EVALUATION OF IN-FILL WELL PLACEMENT AND OPTIMIZATION USING EXPERIMENTAL DESIGN AND GENETIC ALGORITHM

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EVALUATION OF IN-FILL WELL PLACEMENT AND OPTIMIZATION USING EXPERIMENTAL DESIGN AND GENETIC ALGORITHM

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ABSTRACT

Determination of optimal well locations for infill drilling is a challenging task because engineering and geologic variables affecting reservoir performance are often nonlinearly correlated and have some degree of uncertainty attached to them. Numerical models which are the basis of well placement decisions rely on data that are uncertain, which in turn translate to uncertainty in our numerical simulation forecasts.

The objective of this research is to employ an efficient optimization technique to the well placement problem to determine the optimum infill well location. Based on the success of its previous application by other authors in solving the well placement problems, Genetic Algorithm (GA) will be used here as the main optimization engine. An experimental design is used to generate some experimental simulation runs using the uncertain parameters, and these uncertain parameters are used to fit a response surface model of the objective function. The response surface methodology is used to identify the optimum design under conditions of uncertainty to build a proxy model that can be utilized to predict the cumulative oil produced.

Our application of GA to determine the optimal location for infill well placement in a synthetic reservoir is improved by using a set of screening criteria and some engineering judgment to reduce the search space for possible locations. The proxy model generated from the response surface methodology is also combined with GA to determine the optimal locations for three cases of drilling two, four or six additional infill wells in the reservoir modeled in this study.

The study found that response surface models can be used as a proxy tool coupled with GA to provide reliable results; and to reduce the number of simulation runs required for the well placement optimization problem.

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CHAPTER 1

INTRODUCTION AND STATEMENT OF THE PROBLEM

1.1 Introduction

There is a growing demand to develop petroleum reservoirs through the drilling of in-fill wells to exploit the hydrocarbon reserves not properly drained by existing producing wells. Well placement can be referred to as all activities associated with drilling a wellbore to intercept one or more specified locations. The term is usually used in reference to vertical, directional or horizontal wells that are oriented to maximize contact with the most productive parts of reservoirs. As well spacing is decreased, the shifting well patterns alter the formation-fluid flow paths and increase sweep to areas where greater hydrocarbon saturations exist. A wide well spacing will leave some oil and gas bearing sands in areas not penetrated, while a close spacing will cause some oil and gas bearing sands to be penetrated by two wells or more, causing interference and lowering the reserves drained by the wells and economic profit. This study is done to determine the optimal locations for well placement to support field development plans.

One of the most challenging and influential problems associated with drilling in-fill wells is finding the optimum number of wells and their placement in the reservoir. In this problem, there are many variables to consider like geological, well configurations, production variables and economic variables. All these variables, together with reservoir geological uncertainty, make the determination of a suitable development plan for a given field difficult, since the design has to evaluate hundreds or thousands of potential infill alternatives.

The task of optimization of infill well placement is challenging, because the evaluation of the production capacity of many wells may be required, with each evaluation requiring the performance of a simulation run; and for large or complicated reservoir models, the simulation run time can be excessive. The number of simulations required depends on the number of optimization variables, the size of the search space, and on the type of optimization algorithm employed.

Different optimization methods can be used to determine the optimum well locations in a reservoir. This optimization problem is nonlinear and generally contains multiple local minima. Gradient-free optimization algorithms are commonly used for well placement problems because of their computational efficiency. Genetic Algorithm (GA) is one of the Gradient-free optimization methods used in the industry. GA will be used as the main optimization engine in this work because of its success application by several authors in solving complex optimization problems with high dimensionality and nonlinearity. The main focus of this work is to employ an efficient optimization technique for in-fill well placement and optimization; i.e., to determine the best possible locations of infill wells for optimal development of a field. We intend to identify the significant parameters that affect well placement in the reservoir and use some screening parameters to identify potential locations for well placement. The use of Experimental Design (ED) and Response Surface Methodology (RSM) has been shown to be effective tools for uncertainty analysis. They were utilized in this work to consider a range of values for the controlling parameters and to build a proxy model that can be used to predict the objective function. Experimental design methodology offers not only an efficient way of assessing uncertainties by providing inference with minimum number of simulations, but also can identify the key parameters governing uncertainty in production forecast. This information is valuable to guide proper decision making during field development planning.

1.2 Literature Review

In this section, we present a brief review of the work done by various researchers on well placement optimization and the determination of the locations of infill wells in petroleum reservoirs.

1.2.1 Optimization Techniques

The optimization algorithms employed for well placement problems fall into two broad categories: global search stochastic algorithms (gradient-free) and gradient-based algorithms (Yeten, 2003).

A gradient-based optimization algorithm requires the computation of gradients of the objective function. The gradients can be computed using adjoint procedures or numerically. Gradient-based algorithms seek to improve the values of the objective function per iteration by moving in an appropriate search direction. Thus, gradient-based algorithms are computationally efficient, though they are susceptible to getting trapped in local optima. Furthermore, the lack of analytical solutions in most cases, the nonlinearity and non-continuity of oil field optimization problems tend to limit the utilization of standard gradient-based optimization methods (Montes et al., 2001). Gradient-based methods are well tuned for solving well behaved unimodal analytical functions as shown in Fig. 1.1

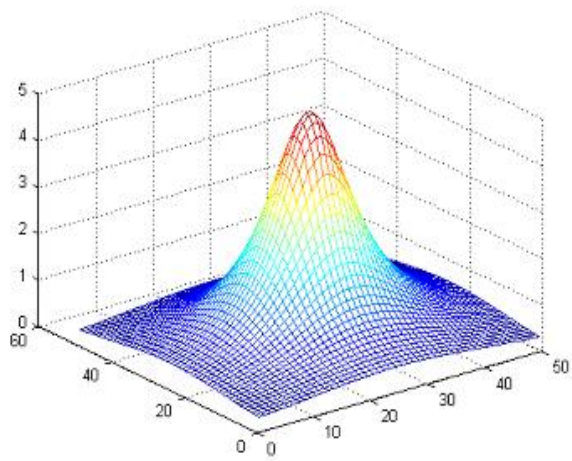

Figure 1.1 Unimodal Surface

The (gradient-free) stochastic optimization algorithms, such as genetic algorithms and simulated annealing are computational models of natural or physical processes. They do not require the

computation of derivatives. In addition, stochastic optimization algorithms possess mechanisms or algorithmic operators to escape from local optima, e.g., the mutation operator in GAs.

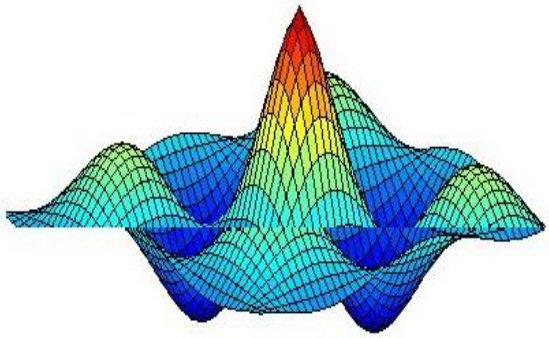

Figure 1.2 Multi-modal Surface

In this study, we will use genetic algorithm, as the optimization problem is nonlinear and generally contains multiple local minima; and GA has the ability to escape from the local optima for a multimodal problem, as shown in Fig 1.2.

1.2.2 Stochastic Optimization Algorithms (Gradient-free Algorithms)

Genetic algorithm (GA) appears to be the most popular stochastic optimization algorithm employed for well placement and other reservoir-management related applications (Yeten et al., 2003). GA is a computational analog of the process of evolution via natural selection, where species (solutions) compete to survive. GA represents potential solutions to the optimization problem as individuals within a population strive for survival. The fitness (solution quality) of the individual evolves as the algorithm iterates (i.e., proceeds from generation to generation). At the end of the simulation, the best individual (individual with highest fitness) represents the solution to the optimization problem (Goldberg, 1989). The two main variants of the GA are the binary GA (bGA) and the continuous GA (cGA). GA-based procedures have been applied to optimize the locations of both vertical wells and nonconventional wells and for well spacing optimization problems (Bittencourt et al., 1997; Artus et al., 2006; Onwunalu, 2010). The solutions obtained using GA can be improved by combining GA and other optimization algorithms, e.g., ant colony algorithm, Hooke-Jeeves pattern search algorithm, polytope algorithm or tabu search (Bittencourt

et al.,1997; Badru et al., 2003; Yeten et al., 2003). These hybrid algorithms have been demonstrated to provide better results and reduce computational expense compared to using only GA. In considering reservoir uncertainty, experimental design (ED) has been combined with response surface to assess uncertainty in reservoir production forecast. Dejean et al. (1999) applied response surface methodology (RSM) and a quadratic model form to optimize well location. Aanonsen et al., (1995) optimized well locations under uncertainty using RSM, incorporating ED and a kriging proxy.

Bittencourt et al. (1997) developed a hybrid binary Genetic Algorithm (bGA), where they combined GAs with the polytope method to benefit from the best features of each method. The polytope method searches for the optimum solution by constructing a simplex with a number of vertices equal to one more than the dimensionality of the search space. Each of the vertices is evaluated and the method guides the search by reflecting the worst point around the centroid of the remaining nodes. The approach was able to optimize the placement of vertical or horizontal wells in a real faulted reservoir by optimizing three parameters for each well: well location, well type (vertical or horizontal), and horizontal well orientation

Guyaguler et al. (2000) applied a hybrid optimization algorithm, which also combines the features of bGAs with the polytope method. Furthermore, several helper functions including Kriging and Artificial Neural Networks (ANN) that act as proxies for the expensive reservoir simulations to reduce the optimization cost were utilized. The theory of the Kriging algorithm is based on the phenomenon that some variables that are spread out in space and time show a certain structure. The algorithm tries to understand this structure and move towards the direction that is expected to achieve desirable results. ANNs are nonlinear statistical data modeling tools that are designed based on the aspects of biological neural networks. It seeks to model complex relationships

between inputs and outputs or to find patterns in data after completion of a training phase of the network that involves building a database from several simulation runs. The results concluded that Kriging was a better proxy than neural networks for tested problems (Guyaguler et al., 2000).

Yeten et al. (2002) applied bGA to optimize well type, location, and trajectory for non-conventional wells. Also, they developed an optimization tool based on a nonlinear conjugate gradient algorithm to optimize smart well controls. Several helper functions were also implemented including ANN and the Hill Climber (HC). An experimental design methodology was introduced to quantify the effects of uncertainty during optimization and they also conducted sensitivity analysis in a similar manner to Guyaguler' study.

Onwunalu (2006) applied a statistical proxy based on cluster analysis into the GA optimization process for nonconventional wells using Yeten's multilateral well model. The objective of applying the proxy is to reduce the excessive computational requirements when optimizing under geological uncertainty. The method is similar to the ANN method in terms of building a database of simulation results. The data base is then partitioned into clusters containing similar objects. The objective function of a new scenario can be approximated by assigning it to one of the constructed clusters. When single wells were optimized the proxy provided a close match to the full optimization by simulation only 10% of the cases. This percentage increased to 50% when multiple nonconventional wells were optimized.

Farshi (2008) converted a well placement and design optimization framework that was developed by Yeten et al. (2002) from bGa to a real-valued continuous Genetic Algorithm (cGA). The results showed that the cGA provides better results when compared to the performance of bGA on the same synthetic models. Moreover, several improvements to the optimization process like imposing

minimum distance between the wells and modeling curved wellbores was implemented by Farshi (2008) to obtain better results.

Emeric et al. (2009) implemented an optimization tool based on GA to optimize the number, location, and trajectory of a number of deviated producer and injector wells. A method to handle unfeasible solutions by creating a reference population consisting only of fully feasible solutions was used. Any unfeasible solution encountered in the optimization was repaired by applying crossover between it and an individual from the reference population until a new feasible solution was obtained. The technique was applied using the whole initial population defined randomly, and another done by including an engineer's proposal in the initial population. Better results were observed in the second strategy using the engineer' proposal and solutions were found to be more intuitive for the tested case.

Abukhamsin (2009) compared two variants of GA, the bGA and the cGA, to make a decision on the more robust algorithm to be used to determine the optimum well location and well design. The different internal algorithm parameters were tuned by the contribution of adding helper tools and hybrid techniques to the search for optimum solutions. After performing sensitivity tests on the algorithm, optimum parameters were selected and more in-depth analysis was performed to reach an optimum field development plan. He concluded that solutions from different runs had different well designs due to the stochastic nature of the algorithm but there were some similarities in well locations. Comparing the bGA and cGA, average results from the cGA were slightly higher and this algorithm appeared to be more consistent when several runs were made. This analysis also showed that better optimization results can be obtained within a shorter period of time when dynamic population sizes are utilized. The use of the HC helper tool with the GA delivered fitter final solutions.

This research will combine some of the approaches taken by Onwunalu (2006) and Abukhamsin (2009) to solve the well placement problem. A statistical tool that incorporates experimental design will be used to build the proxy model. The objective function is the cumulative oil produced. Optimum parameters will initially be selected to determine their impact on cumulative oil produced. The non-significant parameters will be screened out, while the significant parameters will be used for building the proxy models. A response surface methodology will also be used to identify the relationship between the parameters and the objective function. We intend to combine the proxy with some well location screening parameters and genetic algorithm to solve the well placement problem.

