OPTIMIZATION OF WELL PLACEMENT UNDER TIME-DEPENDENT UNCERTAINTY

A REPORT SUBMITTED TO THE DEPARTMENT OF PETROLEUM ENGINEERING

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IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF MASTER OF SCIENCE

By
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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.

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Abstract

Determining the optimum location of the wells is a crucial decision to be made during a field development plan. The quality of the decision is strongly dependent upon the amount of the information available to the decision-maker at the time the decision is made. Knowing that the development phase of a reservoir is a dynamic period in which different categories of information are added to system from distinct sources, one should make the well placement decisions considering these time-dependent contributions of information. This study proposes an approach that addresses the value of time-dependent information to achieve better decisions in terms of reduced uncertainty and increased probable Net Present Value (NPV). A Hybrid Genetic Algorithm (HGA) was used as the optimization method to find the best locations of the wells. In order to find the optimum decisions for different risk attitudes, a utility framework, that enables the assessment of the uncertainty of the well-placement decisions, was used. Through this new approach, production history data obtained from the wells, as they are drilled, are integrated into the well placement decisions. Unlike previous approaches, well placement optimization is coupled with recursive history matching steps. To test the results of the proposed approach, an example reservoir and its realizations, all of which match the history response of the example reservoir, were investigated. At each step of optimization, a reduction in the uncertainty of the multiple realizations was observed, as production history became available.

Acknowledgments

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To Ekin, Özge, Nüzhet, Nilüfer and Şeref…

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Chapter 1

1. Introduction

1.1. General Background

Well placement is one of the crucial decisions made during the exploration and development phase of projects. Most of the time, the large number of possibilities, constraints on computational resources and the size of the simulation models limit the number of possible scenarios that may be considered. In some cases, intuitive reservoir engineering diagnosis may have difficulty in constraining the problem to a manageable size. In addition, nonlinearity between the decision parameters can make the problem more difficult. In these cases, optimization algorithms become extremely valuable in searching for the best development scenario.

1.2. Literature Survey

Various approaches have been proposed for production optimization. Bittencourt (1994) optimized the scheduling of a field using the polytope algorithm. Beckner and Song (1995) applied the traveling salesman framework on a well-placement problem, using Simulated Annealing (SA) to find the optimum locations of the wells. Bittencourt *et al* (1997) hybridized Genetic Algorithms (GA) with the polytope algorithm and tabu search, and named this hybrid optimization technique the Hybrid Genetic Algorithm (HGA).

HGA was observed to improve the economic forecasts and CPU effort during optimization. Pan and Horne (1998) used kriging as a proxy to the reservoir simulator to decrease the number of simulations. Guyaguler *et al.* (2000) showed that the number of simulations required to optimize the injector well locations decrease when a HGA was coupled with a kriging proxy. Yeten *et al.* (2002) coupled GA with hill-climbing methods and an Artificial Neural Network (ANN) proxy to optimize the type, location and trajectory of nonconventional wells. Guyaguler and Horne (2001) assessed the uncertainty of the well placement results using utility theory, together with multiple realizations of the reservoir.

1.3. Problem Description

Previous studies focused on finding the optimum deployment strategies with the least computational effort. However, the effect of time-dependent information on the sequential well placement problem was not investigated. This study proposes a framework that enables optimization of the sequential well placement decisions by maximizing the amount of information obtained from the earlier wells to be drilled. In other words, later well placement decisions are made with greater certainty by utilization of probable production history of the earlier wells once they are drilled and produced. The new approach shows that the full utilization of time-dependent information, although uncertain, may result in more realistic predictions that in turn achieves higher probable income.

Chapter 2

2. Problem Statement

2.1. Motivation

Well placement decisions made during the early stage of exploration and development activities have significant impacts on the future recovery and profitability of the project. In addition, these early decisions have the capability to improve the later placement decisions by providing more information (greater certainty). Therefore, recovery and efficient use of information may add value beyond the amount oil recovered. In this respect, the quality of the placement decision is dependent upon the amount, quality and efficient use of the information at the time of decision. Production data are a component of the information available, Figure 2-1.

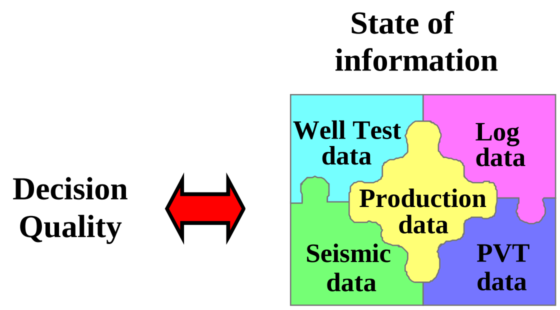

Figure 2-1: Decision quality vs. state of information.

Knowing that the reservoir development phase is a dynamic period in which different types of data are added to the system through time, one should make time-dependent decisions (the subsequent well placements) considering this time-dependent information flow.

In practice, the intention is to drill the wells in the locations most likely to achieve the highest NPV. Due to the reasons mentioned, the trade-off between profitability and the information target should be very well defined in a framework. In other words, an approach that optimizes not only the well locations but also the recovery of information is needed. This study proposes a new approach that places the wells in locations such that subsequent decisions are made with greater certainty and provide higher probable income. In other words, unlike the conventional optimization approaches that maximize only NPV, the new optimization approach is maximizing not only NPV but also information gain namely the conceptual utility of the decision. That maximized utility refers to greater certainty and greater NPV.

2.2. Sequential Well Placement Problem

For greater understanding of the time-dependent uncertainty and its effect on well placement, a simple sequential well-placement scenario is considered. In this scenario, there are two wells, one injector and one producer (Figure 2-2). From these wells, 200 days of production history is available. Using this available history, multiple history-matched models may be generated.

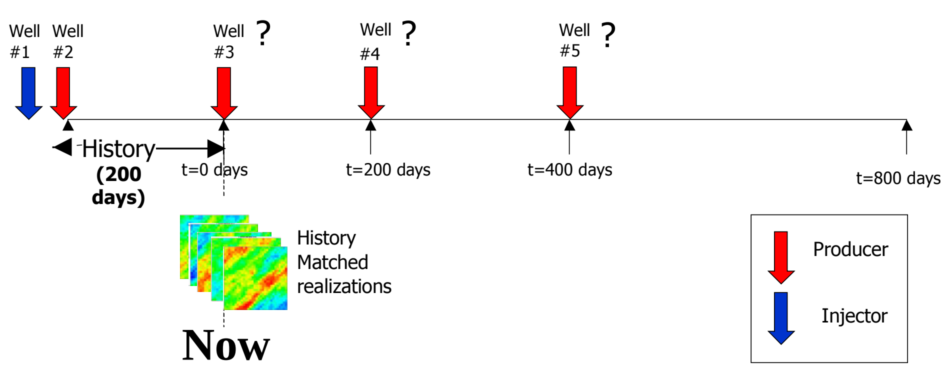

Figure 2-2: Sequential well placement problem.

Given the decision framework;

- The starting time of production of the optimized wells are predetermined as t_1=0, t_2=200 days and t_3=400days.
- The field is going to be deployed for 800 days.
- The decision criterion is the utility, that is a function of the NPV and risk attitude of the decision-maker.

The decision to be made is the optimum location of three wells considering the uncertainty of geological models.

2.3. Existing Solution Approaches

To find the optimum decision of the problem illustrated in Figure 2-2, two solution approaches can be applied, namely the sequential placement approach and the multiplacement approach.

2.3.1. Sequential Placement Approach

In this approach, the location decision of each of the wells is made sequentially. In other words, the decision of Well#3 is made independent of the fact that two more wells are going to be drilled later. From an optimization point of view, only one optimization is performed at a time. Accordingly, optimization of Well#3 considering all geological models is performed first (Figure 2-3). Then, optimization of Well#4 is performed using the same geological models, and finally the decision of Well#5 is made. These three sequential optimizations are made using the same set of geological models.

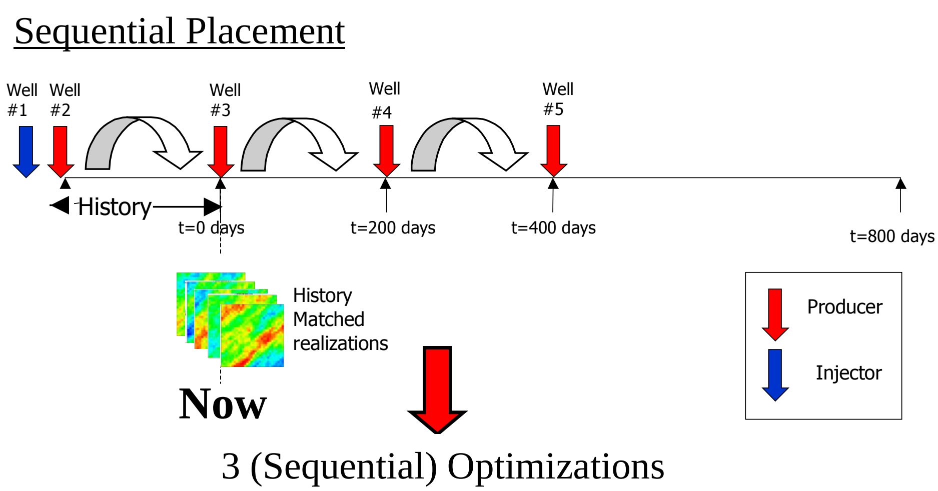

Figure 2-3: Sequential placement approach.

2.3.2. Multiplacement Approach

Guyaguler and Horne (2000) used the multiplacement approach to find the optimum location of 2 producers. Multiplacement approach is different from the sequential approach in that the decision of three well locations is made at one time (Figure 2-4) as opposed to making three sequential decisions (Figure 2-3). In this approach, the optimization of each well location is not performed sequentially and the fact that Well#4 and Well#5 are going to be drilled is considered while making the location decision of Well#3.

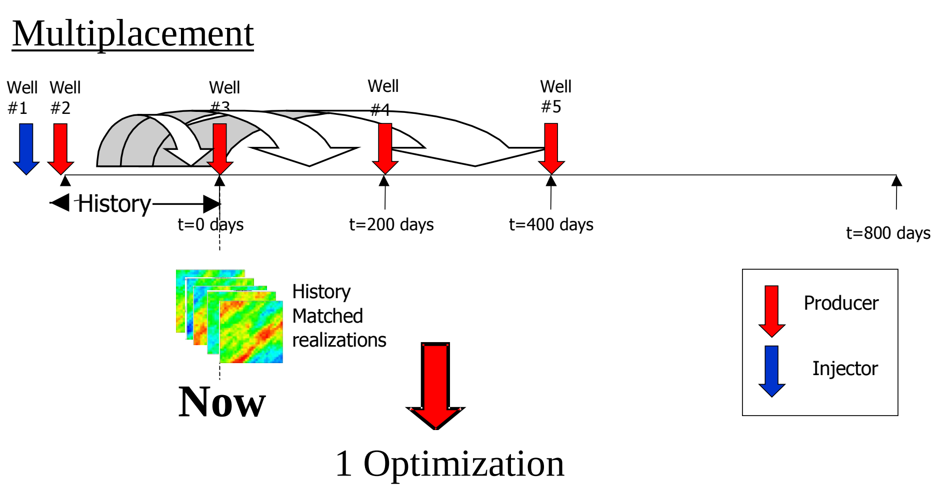

Figure 2-4: Multiplacement approach.

2.4. Shortcoming of Existing Approaches

One important issue is missing in the previous approaches. The information that is going to be obtained from the earlier decisions is known to effect the later decisions. In the sequential placement problem, it is known that once Well#3 is drilled, the information (the production history) that it will provide will affect the placement decision of Well#4 (Figure 2-5). The same situation exists for Well#5, once Well#4 is drilled the information (production data) it is going to provide (together with that from Well#1, Well#2 and Well#3) will impact the placement decision of Well#5. Previous approaches simply ignore this time-dependent uncertainty and freeze the uncertainty level of the reservoir response during the optimizations. Then two important questions arise:

1) How can the time-dependent uncertainty be included into optimization scheme?

2) What would be the improvements obtained using the time-dependent information, which is uncertain but may be modeled and predicted?

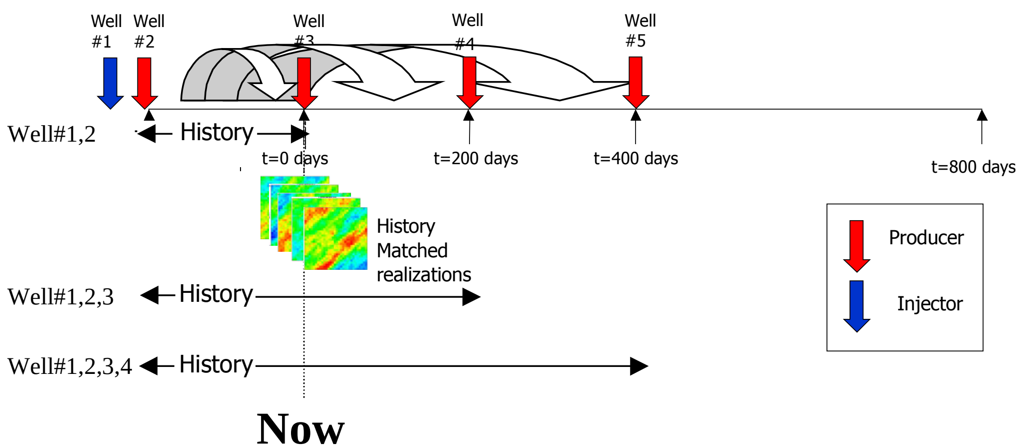

Figure 2-5: Effect of time-dependent data on subsequent well placement decisions.

2.5. Proposed Approach: Multiplacement with "Pseudohistory"

Given the strengths of the existing multiplacement approach and the importance of time-dependent uncertainty, a new approach that integrates these two components is proposed. The idea of this approach is parallel to the previous multiplacement approach in that only one optimization step takes place within the scheme (Figure 2-6). However, as opposed to freezing the geological uncertainty of the multiple history-matched models during optimization, the new approach updates these history-matched models as the new information is added. The new approach includes the time-dependent information and feeds it into the optimization scheme. History-matched models that honor all of the preceding history are used to model the future (time-dependent) response of the wells. This model of the "future history", which we call the pseudohistory, enables the integration of time-dependent information. The new approach enables the subsequent placement decisions to benefit from the reduced uncertainty that will be obtained as the new wells are drilled.

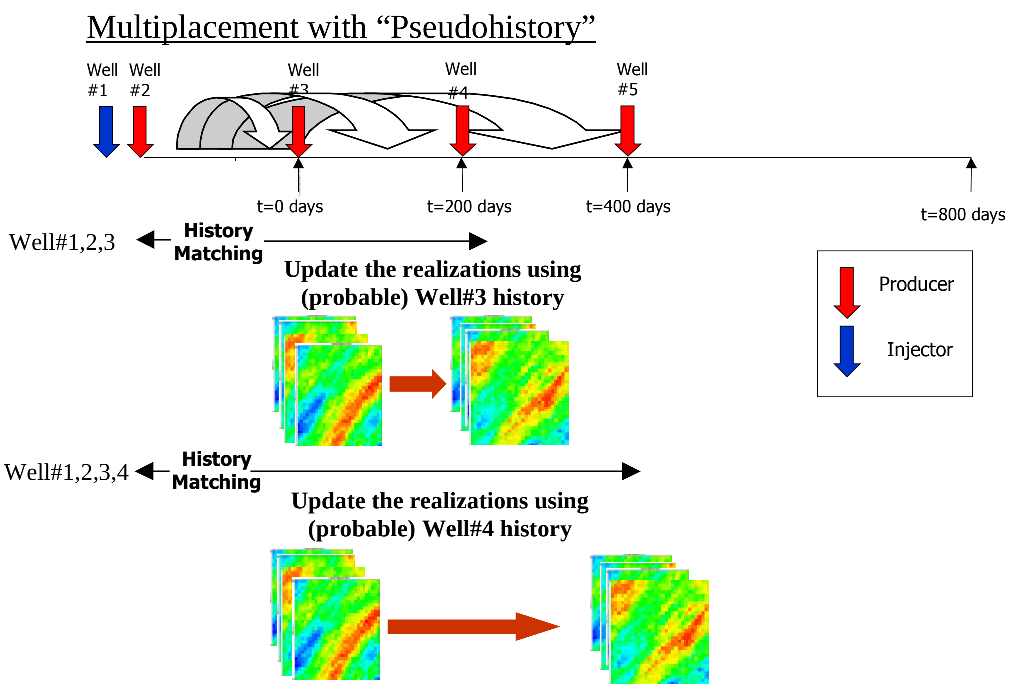

Figure 2-6: Multiplacement with pseudohistory.

Chapter 3

3. Optimization Tools

3.1. Well Placement Optimization

In order to understand how the search for the optimum is made, it is useful to know the general framework and the components of the optimization method. In this study, a Hybrid Genetic Algorithm (HGA), developed by Guyaguler *et al.* (2000) was modified and used as the optimization tool. HGA uses GA as the base search tool and utilizes polytope and kriging algorithms to accelerate the convergence process. In the following sections, GA, polytope and kriging algorithms are described briefly.

3.1.1. Genetic Algorithms

Genetic Algorithms (GA), developed by Holland (1975), are stochastic search algorithms based on the mechanics of natural selection and genetics (Goldberg, 1989). The GA operate with the coding of the parameters instead of the parameters themselves. Unlike the conventional methods, GA search for the best point within a set of points (*population*) instead of searching with a single point (*individual*). Instead of using the derivative or gradient information guide the search; GA only use the objective function value (*fitness*). At each iteration (*generation*) of the GA, a new set of points is reproduced from some of the good points within the previous set. That part of the algorithm mimics the Darwinian natural selection process, which states that the inferior individuals (the solutions with low fitness values) will die and fitter individuals will survive to reproduce better (more fit) offspring.

3.1.2. Polytope Algorithm

The polytope algorithm is a hill-climbing algorithm, and does not require derivative information. This algorithm tries to find the direction that increases the value of objective function. The optimization is made with $n+1$ points to find the optimum value of n parameters. In the first step of the algorithm, for a maximization problem, the parameters are arranged in decreasing order, then the centroid of their values is determined. The worst point is extended through the centroid to a new position, perhaps multiplied by an expansion coefficient (Figure 3-1). By comparing the new point value with the previous values, the direction is chosen and the worst point is replaced.

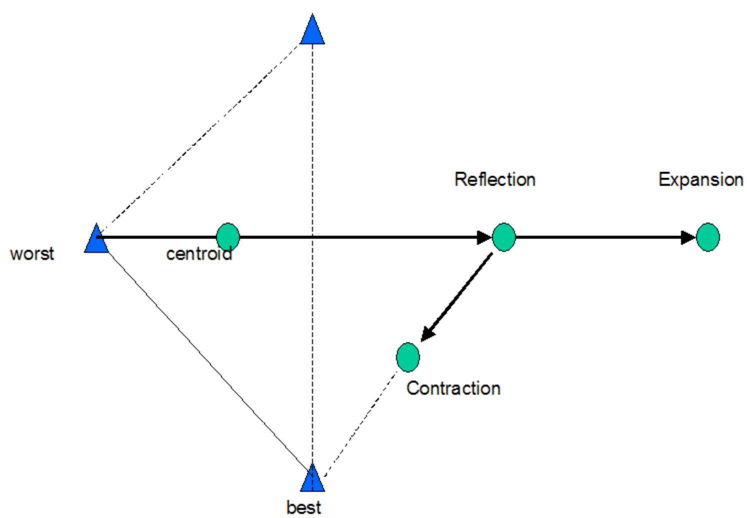

Figure 3-1: Polytope steps.

3.1.3. Kriging Algorithm

The kriging algorithm is an interpolation/extrapolation algorithm that uses the semivariogram information (measure of dissimilarity between spatially distributed points) to estimate the value of a point. HGA uses a kriging proxy to reduce the number of objective function evaluations.

