OPTIMIZATION OF NONCONVENTIONAL WELL PLACEMENT USING GENETIC ALGORITHMS AND STATISTICAL PROXY

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By

Jérôme Onwunalu

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I certify that I have read this report and that in my opinion it is fully adequate, in scope and in quality, as partial fulfillment of the degree of Master of Science in Petroleum Engineering.

Prof. Louis J. Durlofsky (Principal Advisor)

Abstract

The determination of the optimal type and placement of a nonconventional well in a heterogeneous reservoir represents a challenging optimization problem. This determination is significantly more complicated if uncertainty in the reservoir geology is included in the optimization. In this study, a genetic algorithm is applied to optimize the deployment of nonconventional wells under geological uncertainty. In order to reduce the excessive computational requirements of the base method, a statistical proxy based on cluster analysis is applied into the optimization process. This proxy provides an estimate of the cumulative distribution function (cdf) of the scenario performance, which enables the quantification of proxy uncertainty. Knowledge of the proxy-based performance estimate in conjunction with the proxy cdf enables the systematic selection of the most appropriate scenarios for full simulation. The proxy is extended for application to the optimization of multiple nonconventional wells opened at different times. The proxy in this case is referred to as dynamic proxy. For optimization of a single nonconventional well, it is shown that by simulating only 10 or 20% of the scenarios, optimization results very close to those achieved by simulating all cases are obtained. For multiple wells drilled at different times, the dynamic proxy is effective though a relatively high percentage (e.g., 50%) of the cases must be simulated.

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Chapter 1

1. Introduction

Oil and gas fields are increasingly developed using nonconventional wells because of the increased production obtained when these wells are deployed. Nonconventional wells can result in accelerated production, increased cumulative oil/gas recovery and delayed production of unwanted fluids (e.g., water from an aquifer).

Hydrocarbon recovery and/or net present value (NPV) from a field development project can be maximized by optimizing the deployment of nonconventional wells. The number of wells, type, location and trajectory of each nonconventional well can be optimized to maximize an objective function such as NPV or cumulative recovery. However, optimization is difficult because of the large dimensional space arising from the many parameters required to describe a nonconventional well. Various types of nonconventional well configurations are possible and this precludes exhaustive evaluation of each well configuration, because each configuration requires a simulation run.

Nonconventional wells are expensive to deploy and their performance can be severely impacted by uncertainty in the geological model (Joshi, 1991). The uncertainty in geology can be represented by generating multiple, equally probable realizations of the geological model. This results in different performance for the same well configuration evaluated in different realizations of the geological model. Each well configuration must therefore be evaluated for each realization of the geological model, which results in a large number of function evaluations (simulations). For practical applications, a method to reduce the number of simulations for this optimization is required. The goal of this work is to develop and apply an efficient algorithm, namely a statistical proxy, for this optimization.

1.1 Literature review

Several investigators have applied different algorithms to solve the well deployment problem. Bittencourt and Horne (1997), Guyaguler and Horne (2001) and Guyaguler et al. (2002) applied genetic algorithms (GA) to optimize the placement of vertical wells. Optimization under geological uncertainty was considered by Guyaguler and Horne (2001). Yeten (2003) and Yeten et al. (2003) developed a framework for optimization of nonconventional wells using a genetic algorithm under geological uncertainty. The proposed procedure can optimize the number, type and trajectory of a nonconventional well using a generic parameterization of the variables describing the well.

The use of GAs for optimization of well deployment is computationally intensive, requiring many simulations. This is the case because GAs use a generate-and-test paradigm (Cox, 2005) where feasible potential solutions are generated and each is simulated using the function evaluator (simulator and/or economic model). In the well placement optimization, the testing of each solution corresponds to performing a simulation for each well configuration over all realizations of the geological model. Investigators have proposed algorithms using heuristics to reduce the number of simulations required during optimization. Bittencourt and Horne (1997) used a hybrid GA involving GA, tabu search and polytope to reduce the number of simulations required in vertical well placement applications. Pan and Horne (1998) applied least squares and kriging interpolation techniques as proxies to identify promising well configurations. The proxies were constructed from previously simulated well configurations. Guyaguler et al. (2002) also applied a hybrid algorithm using GA, polytope (hill climbing), kriging, and artificial neural networks (ANN) to reduce the number of simulations required. This hybrid algorithm was applied to real field cases and performance using kriging was found to be superior to that from ANN. Yeten (2003) also used a hybrid algorithm involving GA, polytope and ANN for optimization of nonconventional well placement. Polytope was used for the local search when the improvement in the best solution was marginal, especially in later generations. The use of ANN as a proxy provided reasonable agreement between the predicted (prior) and observed (posterior) fitness in the application considered by Yeten (2003).

It is in general difficult to assess the performance of proxies applied in well placement optimization. One approach would be to quantify the difference between the optimal solution and the best solution found using the proxy. However, GAs do not guarantee that the globally optimum solution will be found (Cox, 2005; Duda et al., 2001). Hence it is difficult to compare how well a proxy performs during the optimization.

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, 2005). 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. The statistical proxy discussed in this work falls in the second 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 exhaustive method. Specifically, comparisons are made of the best solution found, run time characteristics, and number of function evaluations for both methods.

1.2 Scope of work

A statistical proxy was developed in Artus et al. (2005) for reducing the number of simulations required for the optimization of nonconventional well placement. The procedure incorporates uncertainty in estimates of fitness by the proxy, geological uncertainty and the decision maker's attitude to risk. The proxy used static attributes of well configurations to determine the prior performance of well configurations before performing full simulation. The statistical proxy was applied to various problems involving optimization of nonconventional well placement.

The statistical proxy procedure was developed in Artus et al. (2005). In this work, the proxy procedure is described and results obtained using synthetic reservoir models are presented. Some of the results presented here also appear in Artus et al. (2005). The proxy is here extended for application to optimization of multiple nonconventional wells when the wells are opened at different times. This modification allows for the inclusion of dynamic attributes in the model building and classification steps as is necessary for these cases.

The initial code for the statistical proxy using static attributes was developed by Vincent Artus. I performed numerous tests on the code, introduced minor enhancements, and generated results for several examples using the static proxy. The examples are presented in Artus et al. (2005). I then modified the code to use dynamic attributes for application to cases when the wells are opened at different times. In the descriptions that follow, the general approach and proxies will be discussed together, though it is important to note that the main contributions of the author are as indicated above.

Chapter 2

2. Nonconventional well optimization with GAs

2.1. Genetic Algorithms

A Genetic Algorithm (GA) is a nondeterministic search technique based on the principles of natural evolution and selection. GAs find 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.

Some of the standard terminology used in the GA literature is explained below. Its use in the well optimization problem is also provided.

- **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.

- **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.

- **Generation** refers to the population of individuals at a given iteration during the optimization.

- **Fitness** of an individual is the outcome of the fitness (or objective) function with the individual as input. **Prior fitness** refers to fitness computed using some proxy/surrogate model while **posterior fitness** generally refers to fitness computed using the actual objective function.

- **Hybridized GA** refers to a GA that uses helper or heuristic algorithms to improve the performance of a simple GA.

2.2 Optimization of nonconventional wells using GA

As discussed in Chapter 1, Yeten et al. (2003) proposed a procedure using a hybridized GA to optimize the number, type, location and trajectory of nonconventional wells. They used a general parameterization of the unknowns describing a nonconventional well where the type, location, trajectory and status (open or closed) were considered as unknowns. The method was applied to several cases involving deployment of nonconventional wells. The GA for optimization of nonconventional well placement used here is based on the procedure described in Yeten et al. (2003). The parameterization of the unknowns employed by Yeten et al. (2003) and in the current study is briefly described in the next section.

Yeten et al. (2003) used binary numbers to encode the parameters to be optimized for each nonconventional well. The chromosomal representation of each nonconventional well configuration is longer than that for vertical wells because of the higher number of parameters required to describe a nonconventional well (e.g., heel and toe for each lateral). As a result, the search space is large compared to applications involving placement of vertical wells (Yeten, 2003; Artus, et al., 2005). Figure 2.1 shows an adaptation of the binary encoding of the unknowns in Yeten (2003) used to represent a dual lateral well.

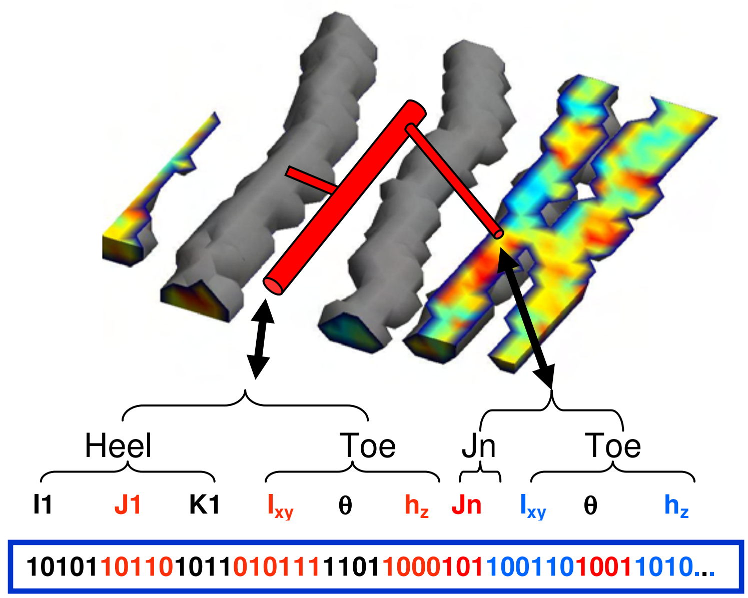

Figure 2.1: Chromosome representation of a dual lateral well (Figure generated by Vincent Artus).

In the binary coding scheme, the parameters describing each nonconventional well are converted to binary bits to form a binary string. The binary strings are concatenated to form the chromosome for each well. The procedure is repeated for multiple wells and concatenation of each well chromosome results in the full chromosome of the individual (Yeten, 2003; Yeten et al., 2003). As noted above, an individual refers to all the wells that define a development scenario. For example, if we consider a case involving placement of 3 wells, an individual then refers to a chromosome consisting of all parameters defining the configuration of the 3 wells.

2.3 GA optimization in the absence of proxies

The use of the basic GA to optimize the deployment of nonconventional wells is described as follows:

1. The GA generates randomly a set of individuals (feasible solutions), each corresponding to a development scenario. The number of solutions generated, designated *N*, determines the population size (Figure 2.2, left).

2. The fitness of each solution is evaluated by performing a reservoir simulation to obtain production profiles which may then be input to an economic model, if the fitness is NPV. Where uncertainty in the geological model is considered, the simulation is repeated using the same well configurations for all realizations of the geological model. In this case, the individual fitness is defined as some function of the performance (cumulative oil or NPV) over all of the realizations; for example, the fitness of the individual can simply be defined as the average of the performance across all realizations.

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' (Figure 2.2, right). GA uses a binary operator called crossover to combine two individuals from the mating pool to generate two new offspring (Figure 2.3, Figure 2.4). Single point crossover was used in all investigations here, though it is possible to use other types of crossover (2 point, uniform, etc.). 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 implementation used in this work applies a bitwise mutation, by randomly flipping the bits in the chromosome of the offspring (Figure 2.3, Figure 2.4). 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; i.e., it describes a non-physical well configuration such as wells/laterals intersecting or extending beyond reservoir boundaries, the individual is not simulated and is assigned a zero or negative fitness. This results in the removal of the infeasible well configuration(s) when the selection operator is applied.

6. The above steps are continued with the solutions evolving from generation to generation. The algorithm terminates when a stopping criterion is reached. There are several criteria that can be used to stop the GA (Cox, 2005). The maximum number of generations is used as the stopping criterion in this work.

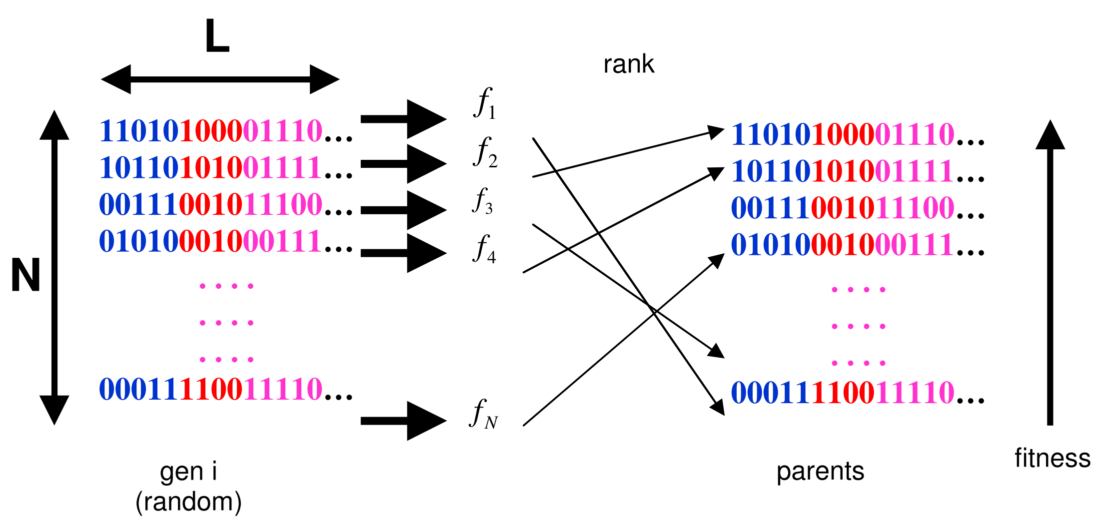

Figure 2.2: N individuals of chromosome length L in generation i.

