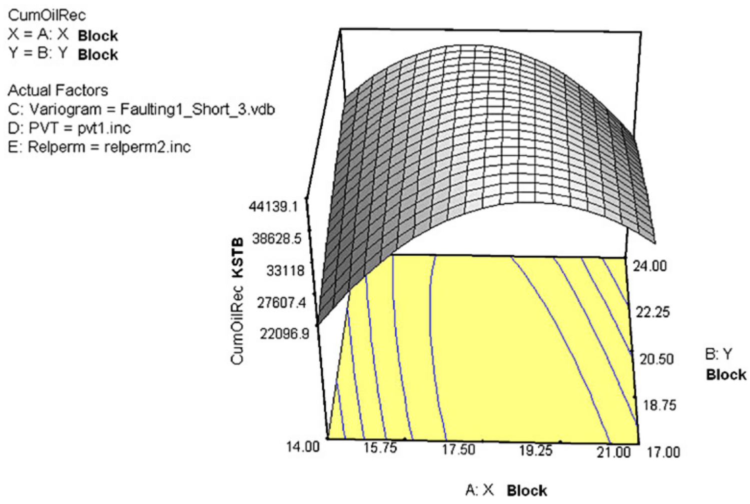

Fig. 11. Response surface for well location from 96 D-optimal design.

is nearly doubled for all the realizations by adding just one more producer at an optimized location using ESS. Fig. 9 gives the three-dimensional response surface for realization 3 for well coordinates (x, y) versus the objective function, the oil recovery. The optimum well location is (9, 23).

Under realistic field operations, there might be many complications for drilling more wells. Other factors need to be addressed, like surface pipe network capacity and drilling platform location and limitations, etc. Such issues are not addressed here and are outside of the scope of this study.

11. Well placement optimization under uncertainties

The goal of optimizing reservoir development plan taking into account uncertainties is the calculation for the optimal combination of the design variables considering all the possible uncertainties. At the end of the study a histogram of the results over the objectives should be created and the interval of confidence, percentiles, range, mean, standard deviation, and coefficient of variability should be specified.

To obtain the best location for additional producer over the four uncertain factors, we first specify the design space

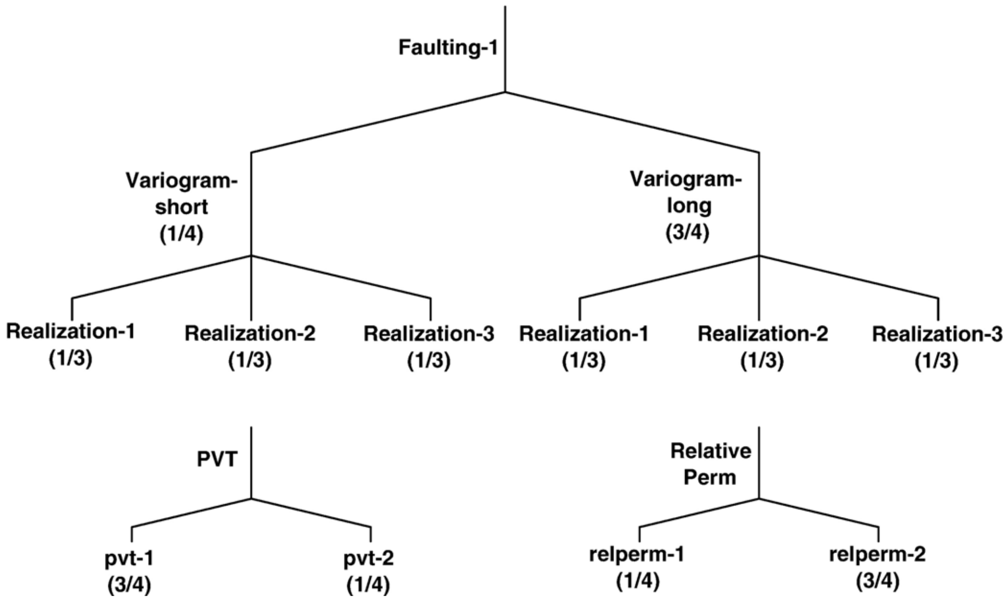

Fig. 12. Probability tree for uncertain variables.