3.1.4. Hybrid Genetic Algorithm

A Hybrid Genetic Algorithm (HGA) developed by Guyaguler *et al.*[0] (2000) was used as the main optimization engine in this study. HGA was designed to utilize the individual strengths of GA and polytope for effective search. In addition to these "helper" algorithms HGA utilizes the kriging algorithm to generate a proxy in order to reduce the number of simulations required to find the optimum.

In HGA, the conventional steps of GA are followed, to which are added the polytope steps and kriging proxy approach. The flowchart of the HGA is presented in Figure 3-2 and can be summarized as follows:

- GA create an initial *population* and evaluates *fitness* of the *individuals* (objective function evaluation).
- Then GA select the *individuals* based on their ranks determined by their fitness values.
- GA operators *crossover* and *mutation* are applied for reproduction.
- Then the polytope algorithm is used to search for a better solution. The polytope is constructed from the fittest of the individuals (current best solutions in the GA) ever encountered in all populations. A function evaluation is performed at the endpoint of the polytope step. As a result of polytope steps, if the solution is improved then the individual with the lowest function value is replaced with the new best solution.
- Within HGA, a database of the completed simulations is constructed and updated whenever a new simulation is made. This database is used to construct the kriging surface. Then estimation for this surface is performed for the points where the simulations have not been performed. At this step HGA performs the search using the kriging surface as the function evaluator instead of the simulator. At the end of this step, the algorithm finds the maximum point on the kriged surface. Then a simulation is launched to verify this optimum. If the result is better than the best

solution of the population, then this new value replaces the worst solution of the population. This step requires only one simulation.

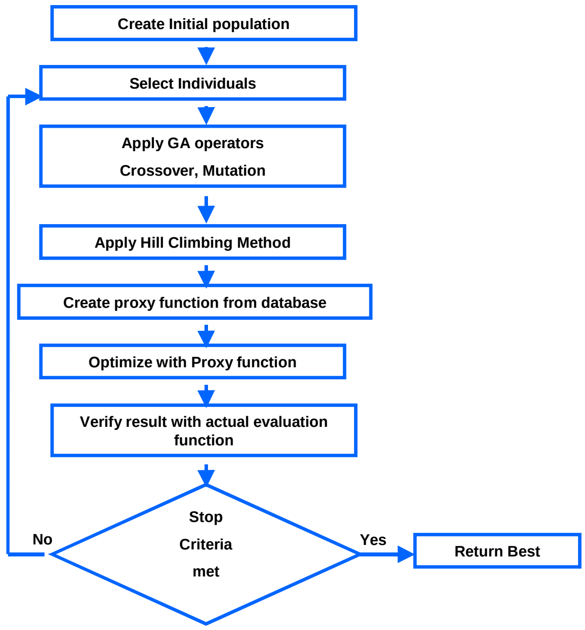

Figure 3-2: Hybrid Genetic Algorithm (Guyaguler et al., 2001).

3.1.5. Terminology

There are some definitions that are important to the understanding the language of well placement optimization using HGA. In this section, the terms are defined in detail and used throughout the remainder of this report.

Test Location

Optimization is an iterative process in which the algorithm tries different candidate solutions during the search for the optimum. In this context, the objective is to find the optimum locations of the sequentially drilled wells. The candidate locations that are proposed by the optimization algorithm during the process are called the *test locations*. The multiplacement approach proposes the test location of all wells at the same time and therefore finds the optimum set of test locations in a single optimization.

Individual

An individual is a member of a population in which there is a predetermined number of individuals. Each individual stands for a particular configuration of test locations with a calculated objective function value (fitness) of NPV. HGA proposes a different set of test locations for each individual.

Generation

A generation is defined as the iteration level of the GA. When the number of generations is stated, that will refer to the number of iteration levels of the HGA.

Realization

The proposed locations of the wells are tested considering multiple geological scenarios called realizations. Therefore, for a given individual there is a fixed number of realizations and the wells are placed at the same locations in all of the different realizations during the evaluation of the objective function value.

3.1.6. Method of Well Placement Optimization Using HGA

The method of optimization is as shown in Figure 3-3. HGA proposes different test locations for different individuals. The objective function is evaluated for each individual based on the combination of NPV values over all of the realizations. Following the rules of *crossover* and *mutation*, fitter individuals are transferred to the next generation (Figure 3-3). From generation to generation, individuals hopefully improve their fitness that causes an overall improvement in the population. When the stopping criterion is met, the fittest individual of the last generation is provided as the optimum.

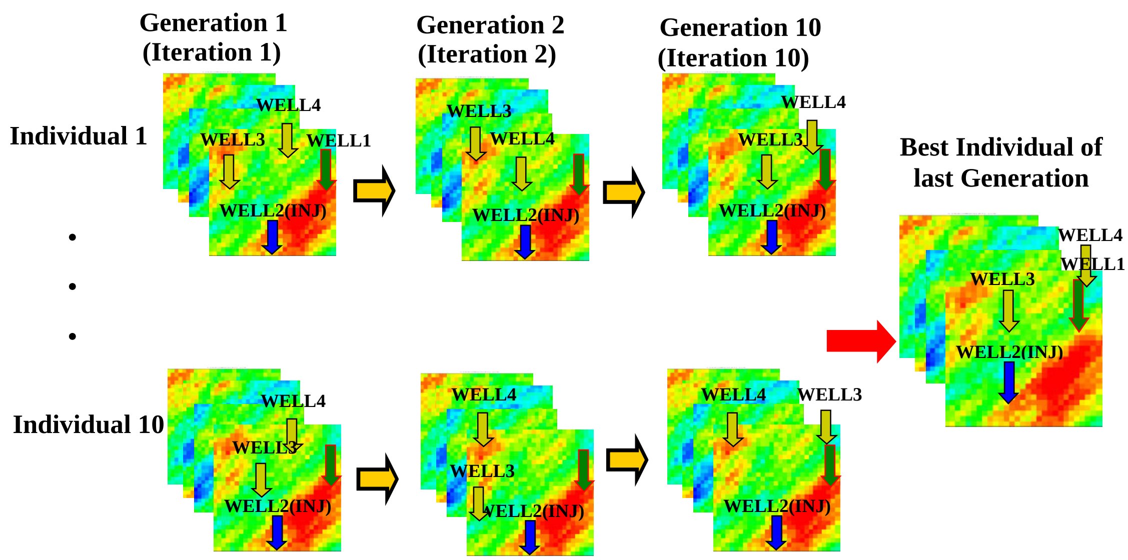

Figure 3-3: Optimization workflow using HGA.

3.2. History Matching Using Gradual Deformation Algorithm

In this study, the gradual deformation algorithm was used for history-matching as in Roggero and Hu (1998). The advantage of this algorithm is that it transforms the history-matching problem into a one-dimensional optimization problem. The algorithm searches for the optimum ρ parameter that is used to generate the petrophysical properties of the reservoir in Gaussian space. There are different versions of gradual deformation algorithm but the procedure applied in this study is as follows (Figure 3-4):

1) Geostatistical parameters such as variogram and histogram of the petrophysical properties are predetermined and a geostatistical simulation is performed to generate two realizations.

2) By using the ρ parameter, the two realizations are combined. During this combination, the variogram and the histogram of petrophysical properties are preserved.

3) The combined realization is transformed into real space.

4) Flow simulation is conducted on this real space realization.

5) The mismatch between the production response of the generated realization and the actual response is calculated. By using the Brent algorithm, a new ρ parameter is

proposed and the merged realization is combined with a new generated realization. The mismatch is calculated again. If the mismatch is improved, the recently combined realization is used for deformation otherwise the old combined realization is used in the next iteration. This process lasts until the stopping criterion is met. Throughout this study the history-matching was performed by using the code implemented by Tureyen *et al.* (2002).

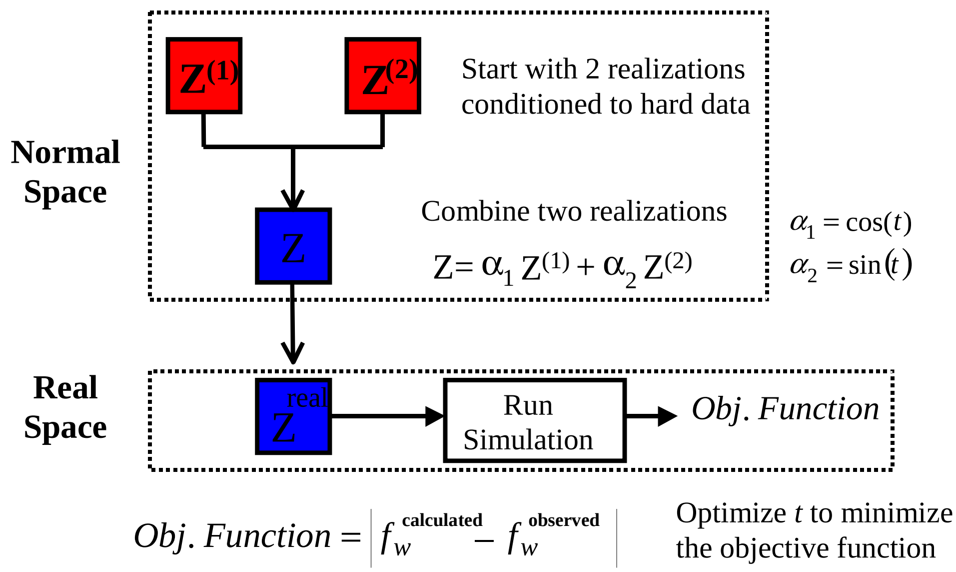

Figure 3-4: Gradual deformation algorithm.

Chapter 4

4. Utility Framework

4.1. Introduction to Decision Analysis

The primary objective of optimization algorithms is to find the optimum decision given the resources and constraints on the problem. The decision is defined as the allocation of resources, irrevocable in the sense that the situation before the decision is made is hard or costly to achieve (Howard, 2003). After defining the decision, a common misinterpretation of the decision and outcome should be clarified. That is because the goodness of decision, most of the time, is assessed wrongly by referring to its outcome. A good decision is defined as the logical decision based on the uncertainties, values and the preferences of the decision-maker (Howard, 2000). A good outcome is the outcome that has high value. Making good decisions increase the possibility of achieving good outcomes. However, even a good decision may result in bad outcomes or a bad decision may produce good outcomes. A simple example of a good decision is driving a car in a sober condition. However, a person who drives without alcohol may have an accident while another person who is totally drunk may get home without any trouble.

4.2. Rules of Actional Thought

The principles that enables us to make good decisions are called rules of actional thought (Howard, 2000). The rules that help the decision-maker to achieve a high quality decision are the probability rule, the order rule, the equivalence rule, the substitution rule, and the choice rule.

Probability Rule

The probability rule states that probabilities should be used to distinguish and incorporate the different deals.

Order Rule

The order rule states that there is always an order that the decision-maker ranks the decisions based on his or her preferences. In the case when the decision-maker is indifferent for two different alternatives, these two alternatives can coexist in the same rank. If the decision-maker prefers A to B and prefers B to C, the order will be in the following form:

$$\mathbf{A > B > C} \quad \textbf{(4.1)}$$

The order rule ensures that the order of prospects will be always consistent. Given the conditions A > B and B > C, the statement C > A violates the order rule.

Equivalence Rule

The equivalence rule states that given the preferences of the decision-maker, the decision-maker can always assign a probability value, p that makes the decision-maker indifferent to getting the best prospect with a probability of p in comparison to getting a lesser prospect for sure (with a probability of 1). This probability is called the *preference probability*.

Given the order A > B > C, the decision-maker may be indifferent between achieving the best prospect A with a probability of *p* and getting prospect B for sure (Figure 4-1). *p* is nothing but the preference probability of the decision maker for the prospect B.

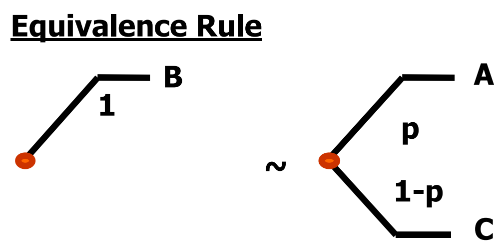

Figure 4-1: The equivalence rule and preference probability.

Substitution Rule

The substitution rule states that substitution of a certain equivalent of a deal with the deal itself is always possible for the the time epoch when the equivalent of that deal exists.

Choice Rule

The choice rule states that for the case where there are two prospects with two different preference probabilities, the decision–maker always chooses the prospect with the higher preference probability.

4.3. Utility and Risk Attitude Concept

A simple decision problem is considered to understand the utility concept. In this problem, the decision-maker, call him John, wants to organize an event with his friends for the weekend, and the alternatives are playing tennis, watching TV and going to a movie. The problem is that John wants to make the best decision under the uncertainty of the weather in the weekend. The rules of actional thought are applied to this decision problem for further understanding. In the first step, using the probability rule, the decision tree was constructed. After listening to the weather forecasts from the TV and radio, the probability that the weekend will be rainy is assigned (Figure 4-2). Next by considering his preferences, John ranks the alternatives from best to worst. Applying the equivalence rule, John assigns a preference probability that makes him indifferent between getting the best choice with that preference probability and getting an alternative for sure. After that, using the substitution rule, the alternatives in the decision tree were substituted with their certain equivalents (Figure 4-3). At the end, abiding by the choice rule, John chose the option that had the highest preference probability.

For each prospect, a conceptual monetary equivalent would be found and that amount is defined as the highest amount of money that John was willing to pay to make that prospect real. In other words, John would be as happy when that prospect happened as in the situation when he already had paid that monetary amount.

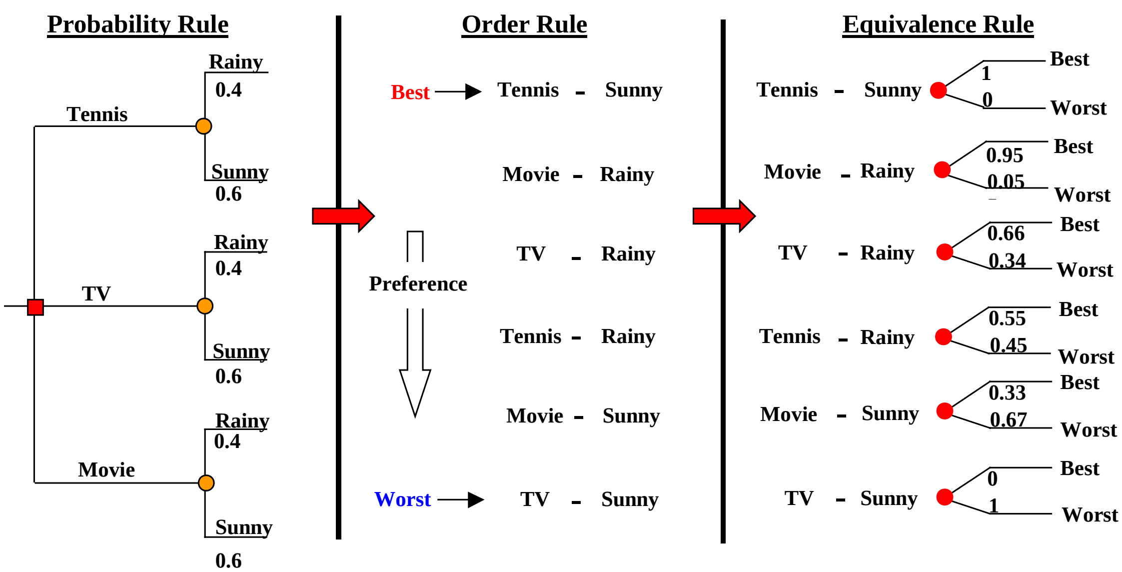

Figure 4-2: Probability rule, order rule and equivalence rule.

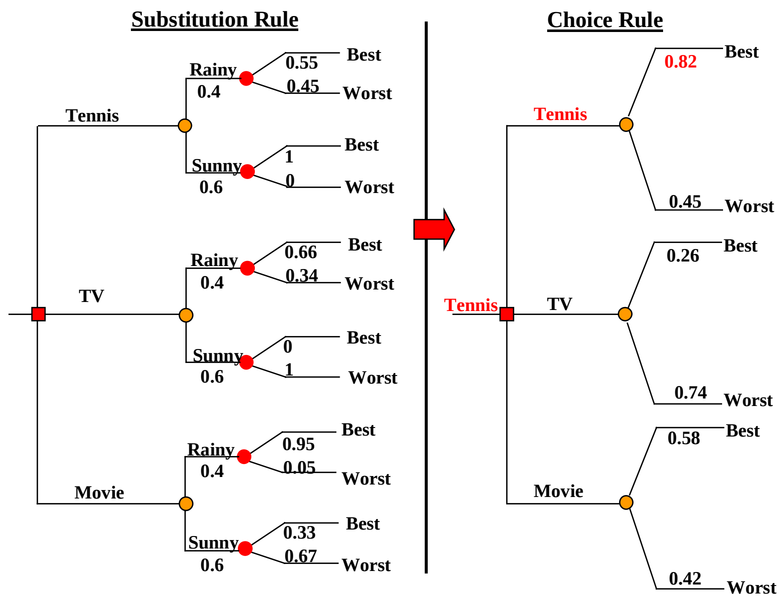

Figure 4-3: Substitution and choice rule.

By using this idea, if John assigned monetary equivalents to the available prospects of the decision problem, the relation between the preference probability and monetary equivalents is shown (Figure 4-4). When the preference probability of the alternatives are plotted against the monetary equivalents, the decision attitude, that is the preference probability of John towards different monetary amounts is mapped. This relation is nothing but the *risk attitude* of John. The curve is defined as the *utility curve* of John for the given range of monetary values. So it turns out that *utility* is basically the *preference probability* of the decision-maker. As can be understood, the utility depends on the wealth of the decision-maker, also the utility curve can behave differently for different ranges of certain equivalents. The advantage of using utility instead of monetary value is that utility provides the optimum decision satisfying the consistency of the preferences of the decision-maker independent of the monetary amount.

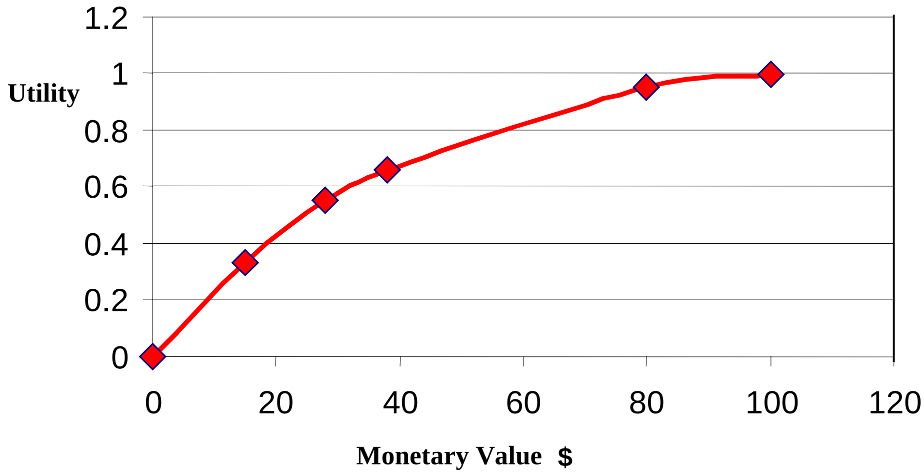

Figure 4-4: Utility curve of a decision-maker.

4.4. Delta Property and Risk Odds

As mentioned in the previous section, the utility and the certain equivalent is a function of the wealth of the decision-maker. For a given range of monetary value, the decision-makers‘s certain equivalent, *ce*, for the deal may change with the same amount as a result of change, Δ, in the monetary amount (Figure 4-5). This is defined as the *delta property*. Changes in monetary values of the prospects will cause a change in the preferences and the utility values of the decision-maker. But for the decision-maker that satisfies the delta-property, this change will not be affected by the wealth, w_o, of the decision-maker. Straight line and exponential utility curves satisfy the delta property. Throughout this study, the decision-maker was assumed to satisfy the delta property that enabled the usage of straight line and exponential utility curves.