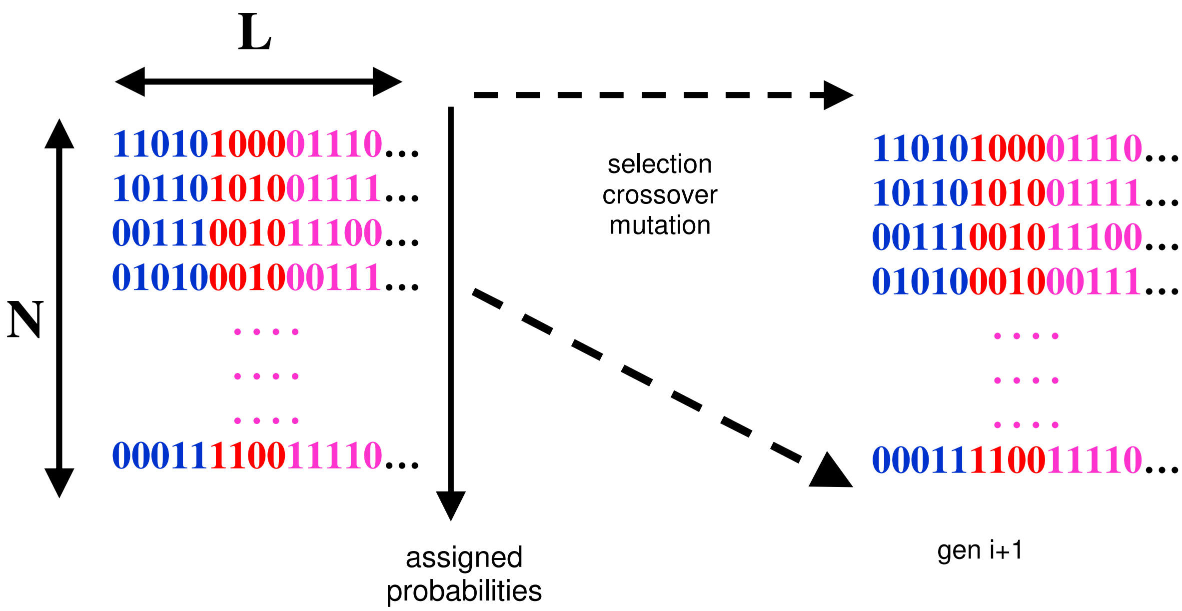

Figure 2.3: Creating new population from old population by applying selection, crossover and mutation operators.

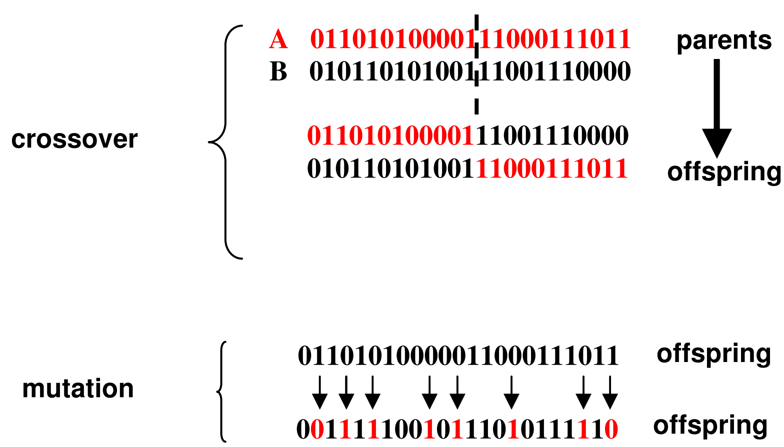

Figure 2.4: Illustration of single point crossover and bitwise mutation operators.

In order to introduce financial considerations into the optimization process, the objective function can be prescribed as the net present value (NPV), defined as the current value of a stream of future payments. The economic model presented below is based on the work of Yeten et al. (2003). The NPV is given by:

$$NPV = \sum_{i=1}^{N} \frac{CF_i}{(1+r)^i} \tag{2.1}$$

where N is the total number of discount periods (years), r is the discount rate and CF_i is the cash flow for the period i, defined as:

$$CF_i = R_i - E_i \tag{2.2}$$

where R_i and E_i are the revenue and expenses. The revenue is directly proportional to the production during the considered period. The cost of a particular development scenario is highly case specific and is influenced by many parameters (Cho, 2003). We define the revenues and expenses due to production during a discount period as:

$$E_i^{OPEX} = Q_i^L C^{OPEX} \tag{2.3}$$

where Q_i^L is the total production of oil, water and gas (in STB or SCF) and C^{OPEX} are operation costs (\$/STB or \$/SCF). The cost of the scenario at the beginning of the project (prior to any production) is given by:

$$E^{SCEN} = \sum_{n=1}^{N^{WELL}} \left[C^{CAPEX} + L_n C^{DRILL} + \sum_{j=1}^{N_n^{JUNC}} C^{JUNC} \right] \tag{2.4}$$

where N^{WELL} is the number of wells, N_n^{JUNC} is the number of junctions for the n^{th} well, C^{CAPEX} is a fixed cost per well, including the cost of the platform and the cost of drilling to the top of the reservoir, C^{JUNC} is the cost of a junction, L_n is the length of the n^{th} well (in feet) and C^{DRILL} is the cost per unit length of drilling the well. Although the cost of drilling varies depending on the type of the segment, the orientation and the well length, we chose to use a constant price in this study. A more general cost function could be easily implemented in this formulation.

In order to account for economic variability, time-dependent discount rates can be applied to production costs and revenues (dual discount NPV model). This introduces another kind of uncertainty, as it can be used to introduce optimistic or pessimistic economic scenarios in the optimization process.

Chapter 3

3. Statistical proxy

The basic genetic algorithm (GA) uses a generate-and-test paradigm where solutions are generated and tested for feasibility and optimality. Using this form of GA for optimization of nonconventional wells will require many simulation runs. The total number of simulations is increased further if the optimization is performed under geological uncertainty. Using the simple GA the number of simulations N_{sim} required for an optimization run is given by:

$$N_{sim} = N_{gen} \times N_{ind} \times N_{real} \tag{3.1}$$

where N_{gen} is the number of generations or iterations, N_{ind} is the number of individuals in a generation (population size) and N_{real} is the number of geological realizations. Equation 3.1 shows that performing the optimization of well placement under geological uncertainty increases the number of simulations by a factor N_{real}. Proxies can be applied to predict the fitness a priori of new individuals. The prior fitness is ranked and a fraction of cases are selected. The posterior fitness of the selected individuals will be evaluated using the reservoir simulator and/or economic model while for the other individuals, the posterior estimate of fitness is taken as the prior estimate.

3.1 Proxy model development

Proxy models use attributes from the well and reservoir and the posterior fitness from all previously simulated individuals. The attributes are the independent variables while the posterior fitness is the target or dependent variable, which is to be estimated. The attributes can be grouped into two main categories: well configuration(s) attributes and well-reservoir attributes. The former describes attributes that are derived solely from the well configuration(s) while the latter describes attributes derived from the well and reservoir interaction. Examples of well configuration(s) attributes are well length, well diameter and number of laterals. Attributes derived from the well-reservoir model interaction include average permeability along the well and volume of channels intersected. For optimizations of nonconventional well placement involving multiple realizations, well configuration attributes will be the same over all realizations while the well-reservoir attributes will be different for each realization.

For a given optimization run, proxy models are built from the attributes and target variables from previously simulated cases. A database consisting of the attributes and targets is constructed from these simulated cases and is continually updated during the optimization. Equation 3.2 describes a model to estimate the fitness of a new individual *I* in realization *n*, denoted $f(I,n)$, in terms of the well and well-reservoir attributes of previously simulated cases:

$$f(I,n) = f\left(X(I)^{well}, X(I,n)^{res}_{static}\right) \tag{3.2}$$

where $X(I)^{well}$ describe the set of attributes derived from the well(s) in individual *I* and $X(I,n)^{res}_{static}$ is the set of static attributes derived from the *n*th realization and individual *I*. Artus et al. (2005) applied a clustering procedure to determine the relationship between the attributes and fitness value. The clustering procedure is based on the fact that similar individuals will tend to have similar performance or fitness. It is then possible to partition the space of attributes into several clusters. The cluster analysis procedure is described in the next section.

3.2 Cluster analysis

Cluster analysis is an unsupervised learning technique that groups data objects based on the data values and the data to data relationship inherent in the data points (Tan et al., 2005). Cluster analysis partitions the data attribute space into different groups so that objects within the same group are more similar to one another and different or dissimilar to objects in other groups. Each group of data objects is called a cluster. The point that minimizes the mean squared error between all data objects in a cluster is called the centroid of the cluster (Duda et al., 2001; Tan et al., 2005).

Artus et al. (2005) used a *K*-means clustering procedure to perform the cluster analysis of data attributes in the data base. A *K*-means clustering procedure partitions the data into *K* clusters, where *K* is user specified. The centroid of each cluster will not in general coincide with an actual data point in the cluster (Tan et al., 2005). The *K*-means clustering procedure is summarized below:

1. Select *K* points as the initial centroids, where *K* is user specified.

2. *K* clusters are formed by assigning each data object to the closest cluster using a distance metric (e.g., Euclidean).

3. Update the centroid of each cluster.

4. Steps 2-3 are repeated until the centroids do not change.

After the clustering procedure, each data point in the database has been assigned to the nearest cluster. Within each cluster, each data point corresponds to an observation with a fitness value. From the fitness values in each cluster, an experimental cumulative distribution function of the fitness values in that cluster can be derived. For example, Figure 3.1 shows the cumulative distribution of fitness (defined as cumulative oil produced) in 6 clusters, for a test case that involved a total of 13 clusters, at the end of the 10^{th} generation. This example involved the optimization of 3 producers and is discussed further in Section 4.2.1. The dashed line shows the *P10, P50* and *P90* values of fitness from the distribution. *F(x)* denotes the probability that the fitness is equal to or less than *x*. Figure 3.2 shows the *P10, P50* and *P90* values for 12 clusters.

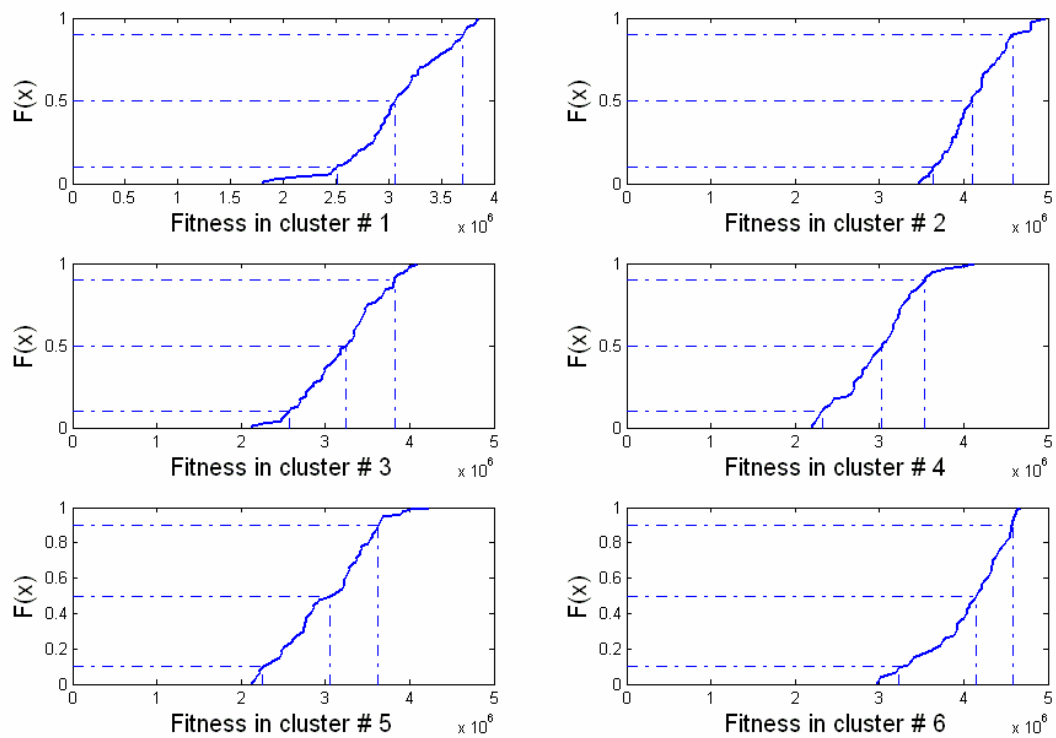

Figure 3.1: Cumulative distribution of fitness in 6 clusters

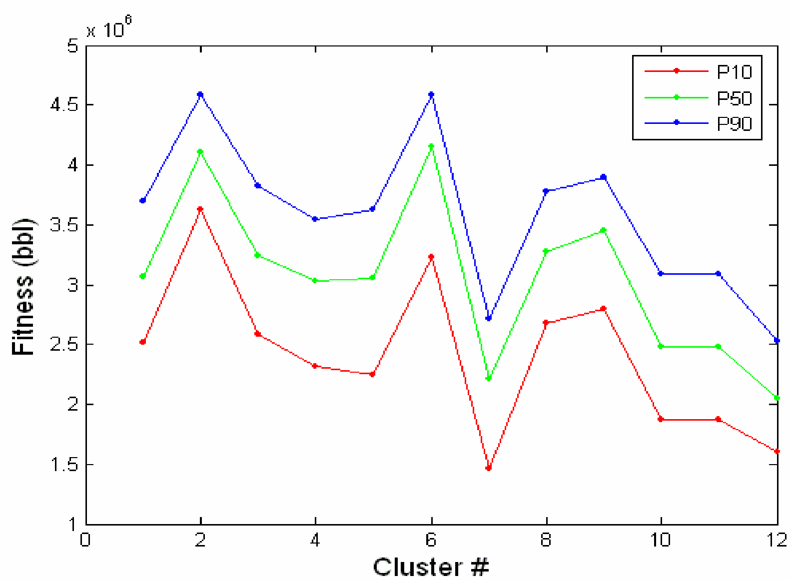

Figure 3.2: *P10, P50* and *P90* values of 12 clusters

The distribution of fitness in a cluster is used to estimate the prior fitness of new individuals assigned to that cluster. The new individual is assigned to the 'closest' cluster by computing the Euclidean distance between the centroid of the clusters and the new attributes derived from the new individual. The cumulative distribution function (cdf) of the assigned cluster is used to estimate the prior fitness of the new individual using a procedure described in the next section.