1.3 Statement of the Problem

Determination of the optimal location of in-fill well is very challenging, as it requires evaluation of hundreds or thousands of potential locations, given reservoir geological uncertainty and the non-linearity of the problem. The uncertainty in the reservoir model (referred to here as geological uncertainty), may lead to uncertainty in the performance prediction for each well configuration. Most of the previous work published had used different proxy tools or helper functions to improve their results and reduce the number of simulations. But these proxies' tools don't take into full account the uncertainties in the geological parameters of the reservoir. Numerical reservoir simulation has to be performed to predict the production profile of the field, for use in evaluating the objective function. However, as each numerical simulation is computationally expensive, proxies could be used to provide an approximate value of the objective function, and this is the approach utilized in this study.

1.4 Scope of Work

This research focuses on evaluation of optimal locations for in-fill well placement, taking into consideration the geological uncertainties in the reservoir model. Optimizing the placement of new wells in a field development project is essential in order to maximize the cumulative oil produced and project's profitability. A synthetic reservoir, PUNQ-S3 model was evaluated and the optimal locations for the in-fill well placement were proposed in this work. In this study, a GA is implemented to optimize the placement of wells, and a statistical proxy based on experimental design is used to reduce the number of simulations and to account for the geological uncertainty in the reservoir model. We also used reservoir production constraint maps to build screening parameters for the well placement optimization problem.

The objectives of this research are;

- To carry out an uncertainty analysis of the various geological and well parameters that would affect the cumulative oil produced (COP), and to identify the significant parameters for further study.
- To use experimental design to build a statistical proxy model in order to reduce the number of simulations required for the optimization of well placement.
- To use genetic algorithm, to optimize the placement of vertical wells in the reservoir, and compare results obtained using the proxy and without the proxy.

1.5 Organization of Thesis

This thesis contains six (6) chapters. Chapter 1 is the introduction and description of the statement of the problem to be solved. Chapter 2 is an overview of the optimization algorithm used for this study. It discusses the different terms and operators in the genetic algorithm, and the optimization process. The use of proxies is also discussed, and some details about the use of experimental design and response surface methodology are presented in this Chapter. Chapter 3 is a brief description of the reservoir model used for the study. It describes the geological properties and production history of the reservoir model. Chapter 4 describes the constraints that were defined in the reservoir model for the well placement problem. It includes the different property maps and engineering constraints that were used to screen likely poor well locations (performers) from the search space of the algorithm. It also discussed the use of experimental design for sensitivity analysis, and the proxy model generated from the response surface methodology. Three cases of well placement are considered for developing the reservoir model, and a combination of proxy model generated from experimental design and genetic algorithm is used to determine the optimal locations of infill wells. Chapter 5 provides the summary, conclusions and the recommendations for future study. The references cited in this work are listed in Chapter 6.

CHAPTER 2

OPTIMIZATION ALGORITHMS

In this chapter, the review of the optimization algorithms is presented to help the reader understand the methodology used in this study. The use of proxies for well placement problem and the implementation of experimental design and response surface methodology to build the proxy models are also explained.

2.1 Overview of Genetic Algorithm

An overview of the GA optimization process and the various terminologies used in GA are discussed here.

2.1.1 Genetic Algorithm (GA)

Genetic Algorithms (GA), a member of evolutionary search algorithms, were introduced by Holland (1975). GA is a stochastic search technique based on the principles of natural evolution and selection. The basic idea revolves around survival of the fittest and solutions are evolved through mating (information exchange) of the best performing solutions. GA finds solutions to optimization problems by generating a large number of possible solutions and then evaluating each solution to determine its level of "fitness" (i.e., value of the objective function). Better solutions are evolved by applying GA operators to previous solutions and this process continues until a termination criterion is met (Yeten, 2003; Onwunalu, 2006). Some terms used in GA include:

- **Individual** is a potential feasible solution to an optimization problem. In the well optimization application, it refers to a set of parameters defining the configuration of well(s). For example, in a case involving placement of N wells, an individual will refer to

the set of parameters that fully describe all N wells to be placed in the reservoir. It can also be called a gene.

- **Chromosome** is a representation of the unknowns (parameters) of an individual which are encoded as binary or real numbers.
- **Population** is a collection of individuals within the generation.
- **Generation** refers to the population of individuals at a given iteration during the optimization.
- **Fitness** is an evaluation of the quality of the objective function value for an individual. The fittest individual in a population would have the highest objective function value when compared to other individuals in the same population.
- **Seed** is the initial population fed to the optimization tool.
- **Selection** is a GA operator through which a number of the fittest individuals are kept in the next generation. This operator assures that every new generation is at least as good as the previous one.
- **Crossover** is another operator that provides the main mating mechanism by which new chromosomes are created. The operator is designed such that an efficient information exchange and inheritance is achieved between generations (see figure 2.1).
- **Mating** is a mechanism used to ensure new genetic material is occasionally introduced to the chromosome. This operator also provides access to different areas of the search space.
- **Parents** are two fit individuals that are randomly selected to go through reproduction.
- **Offspring** is the individual that results after completion of the reproduction procedure.
- **Mutation** is the occasional random alteration of the value of a bit simply by changing a 0 to 1 and vice versa (see figure 2.1).

- **Reproduction** controls how new generations are created. It selects individuals with the best fitness value in the current generation that is guaranteed to survive in the next generation.

2.1.2 GA Operators

A simple GA is composed of three basic operators:

- Reproduction
- Crossover
- Mutation

Figure 2.1 shows the schematic of the crossover and mutation operators.

In this work, we will use binary genetic algorithm to carry out our optimization. The chromosomal representation of each vertical well will contain the parameters required to describe the well. In binary genetic algorithm, the parameters describing each well are converted to binary bits to form a binary string. The string is then attached together to form the chromosome for each well (Yeten, 2003). For a case involving placing additional four (4) wells into a reservoir, an individual will refer to a chromosome consisting of all parameters defining the configuration of the 4 wells. Figure 2.2 shows the major steps of the Genetic Algorithm.

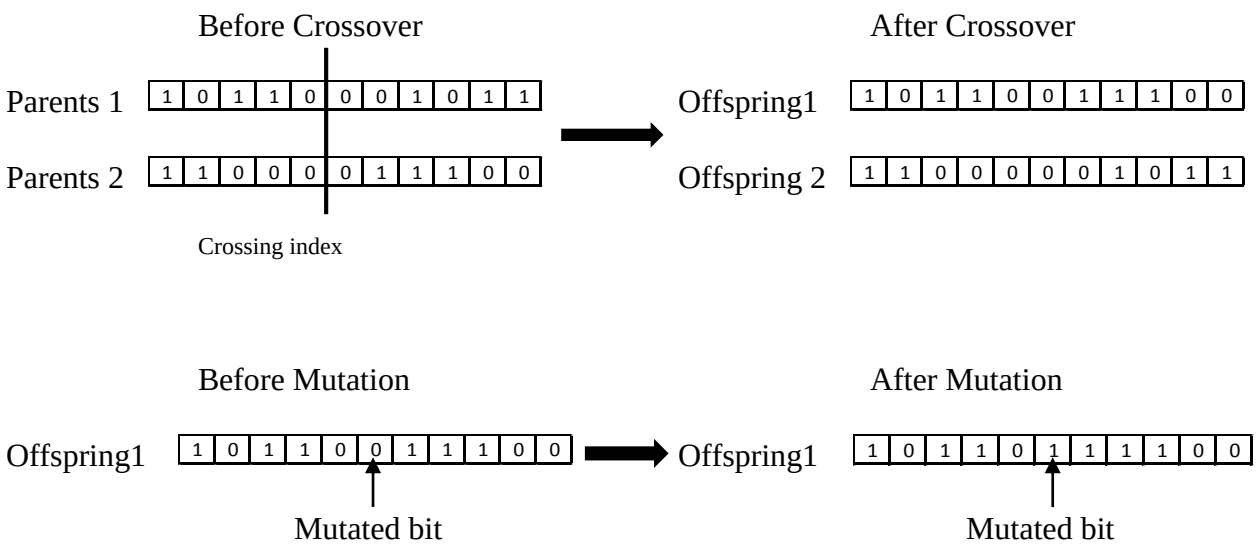

Figure 2.1 Diagrams showing Crossover and Mutation Operators in GA

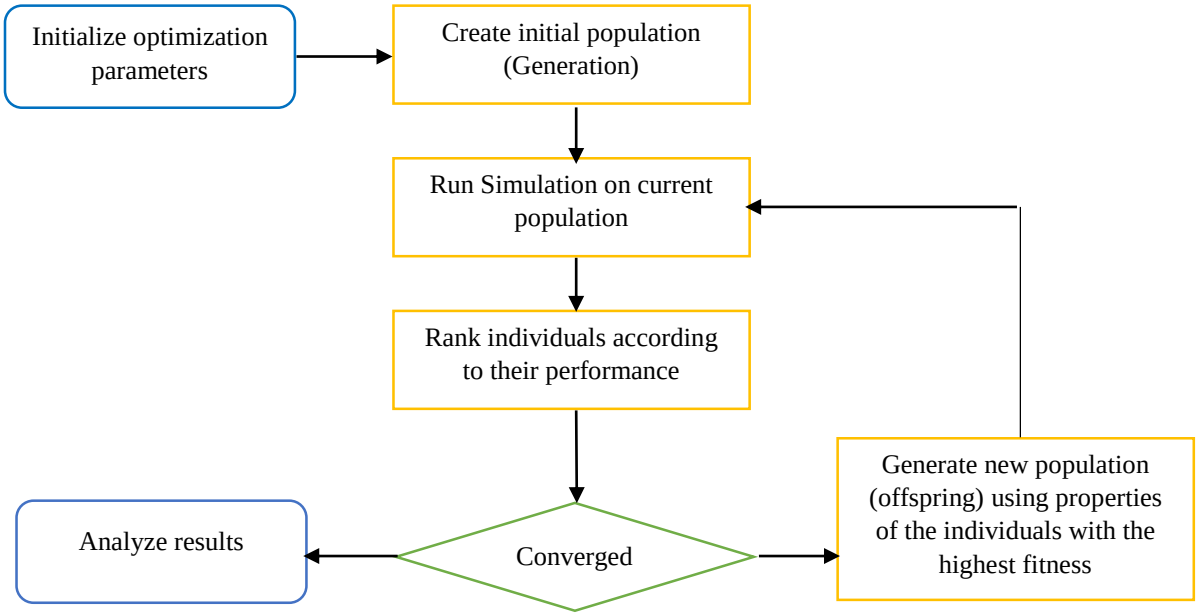

Figure 2.2 Flowchart of Genetic Algorithm methodology

2.2 Use of proxies

A proxy or meta-model is a surrogate mathematical equation which is used to mimic input-output relation of a complicated system. Proxy models can be used to create a fast analysis module by approximating the existing computer simulation model in order to achieve more efficient analysis. Proxies are computationally fast but approximate models which are incorporated into optimization procedures. They reduce computational demands by reducing the number of full simulations performed during the optimization. Proxies can provide estimates of the objective function value of new development scenarios using previously simulated scenarios. Proxy models use attributes from the well and reservoir and the fitness or objective function from all previously simulated scenarios.

The estimated objective function values can then be used to select promising scenarios for simulation during the optimization. Examples of proxies used in well placement optimization include kriging, least squares, neural networks, cluster-based statistical proxies, and neuro-fuzzy methods. Onwunalu, (2006) combined cluster based statistical proxy and GA for optimization of non-conventional wells. Other authors have used proxies based on reservoir parameters to screen well locations, e.g., productivity index, productivity potential, and quality maps of oil and gas produced (Badru et al., 2003).

There are two general applications of proxies and the method for comparing the performance of the proxy algorithm depends on how the proxy is used (Litvak, 2007). Proxy applications can be grouped into two broad classes: those that accelerate the optimization while evaluating all potential solutions and those that reduce the number of function evaluations (e.g., simulations) required. Proxies that accelerate the optimization process use the proxy to generate solutions that will speed

up convergence. Proxies that reduce the number of simulations generally do not influence the solution generating characteristics of the algorithm but they perform function evaluations only for promising cases (Onwunalu, 2006). The statistical proxy discussed in this work falls in the first category. The performance of proxies of this type can be assessed based on comparison of the optimum solution found using the proxy to that from the actual simulation of all the individual runs.

2.3 Experimental Design (ED)

Experimental design is a tool that uses a statistical proxy for analysis. It contains factorial designs, which estimate all main effects; clear of two-factor or higher interactions, in a minimum number of experimental runs. An easy way to estimate a first-degree polynomial model is to use a factorial experiment or a fractional factorial design. This is sufficient to determine which explanatory variables have an impact on the response variable(s) of interest. Once it is suspected that only significant explanatory variables are left, then a more complicated design, such as a central composite design or D-optimal design can be implemented to estimate a second-degree polynomial model, which is still only an approximation at best. However, the second-degree model can be used to optimize (maximize, minimize, or attain a specific target) the objective function. (Salhi et al., 2005; Carreras et al., 2006; Fatemeh et al., 2011)

Design of Experiment (DoE) is an experimental strategy used to efficiently collect experimental data to construct response surfaces. Experimental design (ED) techniques help reduce the parameter space which needs to be explored. Response surfaces are built from observational and simulation data to model parameter effect. This case example presents DoE strategies for the analysis of uncertainty associated with infill well drilling. Our goal is to select the best parameters

for infill well placement optimization and quantify the uncertainty associated with these parameters.

ED may in principle be used to optimize any reservoir response variable (or a combination of variables) with respect to any reservoir management parameter, such as well locations, allocation of well rates, etc. The number of simulations needed is reduced using multiple regression and kriging together with methods for experimental design. The use of multiple linear regression to model the response surface is a common practice in DoE. It uses least square method and other standard statistical testing to quantify the relationship between the input variable and the output response. The most standard way of estimating a response surface is regression. The purpose of least squares is to construct a representative function composed of simple known functions, such as polynomials which minimize the sum of squared residuals between observed/simulated values and the function values. Thus, least squares methods are not data exact.