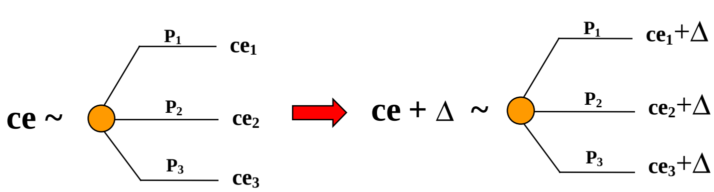

Figure 4-5: Delta property.

4.4.1. Straight-Line Utility Curve

The straight-line utility curve corresponds to the perspective of a risk-neutral decision-maker. The straight-line utility curve is governed by the following equation,

$$u(x) = a + bx \qquad \textbf{(4.2)}$$

where *a* and *b* are constant, *b* > 0 (so that utility increases with increasing monetary value). Using the delta property, the following relation can be derived:

$$u(w_o + ce + \Delta) = \sum_i p_i u(w_o + ce + \Delta) \qquad \textbf{(4.3)}$$

Using the straight line utility curve equation (Eq. 4.2),

$$a + (w_o + ce + \Delta) \times x = \sum_i p_i \times [a + b \times (w_o + ce_i + \Delta)] \qquad \textbf{(4.4)}$$

knowing that,

$$\sum_i p_i = 1 \qquad \textbf{(4.5)}$$

the equation becomes:

$$ce = \sum_i p_i \times ce_i \qquad \textbf{(4.6)}$$

4.4.2. Exponential Utility Curve

Having defined the straight utility curve of a risk-neutral decision-maker, the exponential utility curve that additionally governs the utility behavior of risk-averse and risk-seeking attitudes is defined. The equation governing the exponential utility curve is:

$$u(x) = a + b \times c^y \qquad \textbf{(4.7)}$$

where *a*, *b* and *c* are constant, and *c* can not be equal to 1. Using the delta property, the following relation can be derived:

$$a+b\times c^{(w_o+ce+\Delta)}=\sum_i p_i\times[a+b\times c^{(w_o+ce_i+\Delta)}] \qquad \textbf{(4.8)}$$

knowing that

$$\sum_i p_i=1 \qquad \textbf{(4.9)}$$

the equation becomes:

$$c^{ce}=\sum_i p_i\times c^{ce_i} \qquad \textbf{(4.10)}$$

4.4.3. Risk Odds

The c constant in exponential utility curve is replaced by $1/R$, where R is defined as the risk odds. The equation of the utility curve becomes:

$$u(x)=a+b\times R^{-y} \qquad \textbf{(4.11)}$$

When the simple deal is considered as in Figure 4-6, we can write:

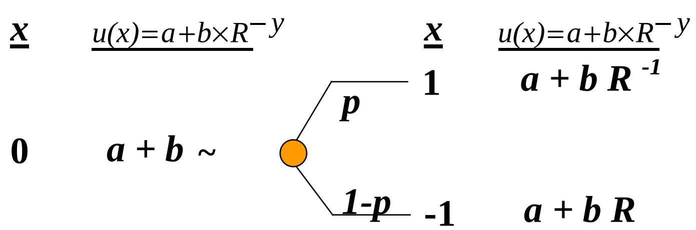

Figure 4-6: The deal for a delta property.

$$a+b=p\times(1+bR^{-1})+(1-p)\times(a+bR) \qquad \textbf{(4.12)}$$

$$a+b=p\times(1+bR^{-1})+(1-p)\times(a+bR)$$
$$a+b=a+b\times[pR^{-1}-(1-p)R]$$
$$1=[pR^{-1}-(1-p)R]$$
$$(1-p)R^2-R+p=0$$
$$R=1,\frac{p}{1-p} \qquad \textbf{(4.13)}$$

The risk neutral case is satisfied with $R=1$.

The risk aversion coefficient, *r*, is defined as:

$$r = lnR \quad \textbf{(4.14)}$$

the utility equation (Eq. 4.11) becomes:

$$u(x) = a + b\, e^{-r\,x} \quad \textbf{(4.15)}$$

r > 0 represents the utility curve of risk-averse attitude whereas *r* < 0 represents the utility curve of risk-seeking attitude. During the course of this study the decision-maker was assumed to follow the delta property. Accordingly the exponential utility curves were utilized. Hence the utility curves for different risk attitudes are as shown in Figure 4-7.

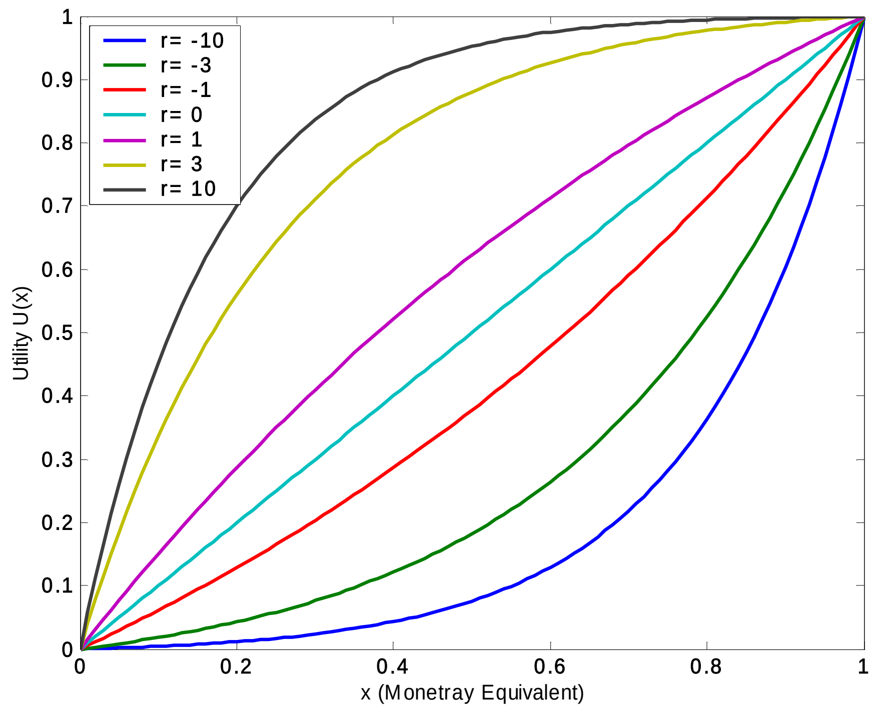

Figure 4-7: Utility curves for different risk-aversion coefficients.

Chapter 5

5. Multiplacement with Pseudohistory

5.1. Pseudohistory Concept

In this section, the components of the new approach will be described together with the modifications made in the objective function calculation. A simple scenario (Figure 5-1) is considered to help understand the pseudohistory concept, where the objective is to find the optimum locations of Well#3 and Well#4 given the time frame of the project (800 days).

In the sample scenario, it is known that once Well#3 is drilled, its future history will affect the optimum decision of Well#4. On the other hand, to apply the proposed approach, the future history of Well#3 is needed for integrating the time-dependent information (Figure 5-1). However, we currently have the information from the past 200 days. The challenge is that the “future” response of Well#3 (once drilled) is not known yet, but the opportunity to model the uncertainty and use that model to predict the future history of Well#3 is available. The challenge is resolved by an approach in which an uncertainty model is used to generate a pseudohistory of the reference model. With this approach, the realizations that honor the available history (the past 200 days) are updated and reconstrained not only to that available history but also to the “pseudohistory” of

Well#3. By performing history matching again, the information already known is expected to be augmented.

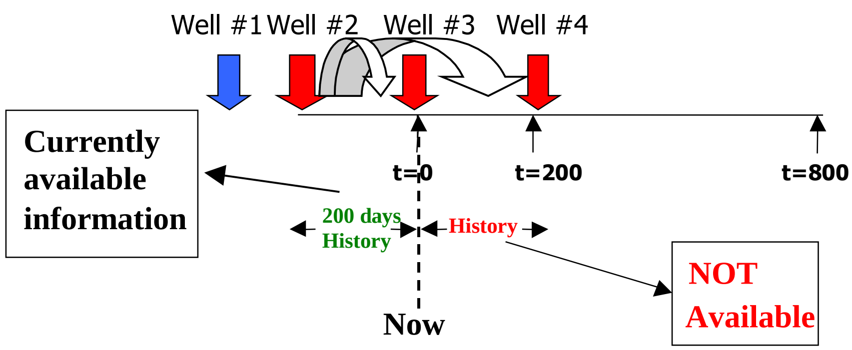

Figure 5-1: Practicality challenge of proposed approach.

Important Remark

At first, the computational load of history matching the already matched realizations again may look excessive. But the fact that the time-dependent information provided by Well#3 (although uncertain) will affect the decision (optimization) of Well#4 should not be ignored. The proposed approach uses this time-dependent information to reduce the uncertainty of the flow response. In other words, the new approach emphasizes and encourages the use of the time-dependent information (although uncertain) in well-placement optimization. The essential message of this study is that subsequent well-placement decisions may be improved if the time-dependent information is utilized better and integrated into the optimization scheme.

5.2. Uncertainty Modeling and Pseudohistory Creation

Having explained the pseudohistory concept, the terms and methodology of pseudohistory creation will be described in this section. There are three different categories of realizations in this problem. The type of the realizations generated and used in the study differentiates the new approach from the old approach. The three different sets are described as follows:

Set-A

The realizations that are only history-matched for the available history (past 200 days) fall into the realization Set-A. Set-A would be the set of realizations used in the old approach, as no time-dependent information is included.

Set-B

The realizations that are history matched not only for the available history (past 200 days) but also for the pseudohistory (predicted future 200 days) that includes the time-dependent (uncertain) information of the earlier decisions fall into the realization Set-B.

Set-C

The realizations that are history-matched for both the available history (past 200 days) and the future (200 days) history obtained from the *reference model* to represent the concept of perfect (certain) time-dependent information fall into the realization Set-C.

Having defined the different types of realizations, five important steps occurring during pseudohistory creation (Figure 5-2) are described as:

1) The optimization algorithm proposes test locations for the wells to be optimized. In other words, the test locations of the optimized wells (Well#3 and Well#4) are proposed at the outset and fixed during the trial of that set of test locations. The test location of the first well (Well#3) is placed in each of the realizations of Set-A.

2) Using the realizations of Set-A, future production is simulated for 200 days until the start of production of the next well (Well#4).

3) As multiple models exist, multiple responses will be observed as a result of the simulations. The NPV of the simulated production is calculated for each realization of Set-A since the idea is to model and utilize the incremental time-dependent uncertainty for subsequent decisions. Knowing that the NPV is the principal criterion for the optimality of the decision considered, the cumulative distribution function (CDF) of NPV is constructed.

4) From this CDF, the realization that corresponds to the P50 NPV value is drawn.

5) The simulated response of the representative realization (P50) of the distribution is called the pseudohistory. The pseudohistory not only honors the past 200 days of history that is already known but also integrates the probable history of the next 200 days. The pseudohistory includes the time-dependent information to enhance the subsequent decisions in an implicit manner (since the test location of Well#4 is already proposed).

In the next step of the new objective function evaluation process, described later in Section 5.3, a new set of realizations (that we called Set-B) will be generated by matching the pseudohistory. Well#4 is placed at the test location in each of the realizations of Set-B together with Well#1, 2 and 3 and the resulting NPV distribution of that set of test locations is evaluated. Existing methods, which do not include the time-dependent information, would use the realizations of Set-A to evaluate the NPV distribution of the proposed set of test locations.

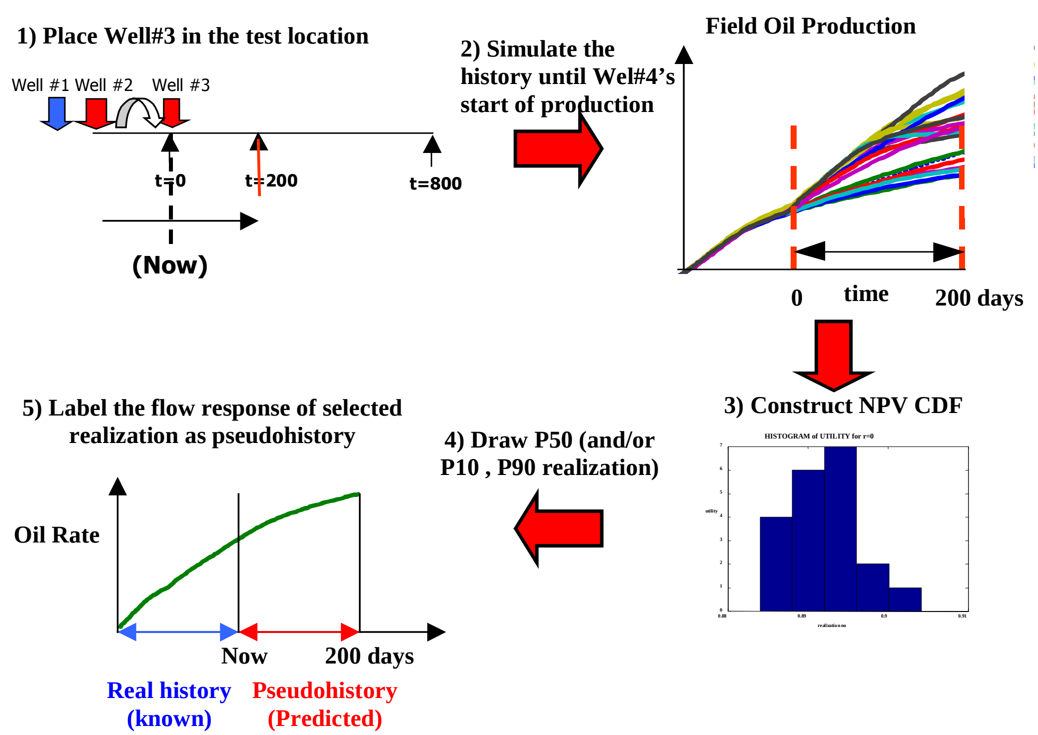

Figure 5-2: Pseudohistory creation.

5.3. Objective Function Calculation

Learning the details of conventional objective function evaluation will enable the understanding the shortcomings of existing approaches and facilitate implementing the new concept. The methodology of objective function calculation determines the general framework of the optimization. Therefore, the proposed approach is implemented in the objective function part of the HGA. Before moving forward to the new methodology, the objective function calculation workflow of previous approaches is described in Figure 5-3 as follows:

1) HGA proposes test locations.
2) The wells are placed in the same test locations on all realizations of Set-A.
3) Flow simulation is performed on each realization of Set-A.
4) The NPV is calculated for each realization of Set-A.
5) The expected value of NPV is assigned to that particular set of test locations (which is an individual in the GA).

This is the conventional methodology for the calculation of objective function for the old approach.

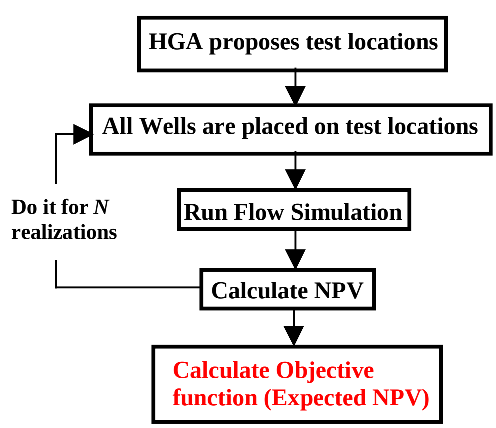

Figure 5-3: Objective function calculation workflow.

The new algorithm in the objective function calculation part of HGA is as follows:

1) HGA proposes test locations for both wells (Well#3 and Well#4) to be optimized. These locations are kept fixed during the evaluation of this individual.

2) By using the steps defined in Section 5.2, the pseudohistory is determined.

3) Using this pseudohistory, history matching using gradual deformation is performed to generate the new history-matched realizations (Realization Set-B). The realizations of Set-B will honor not only the past history but also the effect of time-dependent uncertainty on subsequent decisions.

4) The next well (Well#4) is placed at the proposed test location in each of the reservoir models of Set-B as opposed to using the realizations of Set-A as in previous approaches.

6) Flow simulation will be made for the whole future life of the field life (800 days) on each realization of Set-B.

7) For each realization of Set-B, NPV will be calculated and transformed into utility.

5) The distribution of utility will be constructed.

6) The expected utility will be calculated.

This process is illustrated in Figure 5-4.

5.4. Comparison of Approaches

As understood from Section 5.4, the new approach consists of two main parts. The first part is *information integration* part in which the time-dependent information is imposed. The second part is the *utility framework* part in which utility theory is used to find the optimal solution depending on the risk attitude of the decision-maker. In summary, the new approach has an information adaptive scheme in which history matching is fully automated. At every objective function evaluation step, the CDF of NPV is constructed in a dynamic manner (Figure 5-5). In the old approach, there was no history matching and thus the geological uncertainty of the models remained at the same level during optimization. Accordingly, in the old approach time-dependent information was not considered.

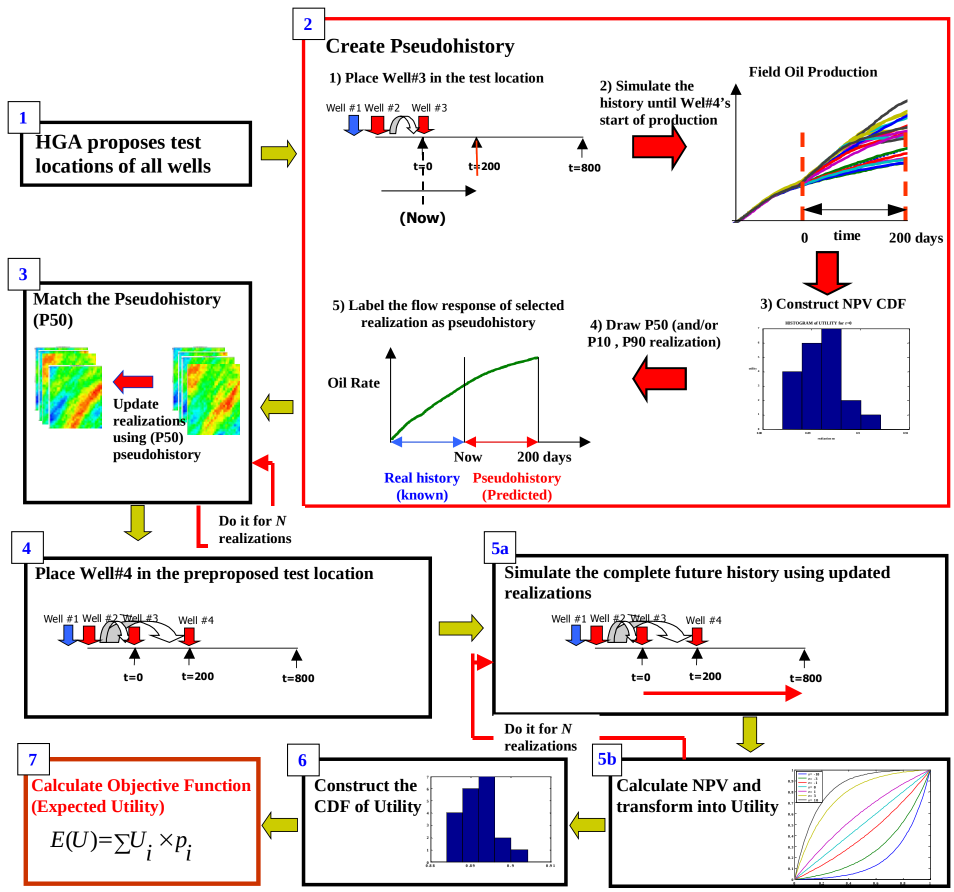

Figure 5-4: The overall workflow of multiplacement with pseudohistory.