3.3 Estimation of prior fitness

For each realization, the prior fitness $f(I,n)^{prior}$ of a new individual I in realization n can be estimated using the distribution of fitness in the cluster where the case *(I,n)* is assigned. As indicated above, attributes for a new individual consist of well attributes $X(I)^{well}$ and well-reservoir attributes $X(I,n)^{res}_{static}$. The well attributes will be constant over all realizations while the well-reservoir attributes will vary from one realization to the other. Both attributes are used to estimate $f(I,n)^{prior}$ for each realization. Since the well-reservoir attributes vary, each individual-realization case *(I,n)* is likely to be assigned to a different cluster. For each individual-realization case *(I,n)*, the cdf of the assigned cluster is used to estimate the prior fitness $f(I,n)^{prior}$ for that case. Thus, different cdfs with different levels of uncertainty are used in the estimation of the prior fitness for each individual. For N_{real} realizations, there are N_{real} estimates of $f(I,n)^{prior}$ which are used to construct an experimental cdf that describes the distribution of fitness in the new individual across N_{real} realizations. From this distribution, we can obtain $f(I)^{prior}_{10}$, $f(I)^{prior}_{50}$ and $f(I)^{prior}_{90}$ values (these correspond to *P10, P50* and *P90*), which can then be combined (as described below) to define an overall prior fitness *F(I)* of the individual *I.*

Two different uncertainties enter into this estimate of prior fitness. These are the proxy uncertainty and the geological uncertainty. Proxy uncertainty enters because we use the target cluster cdf to estimate $f(I,n)^{prior}$ for each realization. The degree of uncertainty in estimates of $f(I,n)^{prior}$ depends on the distribution of fitness in the cluster. If the cluster is tightly packed, the standard deviation of fitness in the cluster will be smaller compared to loosely packed clusters. Aggregation of the N_{real} values of $f(I,n)^{prior}$ incorporates the geological uncertainty, which captures the variation of the performance of individual I over all N_{real} realizations.

The method for combining the different cdfs of the clusters to define an overall prior cumulative distribution function of a new individual is now described. A prior cumulative distribution of fitness for a new individual is obtained by combining the cluster cdfs corresponding to each case *(I,n)* as follows:

$$cdf\{f(I)\}^{prior} = \frac{1}{N_{real}} \sum_{n=1}^{N_{real}} cdf\{f(I,n)\}^{prior} \tag{3.3}$$

Figure 3.3 illustrates the above concepts. The plots on the left represent the distribution of fitness in the cluster used to estimate $f(I,n)^{prior}$. The vertical bar represents the *P10* and *P90* values in each cluster. The blue circles represent the *P50* values of the cluster distribution. The plots on the right in the top and bottom panels of Figure 3.3 represent the cumulative distribution function obtained by combining the cdfs of the N_{real} clusters using equation 3.3. The fitness in this case is cumulative oil produced. The upper and lower set of plots corresponds to two different individuals.

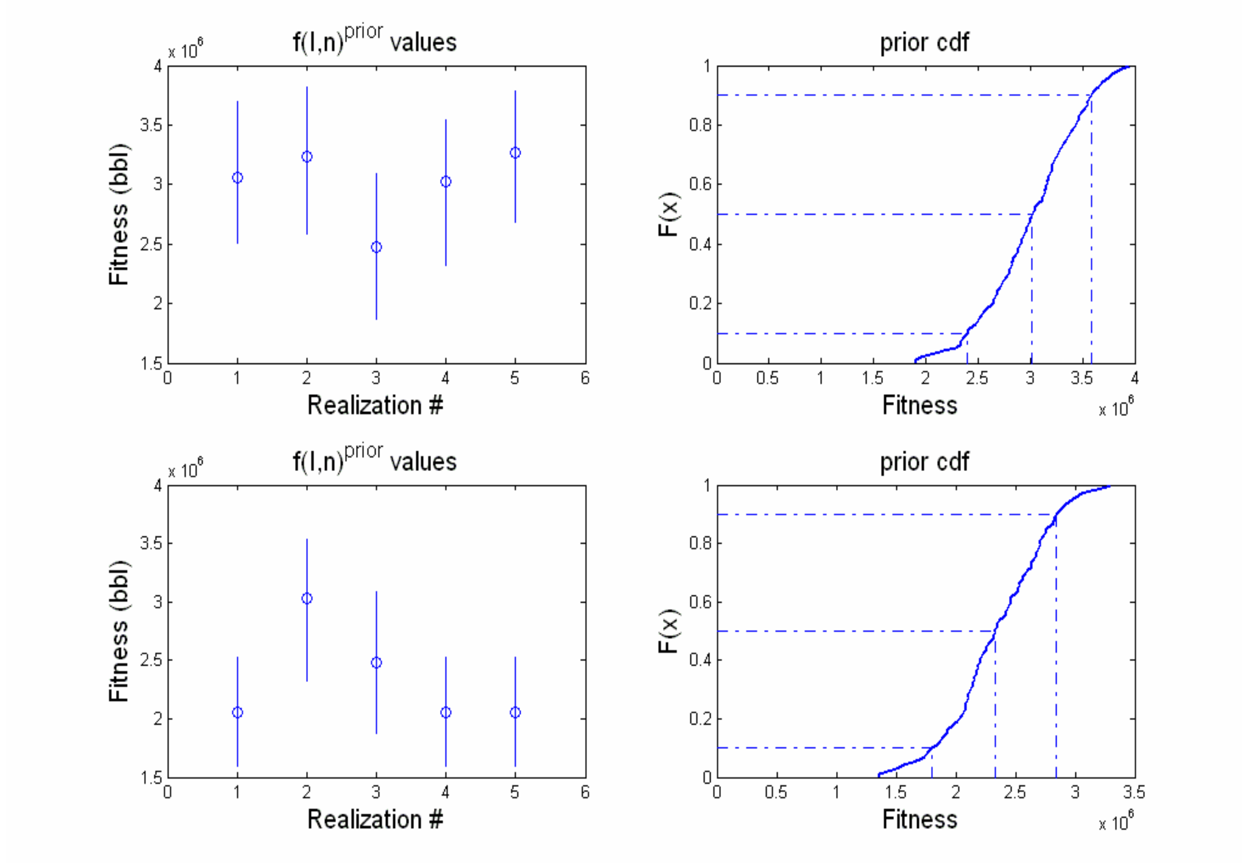

Figure 3.3: Construction of prior cumulative distribution function for new individuals I_1 (upper plots) and I_2 (lower plots).

For each new individual, values of $f(I)_{10}^{prior}$, $f(I)_{50}^{prior}$ and $f(I)_{90}^{prior}$ can be read from the prior cumulative distribution function (right plots of Figure 3.3). The prior value of fitness $F(I)^{prior}$ for each new individual can be estimated using

$$F(I)^{prior} = r_{10} f(I)_{10}^{prior} + r_{50} f(I)_{50}^{prior} + r_{90} f(I)_{90}^{prior} \tag{3.4}$$

where r_{10}, r_{50} and r_{90} represent weights which take values between 0 and 1 depending on the decision maker's risk attitude.

3.4 Estimation of posterior fitness

The posterior fitness of an individual $F(I)^{post}$ is the fitness obtained after simulations have been performed on selected individuals. We wish to identify cases *(I,n)* in which the prior fitness is high but the proxy estimate is uncertain. These cases are the most appropriate for simulation. Individual-realization cases *(I,n)* are selected for simulation based on a parameter $W(I,n)$ that combines the prior estimate of fitness and the spread in the individual's prior cumulative distribution function. $W(I,n)$ is computed for each individual *I* and realization *n* via:

$$W(I,n) = F(I)^{prior} + \alpha\left(f(I,n)_{90}^{prior} - f(I,n)_{10}^{prior}\right) \tag{3.5}$$

where $F(I)^{prior}$ is the prior fitness of individual *I* obtained using equation 3.4 and α is a weighting. Specifically, the first term of equation 3.5 represents the prior estimate of fitness of individual *I* while the second term represents the uncertainty in the distribution of the fitness in realization *n*; α sets the relative weightings of these two effects. In this work, we use $\alpha = 0.50$. Equation 3.5 provides a weight $W(I,n)$ to each individual-realization case *(I,n)*. If the number of individuals in a population is N_{ind}, then in each generation, there are $N_{real} \times N_{ind}$ individual-realization cases and simulations that could be performed. Each case is ranked according to its $W(I,n)$ value. A fraction of individual-realization cases is then selected for simulation based on the $W(I,n)$ values.

The values of $W(I,n)$ computed in equation 3.5 are large for cases with high prior fitness and high uncertainty. For individual *I*, each case *(I,n)* will have the same $F(I)^{prior}$ value but different values of $\alpha\left(f(I,n)_{90}^{prior} - f(I,n)_{10}^{prior}\right)$ since the uncertainties in the cluster cdfs are different. Therefore, the $W(I,n)$ values are higher for individual-realization cases with higher prior estimate of fitness $F(I)^{prior}$ and higher uncertainty in proxy estimates. We reiterate that this strategy for selection of simulation cases selects the most promising individuals and realizations with higher uncertainty. This selection procedure is illustrated in Table 3.1. The values in the table are derived from the plots of Figure 3.3

with $\alpha = 0.50$. Since there are 5 realizations, there are a total of 10 simulation cases that can be performed. Table 3.1 shows the results obtained using equation 3.4 for a risk neutral case with $r_{10} = r_{90} = 0$ and $r_{50} = 1$. Column 5 shows the ranking for the case considered and shows that cases with higher prior fitness values (column 2) and higher uncertainties (column 3) receive the highest rank.

Table 3.1: Example showing the computation of *W(I,n)* for two individuals

Individual	$F(I)^{prior}$ (1e6 bbl)	$\alpha\left(f(I,n)_{90}^{prior} - f(I,n)_{10}^{prior}\right)$ (1e5 bbl)	*W(I,n)* (1e6 bbl)	*Rank*
1	*3.00*	*5.95*	*3.298*	*4*
		6.20	*3.310*	*1*
		6.10	*3.305*	*2*
		4.65	*3.233*	*5*
		6.05	*3.303*	*3*
2	*2.30*	*5.20*	*2.560*	*7*
		6.10	*2.605*	*6*
		4.65	*2.533*	*10*
		5.19	*2.560*	*8*
		5.19	*2.560*	*9*

After some cases are selected for simulation, the prior cdfs are updated based on results from individual-realization cases *(I,n)* which are simulated. The resulting fitness is called posterior fitness $F(I)^{post}$ and the resulting distribution is called the posterior cumulative distribution function of fitness $cdf\{f(I)\}^{post}$. $F(I)^{post}$ is computed as:

$$F(I)^{post} = r_{10} f(I)_{10}^{post} + r_{50} f(I)_{50}^{post} + r_{90} f(I)_{90}^{post} \tag{3.6}$$

where $f(I)_{10}^{post}$, $f(I)_{50}^{post}$ and $f(I)_{90}^{post}$ are computed from $cdf\{f(I)\}^{post}$. The posterior cumulative distribution function $cdf\{f(I)\}^{post}$ is given by equation 3.7:

$$cdf\{f(I)\}^{post} = \frac{1}{N_{real}} \sum_{n=1}^{N_{real}} cdf\{f(I,n)\}^{post} \tag{3.7}$$

where $cdf\{f(I,n)\}^{post}$ is the posterior fitness value of individual *I* and realization *n.* If simulation is performed for case *(I,n)* then $cdf\{f(I,n)\}^{post}$ has no uncertainty because the fitness for case *(I,n)* is known with certainty after simulation. However, if case *(I,n)* is not selected for simulation, then $cdf\{f(I,n)\}^{post}$ is simply equal to $cdf\{f(I,n)\}^{prior}$.