Kriging is a least squares linear regression technique that is easily generalized to multiple dimensions and arbitrarily sampled points. Kriging assumes that points are spatially correlated to each other. The extent of correlation, or spatial continuity is expressed by a covariance function. This covariance model is used to estimate the spatial correlation between the sampled and unsampled points and determines the weight of each sampled point on the estimation. The more spatially correlated a previously sampled value with the estimation location, the more weight it will have on this location. Therefore kriging is data exact, such that it will reproduce the observed value at a sampled location.

For our applications we have used both regression surfaces and kriging for surfaces, to estimate the response surface. All uncertainties were used in the linear regressions. The polynomials adopt the general form:

D-Optimal design DOE

$$y = a_0 + a_1x_1 + a_2x_2 + a_{11}x_1^2 + a_{12}x_1x_2 + \cdots + a_nx_n \quad (1)$$

Where $y =$ response variable, $a_i =$ polynomial coefficients and $x_i =$ uncertainty values.

2.4 Response Surface Methodology (RSM)

One way to reduce the CPU load in the optimization problem is to use response surfaces as proxies to the true reservoir model response. The response surface approximates a response (such as an objective function, or cumulative oil production at a particular time in this study), and is usually a polynomial equation, splines, kriged surface, or a combination of polynomial equations and kriging. Response surfaces require a set of initial model responses (often called "scoping runs") to determine the form of the equations, and are occasionally updated whenever new model responses are evaluated. Running numerical simulations for all the possible locations in the reservoir can be computationally challenging. Instead, we employ proxy models in order to build a good approximation of accumulated outflow from a reservoir when a new well is to be drilled. This leads to a significant reduction in the computation time. After setting up the models, the best model was introduced to a global optimization search using a genetic algorithm. The main idea of RSM is to use a sequence of designed experiments to obtain an optimal response.

The input variables to these simulations are selected using D-optimality. D-optimality is a mathematical procedure to select the optimal runs from a (large) set of possible runs (the candidate

set). Based on a set of candidate experiments, a number of experiments is selected, and an a priori regression equation describing the relations between input and response variables is calculated. This means that, from a set of points (e.g., a full-factorial set), an initial subset is selected according to the number of combinations desired. The methodology then iteratively exchanges design points for candidates in an attempt to reduce the variance of the coefficients that would be estimated using this design. The order of the underlying regression model is quadratic, which means the design matrix returned by the optimization algorithm will include linear, interaction and squared terms.

Note that the required accuracy of the response surface depends on the particular problem. For sensitivity analysis, the required accuracy is much less than if the response surface were used for history matching or well placement optimization.

RSM provides tools for (Zhang et al., 2007):

- 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 objective function in the model.

CHAPTER 3

RESERVOIR MODEL

The purpose of this chapter is to describe the reservoir model and the parameters to be optimized. It introduces the reservoir model, its geological and production properties.

3.1 Reservoir Description

The well-known Production forecasting with Uncertainty Quantification (PUNQ-S3) reservoir model, which is a standard synthetic test case that is based on a real field, was used as the testing model in this study. The PUNQ-S3 model has been taken from a reservoir engineering study on a real field operated by Elf Exploitation (Floris et al., 2001).

The model contains $19 \times 28 \times 5\ uniform\ grid\ blocks = 2660\ blocks$, with an areal dimension of 180×180 m^2, (i.e., the cell sizes are $180m$ in the x and y directions and $18m$ in the z-direction) among which 1761 blocks are active. The reservoir has 5 layers. In each layer, the correlation coefficient between porosity and horizontal permeability is 0.8; correlation between horizontal and vertical permeability is also 0.8. The gas-oil contact and the oil-water contact are located at 2355.0m and 2394.7 m, respectively. As shown in the top structure map (Figure 3.1), the field is bounded to the south and south-west by a fault, and linked to the north, north-west, and east to a fairly strong aquifer. A small gas cap is located in the center of the dome-shaped structure. The field initially contains 6 production wells located around the gas-oil contact. Due to the presence of a strong aquifer, there is no injection well in the reservoir. The geometry of the field has been modeled using corner-point geometry.

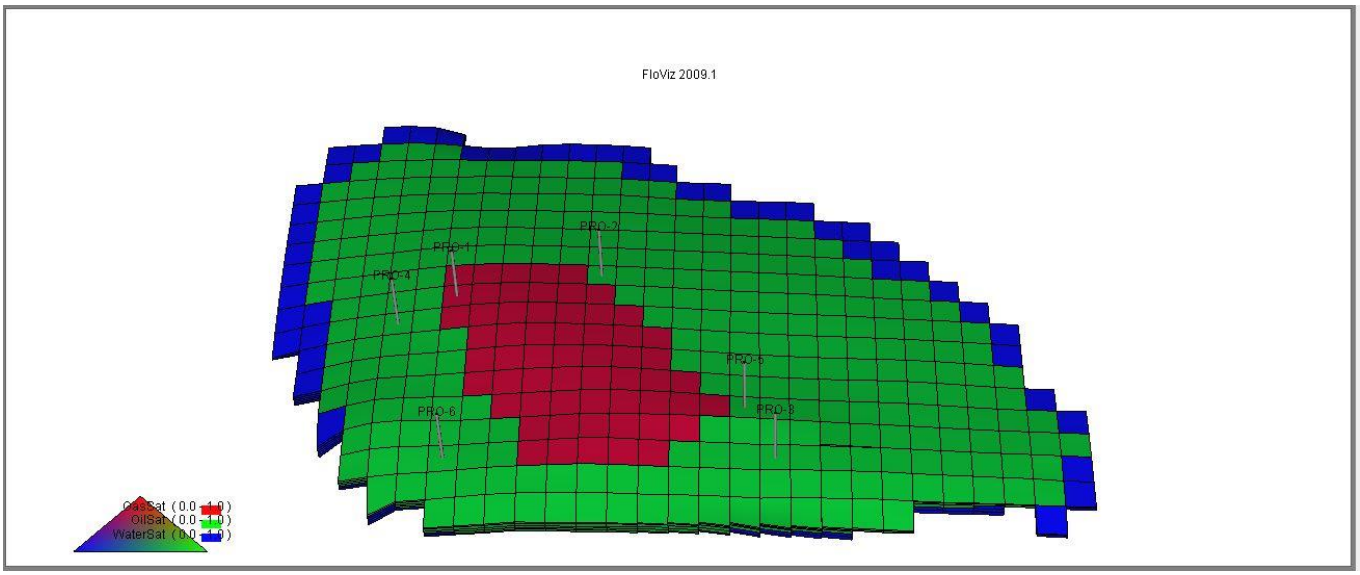

Figure 3.1 Structural map for the PUNQ-S3 reservoir model (Ternary Diagram).

The oil, water and gas densities at surface conditions are 911.93, 1032.04 and 0.83 kg/m^3, respectively. The original six (6) producing wells in the PUNQ-S3 reservoir model are produced for a simulation period of 16.5 years. The "true" total oil recovery after the 16.5 year is 3.92×10^6 Sm^3.

3.2 Production Data Assimilated

All six producing wells were produced according to the following schedule: an extended well testing during the first year, then a shut-in period lasting the following 3 years, and finally a 4-year production period. The well testing period consists of 4 time windows, each of which is 3-month long with constant flow rate. The oil production rate is fixed at 150 Sm^3/day within the 4-year production period and all wells have a 2-week shut-in each year to collect the shut-in pressure. During the first 8 years (0 – 2936 days), well PRO-1, PRO-3 have gas breakthrough; PRO-4 has water breakthrough; none of the other wells have gas or water breakthrough.

The reservoir model described in this chapter will be used to carry out our analysis, to study the application of infill well placement optimization to the PUNQ-S3 reservoir model. The objective is to determine the optimal locations for drilling additional infill well, with already six producing wells from the reservoir model, while considering the uncertainties associated with the geological and reservoir properties of the field. The well placement constraints associated with this model are also discussed and enforced to reduce the likelihood of placing wells in locations that are poor performers or yield unfavorable results (e.g., high water-cut). The next chapter will discuss the constraints used for the well placement optimization problem and their application to the PUNQ-S3 reservoir model.

CHAPTER 4

WELL PLACEMENT OPTIMIZATION

In this chapter, certain constraints will be defined to determine acceptable candidate locations for infill well placement. A sensitivity analysis is carried out on the reservoir model to determine the significant parameters controlling the cumulative oil production. The significant parameters will be used for further analysis and development of the proxy during the uncertainty analysis.

4.1 Constraints for Well Placement Problem

Several constraints have been defined for the initial population. Some of these constraints were imposed to make sure the resulting wells are drillable, while others are put in place to avoid creating solutions that are known to perform poorly because the solutions could violate common petroleum engineering practices. Considering that we have control in the initialization process, the constraints can be easily applied to the initial population. The following constraints are defined for infill well placement problem:

1. The Oil saturation (S_{oil}) at the proposed location for infill well placement must be greater than or equal to the sum of the residual oil saturation (S_{or}) and 10 percent. This means that, any location for infill well placement must have oil saturation higher than the residual oil saturation with at least 10 percent margin. This is done to make sure that the proposed location has reasonable amount of oil to be produced from it. All locations that do not meet up to this constraint are eliminated from the search space. The main idea is to avoid placing wells in locations with low oil saturation. Mathematically, this constraint is: $S_{oil} \geq (S_{or} + 10\%)$.

2. The average pressure at the proposed location must have a value greater than the threshold reservoir pressure. This constraint is put in place to make sure that the average reservoir pressure of the grid block chosen for infill well placement must have enough pressure to produce the oil, which must be higher than the threshold pressure of the reservoir. $\Delta P: \overline{Res\ Pressure} > P_{Res} threshold.$
3. $Well\ will\ be\ placed\ far\ away\ from\ oilwater\ contact, aquifer, faults\ and\ boundaries.$ There are two types of boundaries encountered in this reservoir model, a no-flow boundary or a fault and an aquifer. The direction of flow is always parallel to the no-flow boundary. The well placement constraint for boundary condition is put such that well are not placed close to faults or no-flow boundaries, and are also not placed close to the aquifer to avoid water coning and high water-cut. All candidate locations that are close to faults, aquifer, oil-water contact (OWC) are eliminated from the initial population and removed from the potential locations for infill well placement.
4. $Well\ will\ be\ placed\ on\ active\ blocks.$ The reservoir model has 2660 blocks, out of which 1761 blocks are active. All potential infill well can only be placed and completed in the active blocks of the reservoir model. Also, grid blocks that have wells already placed and producing will be removed from the initial population, as no two wells will be placed in the same grid block, in this work.

4.2 Saturation and Pressure Screening

In this work, pressure and saturation property maps are used to identify potential areas for in-fill drilling. Figures 4.1, 4.2, 4.3, 4.4 are examples of the property maps generated in this study. An oil saturation screening will be carried out for all individuals in the initial population. This aims at

removing individuals that will impair the quality of the initial population and deter the evolution process. The screening process can be considered as a rule-based constraint to avoid creating and simulating potentially known poor performers.

In field development projects, the wells are typically drilled in phases. This introduces a time domain into the optimization problem. In other words, the performance of a well will depend on the time it is opened and the oil saturation and pressure in the vicinity of the well when it is put on production. When the wells are opened at different times, their performance is affected by dynamic properties (e.g., oil/water saturation, pressure) around the wells at the start of production. Dynamic attributes include average saturation around the well, average pressure around the well, average change in saturation around the well, average change in pressure around the well. The average saturation and pressure are determined at the start of the simulation while the average change in saturation and average change in pressure are determined by taking the difference between the saturation and pressure at the start of production and at the end of the simulation run time.

The average pressure at the proposed well location must be greater than the threshold reservoir pressure to make sure that producing well's pressure will be sufficient energy to sustain production for the given period of time. The threshold reservoir pressure used in this study is 120 barsa. Another constraint that is imposed in the well placement problem is, to avoid locating wells close to the oil-water-contact, aquifers, faults and boundaries. This is done to avoid results that would not maximize the objective function.

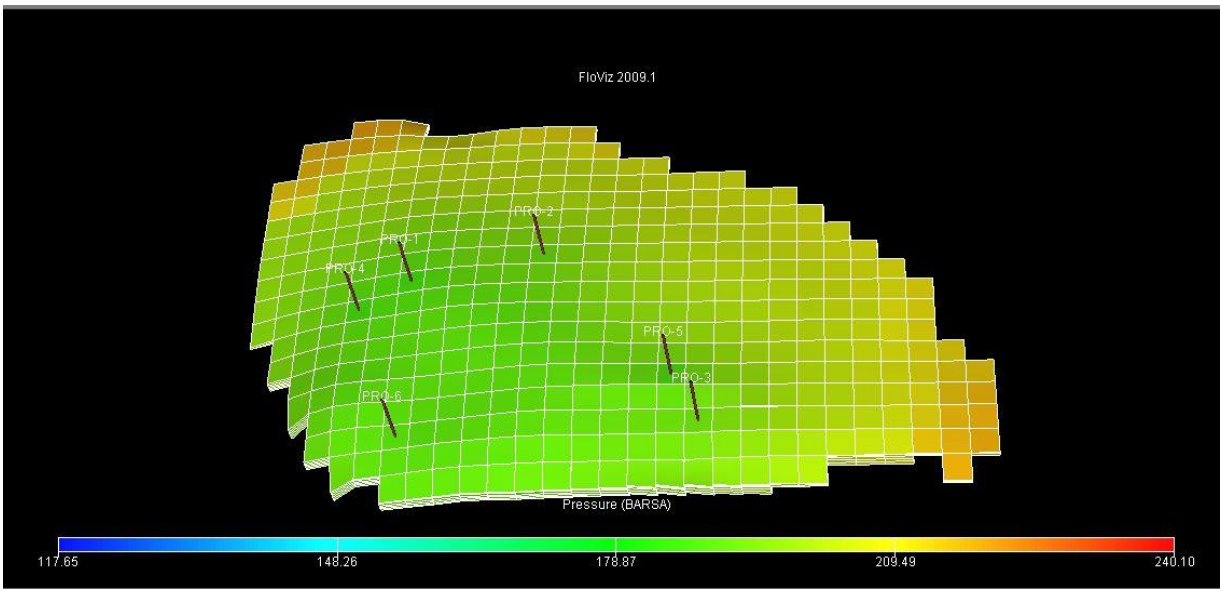

Figure 4.1 Property map showing Pressure distribution in the model.