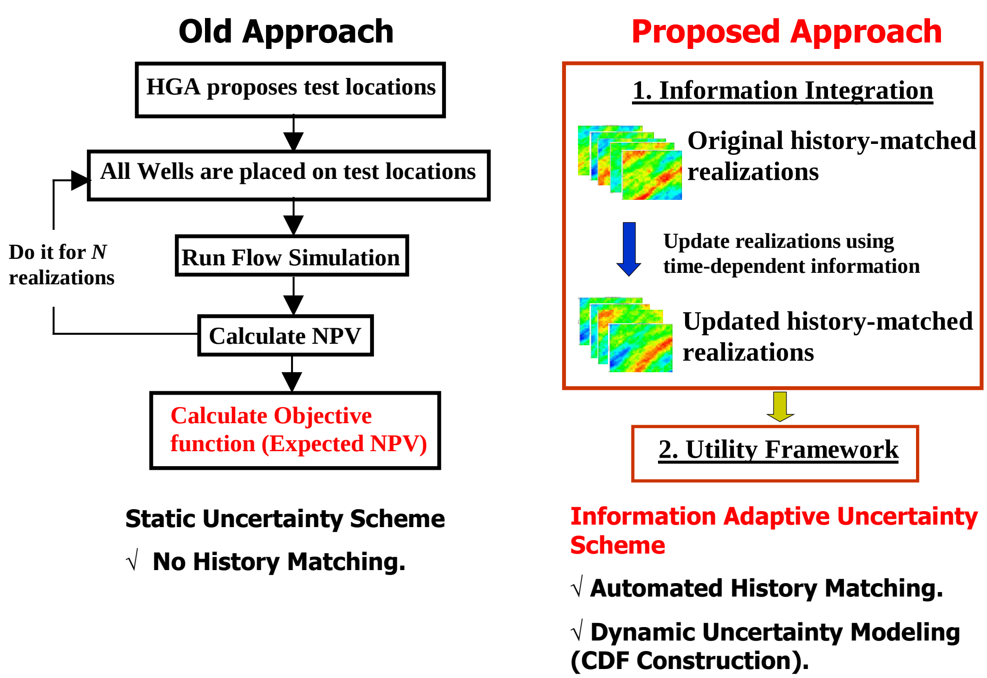

Figure 5-5: Proposed approach vs. old approach.

Chapter 6

6. Analysis of Multiplacement with Pseudohistory

In this chapter, the multiplacement with pseudohistory approach is analyzed on a test scenario using a synthetic model. The results of the proposed approach will be presented in detail. Comparison of old and new approach is made based on the utility and NPV distributions in addition to the representation power of the kriging proxy.

6.1. Synthetic Simulation Model

To investigate the different aspects of the proposed approach, a synthetic simulation model was generated. By predetermining the geostatistical parameters such as the variogram and histogram of the petrophysical parameters, an Unconditional Sequential Gaussian Simulation (SGSIM) was performed to populate the simulation model with permeability values varying from 1 md to 10000 md (Figure 6-1). The resulting output realization of the geostatistical simulation was called the *reference model*. The reference model was designed to have a 30x30x1 grid (a two-dimensional model).

There are a few important points that should be clarified at this stage. The reference model conceptually represents the real field in practice. Accordingly, the production response of the reference model represented the “true” response to be matched during history matching. Throughout this study, the production information obtained from the reference model was referred to as the true history and characterized as perfect information. For the scenario considered, the (past) 200 days of production history was obtained from the reference model. The reference model was used to obtain the perfect information, when necessary, to evaluate the effectiveness of predictions made by the proposed approach.

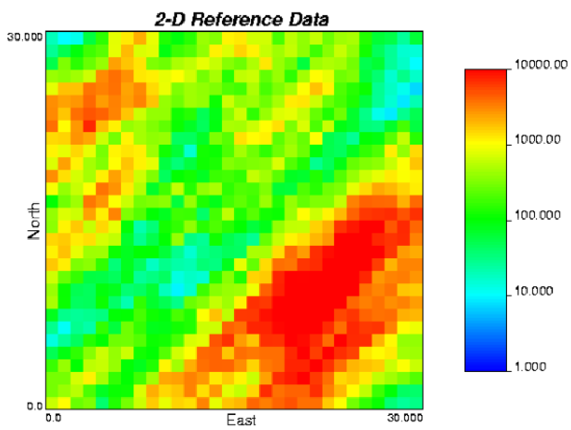

Figure 6-1: Permeability field of the reference model.

6.2. Individual Analysis and Results

6.2.1. Test Case Description

A test case was designed to illustrate the optimization procedure on one of the candidate solutions. In HGA terminology, the test case corresponds to an individual of the population. The scenario mentioned in Section 5.1 was considered (Figure 6-2).

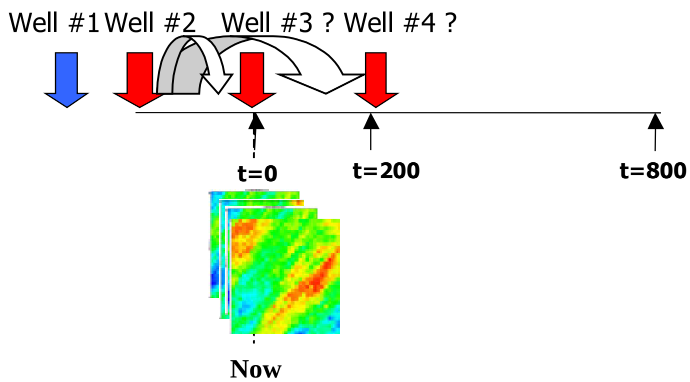

Figure 6-2: Test case description.

In this analysis, 20 equiprobable realizations were utilized. Existing well locations were (23,4) for Well#1 and (17,10) for Well#2 as shown in Figure 6-3. The motivation for focusing first on a candidate solution was to quantify the prior information and analyze the advantage of using the pseudohistory concept embedded into the multiplacement with pseudohistory approach.

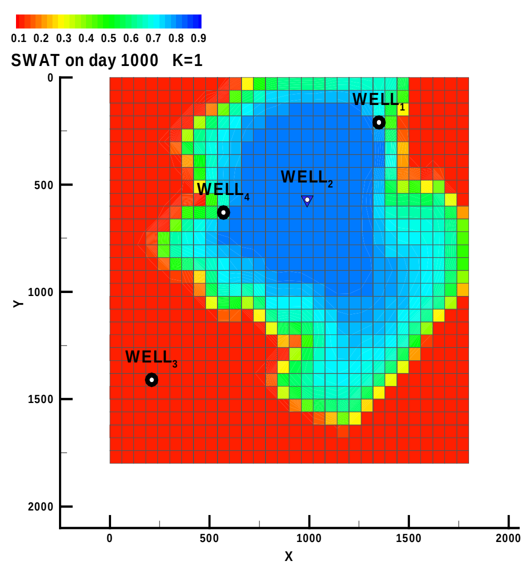

Figure 6-3: Existing wells (Well#1 and Well#2) and the proposed test locations (Well#3 and Well#4).

6.2.2. Objective Function Formulation

The objective function was defined as the maximization of expected utility of the scenario for 800 days of production from multiple geological scenarios. The calculation of expected utility requires a few initial steps. In the first step, net cash flow is calculated

(Eq. 6.1). Within the calculation, all the time-dependent economic parameters are included and the water production is penalized within the formulation as the water handling costs arose by facility handling constraints.

$$\begin{aligned} \textit{Net Cash Flow(t)} = \; & \textit{Oil Production(t)} \times \textit{Oil Price} + \textit{Gas Production (t)} \times \textit{Gas Price} \\ & - \textit{Water Production(t)} \times \textit{Water Handling Cost} - \textit{OPEX} - \textit{CAPEX} \end{aligned} \quad \textbf{(6.1)}$$

Using the simple discounting equation (Eq. 6.2), net cash flow is discounted into Net Present Value (NPV).

$$NPV_i = \sum_t \frac{\textit{Net Cash Flow}_i\ (t)}{(1 + \textit{interest rate})^t} \quad \textbf{(6.2)}$$

To satisfy the consistency of NPV calculations for different realizations, NPV is scaled with a predetermined constant number (Eq. 6.3).

$$\begin{aligned} & NPV_i^{scaled} = \frac{NPV_i}{constant} \\ & NPV_i = \textit{Net Present Value of Event i (realization)} \end{aligned} \quad \textbf{(6.3)}$$

Depending upon the choice of risk-aversion factor, NPV is transformed into utility (Eq. 6.4). If a risk-neutral decision is used, a straight-line utility curve, which is indifferent to NPV, is used. Otherwise, an exponential utility curve is used (Eq. 6.4).

$$U_i(x) = \begin{cases} NPV_i^{scaled} & \textit{for } r=0. \\ \dfrac{1 - e^{-r \times NPV_i^{scaled}}}{1 - e^{-r}} & \textit{for } r \neq 0. \end{cases} \quad \textbf{(6.4)}$$

After calculating the utility value of each realization, the expected utility is calculated by multiplying each utility value by the probability of occurrence of that utility (Eq. 6.5).

$$\begin{aligned} & \textit{Objective function} = \textit{Expected Utility} = \sum U_i \times p_i \\ & U_i = \textit{Utility of event i (realization)} \\ & p_i = \textit{probability that event i (realization) provides } U_i \\ & U_i = f(NPV, r) \end{aligned} \quad \textbf{(6.5)}$$

The calculated value of expected utility is assigned to the individual as the prediction of multiple models for the given set of test locations.

6.2.3. Test Case Results

Following the methodology of the new approach described in Section 5.3, in the first step the HGA was assumed to propose the test locations that were (4,24) for Well#3 and (11,10) for Well#4. Then the first well (Well#3) was placed in the test location on each realization of Set-A that had been history-matched for the available history (past 200 days). In the following step, flow simulation was performed for 200 more days with the existing wells (Well#1, 2 and 3) until the next well (Well#4) production starting time. At that stage, 20 different future predictions were generated, as shown in Figure 6-4. Using the predictions of the realizations of Set-A, the NPV distribution was constructed. The pseudohistory, which is nothing but the production response of the wells of the P50 realization from Set-A, is shown in Figure 6-5.

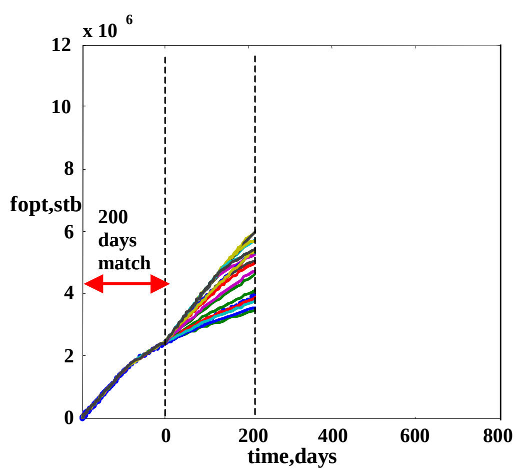

Figure 6-4: Field oil production predictions of the realizations matching the real (past) history for the next 200 days.

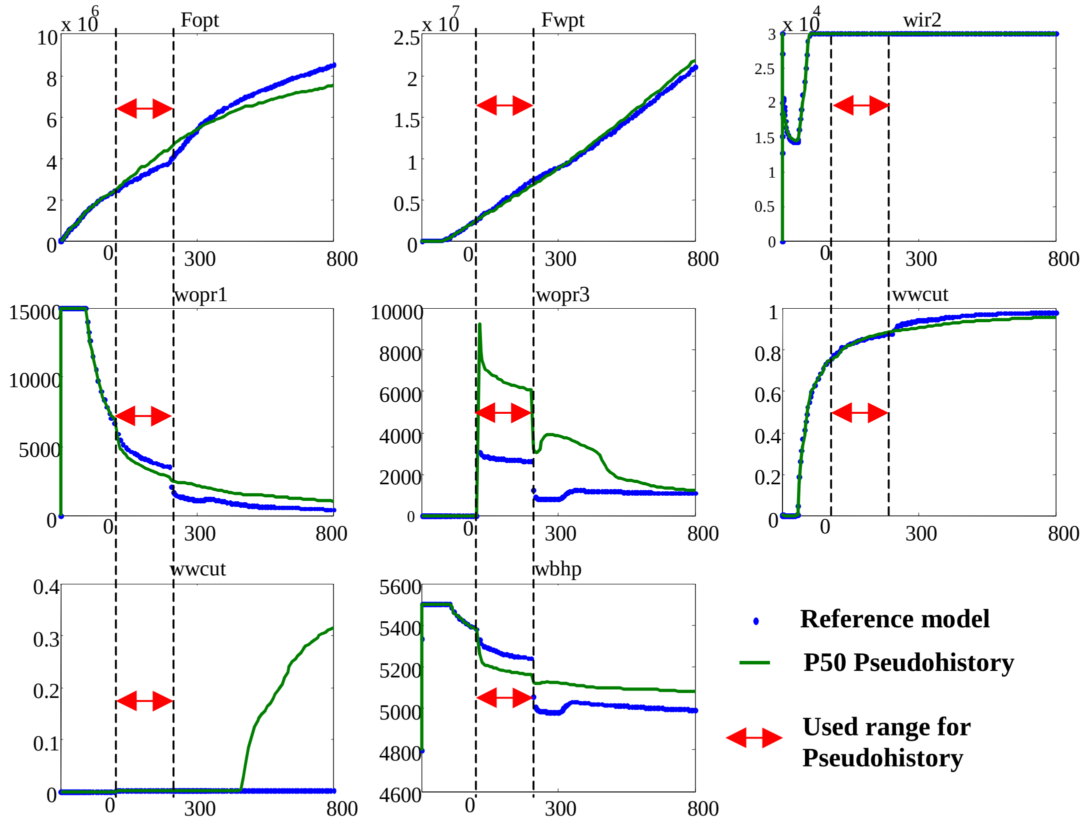

Figure 6-5: Production response of pseudohistory.

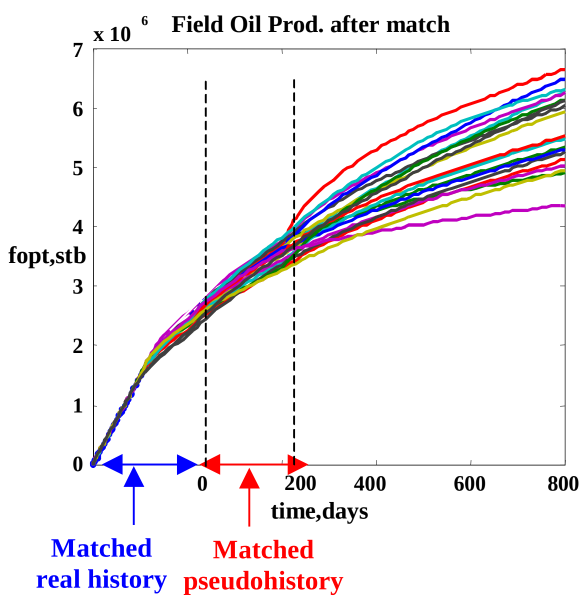

Figure 6-6: Pseudohistory matching results and the predictions of the realizations constrained to not only real history but also pseudohistory.

Utilizing the generated pseudohistory, history matching was conducted 20 times and the 20 new realizations of Set-B shown in Figure 6-6 were generated. After including time-dependent information by pseudohistory matching, the next well (Well#4) was placed at the "preproposed" test location in the realizations of Set-B. Simulating the whole deployment time (800 days), NPV was calculated and transformed into utility values for each realization of Set-B (Figure 6-7).

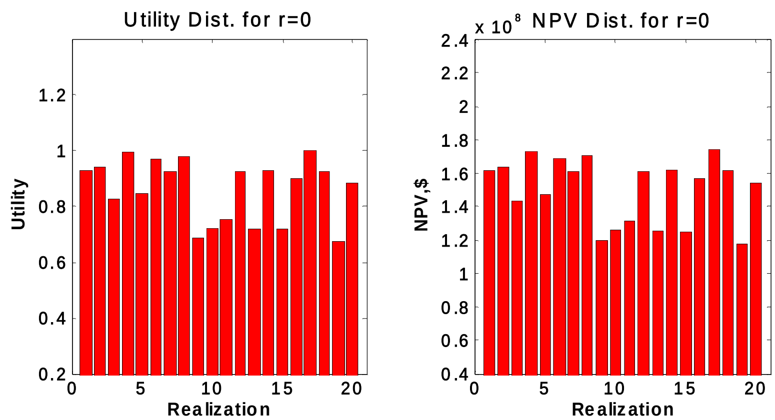

Figure 6-7: Utility and NPV distributions.

Assuming the decision-maker as risk-neutral, the straight-line utility curve was used during NPV transformation. In the final stage, expected utility was calculated as 0.8627 (Figure 6-7) by using the individual utility values obtained from the realizations of Set-B. As a result of transformation of expected utility, the decision was found to have an NPV equivalent of 150 MM $.

6.3. Discussion about Pseudohistory

6.3.1. Motivation of the Usage of NPV Sample CDF in Pseudohistory Determination

History matching using pseudohistory is a new concept therefore it brings out some issues and concerns. In this study, history matching was performed on a well by well basis in the sense that well oil production rates (wopr), watercuts (wcut) and water injection rates (wwir) of the wells were selected to be the parameters to be matched. To accomplish the history matching using the time-dependent information step of the new approach, oil rate and watercut predictions of the P50 realization were utilized. Since these values of watercut and oil rate were nothing but the predictions, the response of P50 realization was referred to as the pseudohistory.

Knowing that the representation power of the pseudohistory is the underlying basis for the utilization of time-dependent information concept, a critical issue about the selection criterion of the P50 realization should be discussed and justified to some degree. In the new approach, the sample CDF of NPV is used as the selection criterion for the P50 realization due to a number of reasons. The first reason is simply that the NPV, which is a function of fopt and fwpt, is the primary decision criterion of the problem. Another reason is the difficulty of the problem under study. The sample CDFs of the parameters of interest for history matching (wopr1, wbhp2, wopr3, wcut1, wcut3 and wwir2) are not guaranteed to be rank preserving. For example, the P50 realization of the sample CDF of wopr1 in the test case was not necessarily the P50 of the sample CDF of wopr3 (Figure 6-8). In this process, rank preservation is obligatory simply because the end result "mixing" histories from different realizations would be inconsistent with the flow physics.

Examining the sample distributions, it turned out that the upper (P90), middle (P50) and the lower tail (P10) of the sample CDFs of the parameters behaved very similarly to a Gaussian distribution. For some parameters like wopr1, wbhp2 and fopt, the upper tail (P90) represented the reference response better whereas the lower tail as shown in Figure 6-9 represented some of the parameters like wopr3 and fwpt better. Wopr3 was the parameter that was represented the worst. One reason was the low degree of prior information contribution from Well#1 and Well#2 to the region where Well#3 was located. During the generation of the realizations of Set-A, the mismatch of the flow response of Well#1 and Well#2 was minimized until the region between Well#1 and Well#2 would be represented well enough to meet the stopping criterion. That resulted in permeability values in the neighborhood of the existing wells that were more similar to the ones of the reference model. The fact that the test location of Well#3 was far away from the region between the history-matched wells Well#1 and Well#2 (Figure 6-3), strengthened the explanation that the prior knowledge was insufficient.