Using equations 3.6 and 3.7, the posterior fitness is defined for all individuals. The selection, crossover and mutation operators described earlier are then applied to create the individuals in the next generation.

3.5 Dynamic statistical proxy

The statistical proxy described earlier uses static attributes in the clustering procedure. This means that all attributes necessary for estimation of prior fitness are obtained before the start of the simulation. This approach is directly applicable to optimization of nonconventional well placement when all the wells are opened at initial time. This form of the proxy is called 'static proxy' henceforth.

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. The use of the static proxy in this type of optimization will be limited because the static attributes do not incorporate these types of data. For example, when all the wells are opened at the same time, wells in high permeability regions will tend to have improved performance (e.g., cumulative oil) compared to wells in low permeability regions. When the wells are opened at different times, this will not be the case if new wells are drilled very close to existing wells. Therefore, the static proxy is of limited use for optimization of multiple nonconventional wells when the wells are opened at different times.

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. The existing proxy procedure is modified to account for this and the new proxy shall be called 'dynamic proxy' because it includes dynamic attributes in the model relating fitness and attributes. The static and dynamic proxies are similar in that the locations of all wells in each individual are known before the start of production. The proxies differ in terms of the set of attributes used for model building (static versus static and dynamic) and how new individual-realization cases are assigned to clusters. The dynamic proxy model development is explained in the next section.

3.6 Dynamic proxy model development

In general, the procedure for estimation of prior fitness and posterior fitness is the same for the static and dynamic proxy. However, a different approach is used for classification of new individual-realization cases (I,n) to a given cluster. In the static proxy procedure, estimation of prior fitness $f(I,n)^{prior}$ is direct once the individual-realization case is assigned to a cluster. In the dynamic proxy procedure, the test pattern is first assigned to a cluster using the Euclidean distance of the centroids and attributes derived from case (I,n). Next, within the assigned cluster, we find the 'closest well pattern' and then use the dynamic attributes of this well pattern as an estimate of the dynamic attributes of the individual-realization case (I,n).

The application of the dynamic proxy is similar to that for static proxy, i.e., we aim to estimate the prior fitness of any new individual prior to the simulation step. The main challenge in the application of the dynamic proxy is that it requires dynamic attributes which are not available at the time of the estimation of the prior fitness. The relationship between the prior fitness of an individual-realization case (I,n) denoted $f(I,n)^{prior}$ in terms of the well and reservoir attributes can be written as:

$$f(I,n)^{prior} = f\left(X(I)^{well}, X(I,n)^{res}_{static}, X(I,n)^{res}_{dynamic}\right) \quad (3.8)$$

where $X(I)^{well}$ is the set of well attributes for individual *I,* $X(I,n)^{res}_{static}$ is the set of static attributes derived for individual *I* and realization *n,* and $X(I,n)^{res}_{dynamic}$ is the set of dynamic attributes derived for individual *I* and realization *n.*

The set of attributes that can be used in the estimation of $f(I,n)^{prior}$ is limited because the dynamic attributes are not known. Therefore, we build the model with the full set of attributes (static and dynamic) and use a subset of attributes (static) to classify new individuals.

The method is similar to the method of classification using partial distance discussed in Duda et al. (2001). The partial distance method is applied to reduce the computational complexity of the *k*-Nearest-Neighbor rule by using only a subset *r* of the full *d* dimensions to compute the Euclidean distance between two *d*-dimensional data vectors ***a*** and ***b***. Partial Euclidean distance D_r is computed using (Duda et al., 2001) :

$$D_r(\boldsymbol{a},\boldsymbol{b}) = \left(\sum_{k=1}^{r} (a_k - b_k)^2 \right)^{1/2} \tag{3.9}$$

where $r < d$. The partial distance method assumes that classification with the Euclidean distance computed using a subset of features $D_r(\boldsymbol{a},\boldsymbol{b})$ is indicative of the classification with the Euclidean distance computed using the full *d* dimensions $D_d(\boldsymbol{a},\boldsymbol{b})$. In Duda et al. (2001), the partial distance was applied to classification where the remaining *d-r* features or attributes are known. In this work, the partial distance was applied with *r* defining the size of the static attributes, which are known at the time of classification. The size of the dynamic attributes is *d-r* and these are unknown at the time of classification of a new individual-realization case *(I,n).*

In applying the dynamic proxy to optimization problems, some number of simulations is first performed and the static and dynamic attributes and objective function values for each simulated case are saved in a database. The *K*-means algorithm is used to partition the database into a predefined number of clusters. The database is updated at each generation with information from simulated individual-realization cases and the clustering step is repeated again.

The detailed procedure for estimation of $f(I)^{prior}$ for individual I using the dynamic proxy is listed below. Steps 1-4 are performed prior to the classification and estimation step. A database of fitness and attributes is built from previously simulated cases during these steps. This ensures that there are enough data points in the clusters during the classification and estimation step. After the database is built, steps 4-14 are repeated in each generation and the database is continually updated.

1. For each individual-realization case (I,n), derive static attributes.

2. After simulation is performed for case (I,n), derive the dynamic attributes.

3. Save static attributes, dynamic attributes and objective function value (cumulative oil or NPV) in a database.

4. Perform K-means clustering of the database using both the static and dynamic attributes.

5. For each new individual I and realization n, derive all the static attributes for each case (I,n).

6. Compute the partial Euclidean distance between the static attributes of this case and the centroid of each cluster.

7. Assign the individual-realization case (I,n) to the cluster with the smallest partial Euclidean distance (Figure 3.4). In Figure 3.4, X represents a new point defined by two attributes. Figure 3.4 shows a hypothetical partition of the attribute space into two clusters with the point X assigned to cluster 1.

8. Within the target cluster in step 7, perform a similarity search between the new individual I and previously simulated cases that fall within this cluster using some distance metric, e.g., Euclidean or cosine similarity index (Ross, 2005; Tan et al.,

2005). Select the closest case in terms of the distance metric selected. This step is illustrated in Figure 3.5, where two previously simulated cases are compared to the new individual. The well template that most closely matches the new individual is indicated in the red box.

9. Approximate the dynamic attributes for the new case *(I,n)* with the closest case found in step 8 above (Figure 3.5).

10. Use the static attributes (exact) and the dynamic attributes (approximate) to estimate the prior fitness of the new individual-realization case *(I,n)* denoted $f(I,n)^{prior}$.

11. Assign weights to individual-realization cases and select a fraction for full simulation. Obtain $F(I)^{prior}$ for all individuals using equation 3.4.

12. Update database of fitness and attributes with results from the simulated cases in step 11.

13. Use equation 3.6 to obtain $F(I)^{post}$ for all individuals.

14. Apply GA operators (selection, crossover, mutation) to create next population.

15. Repeat steps 4-14 for each generation.

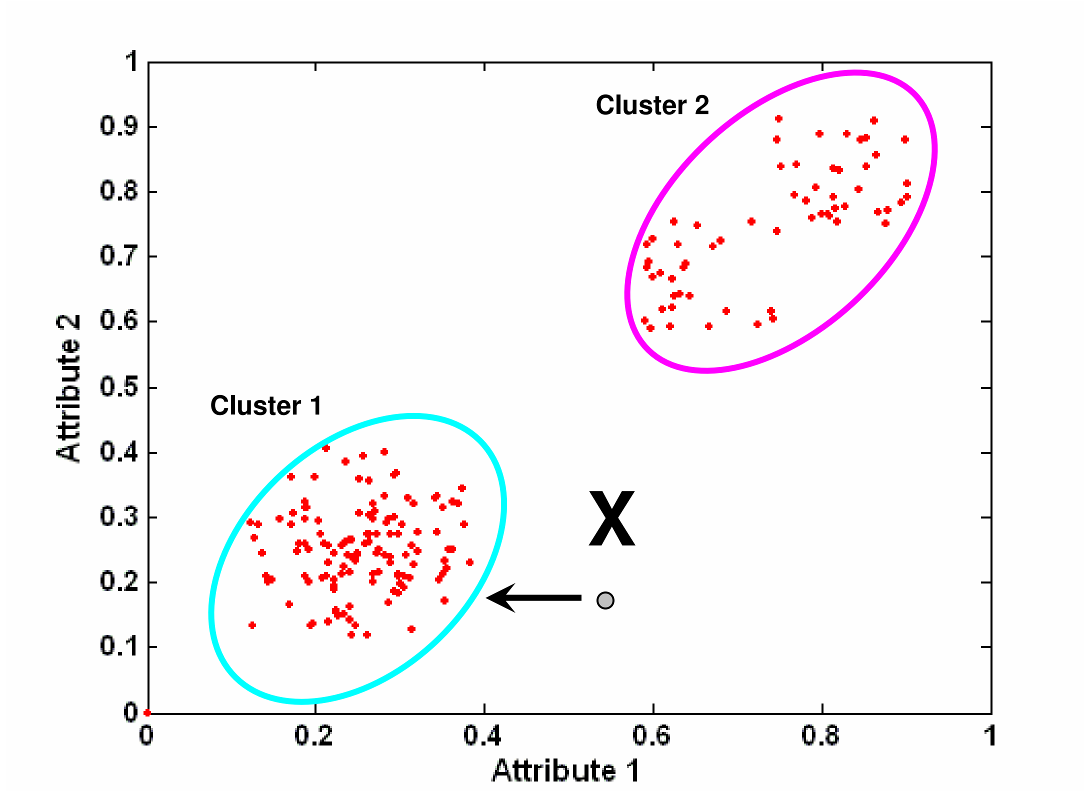

Figure 3.4: Hypothetical partition of attributes 1 and 2 into two clusters.

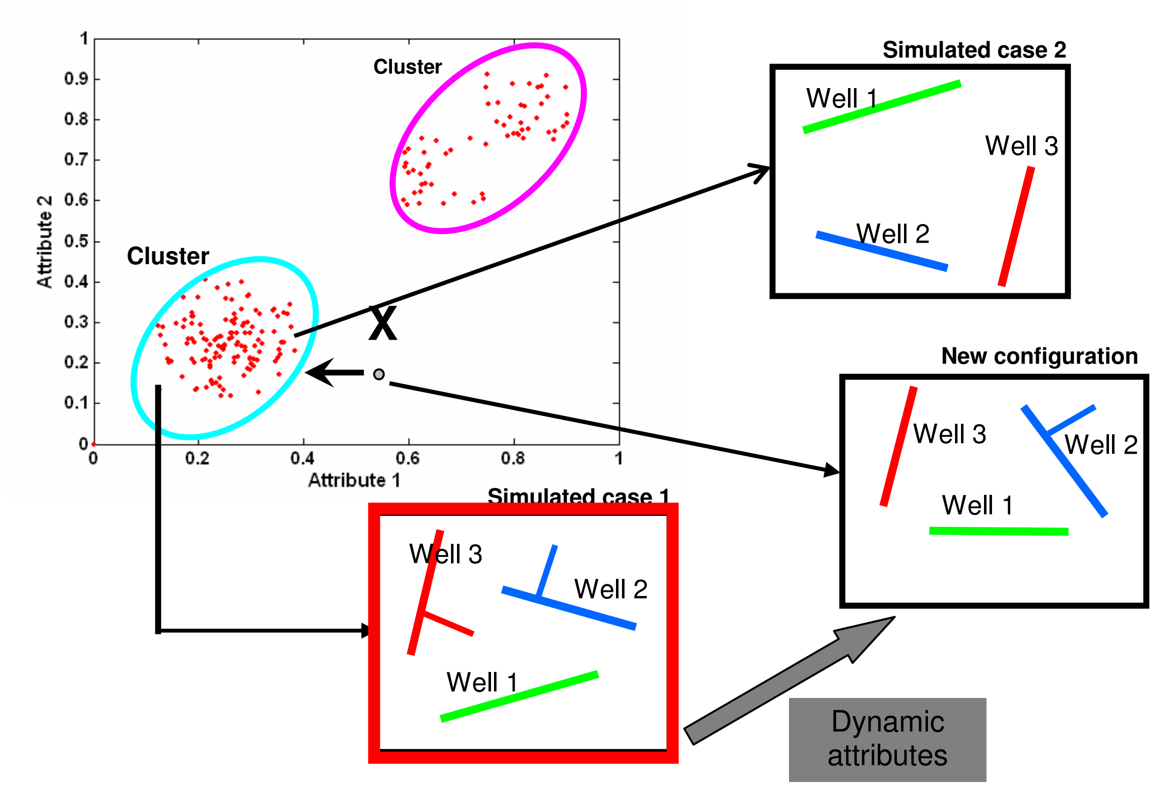

Figure 3.5: Illustration of search procedure to find matching well configurations.

Chapter 4

4. Examples

In this chapter, a series of examples are considered that illustrate the capabilities of the static and dynamic proxy. The examples are divided into two broad categories: examples using the static proxy alone and an example using the static and dynamic proxy. The performance of the proxies is based on a comparison of the best solution found, run time characteristics and the number of simulations required. These metrics are used to compare the performance of the proxy and no-proxy (i.e., simple GA) cases where applicable.

The first three examples in Section 4.1 were presented in Artus et al. (2005). The first three examples using the static proxy were performed using the ECLIPSE simulator (GeoQuest, 2004a) while the example using the dynamic proxy was performed using the IMEX simulator (CMG, 2004).