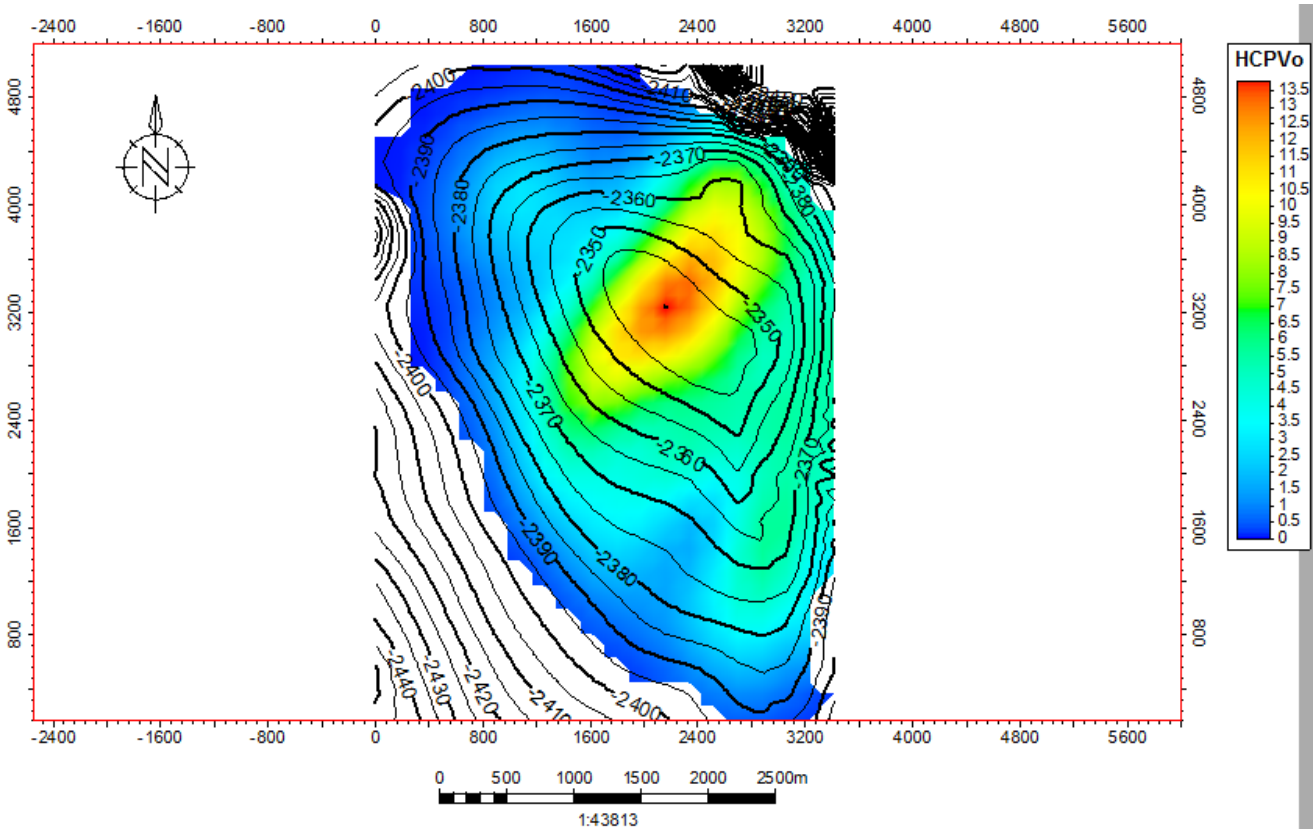

Figure 4.2 HCPVo Contour Map showing Oil saturation at various depths

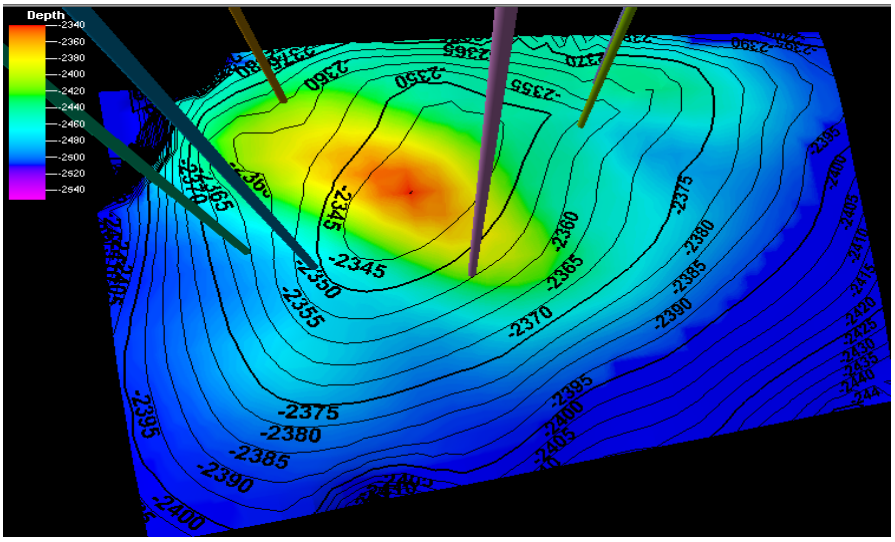

Figure 4.3 Contour maps showing oil saturation at various depth with location of appraisal wells.

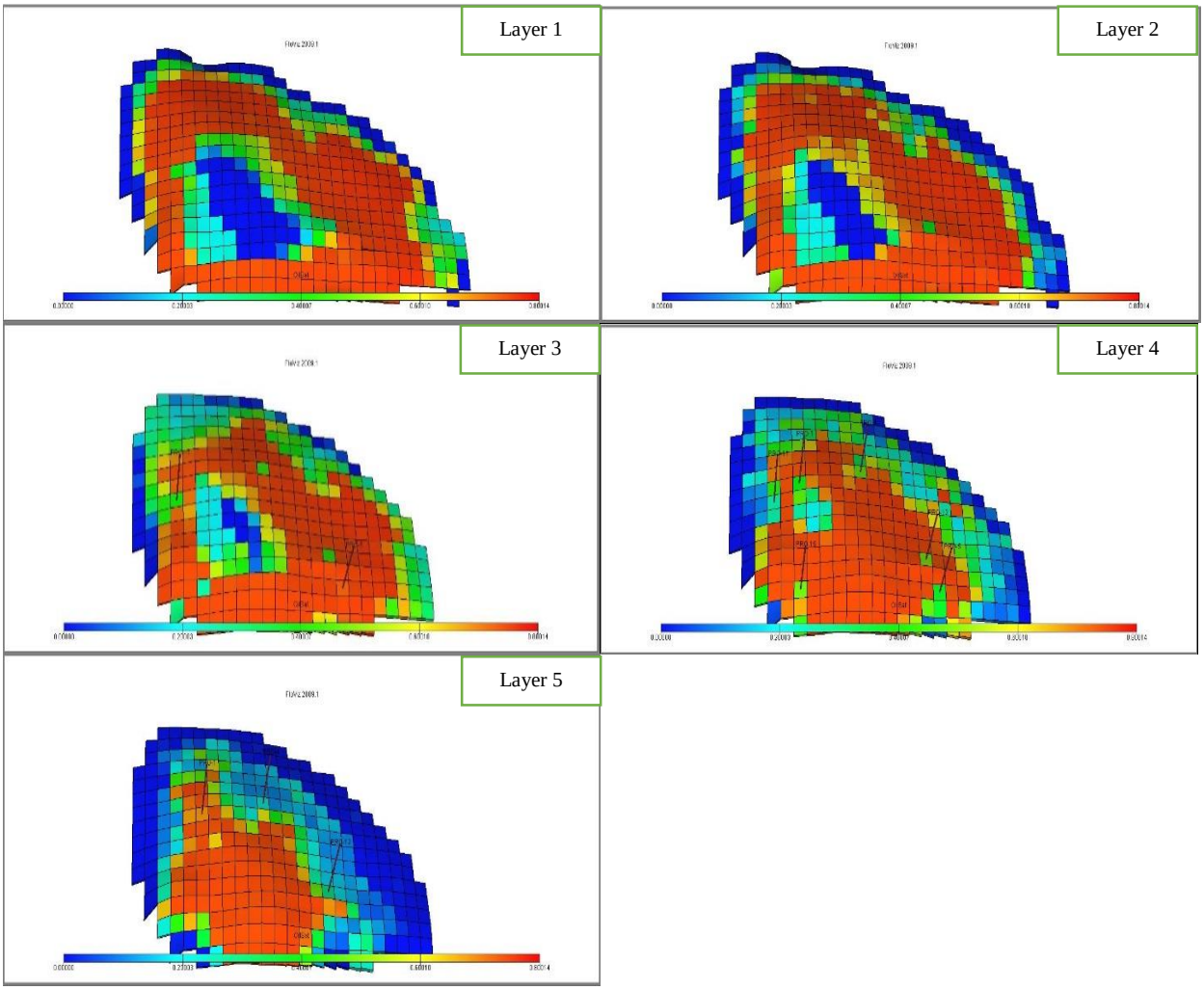

Figure 4.4 Property map showing oil saturation distribution after 16.5 years of production for the five different layers in the model.

4.3 Reservoir Uncertainty

Uncertainties relating to the reservoir model can be investigated and quantified. The range of uncertainty comes from field data, analogues and history matching of the PUNQ-S3 reservoir model. Experimental Design methodology provides a framework by arranging simulation model in such a way as to maximize the information gained from each simulation and to evaluate statistically, the significance of different factors. After illustrating the practical range of uncertainties for each reservoir parameter, it is possible to define these ranges as low, base and high level. The main idea in this study is to find the key uncertain parameters with the most significant impact on the reservoir cumulative oil production.

4.4 Sensitivity Analysis

Many uncertain parameters are present in the simulation of the PUNQ-S3 reservoir model and some of these parameters were studied in this work. The corresponding ranges of these uncertain parameters are presented in the table 4.1 to identify the uncertain parameters with the most significant impact on the objective function, i.e., the cumulative oil production (COP). The base case values of the uncertain parameters were multiplied with high and low multipliers to cover the expected range of uncertainty in the reservoir. A total of 16 simulation runs were carried out using a 2-level factorial design as shown in table 4.2

PARAMETERS	HIGH VALUE	ACTUAL VALUES	LOW VALUE	LOW	HIGH
PERMX	300	414.6	500	0.72	1.25
PERMZ	170	187.9	210	0.9	1.1
PORO	0.17	0.187	0.20	0.9	1.1
AQUIPERM	120	137.5	150	0.87	1.09
OVISC	120	135	150	0.9	1.1
TRANX	0.8	1	1.2	0.8	1.2

Table 4.1 Reservoir Uncertainty parameters.

STD	RUN	A: PERMX	B: PERMZ	C: PORO	D: AQUIPERM	E: OVISC	F: TRANX	COP
1	3	0.72	0.9	0.9	0.87	0.9	0.8	5.33E+06
2	7	1.25	0.9	0.9	0.87	1.1	0.8	5.35E+06
3	2	0.72	1.1	0.9	0.87	1.1	1.2	5.01E+06
4	13	1.25	1.1	0.9	0.87	0.9	1.2	5.91E+06
5	11	0.72	0.9	1.1	0.87	1.1	1.2	5.54E+06
6	5	1.25	0.9	1.1	0.87	0.9	1.2	6.62E+06
7	10	0.72	1.1	1.1	0.87	0.9	0.8	5.94E+06
8	14	1.25	1.1	1.1	0.87	1.1	0.8	5.97E+06
9	16	0.72	0.9	0.9	1.09	0.9	1.2	5.53E+06
10	4	1.25	0.9	0.9	1.09	1.1	1.2	5.52E+06
11	12	0.72	1.1	0.9	1.09	1.1	0.8	4.95E+06
12	15	1.25	1.1	0.9	1.09	0.9	0.8	5.88E+06
13	1	0.72	0.9	1.1	1.09	1.1	0.8	5.46E+06
14	6	1.25	0.9	1.1	1.09	0.9	0.8	6.59E+06
15	8	0.72	1.1	1.1	1.09	0.9	1.2	6.18E+06
16	9	1.25	1.1	1.1	1.09	1.1	1.2	6.19E+06

Table 4.2 2-Level Factorial design for six uncertain parameters.