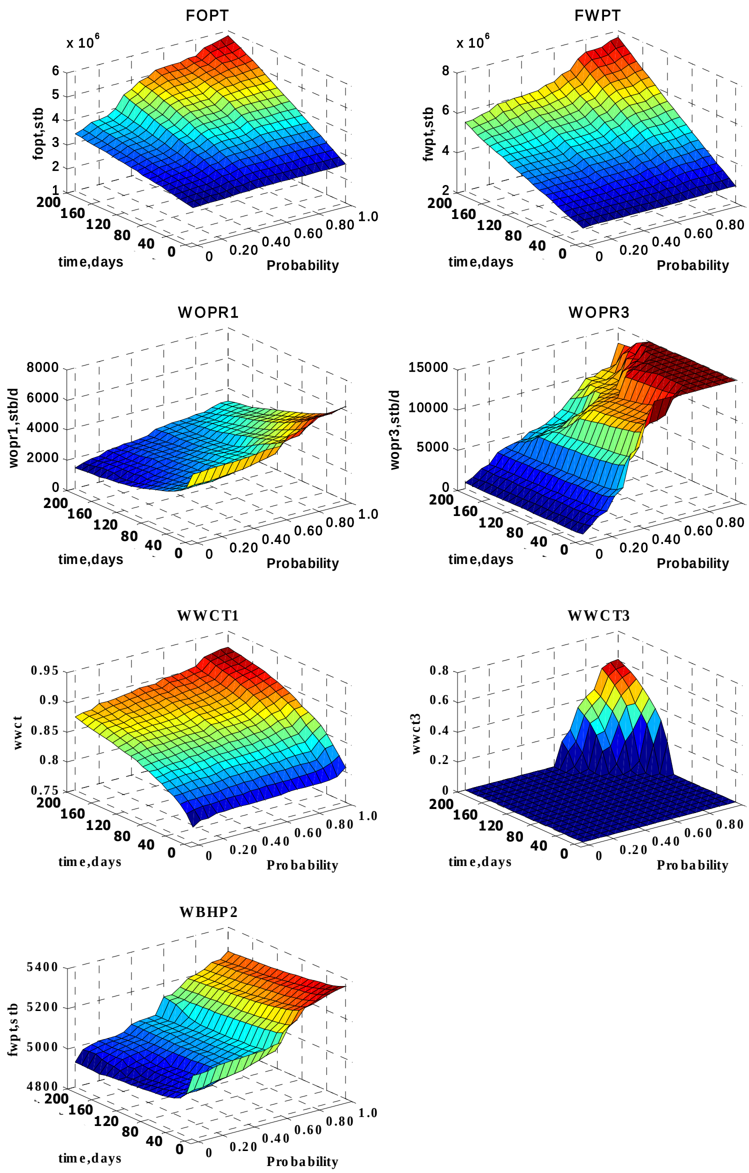

Figure 6-8: Sample distributions of the parameter distributions.

In a second investigation, the effect of the number of realizations of Set-A that were used to construct the distribution was studied. To see the effect of number of realizations on the representation power of pseudohistory, the pseudohistory was created again using 50 realizations in Set A instead of 20.

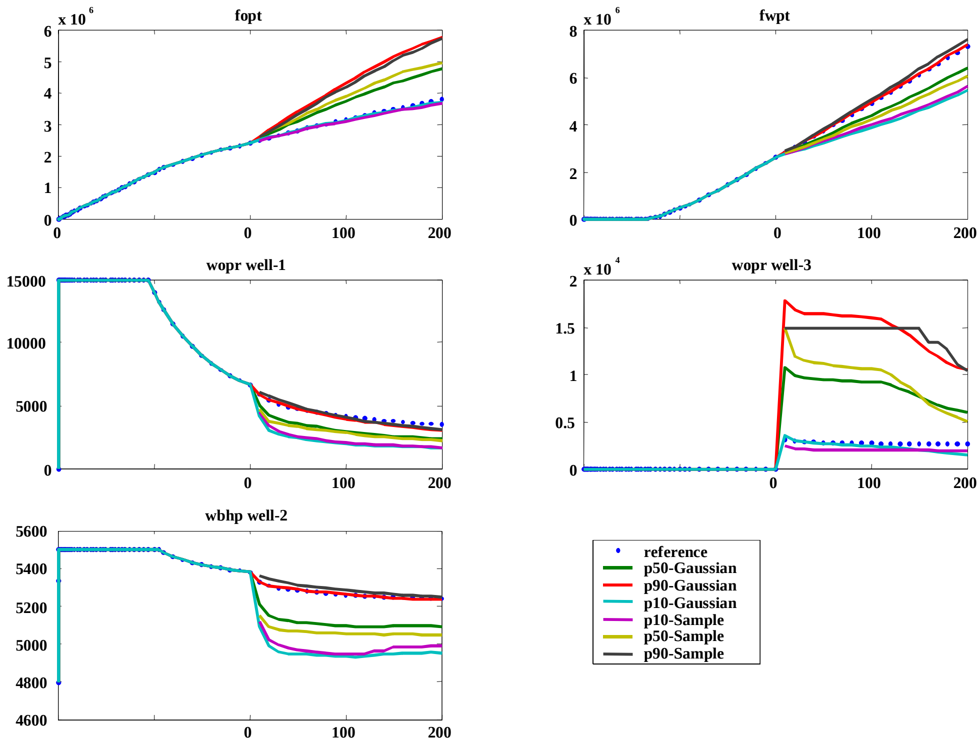

Figure 6-9: Sample vs. Gaussian distribution.

As seen in Figure 6-10, the number of realizations did not affect the representations significantly. The P50 realization of Set-A based on the sample CDFs for 20 and 50 realizations provided pretty much the same response. As shown in Figure 6-11, the expected value of NPV decreased from 140 MM$ to 129 MM$ with a decrease in standard deviation from 44 MM$ to 38 MM$ (Table 6-1). P50 responses of the Gaussian distribution were also added to the comparison. Most of the parameter responses were similar to those of the sample CDFs but when wopr3 and wcut3 were considered together, a drastic increase in the watercut of Well#3 was revealed. From the point of view of pseudohistory matching, that result would mislead the history-matching process into an irrelevant direction. The reason for the occurrence of that artifact could be the averaging that resulted in the effect of one variable compensating for the effect of another.

Table 6-1: Expected value and standard deviation of NPV for 20 and 50 realizations.

Case	20 realizations	50 realizations
Expected Value, MM$	140	129
Standard Deviation, MM$	44	38

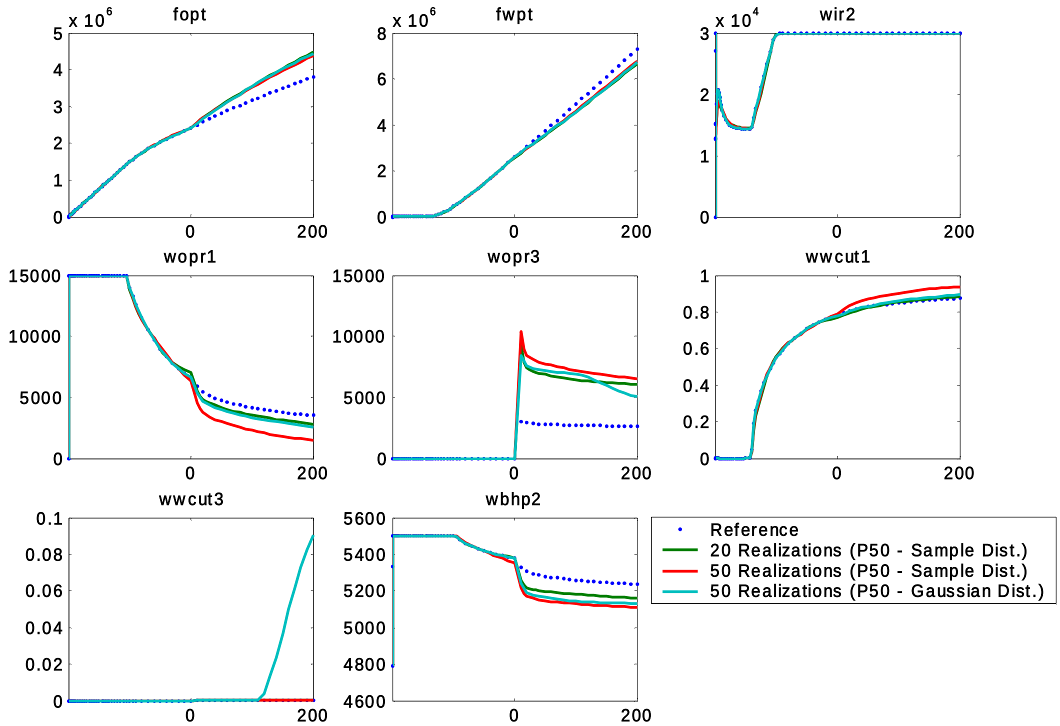

Figure 6-10: NPV and utility distribution of for 50 realizations.

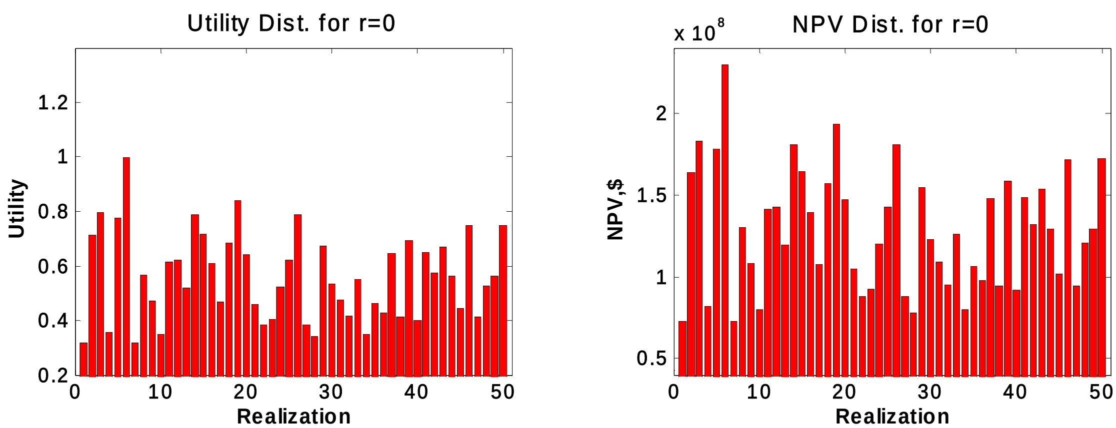

Figure 6-11: The effect of number of realizations on the predictability of pseudohistory.

6.4. Comparison of Approaches

6.4.1. Measure of Effectiveness: Perfect Information Concept

History matching is a tool to generate models with high predictive power. The predictability of the history-matched realization depends upon the degree of geological representation. In other words, the geological representation is determined by the amount of information integrated into the realization during history-matching process. Accordingly, the real objective becomes "generating models with high representative power and predictability through the integration of information" instead of blind history matching.

In this context, the possible effects and improvements of time-dependent (uncertain) information were investigated. History matching using the future history of the "reservoir", the reference model, was characterized as history matching with perfect information. This enabled us to see the best prediction that could possibly be achieved by history matching. The predictions made by perfect information were defined as the measure of effectiveness for the predictions of the proposed and the old approaches.

6.4.2. History Matching Results

In this section, the proposed and old approaches were compared based on the realizations providing predictions. The realizations of Set-A, in this test case, that were history-matched for the available (past 200 days) history are shown in the upper-left of Figure 6-12. Set-B includes the realizations that were history-matched not only for the available history (past 200 days) but also for the pseudohistory (predicted future 200 days) that includes the (uncertain) time-dependent information from the earlier decisions. The realizations of Set-B are shown in the upper-right of the Figure 6-12. Set-C includes the realizations that were history-matched for both the available history (past 200 days) and the future history (200 days) obtained by the reference model that provided perfect (certain) time-dependent information. The realizations of Set-C are shown in Figure 6-12 (lower- middle).

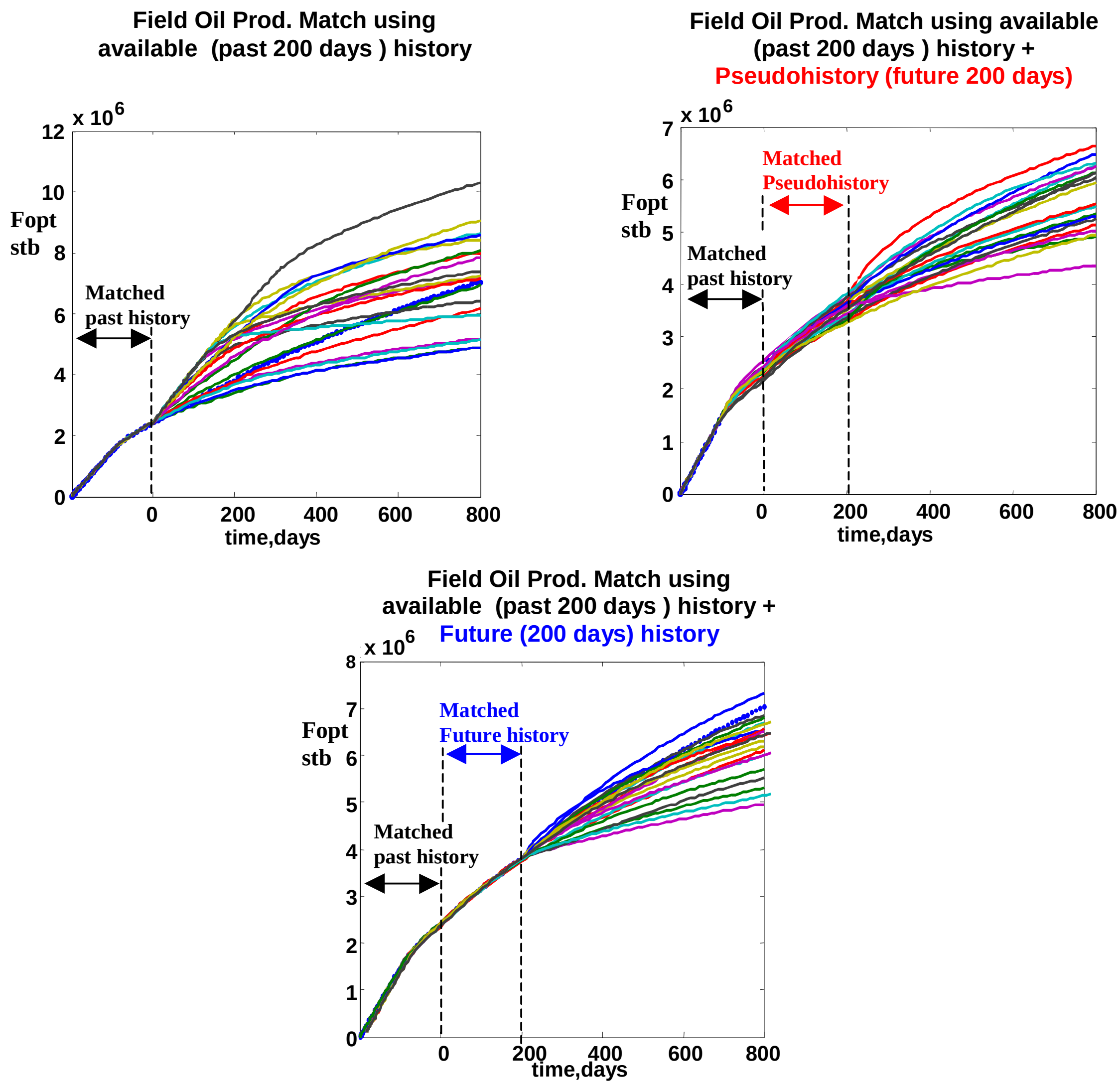

Figure 6-12: Predictions of history-matched realizations for the old approach, Set-A (upper left), proposed approach, Set-B (upper right) and the perfect information, Set-C (bottom center).

The realizations of Set-A used in the prediction of the old approach honored only the information obtained from Well#1 and Well#2. The spread (uncertainty) in the field oil production totals (fopt) of the realizations of Set-B was reduced significantly due to the inclusion of 200 days of additional (predicted) information. The maximum amount of uncertainty reduction was observed in the realizations of Set-C where perfect information was employed. The realizations of Set-B used in the new approach were similar to the ones of Set-C in that between 0-200 days the realizations of Set-B represented the actual response better, as seen in Figure 6-12. Obviously, the reduction in uncertainty was greater in the perfect information case.

6.4.3. Comparison of Utility and Prediction Power

In the previous section, it was observed that the realizations of Set-B used in pseudohistory approach were closer to those of Set-C from the reference model. To compare the prediction power, the utility and NPV distributions were examined. The NPV and utility distributions of the old and new approaches are shown in Figure 6-13. When the time-dependent information was ignored, the variability (standard deviation) of the utility distribution turned out to be 0.1898 (Table 6-2). However when new approach was used, the variability (uncertainty) of the optimum decision decreased to 0.1103. The variability (uncertainty) was calculated to be 0.1334 in the case of perfect information (Table 6-1). The proposed approach reduced the uncertainty (standard deviation) about 42% compared to the theoretical reduction if we knew the future history. An expected utility of 0.6078 was achieved by using the old approach. The proposed approach changed the expected utility from 0.6078 to 0.8627 while the best value (expected utility achieved with perfect information) that could possibly be obtained would be 0.8276. The new approach predicted NPV (150 MM $) better than the old approach (140 MM $), compared to the NPV of the perfect information case which was calculated as 149 MM $. The objective should not only be achieving higher NPV, the idea should rather be achieving more accurate predictions of NPV that probably result in higher incomes. This test case showed the trade-off between the information and the prediction power gain. As the information was injected into the system, the utility, dependent upon both the uncertainty and the NPV, increased. Although this was only the analysis of a test case, this particular comparison provided two important conclusions. The local scale conclusion is that the new approach improved not only the prediction power but also the expected utility of the individual. On the other hand, the global conclusion is that within the framework of the new approach, maximizing the expected utility of different individuals will be equivalent to placing the wells to increase both the certainty and the NPV. The certainty and NPV are improved together using the new approach.

Table 6-2: Comparison expected utility values and corresponding NPVs.

Utility	Old Approach	New Approach	Perfect Information
Exp. Value	0.6078	0.8627	0.8276
Std. Deviation	0.1898	0.1103	0.1334
NPV	140	150	149

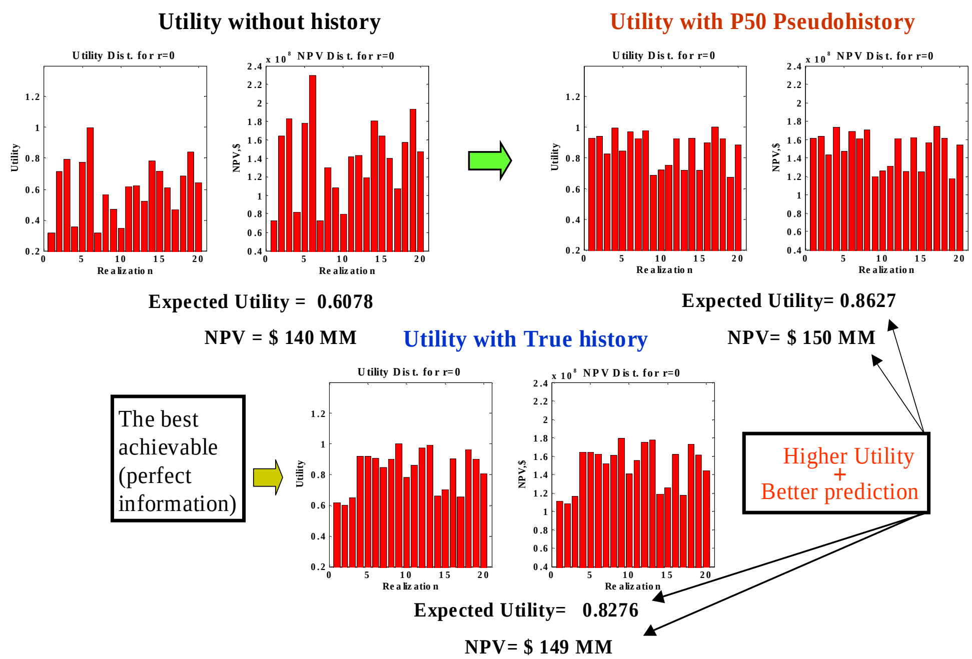

Figure 6-13: NPV and utility distributions for different approaches.