4.1 Static proxy examples

Four examples are presented that illustrate the use of the static proxy described in Chapter 3. These examples involved the optimization of monobore or dual-lateral wells under geological uncertainty.

4.1.1 Example A: Sensitivity to proxy selection

In this example we illustrate the sensitivity of the optimization result to the percentage of scenarios simulated. The well is constrained to be a monobore. The reservoir model is a channelized system. Five realizations constrained to data from three observation wells were randomly generated (Figure 4.1 and Figure 4.2). The key properties of the reservoir are summarized in Table 4.1. Reservoir flow in this case involves only a single phase (oil) and frictional pressure losses in the well are neglected. Permeability is highly heterogeneous but locally isotropic (k_x=k_y=k_z).

Table 4.1: Example A – Reservoir and fluid properties

grid dimensions	$40 \times 40 \times 7$
field dimension	$6000 \times 6000 \times 210$ ft^3
ϕ	0.2
NTG	10 %
$\overline{k_1}$	90 mD
$\overline{k_2}$	1 mD
c	3×10^{-5} psi^{-1}
B_o	1.3

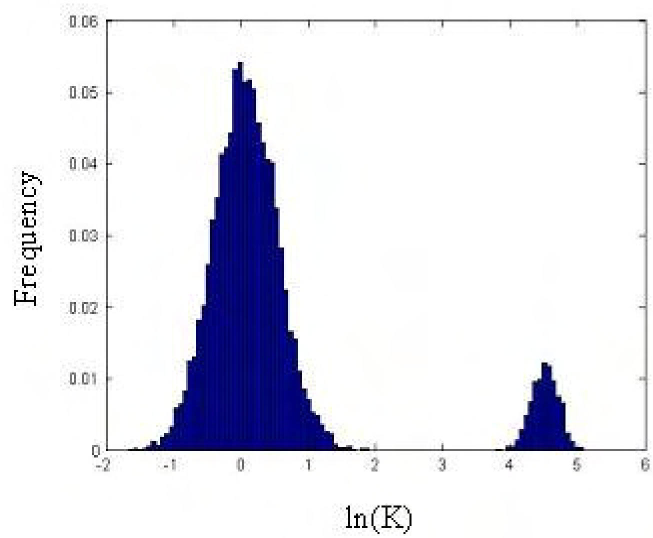

Figure 4.1: Histogram of the logarithm of the permeability field.

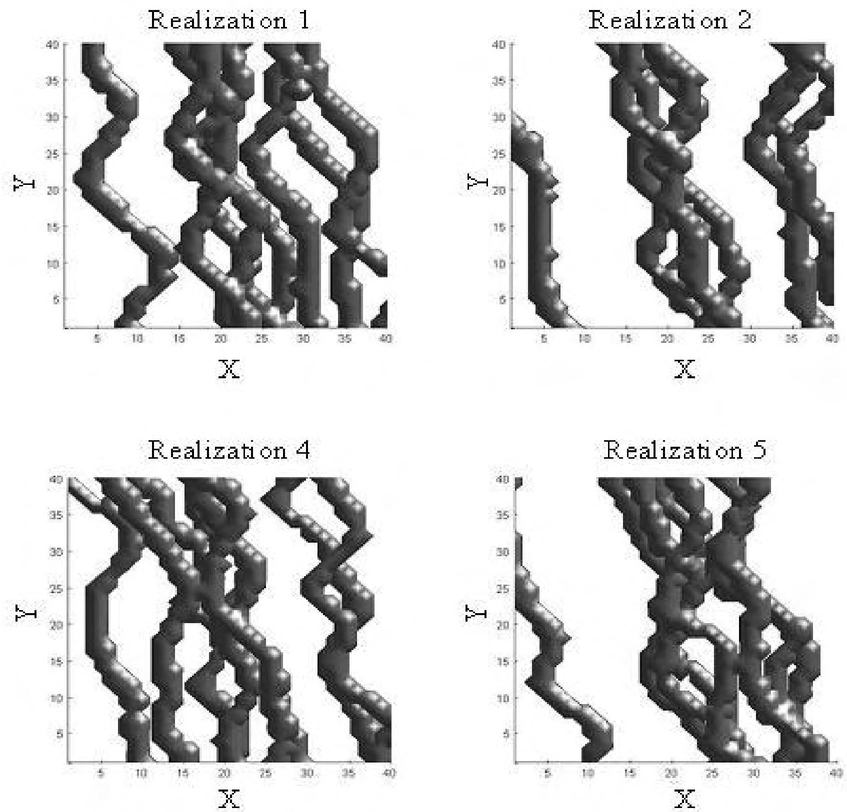

Figure 4.2: Four realizations of the channelized permeability field.

The goal is to determine the placement of a monobore production well to maximize the cumulative oil produced over 500 days of primary depletion. The initial pressure at the top of the reservoir is 3500 psi and the BHP constraint is 3200 psi. The mainbore can be oriented in any direction, but is limited in horizontal extent to a maximum of 1500 ft. We optimize under a risk neutral attitude, which means that we seek to maximize the expected cumulative oil production over the 5 realizations, regardless of the variance.

We base the proxy estimate on 3 attributes expected to correlate with cumulative oil production – well length, volume of channels intersected by the well and average permeability along the well. For a given individual, the determination of the proxy estimate required about 2 seconds CPU for each realization, while each reservoir simulation consumed about 30 seconds. The simulations are very fast for this small problem (11200 cells) so there is only a factor of 15 difference between the proxy calculations and the simulation runs. However, because the CPU time required to determine the attribute values is largely independent of the model size, much greater differences between the times required for deriving attributes and for performing simulations are expected for larger problems.

In this example, we used 30 individuals and 50 generations in the genetic algorithm. The calibration pool was initiated by simulating all of the individuals in each realization in the first generation (for a total of 150 simulations) and was updated at each generation using the simulated cases. Twenty clusters were used to determine the prior fitness of each individual. Prior predictions obtained from a given cluster were used only if the cluster contained more than 10 data points, otherwise a simulation was performed.

Three cases were tested in order to quantify the sensitivity of the optimization results to the percentage of (valid) scenarios simulated. These cases correspond to 5% (case A.1), 10% (case A.2) and 20% (case A.3) simulated, with the remainder estimated using the proxy. Figure 4.3 shows the data in the three-dimensional attribute space after 2 generations. It is evident from the figure that the data tend to cluster based on fitness, which suggests that the variability within a cluster will not be excessive. At the end of the 2nd generation, there are about 300 individuals in the calibration pool (most of the cases in the 2nd generation were also simulated because the clusters did not yet contain enough points). The fitness of all individuals in the calibration pool was then partitioned into 20 clusters using the selected attributes.

The cumulative distribution function of the fitness in all of the clusters is now readily determined. Figure 4.4 depicts the $f_{10}^{prior}(\mathbf{I},n)$, $f_{50}^{prior}(\mathbf{I},n)$ and $f_{90}^{prior}(\mathbf{I},n)$ values of the performance for the 20 clusters (the clusters are now ordered in terms of increasing f_{50}^{prior}). For subsequent generations, we compute the attributes for all new cases and then determine the prior fitness. A subset of cases is then simulated as determined by the procedure described in Section 3.3. In general, there are 8, 15 and 30 actual simulations for case A.1 (5%), case A.2 (10%) and case A.3 (20%) respectively for each generation of the optimization. A comparison of the posterior and actual fitness for case A.1 (from crossvalidation of the calibration pool at generation 10) is shown in Figure 4.5. We see from Figure 4.5 that, although only about 8 simulations are performed at each generation, there is little difference between the prior and posterior fitness. Using cross-validations of the calibration pool, updated after each generation, we compute the correlations between the prior and posterior fitness values with the actual fitness. The regression coefficient between the prior fitness and the actual fitness is seen to be quite high – greater than 0.9 at all generations of the optimization.

In Figure 4.6, we present the fitness of the best individual as a function of generation, while in Figure 4.7 we present the fitness of the best individual as a function of the number of simulations performed. From Figure 4.6 it is evident that cases A.2 and A.3 (10% and 20% simulated) provide very similar results in terms of best fitness, while case A.1 (5% simulated) provides a somewhat lower fitness. However, using only 630 simulations, the best individual in case A.1 is over 90% of the fitness in case A.2 and case A.3 (Figure 4.6).

The key results from Figures 4.6 and 4.7 are summarized in Table 4.2. These results suggest that once a "threshold" percentage of the cases are simulated, the optimization result is relatively insensitive to higher percentages of simulated cases. Note that the number of simulations does not decrease by a factor of 2 when the percent simulated is halved. This is due to the fact that much more than the specified percentage of cases must be simulated in early generations to build clusters with 10 points or more. In more extensive optimizations, halving the percent simulated will result in about half the number of simulations as expected.

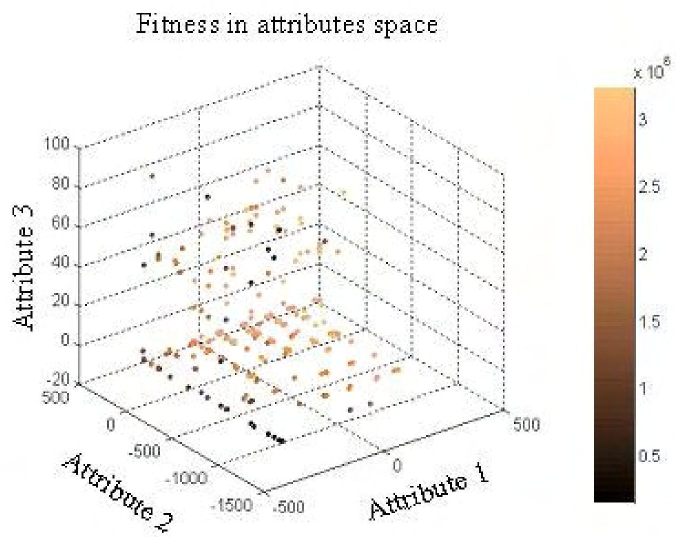

Figure 4.3: Example A – Repartition of the calibration data in the space of the attributes after 2 generations for Case A.2. Color corresponds to the performance. Attributes are well length, volume of channels intersected by the well, and average permeability along the well.

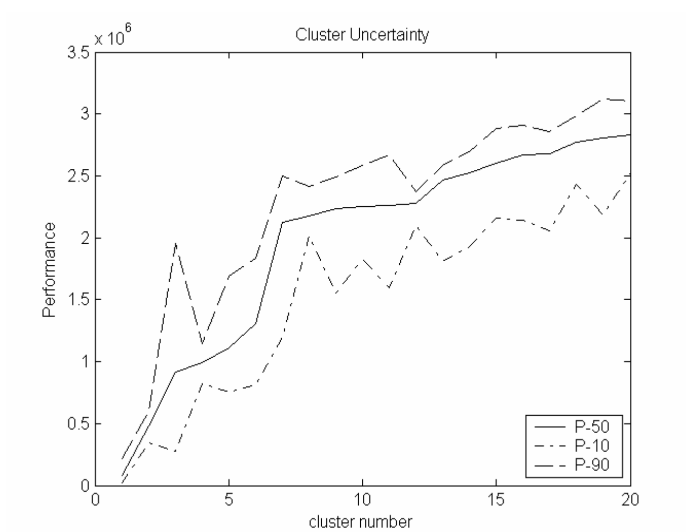

Figure 4.4: Example A – Mean value of the performances for each cluster (solid line). Dashed lines correspond to the confidence interval.

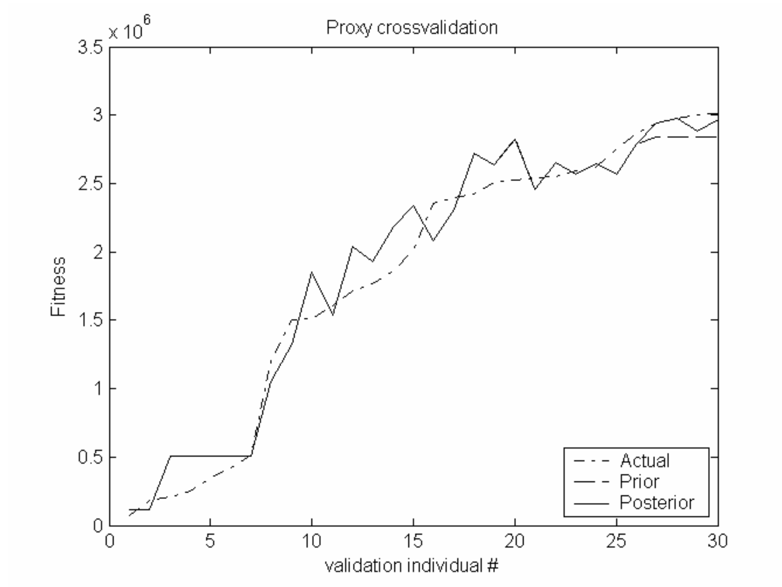

Figure 4.5: Example A – Result of the cross-validation of the calibration pool for case A.1 after 10 generations. Only a priori best cases are updated for posterior estimation of the fitness.