A Pareto chart was used to evaluate the impact of each reservoir uncertainty parameter on the cumulative oil production. The uncertainty parameters that impact the response variables with a 95% level of confidence or the "heavy hitters" were selected for further analysis. These parameters were incorporated in a 3-level D-optimal design (DOD) that required 38 runs. This technique models non-linear effects and interactions, or the non-linear change in the response variable when the uncertainty parameters increase from low to high values. The effect of uncertainty parameters on the response variables can be visualized with the Pareto chart shown in Figure 4.5. The results of the sensitivity analysis shown I Figure 4.5 indicate that OVISC, PORO, TRANX and PERMX parameters have the most significant effect on the objective function (COP), while PERMZ and AQUIPERM show no significant effect on COP, and they will be removed from further analysis.

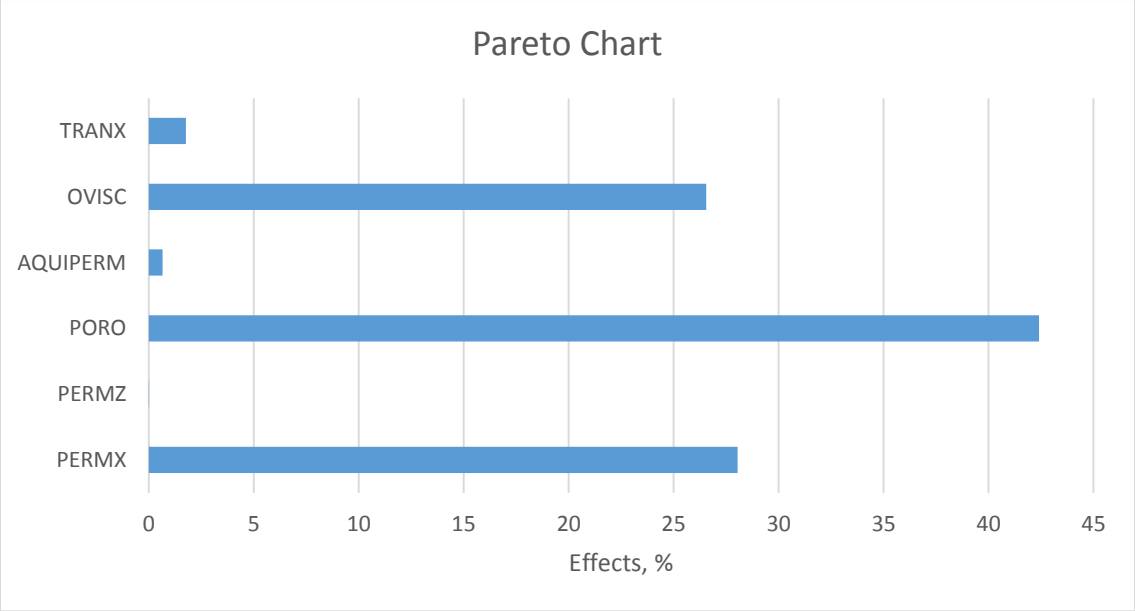

Figure 4.5 Pareto Chart showing percentage contribution of parameters on the objective function.

To make efficient decisions over the reservoir development plan, the most effective uncertain parameters on the reservoir behavior must be studied and the probabilistic production of the reservoir has to be forecasted.

After identifying the practical ranges of uncertainties for each reservoir parameter, it was possible to classify these ranges in three levels. Then RSM is applied to a selected set of the 3D simulations corresponding to known three level patterns.

4.5 Generating Response Surface Model

The use of a multiple linear regression to model the response surface is common practice in experimental design. The technique uses the least square method and other standard statistical testing to quantify the relationship between the input variables and the output response. Linear effects are modeled with a first-order polynomial, while non-linear effects are modeled with a quadratic or higher order polynomial (Carreras et al., 2006).

The most standard way of estimating a response surface is regression. For our RSM applications we have used both regression surfaces and kriging interpolation for surfaces. A DOD gives the most precise estimate of the response variable. The values of the input variables to be used for simulation are selected using D-optimal in response surface design. The well co-ordinates (i, j) were represented as (iCOR, jCOR) respectively in the design. Four of the significant reservoir parameters from the 2-factorial design were used for the D-optimal design and the well co-ordinates (i, j) were also included in the design to generate the response surface. A total of 38 experimental runs were carried out for the six uncertain parameters. Random candidate points were generated by the d-optimal design as presented in table 4.3. The results are shown in table 4.4.

Table 4.3 Results from response surface d-optimal experimental runs

STD	RUN	A: PERMX	B: PORO	C: OVISC	D: TRANX	E: iCOR	F: jCOR	COP (MMSTB)
1	27	1.20	1.10	1.10	0.80	6	8	49.314
2	19	1.20	1.10	0.90	0.80	16	24	54.215
3	23	0.72	0.90	1.10	0.80	16	24	44.099
4	31	1.20	0.90	0.90	0.80	6	8	46.469
5	26	1.20	1.10	0.90	1.20	6	24	52.162
6	15	0.72	1.10	1.10	1.20	6	8	48.046
7	30	0.72	0.90	0.90	0.80	16	8	46.351
8	24	0.72	1.10	1.10	0.80	16	8	49.681
9	21	0.72	0.90	0.90	1.20	6	8	45.331
10	6	1.20	0.90	1.10	1.20	6	8	44.759
11	11	1.20	0.90	1.10	0.80	16	8	45.871
12	36	1.20	1.10	1.10	1.20	16	24	52.123
13	18	0.72	0.90	1.10	1.20	6	24	43.029
14	29	0.72	0.90	0.90	0.80	6	24	45.214
15	38	0.96	1.10	1.10	0.80	6	24	48.346
16	2	1.04	1.10	0.90	0.80	6	8	51.270
17	32	0.96	0.90	0.90	1.20	16	24	48.273
18	34	0.96	1.00	1.00	0.80	11	16	50.670
19	9	0.72	0.90	1.10	0.80	6	8	42.266
20	17	0.72	1.10	0.90	1.20	16	8	53.015
21	1	1.20	0.90	1.10	0.93	9	24	44.497
22	8	0.72	1.10	0.90	1.07	13	24	51.038
23	10	1.20	0.90	1.00	1.20	16	24	47.887
24	12	0.72	0.97	1.10	1.07	16	8	46.573
25	35	1.20	1.03	0.90	1.20	13	8	51.336
26	22	1.20	1.10	0.97	1.07	16	8	53.788
27	14	0.72	0.90	1.03	1.20	13	8	44.333
28	33	1.20	0.90	0.90	1.07	16	13	48.693
29	4	1.20	1.10	1.10	1.20	6	16	49.728
30	7	1.20	0.90	0.90	1.20	6	16	47.026
31	5	0.72	1.10	1.10	1.20	11	24	48.026
32	13	1.20	1.10	1.10	0.80	16	19	50.738
33	3	1.20	0.97	0.90	0.80	6	24	48.755
34	16	1.20	0.90	1.10	0.93	9	24	44.497
35	20	0.72	0.90	1.10	0.80	16	24	44.099
36	37	0.72	1.10	0.90	1.20	16	8	53.015
37	25	1.04	1.10	0.90	0.80	6	8	51.270
38	28	0.96	0.90	0.90	1.20	16	24	48.273

Response:	COP					
*** WARNING: The Cubic Model is Aliased! ***						
*** WARNING: The Quartic Model is Aliased! ***						
Sequential Model Sum of Squares						
Source	Sum of Squares	DF	Mean Square	F Value	Prob > F	
Mean	8.85E+16	1	8.85E+16			
Linear	3.72E+14	6	6.21E+13	174.97	< 0.0001	Suggested
2FI	1.94E+12	15	1.29E+11	0.23	0.9968	
Quadratic	6.99E+12	6	1.17E+12	5.64	0.0085	Suggested
Cubic	2.07E+12	5	4.13E+11	6.37E+07	< 0.0001	Aliased
Quartic	0	0				Aliased
Residual	0	5	0			
Total	8.89E+16	38	2.34E+15			
"Sequential Model Sum of Squares". Select the highest order polynomial where the additional terms are significant and the model is not aliased.						
Lack of Fit Tests						
Source	Sum of Squares	DF	Mean Square	F Value	Prob > F	
Linear	1.10E+13	26	4.23E+11			
2FI	9.06E+12	11	8.24E+11			
Quadratic	2.07E+12	5	4.13E+11			
Cubic	0	0				
Quartic	0	0				
Pure Error	0	5	0			
Lack of Fit Tests". Want the selected model to have insignificant lack-of-fit.						
Model Summary Statistics						
Source	Std. Dev.	R-Squared	Adjusted R-Squared	Predicted R-Squared	PRESS	
Linear	5.96E+05	0.9713	0.9658	0.9628	1.43E+13	Suggested
2FI	7.52E+05	0.9764	0.9453	0.8867	4.34E+13	
Quadratic	4.54E+05	0.9946	0.9801	0.7366	1.01E+14	Suggested
Cubic	0	1	1	+		Aliased
Quartic	+					Aliased
+ Case(s) with leverage of 1.0000: PRESS statistic not defined						
"Model Summary Statistics". Focus on the model maximizing the "Adjusted R-Squared" and the "Predicted R-Squared".						

Table 4.4 Model summary from experimental runs for d-optimal response surface design.

To select the appropriate model, the statistical approach was used to determine which polynomial best fits the equation among linear model, two-factor interaction model (2FI), quadratic model, and cubic model. The results are shown in table 4.4. The criterion for selecting the appropriate model is to identify the highest polynomial model, where the additional terms are significant and the model is not aliased. Although the cubic model is the highest polynomial model, it is not selected because it is aliased. Aliasing is a result of reducing the number of experimental runs. When it occurs, several groups of effects are combined into one group and the most significant effect in the group is used to represent the effect of the group. Essentially, it is important that the model is not aliased. In addition, other criteria are applied to select the model that has the maximum "Adjusted R-Squared" and "Predicted R-Squared". Thus, the fully quadratic model was selected to build the cumulative oil production (COP) response surface in the subsequent optimization process.

ANOVA for Response Surface Quadratic model:

$$COP = -1.75\text{E } 08 + (2.98\text{E } 07 \times \text{PERMX}) + (2.22\text{E } 08 \times \text{PORO}) + (1.91\text{E } 08 \times \text{OVISC}) - (7.95\text{E } 06 \times \text{TRANX}) - (7.66\text{E } 05 \times \text{iCOR}) + (2.55\text{E } 05 \times \text{jCOR}) - (1.45\text{E } 07 \times PERMX^2) - (1.00\text{E } 08 \times PORO^2) - (9.96\text{E } 07 \times OVISC^2) + (2.19\text{E } 05 \times TRANX^2) + (3.17\text{E } 04 \times iCOR^2) - (3.90\text{E } 03 \times jCOR^2) - (2.45\text{E } 06 \times \text{PERMX} \times \text{PORO}) + (4.51\text{E } 06 \times \text{PERMX} \times \text{OVISC}) - (6.43\text{E } 05 \times \text{PERMX} \times \text{TRANX}) - (1.46\text{E } 04 \times \text{PERMX} \times \text{iCOR}) + (1.58\text{E } 04 \times \text{PERMX} \times \text{jCOR}) - (6.77\text{E } 06 \times \text{PORO} \times \text{OVISC}) + (9.51\text{E } 06 \times \text{PORO} \times \text{TRANX}) + (5.71\text{E } 05 \times \text{PORO} \times \text{iCOR}) - (1.20\text{E } 05 \times \text{PORO} \times \text{jCOR}) + (6.83\text{E } 05 \times \text{OVISC} \times \text{TRANX}) - (1.88\text{E } 05 \times \text{OVISC} \times \text{iCOR}) - (6.28\text{E } 04 \times \text{OVISC} \times \text{jCOR}) - (1.41\text{E } 05 \times \text{TRANX} \times \text{iCOR}) + (2.61\text{E } 04 \times \text{TRANX} \times \text{jCOR}) + (1.65\text{E } 03 \times \text{iCOR} \times \text{jCOR}) \quad (2)$$

$Where$:

$COP = Cummulative\ Oil\ Produced\ (stb)$
$Permx = Horizontal\ permeability (md)$
$Poro = Porosity\ (percent)$
$Ovisc = Oil\ viscosity$
$iCOR = well\ location\ on\ the\ i - cordinate\ of\ the\ grid$
$jCOR = well\ location\ on\ the\ j - cordinate\ of\ the\ grid$

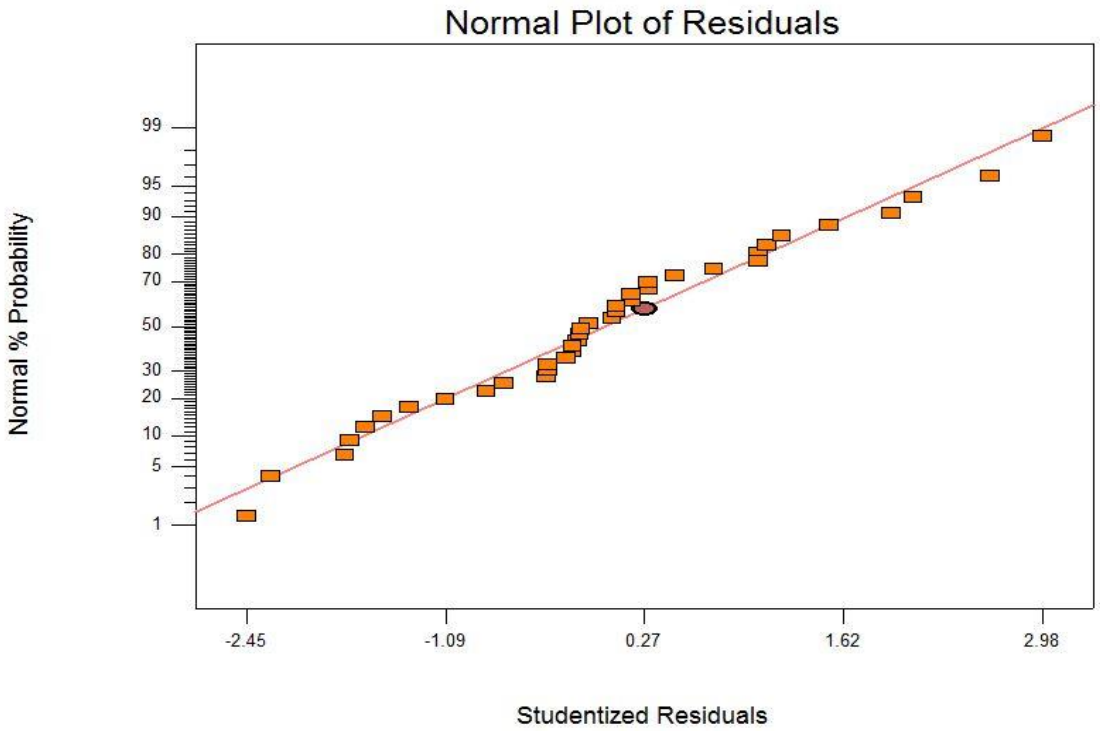

Figure 4.6 Normal Plot for the residuals in the experimental runs.