6.4.4. Utility Distribution for Different Risk Attitudes

In the previous case, the predictions were improved for a risk-neutral decision-maker by using the new approach. The risk-aversion coefficient (*r*) was changed from –10 (risk-seeking) to 10 (risk-averse) attitude to test the behavior of the utility distributions for different risk attitudes. As seen in Figure 6-14, the results showed that in the case where no time-dependent information was utilized, the uncertainty level was high. Additionally, there were big differences in the expected utility values for different risk attitudes. The results of the new approach were justified by making the comparison to the case with perfect information. When the new approach was analyzed, the 99% confidence intervals of the optimum decisions were observed to have narrowed. Also, the expected utility values became similar for different risk attitudes. The sensitivity of the expected utility of the different risk attitude decision-makers decreased with the use of the proposed approach.

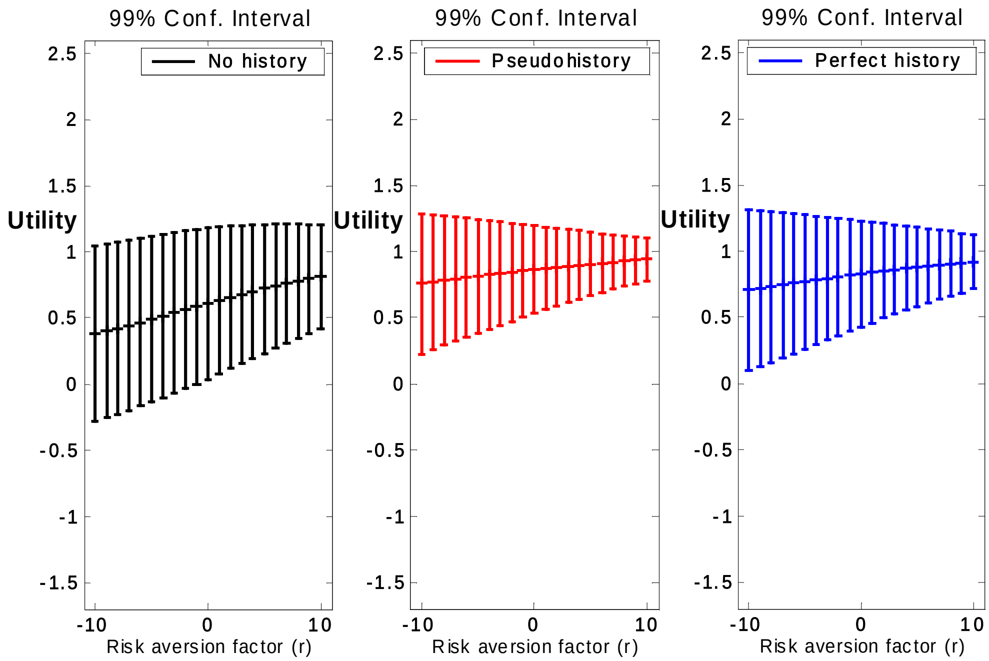

Figure 6-14: 99% confidence intervals of utility for different risk attitudes.

6.4.5. Utility Loss Function

Utility loss is defined as the difference between the utility that would be achieved with the perfect information and the utility achieved by the approach used. In Figure 6-15, the behavior of the utility loss function is shown for both approaches. The change of the utility loss with respect to risk-aversion factor is shown with the dashed line for the old approach and with the solid line for the new approach. Figure 6-15 shows the two advantages of using the new approach. The first advantage is that the overall utility loss decreased. The second advantage is that the sensitivity of the utility loss to risk attitude decreased.

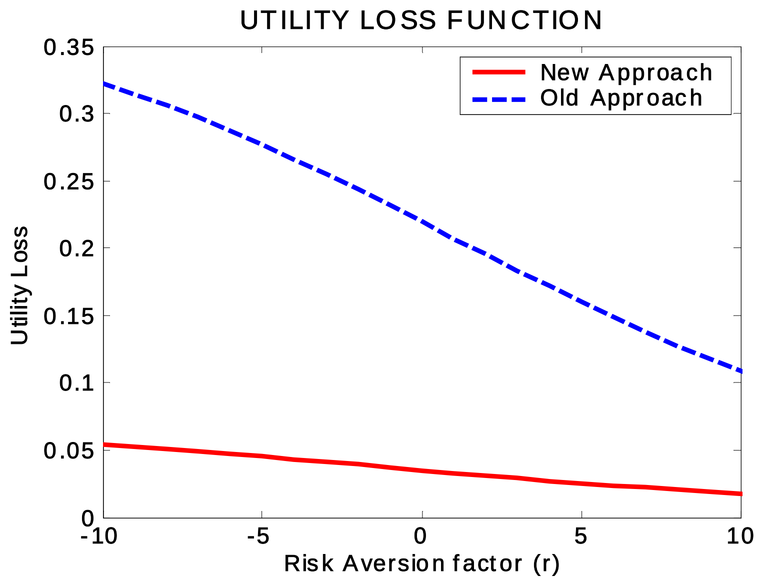

Figure 6-15: Utility loss function vs. risk-aversion coefficient.

6.4.6. Use of Proxy and its Analysis

As mentioned before, the HGA uses a kriging proxy, that decreases the required number of simulations, to accelerate the convergence process. The kriging proxy has the capability of estimating unsampled locations (the locations where no actual simulations are performed) while honoring the available *hard data* (performed simulations at sampled locations). Through the use of krgiging, the optimum point from the kriged surface is found and called the pseudomaximum. HGA performs a single simulation at the pseudomaximum to verify if the pseudomaximum is a better value than the current maximum. If this simulation reveals that the estimated point is better than the current maximum, the maximum is replaced with this point. The accuracy of the kriging proxy increases as the number of simulations increases.

It was observed that for a given set of test locations, the new approach improved the prediction power. In this part, the change of predictability for the location of Well#4 was investigated for the given location of Well#3. In Figure 6-16, the proxies constructed by simulating 56 locations are shown. The *i* and *j* axes shows the location, while the vertical axis shows the corresponding NPV estimation for that particular (*i* , *j*). The proxy that was constructed using the realizations of Set-A, overestimated and underestimated the values of particular test locations of Well#4 (upper-left of Figure 6-16) in comparison to the reference model. Overestimation and underestimation would result in an inefficient proxy. However, the proxy shown in the upper-right of Figure 6-16 constructed by the realizations of Set-B did improve the estimation capability. The overestimated and underestimated regions available in the proxy of the old approach were improved with the new approach. The essential message of this comparison is that using the new approach the predictive power improved not only for a single set of test locations of Well#3 and Well#4 but also for 56 different test locations of Well#4 for the given test location of Well#3. From the optimization point of view, the contrast between the maximum and minimum was investigated. All the NPVs of the proxy surfaces presented in Figure 6-16 were scaled with the maximum NPV of their surface. In this comparison, the true search space of Well#4 for given the test location of Well#3 was also constructed. Exhaustive simulations of Well#4 were performed and the actual search space was identified (at lower left of Figure 6-17).

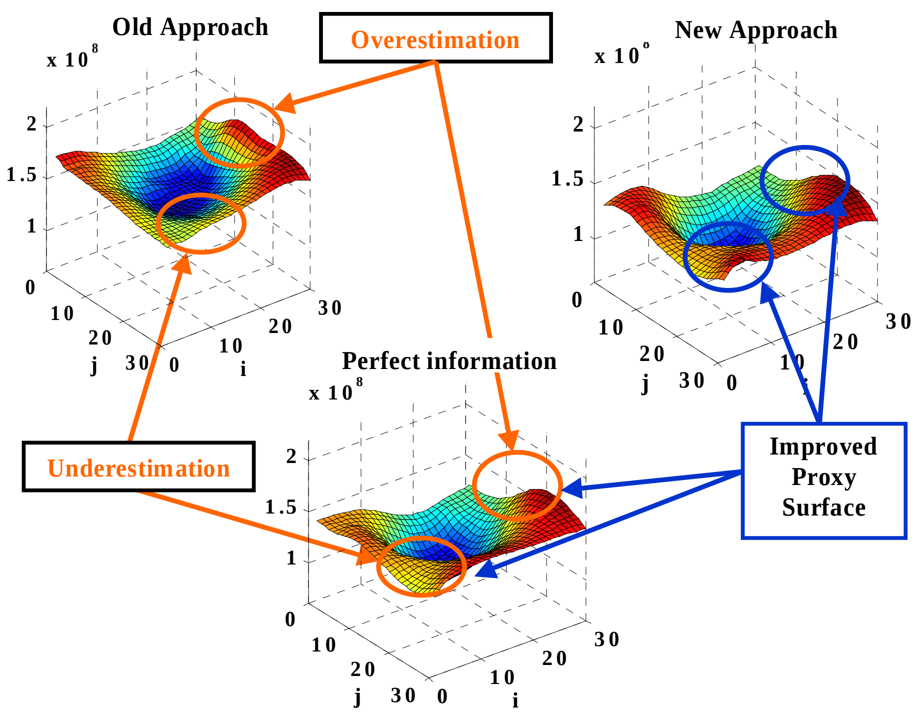

Figure 6-16: Comparison of three-dimensional proxy surfaces.

The proxy of the old approach, the new approaches, the perfect information case and the true solution surface are shown in Figure 6-17. The contrast maps provided a good idea about the structure of the search space, which is important for the polytope search and the overall optimization scheme. As seen in the upper-left of Figure 6-17, the proxy surface of the old approach is smooth. The side effects of the overestimated regions appear as high contrasts which means that optimization using the proxy surface of the old approach would tend to go to the wrong directions (overestimated regions) and cost a number of function evaluations. As can be seen from the upper-right of Figure 6-17, the new approach removed that smoothness and added "information" to the proxy. The strong characteristics of the true solution surface are shown in the lower-left of the Figure 6-17. The general trend of the actual surface is well represented by the new approach. This good representation in turn would increase the efficiency of the proxy and decrease the number of simulations required during optimization.

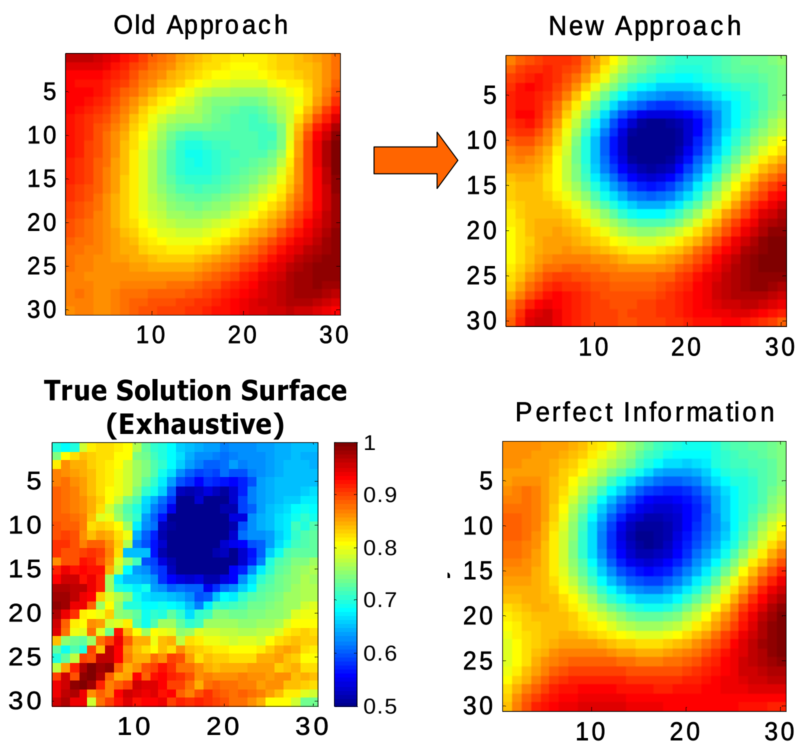

Figure 6-17: Two–dimensional proxy of the old approach (upper-left), new approach (upper-right), perfect information (lower-right) and the actual (exhaustive).

As mentioned earlier, as the number of simulations increase, the prediction power of the proxy increases because the number of data points that kriging honors increases. Knowing that the idea is the efficient use of the additional information (simulations), the

NPV loss of 28 different locations of Well#4 used by the proxy was analyzed. As shown in Figure 6-18, the NPV losses of 25 out of 28 locations were improved through the use of the new approach. This showed that it is highly probable to achieve smaller NPV loss if time-dependent information is utilized. Knowing that the proxy construction is a sequential process, each prediction is affected by the previous prediction to some degree. In other words, overprediction or underprediction results in a loss in later predictions. To screen the effect of wrong predictions through time, the absolute cumulative NPV gain by using the new approach is plotted in Figure 6-19. The NPV gain was observed to increase exponentially as the number of simulations increased. This shows that the NPV gain by using the new approach increases significantly as the new information is added to the system.

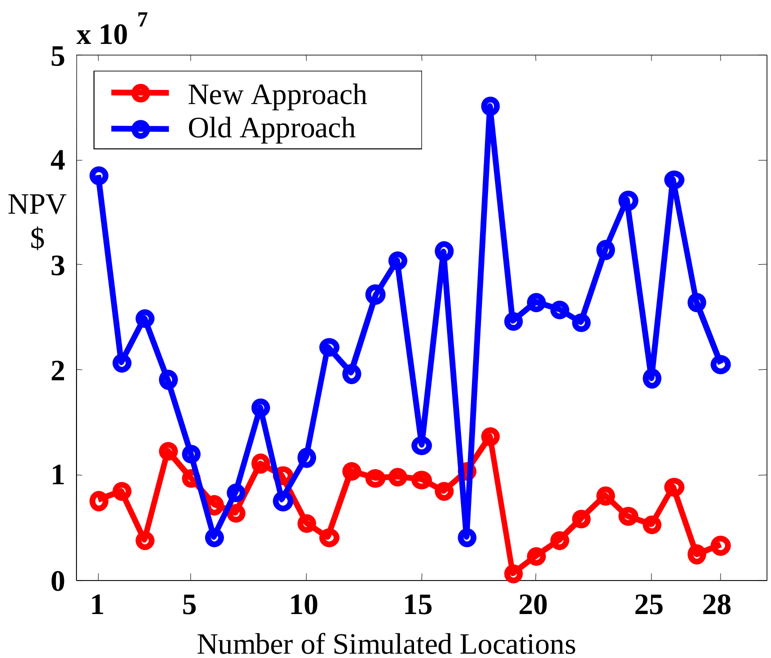

Figure 6-18: NPV loss vs. number of simulated locations.

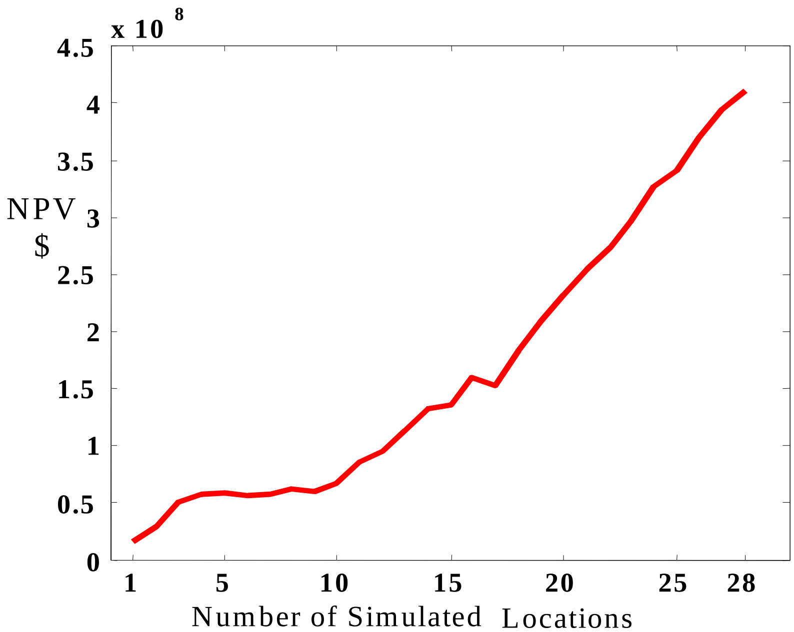

Figure 6-19: Absolute cumulative NPV gain vs. number of simulated locations.

6.5. Remarks

The perfect information case acted as an appropriate benchmark in terms of comparison because it shows the best attainable result by using time-dependent information. The test case provided a good insight for the possible improvements in prediction power by using the new approach. The pseudohistory approach proved its usefulness by coming close to the "perfect information" benchmark.

Chapter 7

7. Full Optimization of Well Placement

In this chapter, the results of the well placement optimization using the proposed approach are presented. Optimization is analyzed in two main cases. In the first case, optimization of well placement is performed for the risk-neutral attitude and the results of the alternative approaches are discussed.

7.1. Why Optimization?

The objective of the example is to find the optimum the optimum location of Well#3 and Well#4. Since the wells are vertical, the location problem turns into finding an *i* and a *j* index for each well, Well#3 and Well#4. In order to find the exact optimum solution, one should consider all of the possibilities available in the search space. The search space of this type of sequential placement problem can be formulated as in Eq. 7.1.

$$\begin{aligned} &\textit{Search Space} = Nw \times \prod_{w_i=0}^{Nw-1} [(Nx \times Ny) - (Nw + w_i)] \\ &Nw = \textit{Number of optimized wells} \\ &Nx = \textit{Number of grid blocks in x - direction} \\ &Ny = \textit{Number of grid blocks in y - direction} \\ &wi = \textit{index} \end{aligned} \qquad \textbf{(7.1)}$$

For the problem considered, the variables in Eq. 7.1 were $Nw = 2, Nx = 30, Ny = 30.$, so the search space was calculated as follows:

$$Search\ Space = 2 \times \prod_{w_i = 0}^{1} [(30 \times 30) - (2 - w_i)] = 2 \times 898 \times 897 = 1{,}611{,}012 \text{ points}$$

Finding the true optimum solution for the problem would require 1,611,012 objective function evaluations. From the simulation point of view, it was computationally infeasible to perform that many simulations given the time frame of the problem. Accordingly, the necessity and motivation of the usage of an optimization algorithm for finding the optimum location of the wells became clear.

7.2. Case Specifications

In this example case, optimization of well placement was performed for the risk-neutral attitude. Optimization parameters, which are shown in Table 7-1, were determined considering the specifications and computational constraints on the problem. The stopping criterion was selected as ten generations of the HGA. Crossover probability (p_c) and mutation probability (p_m) that control the diversity of the individuals within the population were determined as 0.8 and 0.25. Rank-based selection, in which the rank of the individuals in the population determines its fitness, was used. Rank-based selection enabled the elimination of unfavorably scaled fitness values. For each approach, eight realizations of the reservoir were used during the optimization process. Economic parameters are shown in Table 7-2.

Table 7-1: Optimization parameters.

Population size	15
Crossover probability	10
Mutation probability	0.8
Selection type	0.25
Decision criterion	rank-based
Risk attitude	risk-neutral

Table 7-2: Economic parameters.

Annual interest rate (fraction)	0.1
Oil price ($/bbl)	30
Water handling cost ($/bbl)	3
a for r = 0	0
b for r = 0	1
a for r = 1	1
b for r = 1	-1
Constant for NPVscaled (MM$)	300

7.3. Optimization Results with Pseudohistory

Using the specified optimization parameters, an optimization run was performed using the proposed approach. A summary of the optimization run is tabulated in Table 7-3. The minimum, average and maximum utility values of the last generation of the optimization run are seen. The optimum locations of Well#3 and Well#4 correspond to the individual that had the highest utility in the last generation. The highest utility value achieved (0.7038) was provided by the locations of (1,15) for Well#3 and (20,30) for Well#4. That maximum utility of 0.7038 has an equivalent of 211 MM$ of NPV for the risk-neutral case.