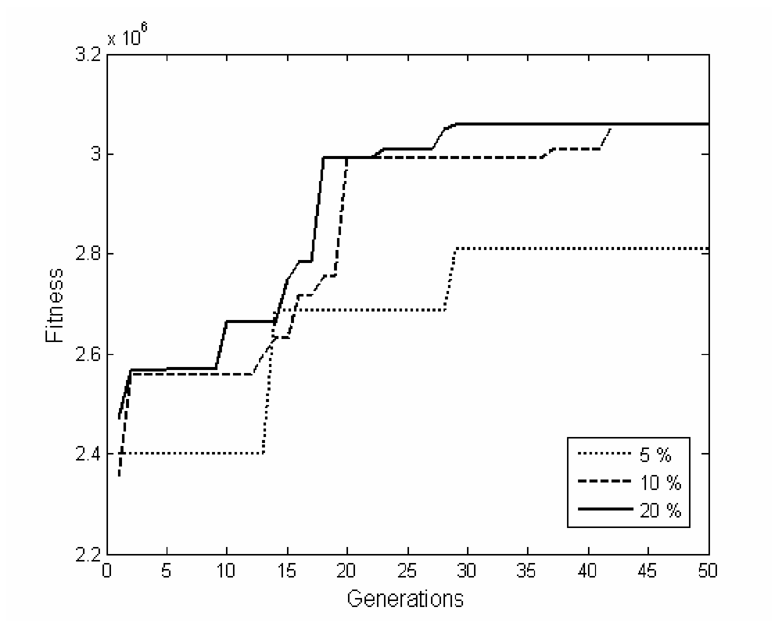

Figure 4.6: Example A – Evolution of the best individual in the population with the number of generations.

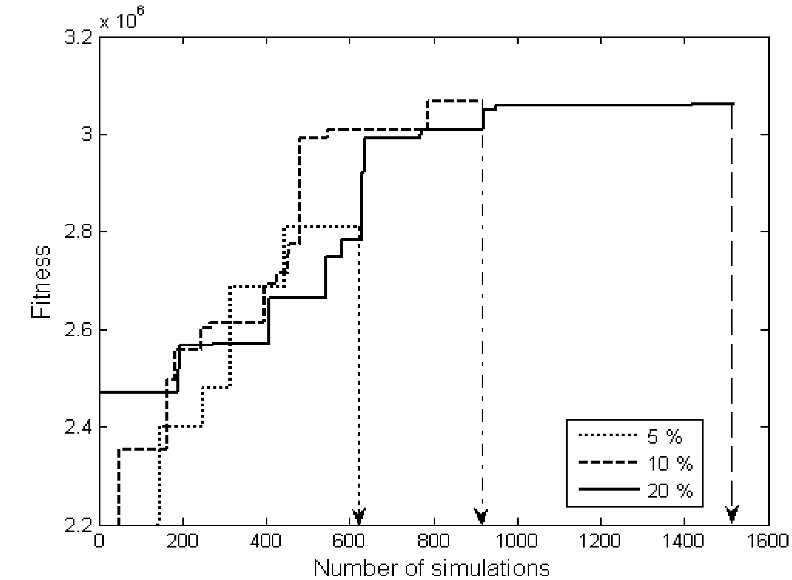

Figure 4.7: Example A – Evolution of the best individual in the population with the total number of simulations.

Table 4.2: Example A – Results with different percentages of cases simulated.

	5%	10%	20%
Fitness of the best scenario (bbl)	2,809,000	3,066,000	3,060,000
Number of simulations	630	918	1520

4.1.2 Example B: Optimization of a monobore production well

In this example, we again optimize the placement of a monobore producer in order to maximize the cumulative oil production after 500 days of primary depletion. We consider the same reservoir properties and constraints as in Example A (Table 4.1), except here we consider 10 realizations constrained to the 3 vertical observation wells. Our goal here is to assess the proxy by comparing optimization results obtained by simulating all cases with those achieved through use of the statistical proxy. Maximum well length is again 1500 ft and the optimization was again performed with 30 individuals (50 generations) under a neutral risk attitude. Following the initial generations (in which high percentages of individuals were simulated to generate 20 clusters with at least 10 data points per cluster), the proxy was applied to select 10% of the valid population for simulation at each generation (with the remainder of the individuals assessed through use of the proxy).

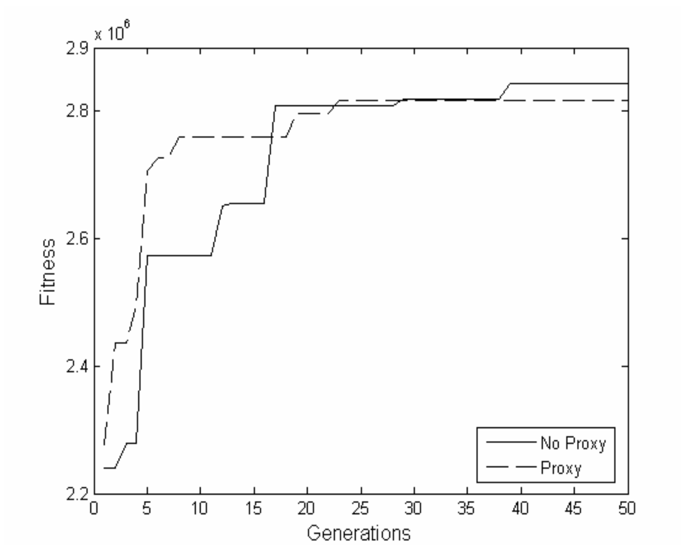

Figure 4.8: Example B – Evolution of the best individual in the population with the number of generations.

Figure 4.8 presents the evolution of the best individual over the course of the optimization. The solid line shows the result when all cases are simulated (no proxy) and the dashed line the result when the proxy is applied. From Figure 4.8, we see that the no proxy case provides a slightly better fitness (see also Table 4.3). It is apparent from Figure 4.9, however, that the proxy result is achieved using more than a factor of 7 fewer simulations. It is thus apparent that the use of the proxy is able to greatly reduce the number of simulation runs while impacting only slightly the optimal fitness.

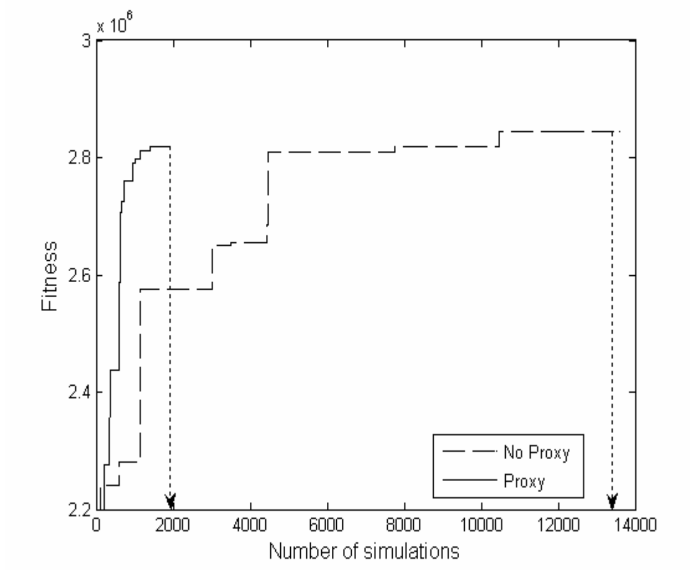

Figure 4.9: Example B – Evolution of the best individual in the population with the total number of simulations.

Table 4.3: Example B – Comparison of the performances of the best wells found with and without proxy.

	With proxy	Without proxy
Average performance (bbl)	2,831,000	2,872,000
Standard deviation (bbl)	219,300	279,100
Number of simulations	1,873	13,597

The positions of the optimal wells, as determined by the optimizations with and without the proxy, are shown in Figure 4.10. The optimal wells clearly differ between the two optimizations, though in both cases they lie near the center of the reservoir and contact several channels. This figure suggests that a number of different wells may provide comparable optimums, though it is interesting to see that in this case the two optimizations result in wells that are similar.

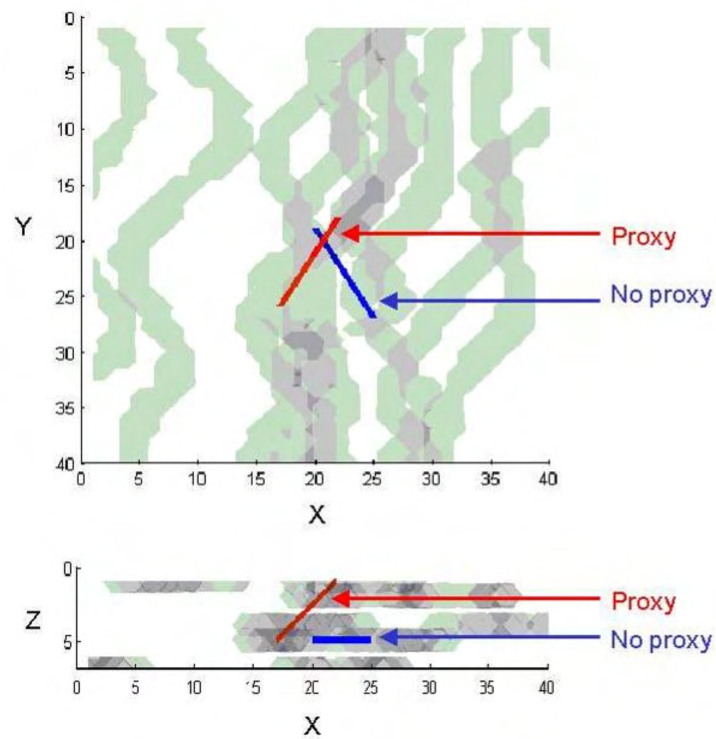

Figure 4.10: Example B – Optimal well locations found with and without proxy.

4.1.3 Example C: Optimization of a dual-lateral producer

In this example, we optimize the placement of a dual-lateral production well. We again seek to maximize the cumulative oil production over 500 days of primary depletion. We consider the same reservoir properties as in Example A (Table 4.1), using 5 realizations constrained to 3 vertical observation wells. We again specify a BHP constraint of 3200 psi with an initial reservoir pressure of 3500 psi. The well in this case is required to have two laterals. The mainbore and the laterals can be oriented in any direction, and their horizontal lengths can take values from zero (for a vertical segment) to a maximum of 1500 feet. We again used populations of 30 individuals and ran the optimization for 50 generations. The strategy toward uncertainty was risk neutral. In the optimizations using the proxy we populated the clusters as described in the previous examples. When the proxy was applied, 20% of the cases were simulated.

Figure 4.11 compares the fitness of the best individual over the course of the optimization when all cases are simulated and when the proxy is applied. The optimization results are also summarized in Table 4.4. It is evident that the proxy optimizations actually achieve a slightly better solution than the optimization without the proxy, in which all cases are simulated. This would not be expected in general and is likely due to the stochastic nature of the GA. The proxy optimizations require about a factor of 4 fewer simulations (Figure 4.12). The optimum well locations for both cases are shown in Figure 4.13. Although the locations differ, it is clear that the wells in both cases contact several channels and are located around the middle of the reservoir.

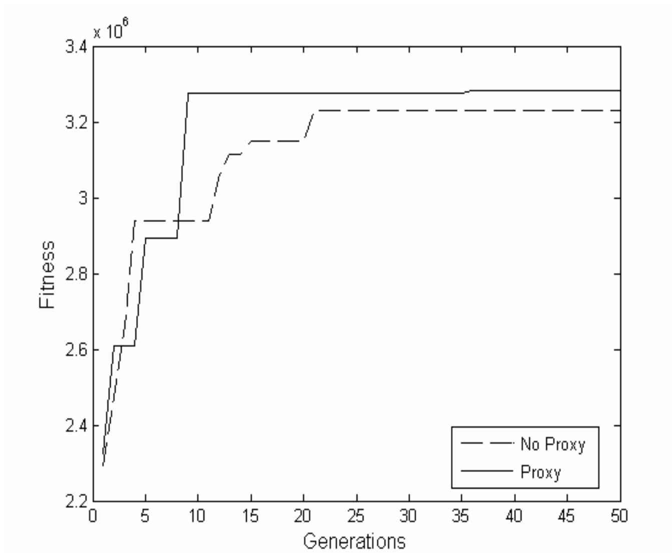

Figure 4.11: Example C – Evolution of the best individual in the population with the number of generations.

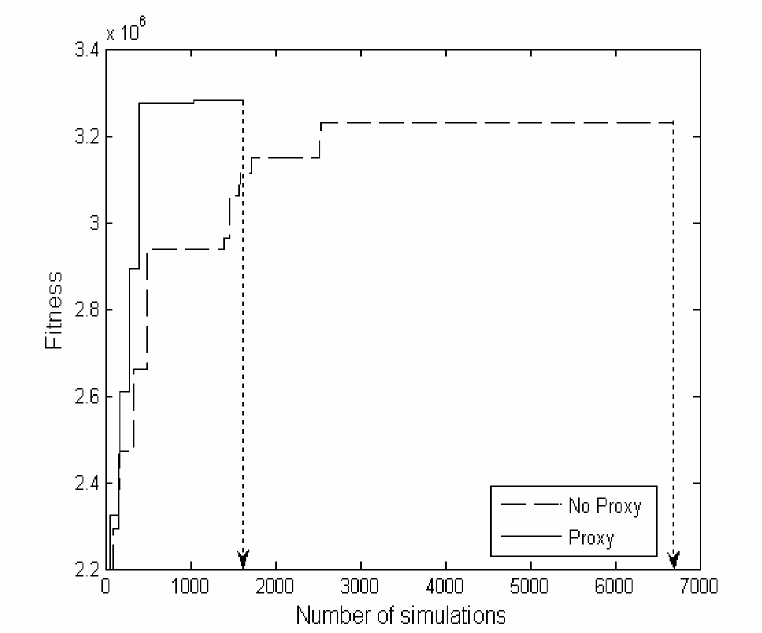

Figure 4.12: Example C - Evolution of the best individual in the population with the total number of simulations.