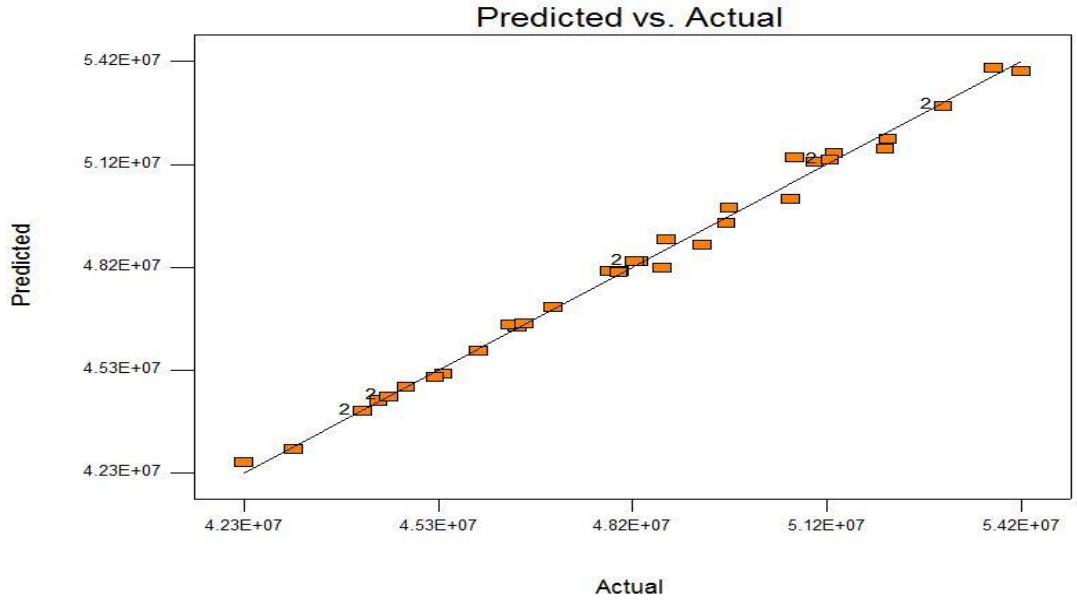

Figure 4.7 Predicted versus Actual plot.

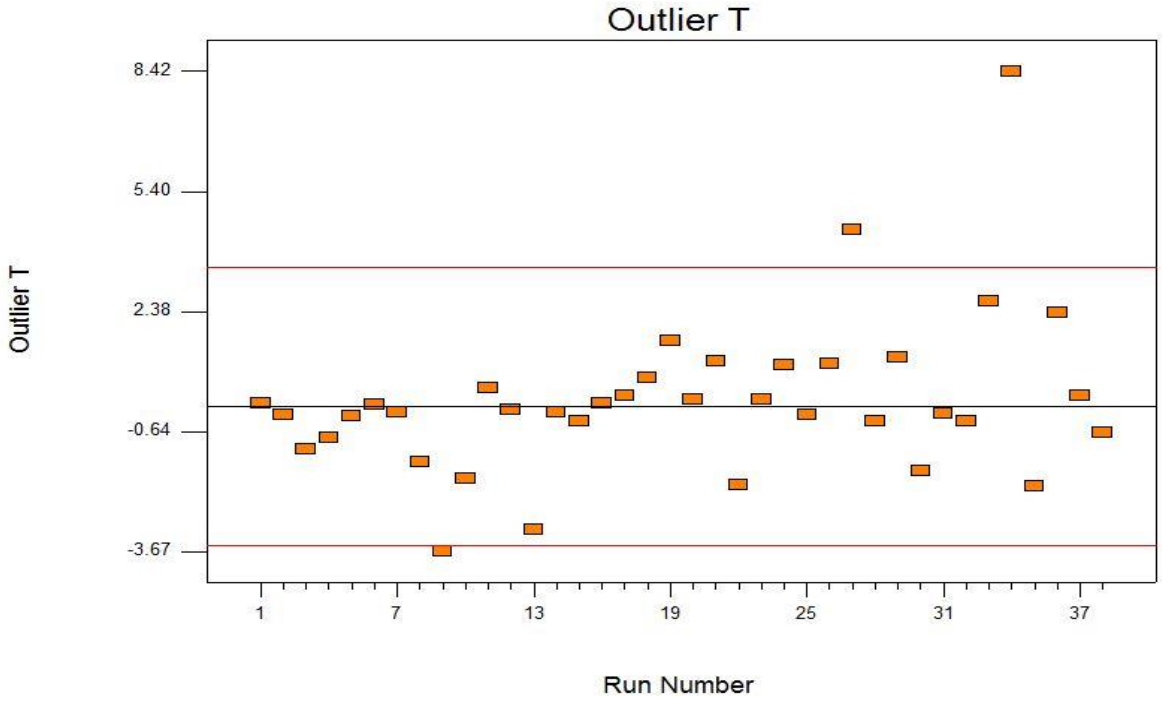

Figure 4.8 Simulation run number to determine the range of outliers

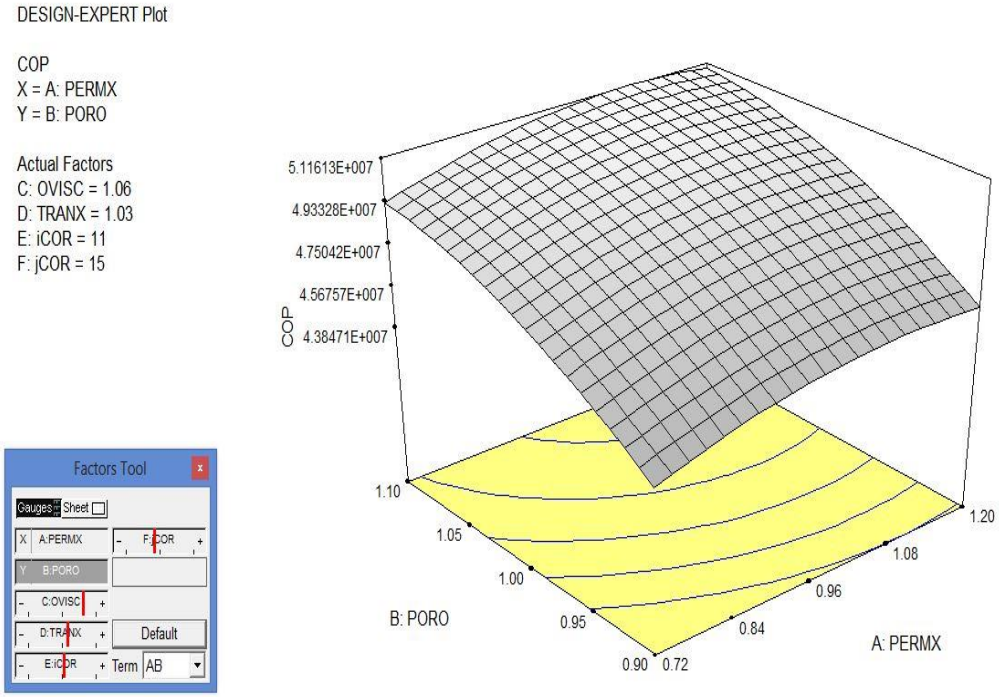

Figure 4.9 3-D maps plot showing the interaction between Porosity and PermX, with the COP

Figures 4.6 through 4.8 show the diagnostics graphs. The normal plot of residuals is the number of standard deviations of the actual values from their respective predicted values. The size of the studentized residual should be independent of its predicted value. In other words the spread of the studentized residuals should be approximately the same across all levels of the predicted values as shown in figure 4.6. All the points in the "Normal Plot of Residuals" fall on the straight line, meaning the residuals are normally distributed. Figure 4.7 shows the plot of "Predicted vs. Actual", illustrating whether the generated equation of cumulative oil production (COP) response surface accurately predicts the actual COP values. It can be seen that the generated COP response surface models provide a good match between the predicted values of COP the actual values of COP. This means that the generated COP response surface models are reliable. Figure 4.8 shows the outlier plot used to identify points outside the ±3.5 standard deviation limits. Majority of the points in this case (Figure 4.8) fall within the standard deviation limits with the exception of two points. Figure 4.9 shows the 3D surface of the porosity and permeability with cumulative oil production, COP. It shows that there exists an optimal combination of porosity and permeability to get the highest cumulative oil recovery. For example, using a porosity multiplier of 0.9, the COP first increases and then decrease with decreasing horizontal permeability.

4.6 Implementing Genetic Algorithm (GA)

The procedure for implementing the genetic algorithm includes the following steps.

1. The GA generates randomly a set of individuals (feasible solutions, N), each corresponding to a development scenario of drilling a set of infill wells at candidate locations that have met the constraints stated earlier.

2. The fitness of each solution is evaluated by using the proxy model to predict the cumulative oil recovery from producing the set of infill wells of Step 1.

3. A set of individuals in the present generation is selected based on their fitness to act as parents. The selected individuals or parents are placed in a 'mating pool'. GA uses a binary operator called crossover to combine two individuals from the mating pool to generate two new offspring. The crossover operator is applied according to a predefined crossover probability, P_c.

4. A mutation operator is applied to each of the newly generated offspring according to some pre-specified mutation probability. The mutation operator is applied according to a predefined mutation operator, P_m.

5. Application of the crossover and mutation operators leads to new individuals or well configurations and these constitute the members of the population in a new generation. Step 2 is repeated for all feasible individuals. If a new individual is infeasible, the individual is not simulated and is assigned a zero or negative fitness.

6. The above steps are continued with the solutions evolving from generation to generation. The algorithm terminates when a stopping criterion is reached. The maximum number of generations is used as the stopping criterion in this work.

The parameters used for the genetic algorithm are shown in table 4.5.

Table 4.5: Genetic Algorithm Parameters

GA Parameters	Values
Population size (popsize)	12
Crossover probability (P_c)	0.6
Mutation Probability (P_m)	0.4
Maximum Generation (maxgen)	30

4.7 Case Study: Inter-well Spacing and Optimal number of wells to be drilled

A set of experiments were carried out to evaluate the different inter-well spacing arrangements and its relationship with the number of wells drilled. Three case studies were evaluated. The evaluation was to determine the optimal location of drilling two, four and six additional infill wells, respectively. The optimal locations of the wells were estimated using the genetic algorithm toolbox from MATLAB. Initially, there were 6 wells in the reservoir. The six wells initially produced for 16.5 years and a production forecast was then carried out for an additional 18.5 years; i.e., total of 35 years of combined production, in all three cases. Three different inter-well spacing were considered (590ft, 744ft and 1053ft inter-well spacing). The cumulative oil produced was calculated from the resulting 27 runs and plotted as a histogram shown in figure 4.10. The results obtained from the simulation runs of the case study are summarized in the following section.