Table 7-3: Summary of the optimization runs using the new approach and optimum locations Well#3 and Well#4.

Minimum Utility	0.3725
Average Utility	0.5561
Maximum Utility	0.7038
Well#3	(1,15)
Well#4	(20,30)
Maximum NPV (MM$)	211.1

As should be remembered, in this approach the optimum location configuration was found considering eight different realizations, all of which honor not only the past 200 days of history but also the 200 days of pseudohistory modeled by time-dependent information. This optimization run provided the optimum location of Well#4, (20,30) considering the production history of Well#3 (1,15). The permeability maps of the realizations of Set-B that were generated by the inclusion of time-dependent information of Well#3 are shown in Figure 7-1. The reference model is also shown in the bottom of Figure 7-1. As proposed by the new approach, in the neighborhood of the location of Well#3, (1,15), the permeability values of the realizations of Set-B turned out to be closer to those of the reference model. That means that the inclusion of the production history of Well#3 resulted in improvements in the geological representation in most of the realizations. The pseudohistory generated and used for the best scenario of the proposed approach was selected based on the NPV distribution obtained by the realizations of Set-A.

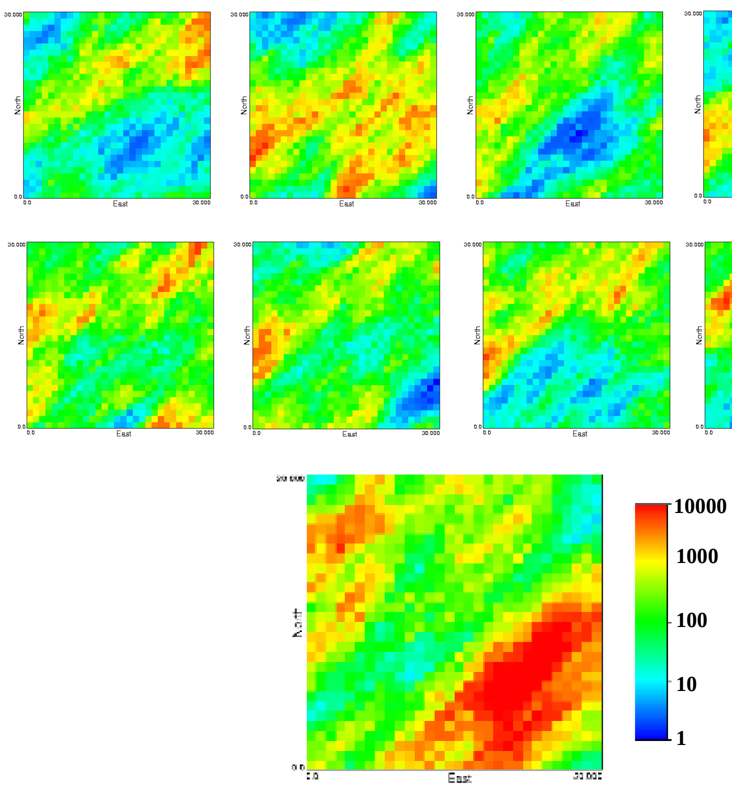

Figure 7-1: The permeability maps of the history-matched realizations generated by matching the pseudohistory are shown in the first and second row together with the reference model shown in the bottom.

Using the pseudohistory, history matching was performed and the uncertainty in the flow response was reduced considering the time-dependent information of Well#3. The field oil production total (fopt) and field water production total (fwpt) predictions of the realizations are shown in Figure 7-2. In the upper part of the Figure 7-2, fopt and fwpt before history matching are shown. As seen in Figure 7-2, the spread in both of the production responses (fopt and fwpt) reduced. As can be seen from Figure 7-3, the optimum well configuration sweeps the oil efficiently in each realization of Set-A. Knowing the objective of maximizing the utility, the optimization that provided the highest utility was studied in more detail. The overall sweep of each realization were also quite different which in turn caused in the deviations in NPV and utility calculation (Figure 7-3).

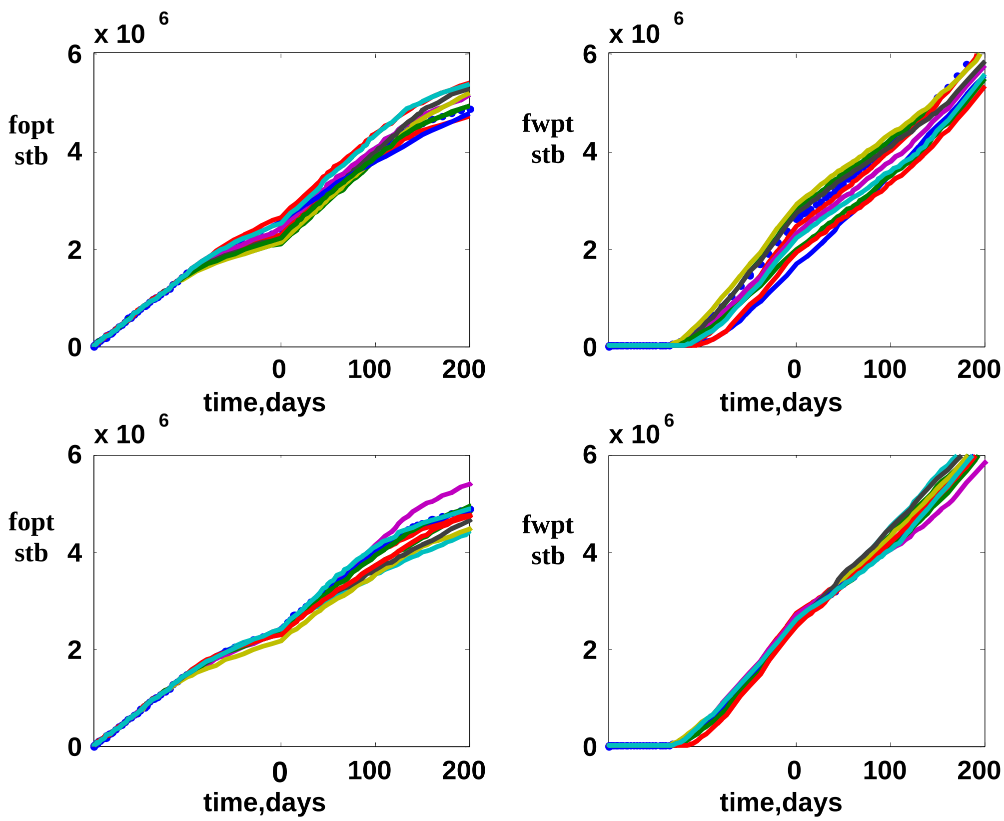

Figure 7-2: Field oil production total (fopt) and field water production total (fwpt) of the realizations before match (upper figures) and after match (lower figures).

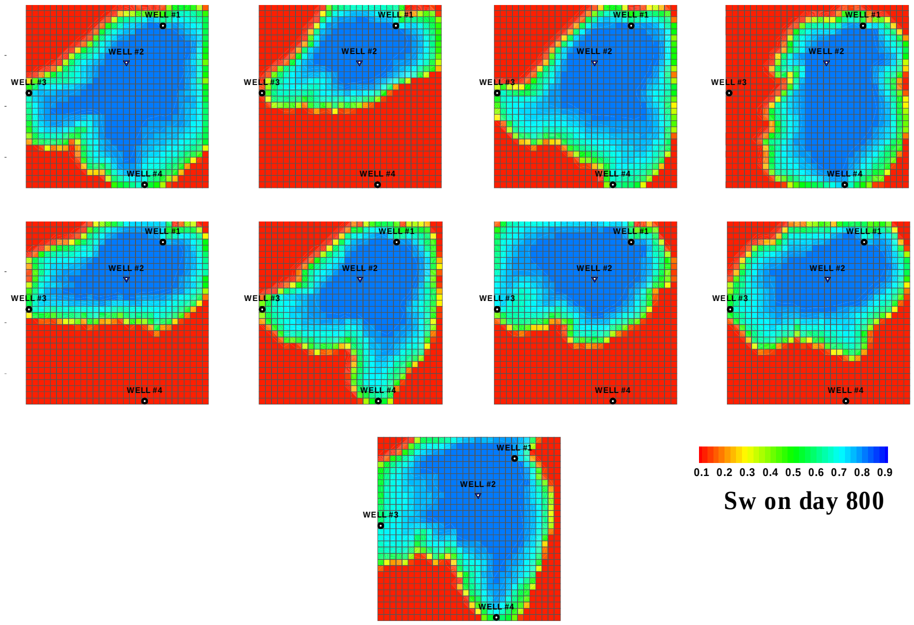

Figure 7-3: Saturation map of the different realizations and the reference model (bottom) for the optimum Well#3 at (1,15) and Well#4 at (20,30).

7.4. Optimization Results with Future (Perfect) History

Having examined the results of the proposed approach, the optimization was repeated using the true future history using the realizations of Set-C instead of Set-B. As mentioned earlier, the production information of Well#3 is integrated into the optimization scheme by matching the true future history of the reservoir as opposed to matching pseudohistory as in the proposed approach. Most of the minimization of the mismatch was observed to occur in the first 10 iterations (Figure 7-4). As a result of optimization, the highest utility value of 0.7414 was achieved by the locations of (28,30) for Well#3 and (18,23) for Well#4. This best configuration has an NPV equivalent of 222.4 MM $. For this case, the individual that has the minimum, the maximum and the average utility at the last generation are listed in Table 7-4. Matching the “future” response of the reference model enabled us to achieve the best history–matched realizations. If the optimum well locations of the best scenario were considered, the oil production rates of Well#1 and Well#3 in the realizations of Set-C are shown in Figure 7-5. Matching the “future” response of the reference model enabled us to achieve the best history–matched realizations.

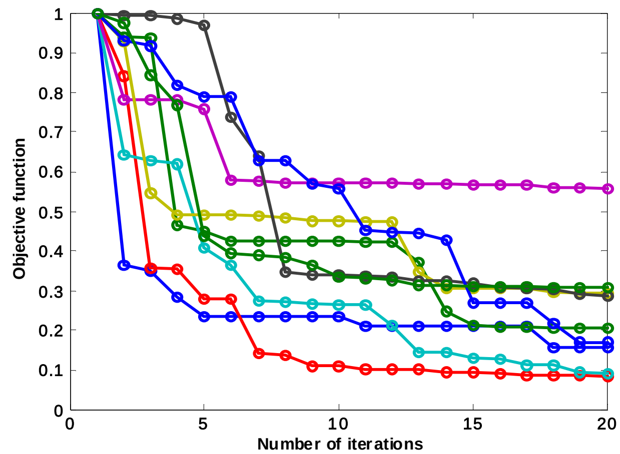

Figure 7-4: Objective function versus iteration for the history matching each of the realizations.

Table 7-4: Summary of the optimization run for the perfect information case.

Minimum Utility	0.4388
Average Utility	0.5895
Maximum Utility	0.7414
Well#3	(28,30)
Well#4	(18,23)
Maximum NPV (MM$)	222.4

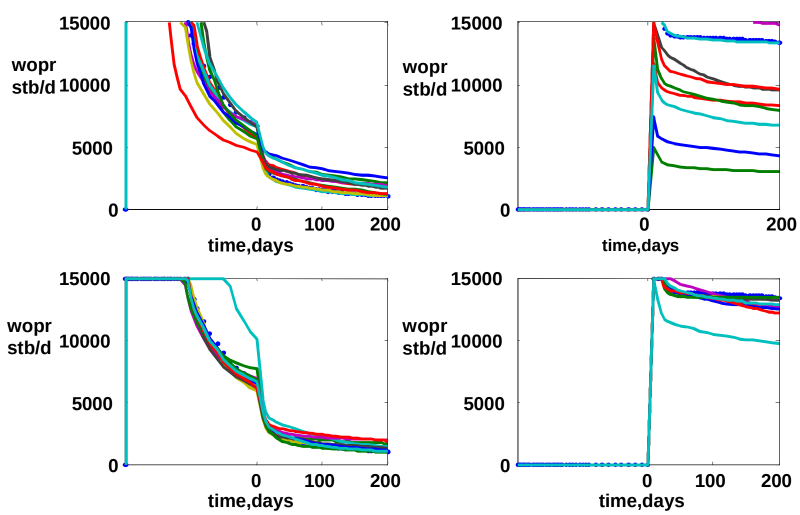

Figure 7-5: Well oil production rate (wopr) of Well#1(upper-left) and Well#3 (upper-right) before and after matching future history (lower figures).

7.5. Optimization Results without Future History

In this case, well optimization was performed using the old approach which uses only the realizations of Set-A throughout the optimization process. Due its computational load, five optimization runs were conducted to find the optimum well configuration. Maximum utility achieved was 0.6067. The optimum well location was output as (2,22) for Well#3 and (22,30) for Well#4 from the best optimization case. The results of the different optimization runs are shown in Table 7-5. Some of the optimization runs e.g: Run-1, Run-2 resulted in similar optimum locations for both wells that in turn caused the achievement of similar NPV values of 182 and 181 MM$.

Table 7-5: Summary of the optimization runs for the old approach.

	Run-1	Run-2	Run-3	Run-4	Run-5
Minimum Utility	0.1937	0.4158	0.3946	0.4797	0.4652
Average Utility	0.4647	0.5309	0.5165	0.5326	0.5260
Maximum Utility	0.6067	0.6035	0.5914	0.5907	0.5835
Well#3	(2,22)	(3,22)	(2,19)	(1,19)	(24,27)
Well#4	(22,30)	(23,30)	(27,28)	(22,29)	(3,21)
NPV (MM$)	182.0	181.0	177.4	177.2	175.0

7.6. Optimization on the Reference Model

All approaches were applied using multiple realizations of the reservoir in an effort to predict the true optimum in the real reservoir. Having the reference model provided the advantage of finding the optimum on the true reservoir. However, due to the large search space of the problem mentioned in Section 7.1, it was not computationally feasible to perform exhaustive simulations. Accordingly, deterministic optimization was performed on the reference model ten times to find, hopefully, the true optimum. In Table 7-6, the summary of the optimization runs is tabulated. The best well locations that provided a utility value of 0.8345 (NPV = 250 MM$) were found as (4,28) for Well#3 and (2,19) for Well#4. 126.2 simulations on average were performed in ten generations of the HGA. The utility values of the minimum, the maximum and the average were plotted for each of the optimization runs as shown in Figure 7-6.

Table 7-6: Summary of the optimization runs on the reference model.

Well#3 (Best)	(4,28)
Well#4 (Best)	(2,19)
Maximum Utility	0.8345
Average Utility	0.8087
Average Number of simulations	126.2
Std,. Dev. of Utility	0.0363

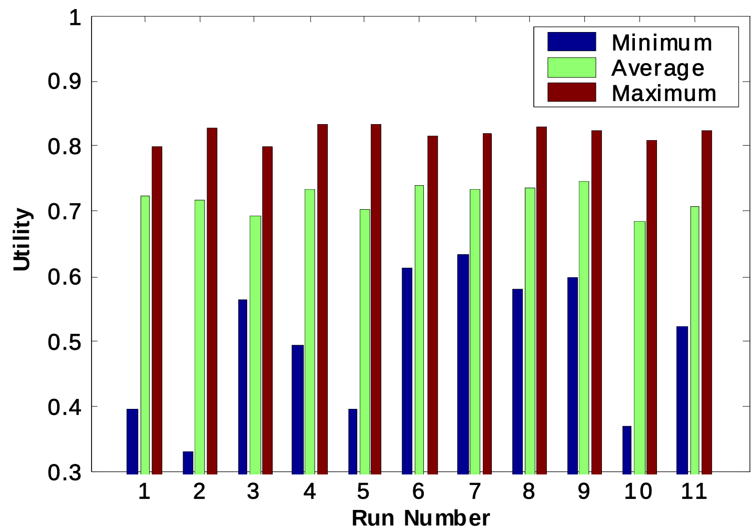

Figure 7-6: The minimum, maximum and the average individual of the last generation for each of the optimization runs.

The trend of the minimum, maximum and the average individual of the best optimization run (Run-4) are shown in Figure 7-6. The maximum increased very quickly whereas the average of the population increased gradually. The minimum individual oscillated about the utility level of 0.15. In terms of global optimization purposes, increasing the minimum was not desirable to prevent convergence to a local minimum. If the difference between the maximum and the minimum became smaller, that would mean that the variability of the population would be less. The progress of the optimization is shown in Figure 7-8 in the saturation maps for different generations of the best optimization case. As can be seen from Figure 7-8, in the first generation the HGA luckily found good locations. In the 3rd generation (upper-left of Figure 7-8), HGA moved Well#3 to a relatively farther location while moving Well#4 to a closer position. That small fine-tuning resulted in a 200 M$ increase in the NPV from the initial generation to the 3rd

generation. In the later generations the HGA placed both wells in the high permeability zones, which caused an additional 400 M$ in the NPV. In the last generation the optimum location of the wells stabilized in the locations that maximized the overall sweep efficiency. This enabled the achievement of a final NPV value of 250 MM$.

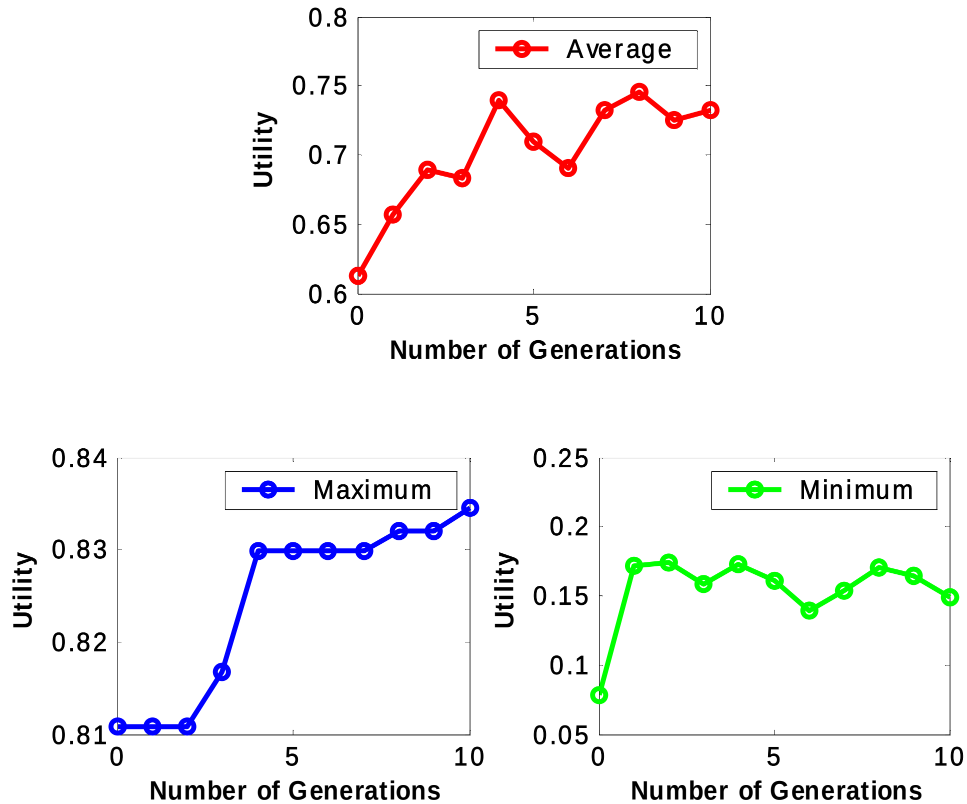

Figure 7-7: Minimum, maximum and average individual of Run-4.