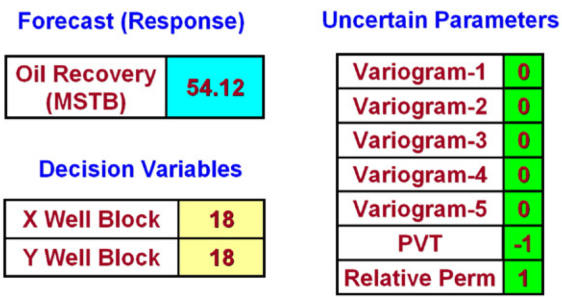

Fig. 13. Optimization results under uncertainties.

as given in Table 3. The reason we did not take "Faulting" as one of the uncertain factors is because different faulting scenario requires different reservoir mesh as we mentioned before. It is meaningless to optimize well location for a reservoir with two different meshes. The previous verification study has narrowed down the area of the optimal well location to gridblocks 14 through 21 in x direction and 17 through 24 in y direction and this is the range we used for these two decision variables.

With this setting, the D-optimal design of Design-Expert provided a 96-simulation plan for UT_IRSP to run. We included this plan in the instruction input file and run the simulations in a distributed mode. Upon the completion of these simulations, oil recovery for each simulation was fed back into the D-optimal design to analyze the statistics and generate the response. Fig. 10 shows the Excel diagram for one of the output files generated by the post-processor of UT_IRSP. The final cumulative oil recovery ranges from 16 MSTB for the Simulation Number 55 to 67 MSTB for Simulation Number 94. The response surface of well location versus the objective is shown in Fig. 11. There seems an optimal line of $x=18$ for the well location.

A Crystal Ball model was created according to the quadratic polynomial response that we obtained from DOE and RSM. Before we can simulate the response with the goal of maximizing the average oil recovery, the probability for each of the uncertain scenarios is first calculated. In this study, a probability value was arbitrarily assigned to each scenario as shown in Fig. 12. There are 10 uncertain scenarios of discrete type. Two scenarios are from "PVT" and "Relperm" respectively. For the six scenarios from geological model, we need to multiply the two probabilities to obtain the final probability. Since the degree of freedom is five, when all of the first five are set to level zero we will then obtain the probability for the last scenario. Fig. 13 is a screen capture of Crystal Ball. The optimized oil recovery is 54.12 MSTB for the selected uncertain and decision variables.

After about 500 Monte Carlo simulations, the optimum well location was found to be a grid coordinate of (18, 18) by the OptQuest. The probability density distribution is shown in Fig. 14. The mean of the final oil recovery is 54.9 MSTB with a coefficient of variability of 0.18. The overall uncertainty is small and the risk is low. Note that we did not take the variability of "Faulting" into account because of the difficulty with two different meshes involved.

From the data on percentiles of the cumulative oil recovery provided by Crystal Ball, we should have 80% confidence in having oil recovery between 42.7 and 67.2 MSTB.

12. Summary and conclusion

A user-friendly and efficient platform, UT_IRSP, has been designed and successfully implemented. UT_IRSP approach is used in a well placement design

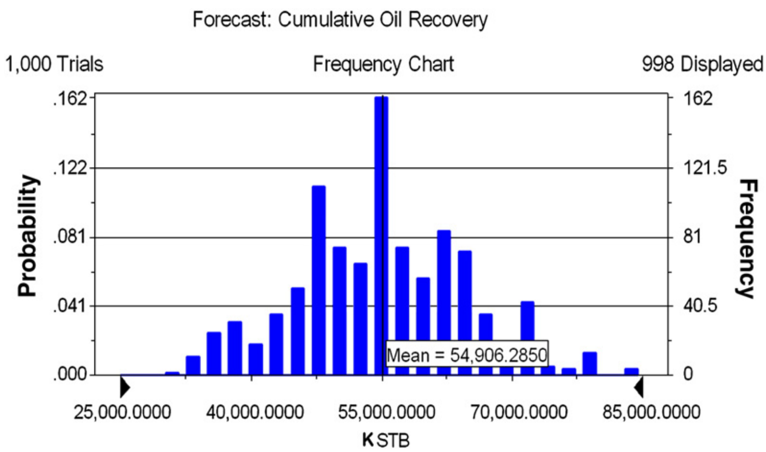

Fig. 14. Cumulative oil recovery probability density distribution.

and optimization exercise. Based on the case study presented and our experience in using this approach, the following can be summarized:

- "Faulting" is the most sensitive parameter.
- The conjunct effects between "faulting" and "variogram", and "faulting" and "Relperm" are also important.
- The optimized location for an additional producer is (18, 18) with a mean oil recovery of 54.9 MSTB and the coefficient of variability of 0.18.
- The oil production increases from 25.8 to 54.9 MSTB with the placement of an additional producer.
- This case study shows that DOE can reduce the search area for the well placement problem. Subsequently, the ESS approach can be applied over the reduced area in order to find the most probable location that produces the highest hydrocarbon recovery.

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