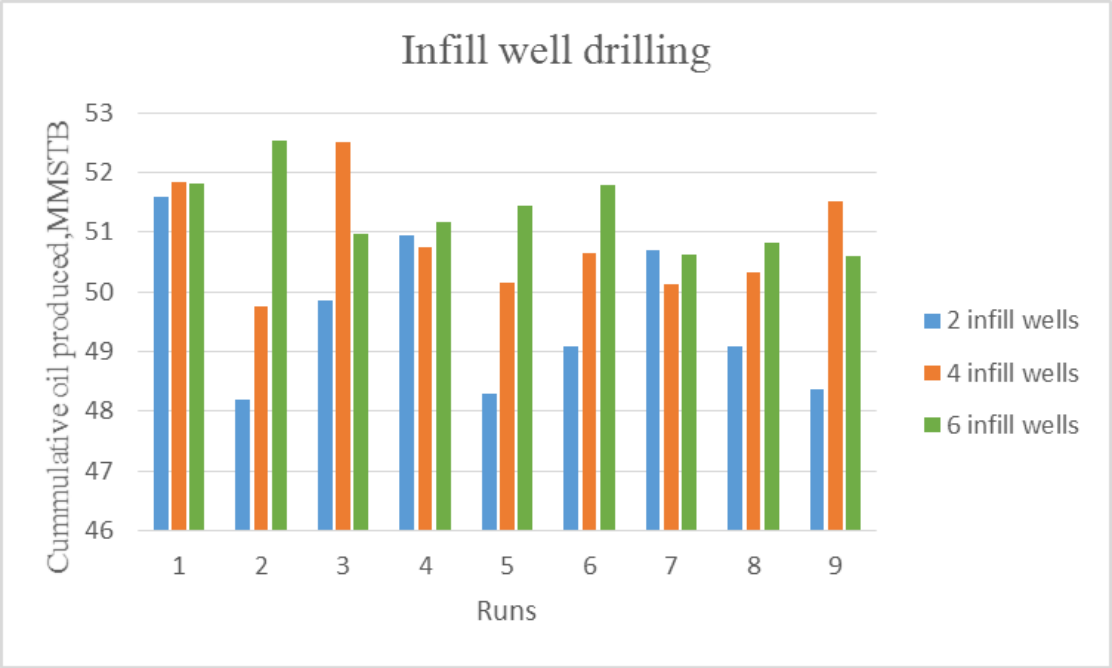

Figure 4.10 Histogram of 27 simulation runs (response is COP in MMSTB)

4.8 Summary of Results from the Case Study

The case study was used to determine the optimal locations to place the infill wells in the reservoir model. Figure 4.11 and Figure 4.12 show the results of Case 1, the drilling of two additional infill wells in the reservoir. Note that Figure 4.11 shows the cumulative oil production versus time and Figure 4.12 illustrates the optimal well locations for Case 1. Figure 4.12 shows the plane grid of the reservoir model. The regions of aquifer location and the location of the six appraisal wells initially drilled are shown in the figure. The optimal locations of two additional infill wells are clearly shown in the figure. The results for Case 2 (i.e. drilling four additional infill wells) are displayed in Figures 4.13 and 4.14; and for Case 3 (drilling six additional infill wells) are shown in figures 4.15 and 4.16. The plots of the cumulative oil recovery cover the 35-year production period. All wells had similar production history for the first 16.5 years, and the model provided different cumulative oil recovery at the end of the 35 years production forecast depending on the number and locations of the additional in-fill wells.

From figure 4.10 the highest cumulative oil production (COP) varied from 51.54MMSTB, 52.44MMSTB and 52.51MMSTB for the two, four, and six additional infill wells, respectively. The results indicate that no significant improvement in the incremental oil recovered from drilling six additional wells. The recommended field development plan guided by the results of the well placement optimization case study is to drill four additional infill wells in the reservoir. Thus, Case 2 will provide the optimal recovery from the reservoir and is the ideal infill well field development plan for the given period of production time (35 years).

CASE 1: SIX APPRASIAL WELLS AND TWO ADDITIONAL INFILL WELLS DRILLED.

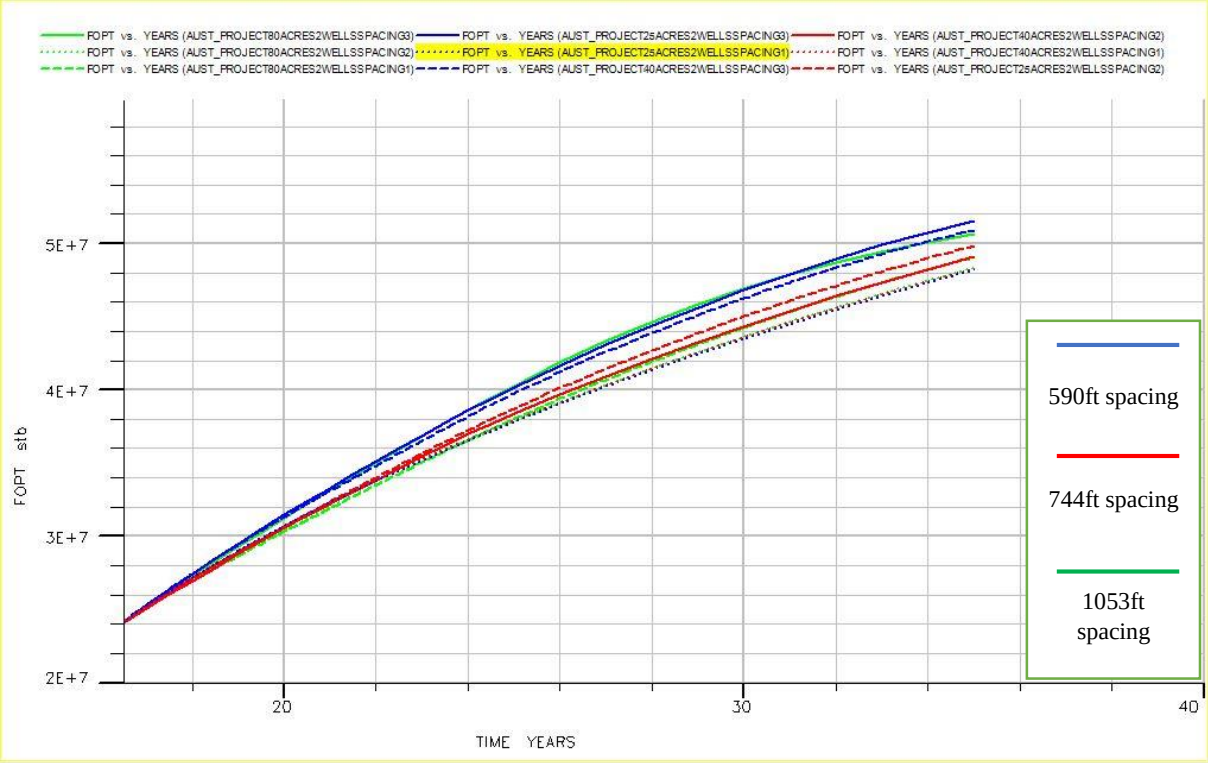

Figure 4.11 Field Oil Production for different inter-well spacing with two additional infill wells

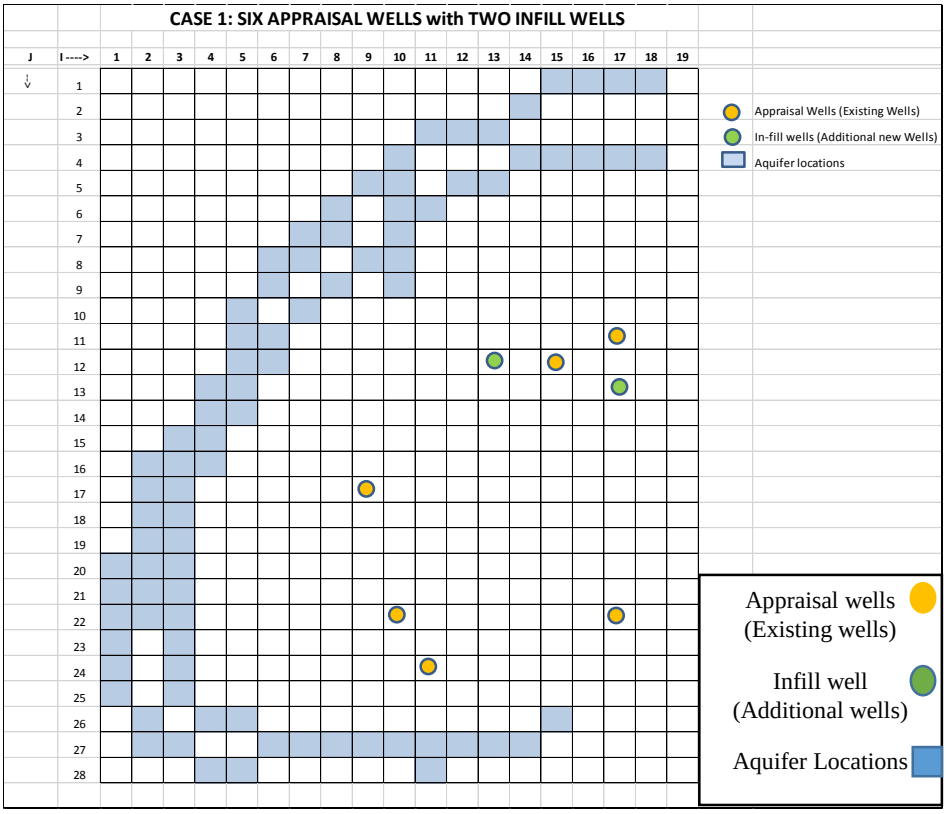

Figure 4.12 Optimal location for two additional infill wells

CASE 2: SIX APPRASIAL WELLS AND FOUR ADDITIONAL INFILL WELLS DRILLED.

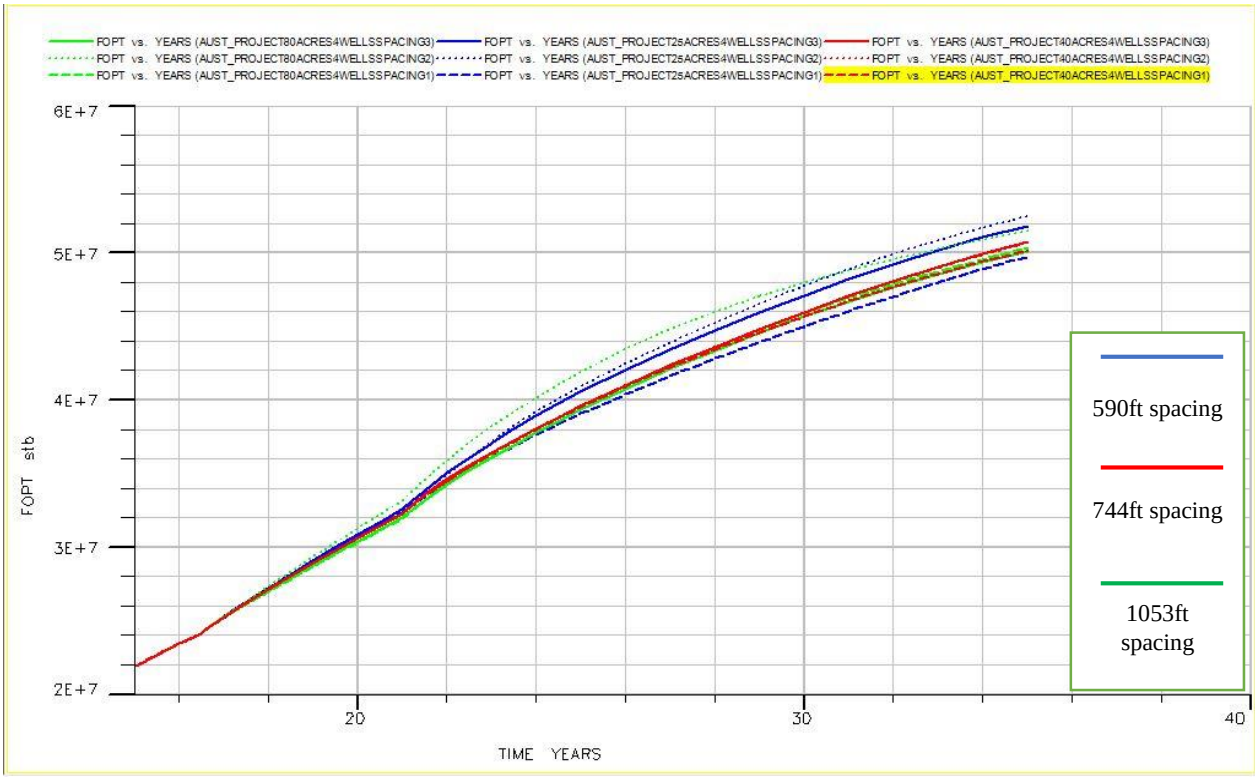

Figure 4.13 Field Oil Production for different inter-well spacing with four additional infill wells

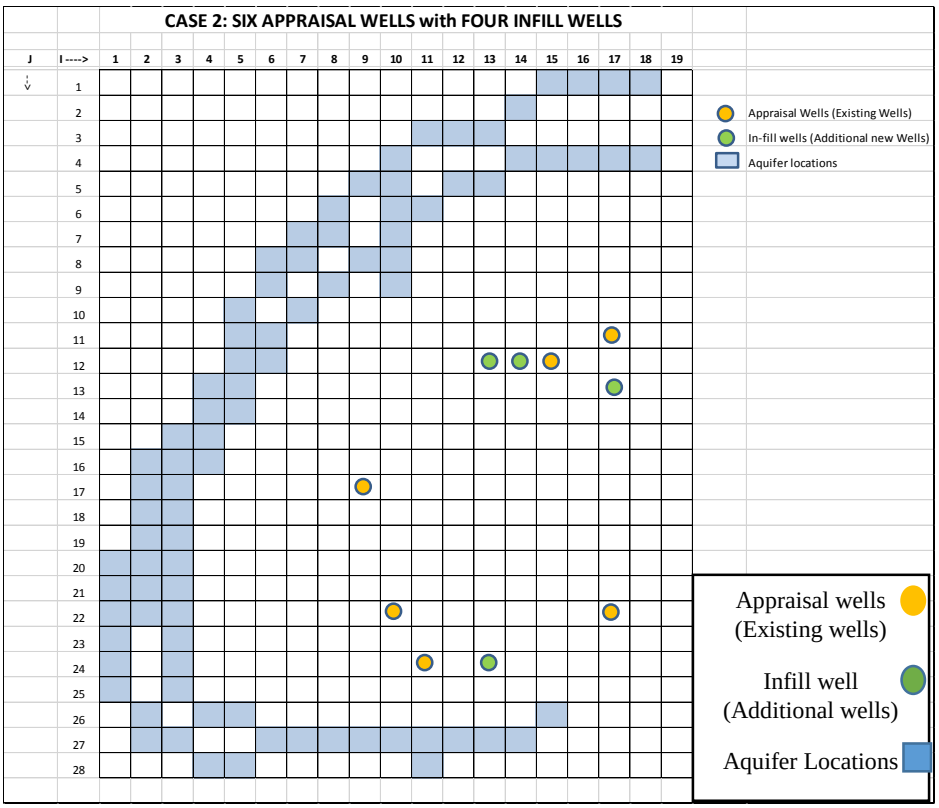

Figure 4.14 Optimal location for four additional infill wells

CASE 3: SIX APPRASIAL WELLS AND SIX ADDITIONAL INFILL WELLS DRILLED.