Table 4.4: Example C – Comparison of the performances with and without proxy.

	With proxy	Without proxy
Average performance (bbl)	3,269,000	3,067,000
Standard deviation (bbl)	164,300	463,100
Number of simulations	1,626	6,677

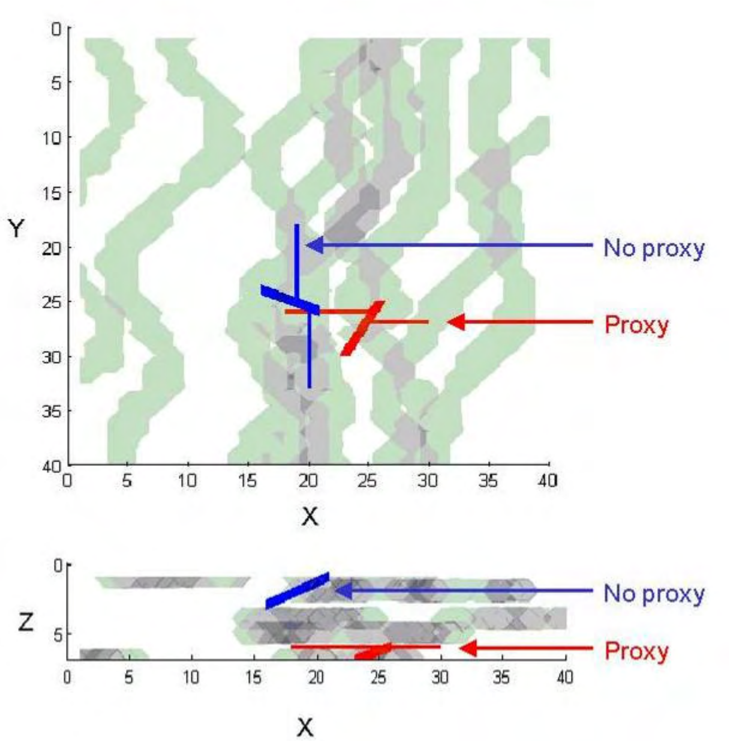

Figure 4.13: Example C – Comparison of the best wells found with and without proxy.

4.1.4 Example D: Optimization of a monobore under varying risk attitudes

In this example, we investigate the effect of varying risk attitudes in the optimization of a monobore producer. The same reservoir model is used here as in previous examples. The proxy was used in these optimizations, with 10% of the cases simulated. Different risk attitudes are considered and we study their effect on the optimization result. Five realizations of the channelized reservoir are used in this example. Three different runs are performed for a risk averse (r_{10}=0.7, r_{50}=0.3, r_{90}=0), risk neutral (r_{10}=0, r_{50}=1, r_{90}=0) and risk seeking (r_{10}=0, r_{50}=0.3, r_{90}=0.7) decision maker and we aim to optimize the cumulative oil produced for each case. As pointed out in Section 3.3, the risk attitude affects how the fitness of an individual is defined. Optimizing under risk averse conditions, for example, favors individuals with low variability in fitness across all realizations. Under risk neutral conditions, the mean of the fitness across all realizations is optimized.

Figure 4.14 shows the evolution of the best solution versus the number of generations of the GA. The fitness of the optimal solution found under risk seeking conditions is the highest while the solution under risk averse conditions is the lowest, as would be expected.

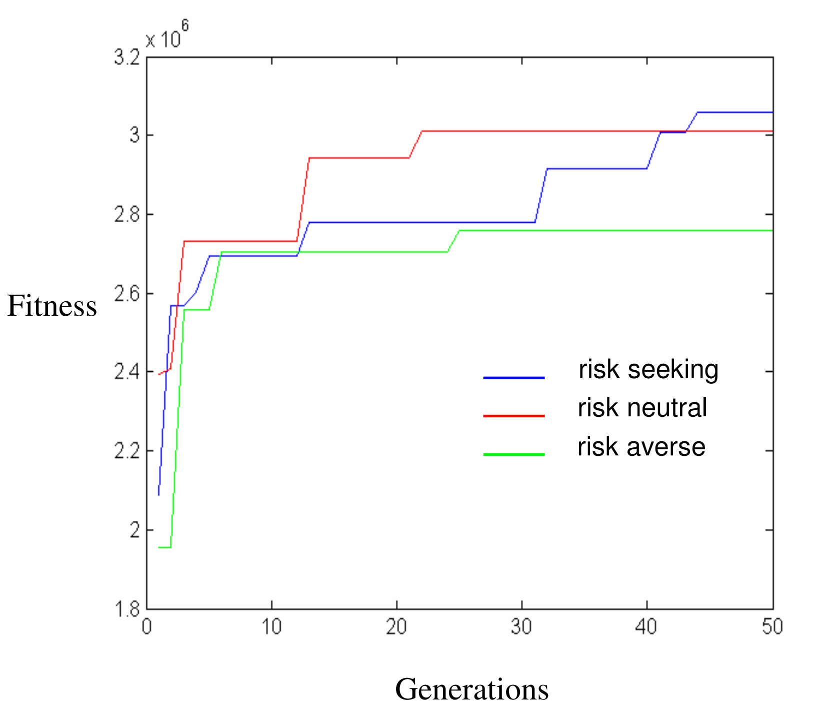

Figure 4.14: Example D - Evolution of best solution with the number of generations.

Figure 4.15 shows the performance (cumulative oil produced) of the best solution across the five realizations. Table 4.5 summarizes the results obtained in this example.

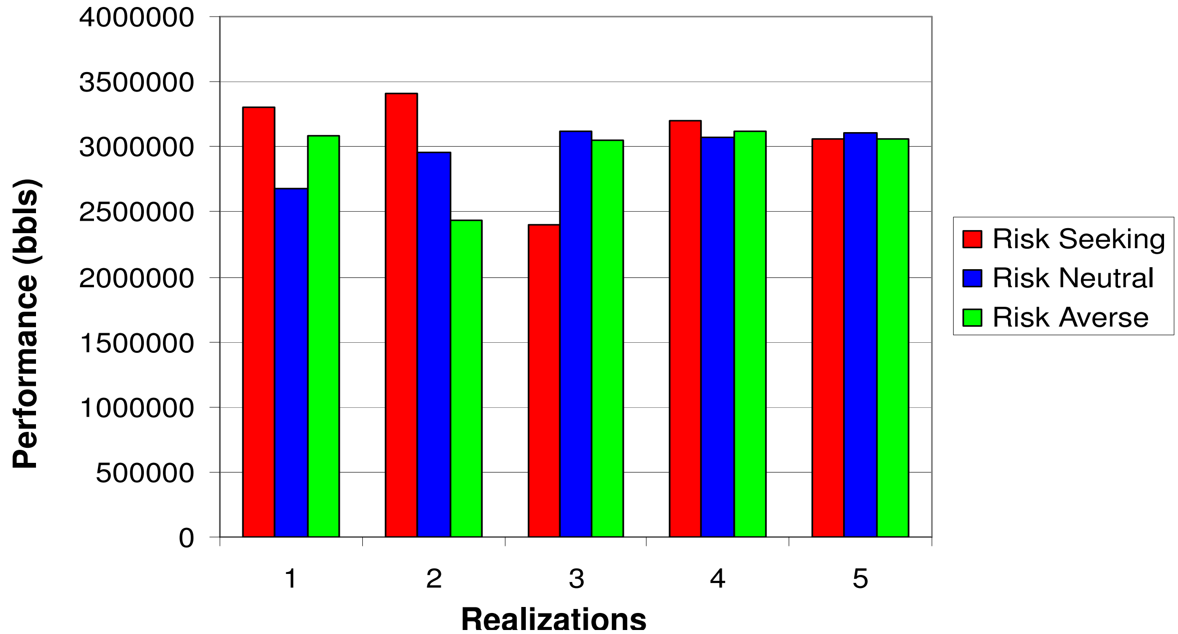

Figure 4.15: Example D – Performance of best solution across the five realizations.

Although the solution for the risk seeking case has the highest performance, the variability of the performance (standard deviation) across all realizations is the highest. The solution for the risk averse case has the lowest fitness but also displays the least variability of performance across the five realizations. The result for the risk neutral case lies between those of the risk seeking and risk averse solutions.

Table 4.5: Comparison of the performance the optimization of under different risk attitudes.

Risk attitude	Mean fitness (bbl)	Std. Fitness (bbl)
Seeking	3,076,270	397,345
Neutral	2,984,652	184,753
Averse	827,473	77,683

Figure 4.16 shows the location of the best well using the three risk attitudes. Although the wells are located at about the same location in the model, the well lengths and orientations differ. The risk attitude of the decision maker clearly affects the variability of the fitness of the best well across all realizations, as demonstrated in this example.

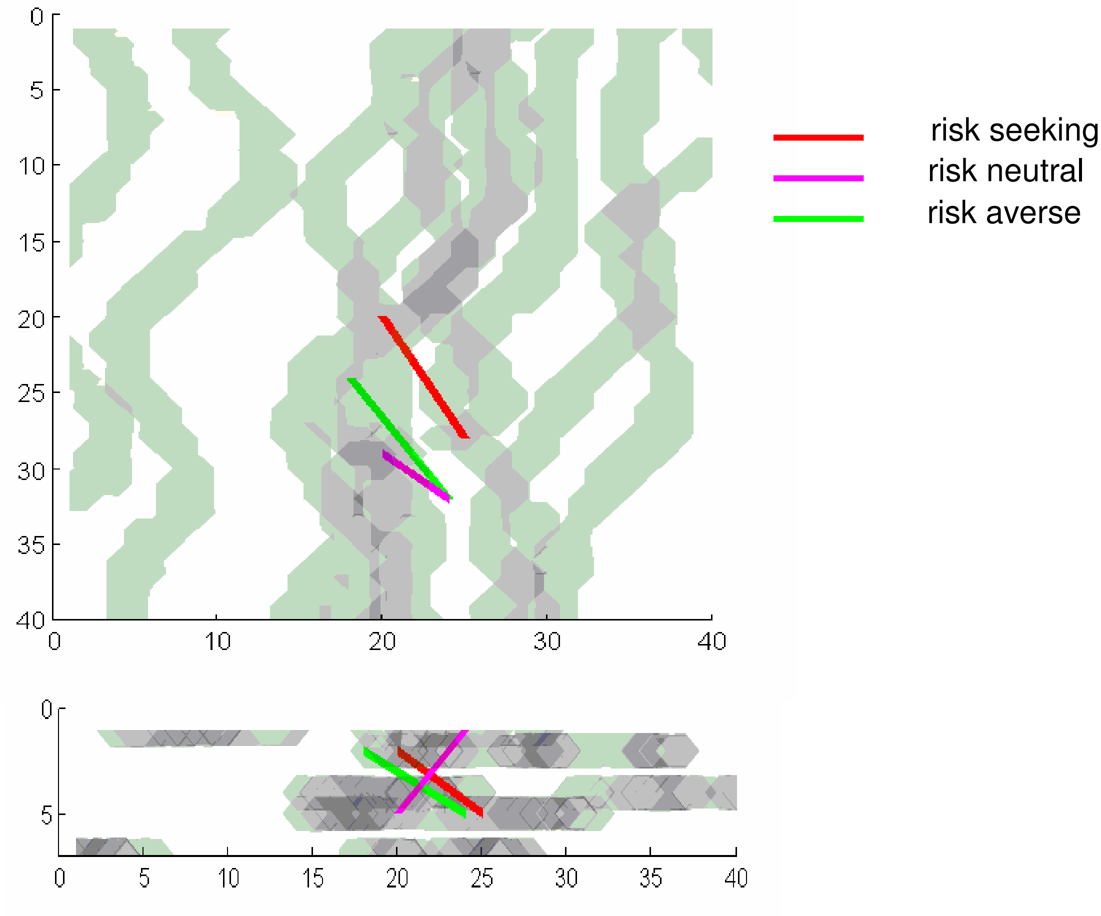

Figure 4.16: Example D – Comparison of the best well locations for three different risk attitudes: risk averse, risk neutral and risk seeking.

4.2 Dynamic proxy example

4.2.1 Example E: Optimization of multiple wells drilled at different times using the dynamic proxy

The previous examples involved use of only the static proxy. This example involves the optimization of 3 monobore production wells drilled at different times during the production life of the field, and we apply the dynamic proxy. Three phases are considered, with each phase corresponding to the drilling and opening of one well. Phases are separated by a period of 200 days and the total production time is 1000 days. Figure 4.17 shows a production rate profile for 3 producers that are opened at the specified times. In Figure 4.17, production starts with Well-1 (red line) which produces for 1000 days. Well-2 (blue line) is assumed to be drilled and opened instantaneously at day 200 and produces for 800 days. Similarly, Well-3 (green line) starts production at day 400 and produces for 600 days.