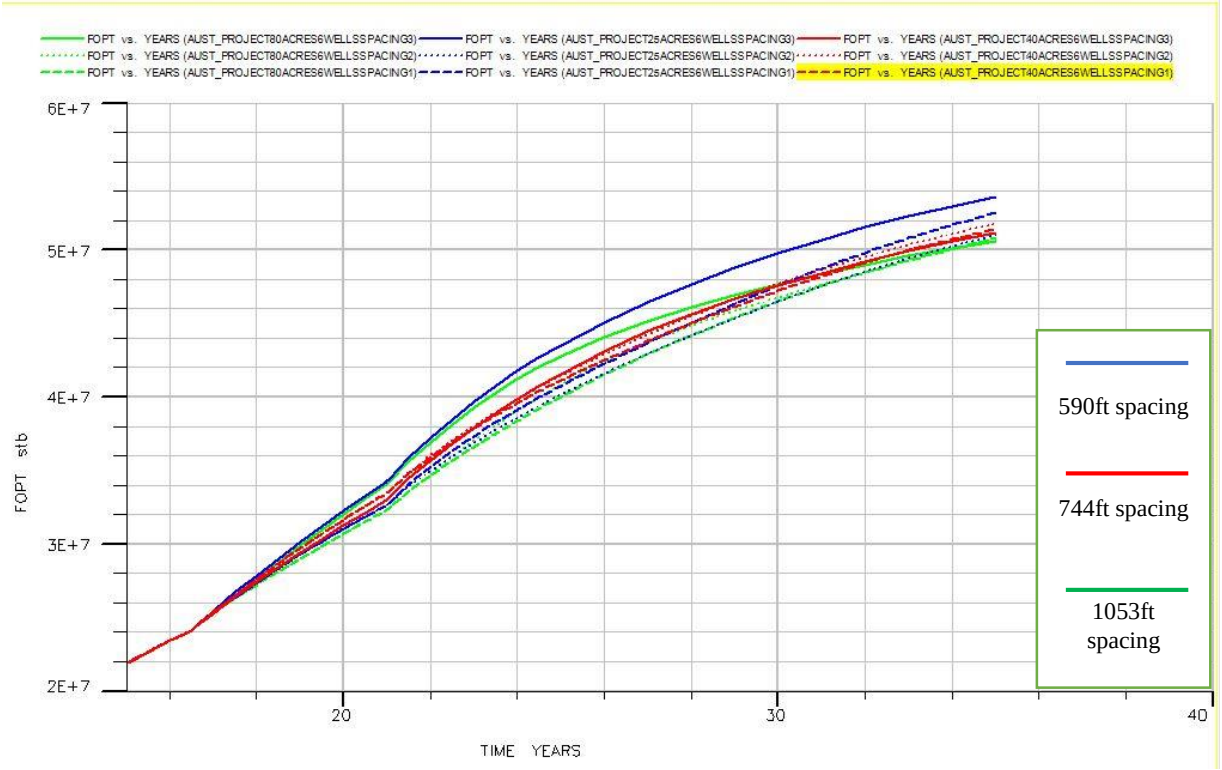

Figure 4.15 Field Oil Production for different inter-well spacing with six additional infill wells

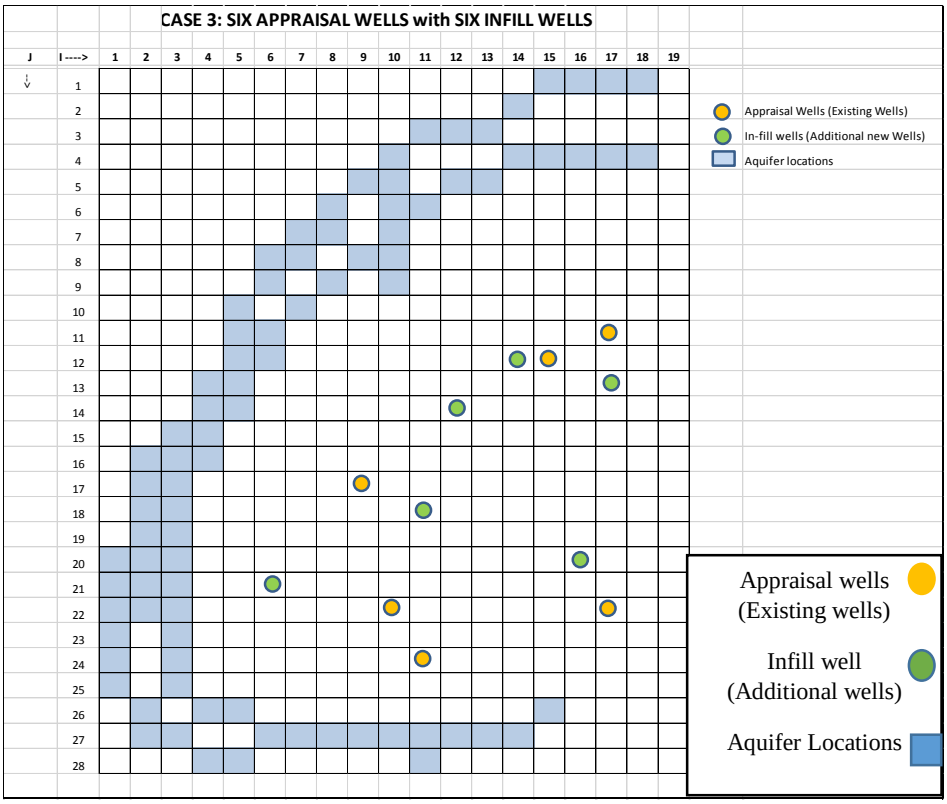

Figure 4.16 Optimal location for six additional infill wells

CHAPTER 5

CONCLUSIONS AND RECOMMENDATIONS

5.1 Summary and Conclusions

In this thesis, we have defined a new optimization approach under geological uncertainty with a reduced number of reservoir simulations. The approach uses the objective function evaluations of selected number of well locations and reservoir attributes to build a proxy model. The proposed approach can be combined with any optimization algorithm. In this work, we show an application using proxy model generated from experimental design and response surface methodology, and its combination with the genetic algorithm to solve the well placement problem. The application of the screening parameters and different property maps as tools for constraining well locations and placement was also shown to provide better results for the optimization process.

The response surface methodology was used to obtain the optimal design for oil production by studying the uncertainty parameters in order to optimize reservoir and infill well locations. We applied this method to analyze 6 uncertain parameters, including vertical permeability, horizontal permeability, aquifer permeability, porosity, oil viscosity, and transmissibility and to determine the significant parameters for building the proxy model. This approach worked well in the optimization process; it allows performing fewer simulation runs and consuming less CPU-time because of the screening and proxy features. On the benchmark reservoir case, PUNQ-S3, the proposed approach is shown to be able to capture the geological uncertainty while using only a reduced number of reservoir simulations, and to identify optimal locations for infill well placement.

The following conclusions can be derived from the results of this study.

1. The use of screening parameters and constraints helped reduced the complexity of the problem by reducing the search space for well placement and also improved the results of the optimization process, by eliminating known poor well locations (performers).
2. A sensitivity analysis on reservoir and geological uncertainties is adequate to identify the significant parameters that can be further investigated and included in the proxy model and detailed uncertainty analysis.
3. There is an optimal number of wells required to develop a reservoir, above which there will not be significant increment in the cumulative oil produced, and this optimum can be determined for each field.
4. The results also show that the locations of infill wells in the three different scenarios (two, four and six additional infill wells) had impact on the cumulative oil recovery. The case of drilling four additional infill wells was the optimal well placement recommended for the field studied in this work.

5.2 Recommendations for Future Work

The following set of recommendations is suggested for further research using this methodology.

1. The results of this research are not comprehensive. In order to improve the results, the problems addressed in the thesis should be critically investigated and a more rigorous analysis of the uncertainty relating to the well placement problem should be carried out.

2. There was no economic analysis done in this work, and it is recommended that further work should include an economic analysis to improve the decision to drill additional wells.
3. This work did not account for the minimum distance between wells that will properly guide the optimal locations for infill placement. It is recommended that future work should include the minimum inter-well spacing to understand its impact on the well placement.

NOMENCLATURE

ANN	artificial neural network
ANOVA	analysis of variance
BGA	binary genetic algorithm
CGA	continuous genetic algorithm
COP	cumulative oil produced
DOD	d-optimal design
DoE	design of experiment
ED	experimental design
FOPT	field oil production total
GA	genetic algorithm
HC	hill climber
OWC	oil-water contact
PERMX	horizontal permeability
PERMZ	vertical permeability
PORO	porosity
AQUIPERM	aquifer permeability
OVISC	oil viscosity
TRANX	transmissibility
P_c	crossover probability
P_m	mutation probability
PRO	producer
PUNQ-S3	production forecasting for uncertainty quantification
RSM	response surface methodology
S_{oil}	initial oil saturation
S_{or}	residual oil saturation
2FI	two factor interaction

REFERENCES

Aanonsen, S. I., Eide, A. L., Holden, L. and Aasen, J. O. (1995). "Optimizing Reservoir Performance under Uncertainty with Application to Well Location," paper SPE 30710 presented at the 1995 SPE Annual Technical Conference & Exhibition, Dallas, Texas, October 22-25.

Abukhamsin, A Y. (2009). Optimization of well design & location in a real field. Master's Report, Department of Energy Resources Engineering, Stanford University, California.

Artus, V., Durlofsky, L. J., Onwunalu, J. E., and Aziz, K. (2006). Optimization of nonconventional wells under uncertainty using statistical proxies. Computational Geosciences, 10(4):389–404.

Badru, O., and Kabir, C. S. (2003). Well placement optimization in field development. Paper SPE 84191 presented at the SPE Annual Technical Conference and Exhibition, Denver, Colorado, U.S.A., 5-6 October.

Bittencourt, A. C., and Horne, R. N. (1997). "Reservoir Development and Design Optimization", paper SPE 38895 presented at the SPE Annual Technical Conference and Exhibition, San Antonio, TX, October 5-8.

Carreras, P. E., Turner, S.E., and Wilkinson, G. T. (2006). Development Strategy Assessment using Design of Experiments and Response Surface Method. SPE 100656.

Dejean, J.P., and Blanc, G. (1999). Managing Uncertainties on Production Prediction Using Integrated Statistical Methods, SPE Annual Technical Conference and Exhibition Proceedings, Houston, Texas, October 3–6.

Emeric, A., Silva, E., Messer, B., Almeida, L., Szwarcman, D., Pacheco, M., & Vellasco, M. (2009). Well Placement Optimization Using a Genetic Algorithm with Nonlinear Constraints,

paper SPE 118808 presented at the SPE Reservoir Simulation Symposium, The Woodlands, Texas, 2-4 February.

Farshi, M. (2008). Improving Genetic Algorithms for Optimum Well Placement, Master's Report, Department of Energy Resources Engineering, Stanford University.

Fatemeh, M., and Nasser, A. (2011). Experimental Design in Reservoir Simulation: An Integrated Solution for Uncertainty Analysis; a Case study.

Floris, F.J.T., Bush, M.D., Cuypers, M., Roggero, F., & Syversveen, A.R. (2001). Methods for Quantifying the Uncertainty of Production Forecasts: A Comparative Study. Petroleum Geoscience, 7(SUPP), 87-96.

Goldberg, D. E. (1989). Genetic Algorithms in Search, Optimization, and Machine Learning. Addison-Wesley, Reading, Massachusetts, U.S.A.

Guyaguler, B., Horne, R.N., Rogers, L. and Rosenzweig, J.J. (2000). "Optimization of Well Placement in a Gulf of Mexico Waterflooding Project," paper SPE 63221 presented at the 2000 SPE Annual Technical Conference and Exhibition, Dallas, Texas, October 1-4.

Holland, J. H. (1975), Adaptation in natural and Artificial Systems. Ann Arbor, The University of Michigan Press.

Litvak, M., Gane, B., Williams, G., Mansfield, M., Angert, P., Macdonald, C., McMurray, L., Skinner, R., Walker, and G.J. (2007). Field Development Optimization Technology. Paper SPE 106426 presented at the 2007 SPE Reservoir Simulation Symposium, Houston, 26–28 February.

Onwunalu, J. E. (2006). Optimization of Nonconventional Well Placement Using Genetic Algorithms and Statistical Proxy, Master's Report, Department of Energy Resources Engineering, Stanford University, California.

Onwunalu, J. E. (2010). Optimization of Field Development Using Particle Swarm Optimization and New Well Pattern Descriptions. PhD thesis, Department of Energy Resources Engineering, Stanford University.

Salhi, M. A., Vanrijen, M., Wei, L.,Dijk, H., Alias, Z., Upadhyaya, A., and Lee, H. (2005). Structured Uncertainty Assessment for a Mature Field through the Application of Experimental Design and Response Surface Methodology. Paper SPE 93529.

Yeten, B. (2003). Optimum Deployment of Nonconventional Wells, Ph.D. dissertation, Department of Energy Resources Engineering, Stanford University, California.

Zhang, J., Delshad, M., Sepehrnoori, K. (2007). Development of a framework for optimization of reservoir simulation studies, Journal of Petroleum Science and Engineering 59, 1-2, 135–146.