The reservoir and well parameters used for this example are as described in the previous examples. The genetic algorithm has 30 individuals in each generation and the algorithm was run for 50 generations. Three optimization runs were performed for this case with the following proxy options: no-proxy, static proxy (using only static attributes) and dynamic proxy (using static and dynamic attributes). The results obtained from the optimization with each proxy option are compared. When the proxy is used (static or dynamic), 50% of the individuals in each generation are simulated.

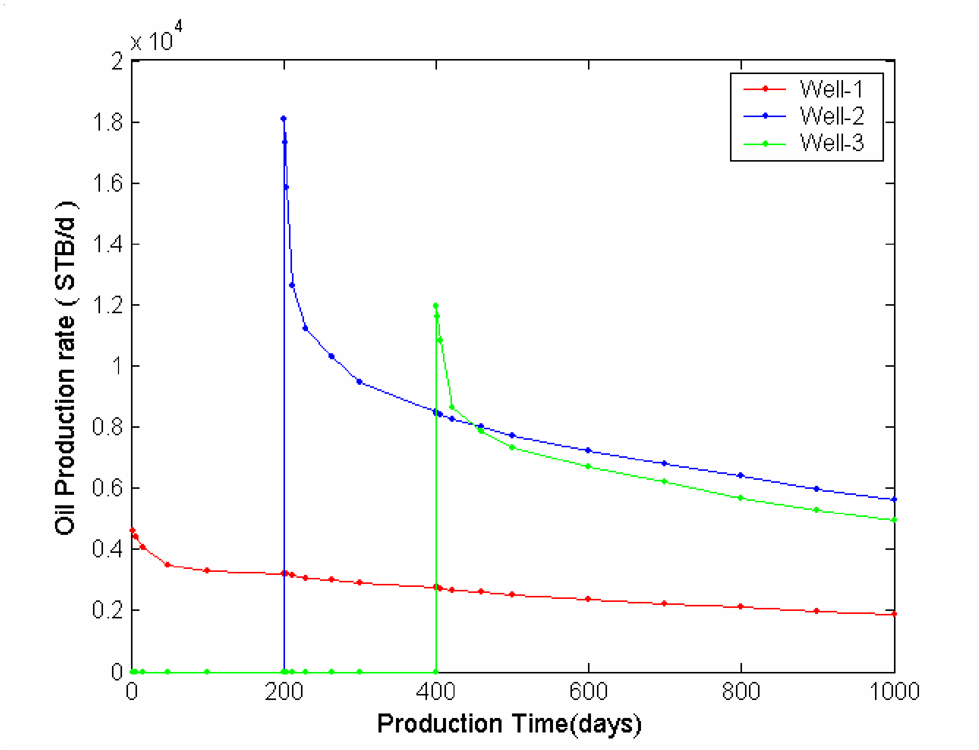

Figure 4.17: Example of production profile for 3 wells drilled at 200 day interval.

The objective is to find the optimal location of the three producers by maximizing the NPV. The NPV is computed using equations 2.1 to 2.4. Table 4.6 summarizes the parameters that are used in the NPV calculation.

Table 4.6: Example E – Parameters used for NPV calculation.

Discount rate (%)	10
junction cost ($)	300,000
Oil price ($/bbl)	40
Opex ($/bbl)	3
Capex ($)	2,000,000
drilling cost ($/ft)	500

The static attributes that are used are well length, volume of channels intersected and average permeability along the each well (these are the same as in previous examples). Dynamic attributes include average saturation along the well, average pressure along the well, average change in saturation along the well, average change in pressure along the well and change in oil volume around the well. The dynamic attributes are derived as described in Section 3.6. 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, which is 1000 days. These dynamic attributes are combined with the static attributes for the dynamic proxy case, while in the static proxy case, only the static attributes are used. In the clustering procedure, 20 clusters were used.

The best solution found using the static proxy was ~ 72% of that found by the no proxy optimization, while the dynamic proxy found a solution with fitness that is about 90% of the fitness found by the no proxy case. The dynamic proxy case required only about half as much the number of simulations as the no proxy case. Figure 4.18 demonstrates that the dynamic proxy has better performance for early generations but it stalls after about 15 generations, compared to the other cases. The dynamic proxy is therefore essential for this case, though there is still room for improvement.

Figure 4.19 shows a comparison of the cumulative oil produced for the optimization using the three options. The cumulative oil produced for the solution with the dynamic proxy accelerated production compared to that from the static proxy, though production is less than in the no proxy case. These results are of course consistent with those in Figure 4.18.

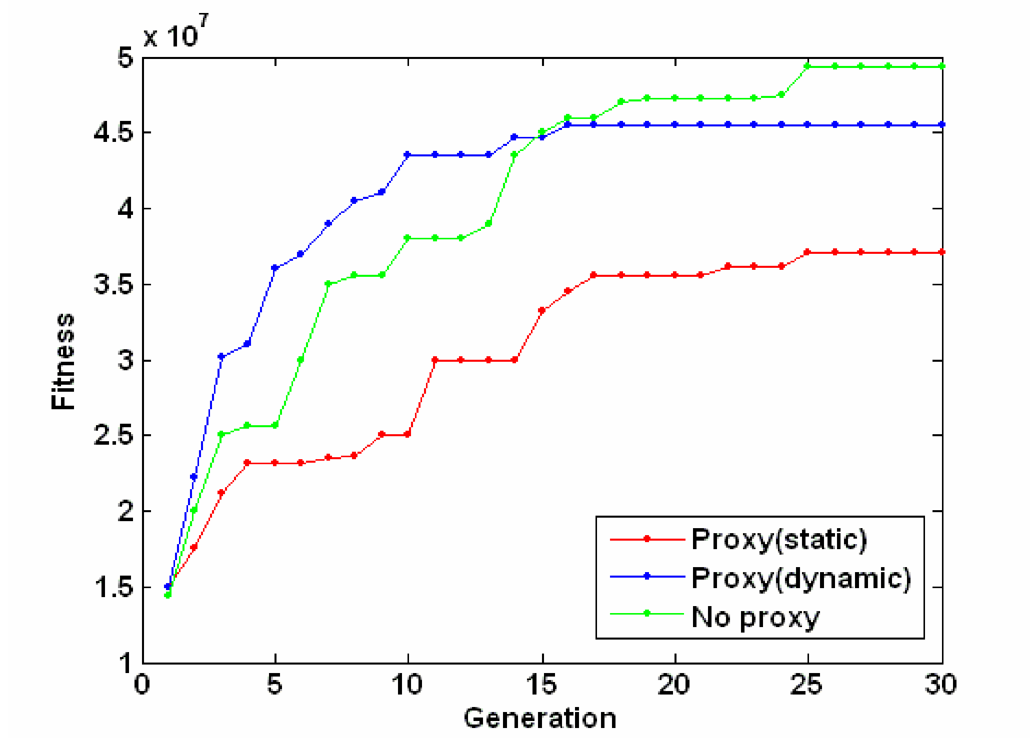

Figure 4.18: Example E – Evolution of the fitness of best solution versus number of generations.

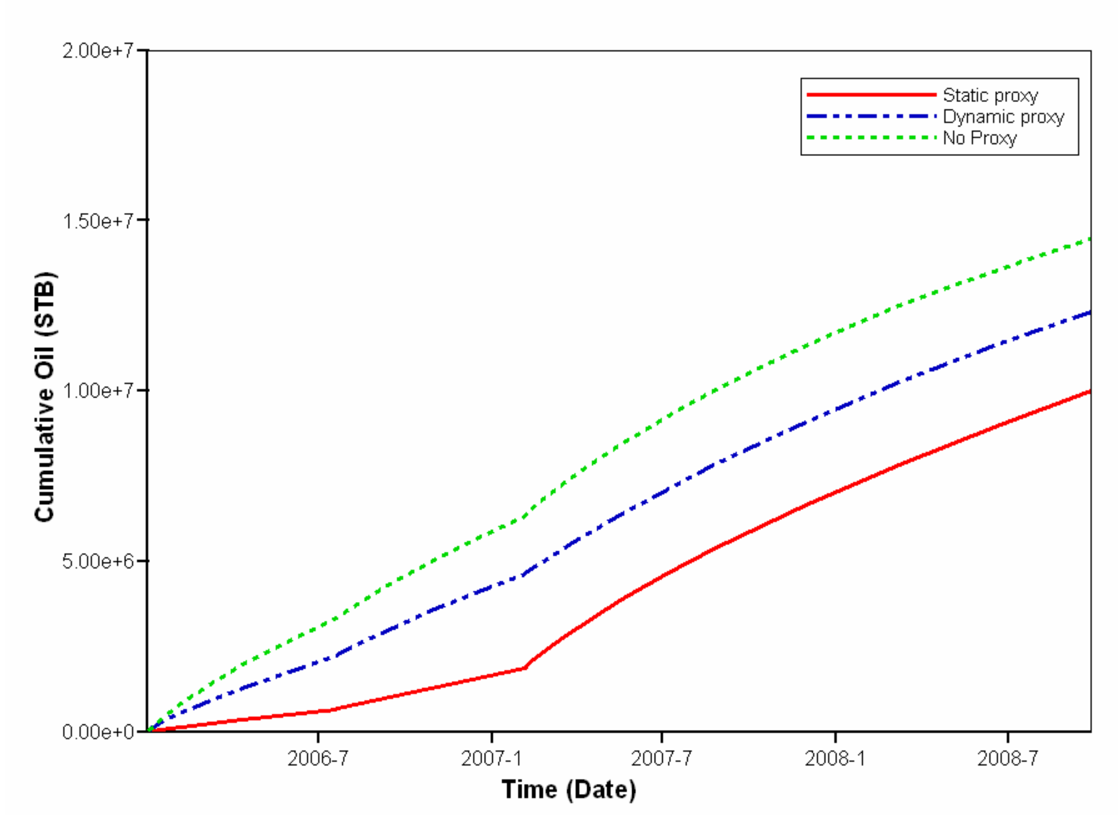

Figure 4.19: Example E - Cumulative oil produced for the best individual found in each case.

Tests were performed to investigate the performance of the dynamic proxy using smaller percentages simulated. Simulating 10-20%, the solution found for the dynamic proxy was only around 40-50% of the solution found from the exhaustive run. The static proxy performed very poorly when smaller percentages were simulated. Further development is required to improve the performance of the dynamic proxy when low percentages of cases are simulated.

Chapter 5

5. Conclusions and future work

5.1 Conclusions

In this work, a statistical proxy was applied for the optimization of the deployment of nonconventional wells under geological uncertainty. The conclusions from this study are:

- Cluster analysis based on calibrating simply computed attributes (e.g., well length, number of channels intersected) to simulation results provides a means for forming prior cdfs for the performance of a well in a particular geological model. By combining these proxy estimates for multiple geological realizations, a prior cdf for well performance, which accounts for both geological and proxy uncertainty, can be developed.
- The prior performance estimate, in conjunction with the proxy uncertainty, can be used to select a subset of cases most appropriate for full simulation. The fitness of the remainder of the cases is determined using the proxy. It was demonstrated that the proxy is effective in terms of identifying appropriate cases for simulation and that a high degree of correlation exists between the proxy estimate and the simulated result.
- In examples involving the optimization of a single monobore or dual-lateral well, the use of the static proxy was shown to provide excellent results. Specifically, by simulating only 10% of the cases (as determined by application of the proxy), optimums very close to those achieved by the full procedure were attained.
- The decision maker's risk attitude can be incorporated into the optimizations involving multiple realizations. The proxy allows a flexible definition of prior fitness of individuals by using a cdf of fitness for computing prior fitness of new individuals. An example demonstrated the effect of different risk attitudes on the best solution found by the GA using a statistical proxy.

- In the example involving multiple nonconventional wells drilled at different times, the dynamic proxy improved the solution compared to the static proxy. However, a larger percentage (50%) of cases was required to be simulated in each generation.

5.2 Future work

The following items are proposed to improve the use of the statistical proxy for optimization of nonconventional well placement.

- The GA is a stochastic algorithm and results will differ each time the algorithm is run. Therefore, the proxy and no proxy cases should be run several times (with different initial populations) and the average behaviors compared.

- Further tests should be performed using the statistical proxies (static and dynamic) to understand the effects of attributes and proxy performance on the optimization result.

- Optimization algorithms other than the GA considered here should be explored for nonconventional well optimization.

Nomenclature

C	cost , \$/bbl, \$/MMSCF or \$/junction
cdf	cumulative distribution function
CF	cash flow, \$
E	expenses , \$
f	objective function value e.g. cumulative oil or NPV
$\langle f(I) \rangle$	expectation of f for scenario I
$F(I)$	fitness of individual I computed over N_{real} realizations
I	development scenario, individual
(I,n)	individual-realization case
L	chromosome length or length
N	number
NPV	net present value, \$
p	probability, fraction
Q	cumulative production during a period, STB, SCF
r	weight, fraction
R	revenue, \$
W	weight, fraction
α	scaling factor, fraction
σ	standard deviation

ϕ	porosity, fraction

Subcripts

10	probability that true fitness greater than 0.10
c	crossover, rock compressibility (psi^{-1})
gen	generation
i	index
I	individual, scenario
ind	individual
m	mutation
n	index
o	oil
post	posterior
prior	prior
real	realization
sim	simulation

Superscripts

DRILL	drilling
JUNC	junction
SCEN	scenario
WELL	well

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