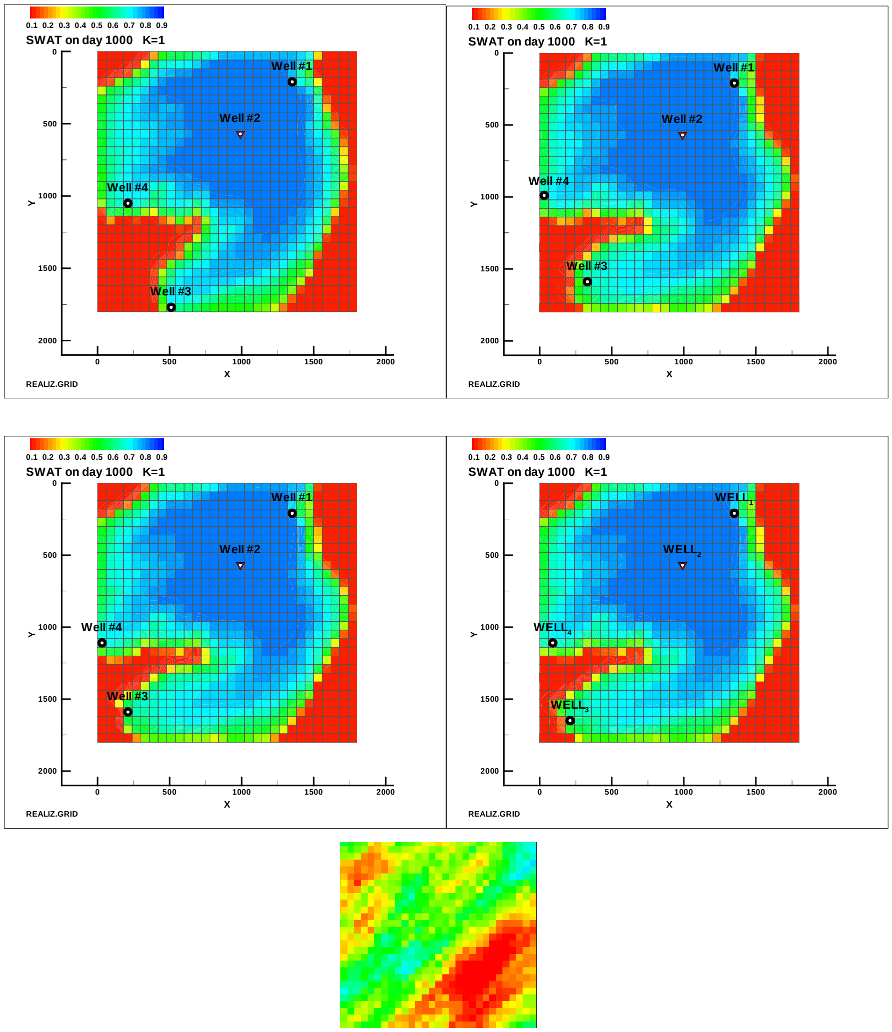

Figure 7-8: Best individuals of the 1st generation (upper-left), 3rd generation (upper-left), 5th generation (lower-left) and 10th generation (lower-right) on the saturation map of the reference model. The permeability map of the reference model in the bottom. Red zones show high permeable zones whereas green zones show low permeable zones.

7.7. Comparison of the Approaches

The main motivation of using the new approach is to characterize and utilize the time-dependent information to make the later decisions with greater certainty. In the scenario considered, Well#3 was the source of the time-dependent information to improve the decision of Well#4. The comparison between the new and the old approach was performed in terms of relative uncertainty reduction, the expected utility and the predictive capability. In this part of the comparison, the optimum well locations found by the two approaches were placed on the realizations of Set-A. At first the mean and the standard deviation of NPV were calculated to quantify the uncertainty level. This stage basically represented the initial level of uncertainty of NPV for the given location of Well#3. The standard deviations of the NPVs were found to be 43.5 MM$ for the new approach and 49 MM$ for the old approach (Table 7-7). The mean NPV of the old approach, 152 MM$ was higher than that of the new approach, 142 MM$. To eliminate the effect of mean on the uncertainty level, coefficients of variation that are found by scaling the standard deviations with the means, were calculated. In the next step, the optimum Well#4 locations found by both approaches were placed in each realization of Set-A and the mean and standard deviation of the NPVs were calculated again. As seen from Table 8, the relative uncertainty reduction using the new approach, 13.06 %, was twice as much as the reduction, 5.25 %, using the old approach. The optimizations using both approaches showed that the expected utility of the project increased from 0.6067 to 0.7038 with the inclusion of time-dependent information. The increase in the utility and relative uncertainty reduction showed that usage of the time-dependent information may result in significant improvement in the utility of the project.

Table 7-7: Summary of the uncertainty level of the NPV for the old and the new approach.

	New approach	Old approach
Mean NPV, 200d	141830000	152120000
Std. dev. NPV, 200d	43542000	48788000
Std.dev./mean NPV, 200d	0.31	0.32
Std.dev./mean NPV, 800d	0.27	0.30
Relative Reduction (%)	13.06	5.25
Optimization Outputs	0.7038	0.6067

Prediction Capability

In order to understand how well both approaches did in terms of optimization, the optimum well locations of the both approaches were placed in the reference model. In Figure 7-9, the saturation maps at 800 days show the optimum locations of the wells provided by the two approaches. The areal sweep was better for the case of the new approach. Although the optimum locations looked very similar, the difference in the sweep resulted in a significant increase of NPV from 213.5 MM$ to 230 MM$ while the best wells of the true model provided 250 MM$ (Table 7-8). As understood from this section, time-dependent information not only reduced the uncertainty but also improved the prediction capability of the optimization scheme.

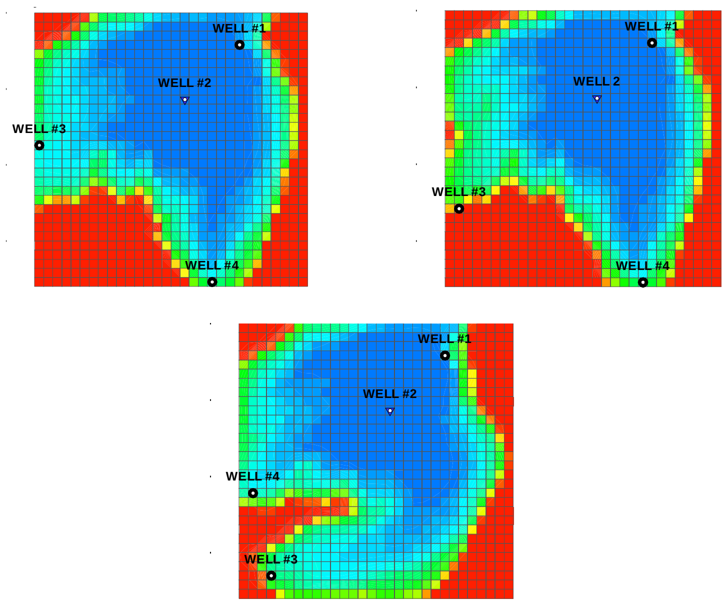

Figure 7-9: Optimum wells of the new approach (upper-left), old approach (upper-right) and true model on the saturation map of the reference model on day 800.

Table 7-8: True solution and the predictions and coressponding optimum location of the wells for both approaches.

Optimization Results	NPV (MM$)	Well#3	Well#4
Reference Model	250.3	(4,28)	(2,19)
New Approach	232.8	(1,15)	(20,30)
Old Approach	213.5	(2,22)	(22,29)

Chapter 8

8. Concluding Remarks

8.1. Concluding Remarks and Observations

Knowing the importance and the "utility" of the production information to the well placement design, a new approach that utilizes the time-dependent information was developed and integrated into an existing optimization algorithm. The new approach has the capability to model the uncertainty of the flow response of the reservoir in an automated manner. The approach has a dynamic structure so that it can create the CDF of the flow parameters e.g. watercut, oil production rate whenever a new test location is proposed. Not only does the new approach maximize the recovery of oil but it also improves the sequential decisions by maximizing the prior information level.

The following important improvements were achieved through the use of "pseudohistory" concept:

1. Considering a sample pair of test locations, the proposed approach improved the uncertainty (standard deviation) about 14% in absolute terms. The expected utility of the individual increased from 0.6078 to 0.8627 while the best value (expected utility achieved with perfect information) that could possibly be obtained would be 0.8276.

The utility increased as the prediction power increased with the decreasing uncertainty.

2. The sensitivity of the utility loss with respect to risk-attitude decreased with the use of new approach.

3. The proxy of the new approach represented the perfect information closely enough that given the test location of Well#3, 25 out of 28 simulation of location resulted in NPV gain.

4. Full optimization of well placement with the new approach provided well locations that increased the amount of certainty about 100% compared to the old approach.

5. The utility of the overall optimization improved and supported the conclusions made at the individual scale in that the expected utility increased from 0.6067 to 7038 while the utility of the perfect information case was 0.7414. NPV predictions of the old approach were improved 16% while the maximum possible amount of improvement would be 23%.

In summary, the results of this study showed that the inclusion of time-dependent uncertainty during well placement is a better strategy than ignoring the dynamic information flow into the system.

8.2. Future Work

The new approach includes recursive history-matching procedures. Therefore the computational time of the optimization increases significantly due to the number of history-matching steps. Any history-matching algorithm that reduces the computational load would help to extend the applicability of the research.

Nomenclature

t	=	Time
i	=	I index of the location
j	=	J index of the location
ρ	=	Deformation parameter
ce	=	Certain Equivalent
w_o	=	Initial wealth
Δ	=	Change in the monetary amount
U	=	Utility
NPV	=	Net present value
a	=	Constant in utility equation
b	=	Constant in utility equation
c	=	Constant in utility equation
x	=	Monetary value
R	=	Risk odds
r	=	Risk-aversion coefficient
p_i	=	Probability that event i occures
$OPEX$	=	Operating expenditures
$CAPEX$	=	Capital expenditures
P_m	=	Mutation probability
p_c	=	Crossover probability

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Appendix A

A. Program Details for the New Approach

Multiplacement with pseudohistory (MPH) is an approach that enables the optimization of the location of sequential wells including time-dependent information. The approach embeds recursive history-matching steps into the optimization algorithm (HGA) to output the optimum well configuration.

A.1 MPH parameter file and the definition of keywords

MPH provides the ability to perform optimization in a user-defined mask.

What is a mask?

The mask is a file that defines the feasible well locations. In this file, infeasible well locations are specified with 0 and feasible well locations are specified by 1. This mask prevents the MPH to put the wells in an aquifer or in dead cells during the producer search.

A.1.1 Keywords

Optimize_Option ***Value***

Value = 0, optimize locations without using pseudo/future history.

(value should be set to 0 to use the database of the pseudohistory.)

Value = 1, optimize locations using history.

Use_Pseudo_history ***Value***

Value = 0, Use perfect history (for optimize_option=1).

Value = 1, Use pseudohistory.

Value = 2, Use pseudo history from the database (exhaustive dataset).

Zvalue_for_pseudohistory ***Value***

Value = The Z standard normal random variable corresponding to the target probability (eg:0 for P50 case).

Number_of_realizations(nr) **Value**

Value = Number of realizations to be used in optimization.

realization_name **Value**

Value = Name of the include file that contains the permeability values of the realization for the simulation model (Eclipse 100 format). This keyword should be repeated as the number of realizations specified.

Number_of_wells_to_be_optimized **Value**

Value = Number of wells to be optimized.

Use_Utility_Framework **Value**

Value = 0, Perform NPV based optimization.

Value = 1, Perform utility based optimization.

NX ***nx***

nx = Number of grid blocks of the simulation model in x-direction

NY ***ny***

Ny = Number of grid blocks of the simulation model in y-direction

NZ ***nz***

nz = Number of grid blocks of the simulation model in z-direction

Total_number_of_wells ***existing_wells_no***

existing_wells_no = total number of wells exists in the model.

Well ***v1 v2 v3 v4 v5 v6 v7 v8 v9 v10 v11 v12 v13 v14..v15 v16 v17 v18 v19 v20.***

NOTE: All values (v1 to v20) should be in the same line

v1 = Name of the well.

v2 = 0 if the well is not optimized, 1 if the well is optimized.

v3 = i index of the location of the well.

v4 = j index of the location of the well.

***v5* =** *k1 index (upper)completion of the well.*
***v6* =** *k2 index (lower) completion of the well.*
***v7* =** Datum depth of the reservoir**.**
***v8* =** Type of the fluid (WATER for injector or OIL for producer.
***v9* =** Status of the well.
***v10* =** Control status of the well (OPEN or SHUT) **.**
***V11* =** Saturation table number for connection relative permebilities (see COMPDAT keyword in Eclipse 100 Reference Manual).Default is 0.
***V12* =** Transmissibility factor for connection . Default is -1.
V13 = wellbore diameter.
v14 = Group name of the well.
V15 = status of the well.
V16 = control mode.
V17 = Oil Rate target.
V18 = multiplier (4 for producer and oil rate target, 3 for injector and rate target).
V19 = BHP target.
V20 = time of the well opening**.**
V21 = cost of the well.

Include_file_name_1 ***file_name***
file_name = Name of the file that contains keywords and values regarding WELSPECS(ECLIPSE 100).

Include_file_name_2 ***file_name***
file_name = Name of the file that contains keywords and values regarding COMPDAT(ECLIPSE 100).

Include_file_name_3 ***file_name***
file_name = Name of the file that contains keywords and values regarding WCONPROD(ECLIPSE 100).

Include_file_name_4 ***file_name***
file_name = Name of the file that contains keywords and values regarding WCONINJ(ECLIPSE 100).

Include_file_name_5 ***file_name***
file_name = Name of the file that contains keywords and values regarding WCONPROD(ECLIPSE 100).

Include_file_name_6 ***file_name***
file_name = Name of the file that contains keywords and values regarding RUNSUM(ECLIPSE 100).

Active_mask_file_name ***file_name***
file_name = Name of the file that contains the feasible well locations.

CAPEX ***Value***
Value = Capital Expenditures ($).

OPEX ***Value***
Value = Operating Expenditures ($).

Rate ***Value***
Value = Annual interest rate (fraction).

Oil_price ***Value***
Value = Price of oil ($ per bbl).

Gas_price ***Value***
Value = Price of Gas ($ per bbl.

Water_handling_cost ***Value***
Value = Water handling cost ($ per bbl).

a_for_r_eq_0 ***Value***
Value = Capital Expenditures ($).

b_for_r_eq_0 ***Value***
Value = Capital Expenditures ($).

a_for_r_eq_0 ***Value***
Value = Capital Expenditures ($).

b_for_r_eq_0 ***Value***
Value = Capital Expenditures ($).

r_(risk_aversion_coefficient) ***Value***
Value = Capital Expenditures ($).

Scaler ***Value***
Value = Arbitrary value to scale NPV values ($).

No_time_interval ***Value***
Value = Number of time intervals for the sequential wells to be drilled.

Production_time_days ***Value***
Value = Production time of each wells.

Time_step ***Value***
Value = Time step interval between each well (days).

`No_time_step` ***`Value`***

`Value` `= Number of time steps for each time interval.`

Example MPH Parameter File

```
-------------------------------------
Stanford University
Department of Petroleum Engineering
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Umut Ozdogan
-------------------------------------
WELL OPTIMIZATION PARAMETER FILE
-------------------------------------
Optimization Options
-------------------------------------
Optimization_Option                 0
Use_pseudo_history                  2
Zvalue_for_pseudo_history           1
Number_of_realizations(nr)          3
realization_name                    realf_ecl_1.out
realization_name                    realf_ecl_2.out
realization_name                    realf_ecl_3.out
Number_of_Wells_to_be_optimized     2
Use_Utility_Framework               1
---------------------------------------
Model Size
---------------------------------------
NX                                                     30
NY                                                     30
NZ                                                     1
------------------------------------
WELL DATA FOR SIMULATION MODEL
------------------------------------
Total_Number_of_Wells                     4
Well_1   WELL_1  0 23  4 1  1  8450   OIL   OPEN 0 -1 0.5 G OPEN  ORAT 15000 4 4000 100 0
Well_2   WELL_2  0 17  10 1  1  8450  WATER OPEN 0 -1 0.5 G OPEN  BHP 30000 3 5500 200 0
Well_3   WELL_3  1  4  24 1  1  8450   OIL   OPEN 0 -1 0.5 G SHUT  ORAT 15000 4 4000 300 0
Well_4   WELL_4  1  0   0 1  1  8450   OIL   OPEN 0 -1 0.5 G SHUT  ORAT 15000 4 4000 300 0
------------------------------------
INCLUDE FILES
-------------------------------------
Include_file_name_1              WELSPECS.INC
Include_file_name_2              COMPDAT.INC
Include_file_name_3              WCONPROD.INC
Include_file_name_4              WCONINJ.INC
Include_file_name_5              WCONPROD2.INC
Include_file_name_6              RUNSUM.INC
Active_mask_file_name            active_mask3.txt
-------------------------------------
ECONOMICAL PARAMETERS
-------------------------------------
CAPEX                         0
OPEX                          0
RATE                          0.10
OILPRICE                      30
GASPRICE                      1
WATERPRICE                    -3
-------------------------------------
UTILITY FRAMEWORK PARAMETERS
-------------------------------------
a_for_r_eq_0                              0
b_for_r_eq_0                              1
a_for_r_Not_eq_0                          1
b_(should_be_positive_for_r_Not_eq_0)    -1
r_(Risk_aversion_coefficient)             0
scaler(arbitrary_for_NPV)         1000000000
------------------------------------
PRODUCTION INFORMATION
------------------------------------
No_time_interval                 3
Production_time_days             200 400 1000
time_step                        10  10   10
```

```
number_of_timesteps            20  20   60
```

Important Note

In order to achieve the most applicable and profitable field development scenario, it is recommended to be careful while constructing the optimization set-up. The optimization set-up consists of five major steps which are:

1. Preparation of the MPH parameter file.

2. Preparation of the data file of the simulation model to be optimized.

3. Preparation of HGA parameter file.

4. Preparation of the active mask.

1. Preparation of MPH parameter file

In this step, a determination is made as to which parameters to optimize, and the necessary changes are made in the parameter file.

2. Preparation of the deck of the simulation model to be optimized

In this step, the data file is prepared by specifying the include files in proper locations within in the deck. The multiplacement with pseudohistory approach basically creates six major include files:

WELSPECS.INC, COMPDAT.INC, WCONPROD.INC, WCONINJ.INC, and RUNSUM.INC which include the information about the well definition, completion and RATE AND BHP constraints of the wells. The following example shows the prepared deck, the include files and their content. For more information, see WELSPECS, COMPDAT, WCONPROD, WCONINJ, RUNSUM.

Example deck for optimization

```
RUNSPEC

DIMENS
30 30 1/

OIL
WATER

FIELD

TABDIMS
-- NTSFUN  NTPVT  NSSFUN  NPPVT  NTFIP
     1        1       16       12     /
WELLDIMS
-- MaxNo  MaxPerf  MaxGroup MaxWell/Group
     5      100        5         5 /

-- Specify the starting date of the simulation
START
  1 'JAN' 2000 /

NSTACK
30 /
UNIFOUT

GRID    ================================================================
-------- IN THIS SECTION , THE GEOMETRY OF THE  SIMULATION GRID AND THE
-------- ROCK PERMEABILITIES AND POROSITIES ARE DEFINED.
------------------------------------------------------------------------
--  THE X AND Y DIRECTION CELL SIZES ( DX, DY ) AND THE POROSITIES ARE
--  CONSTANT THROUGHOUT THE GRID. THESE ARE SET IN THE FIRST 3 LINES
--  AFTER THE EQUALS KEYWORD. THE CELL THICKNESSES ( DZ ) AND
--  PERMEABILITES ARE THEN SET FOR EACH  LAYER. THE CELL TOP DEPTHS
--  ( TOPS ) ARE NEEDED ONLY IN THE TOP LAYER ( THOUGH THEY COULD BE.
--  SET THROUGHOUT THE GRID ). THE SPECIFIED MULTZ VALUES ACT AS
--  MULTIPLIERS ON THE TRANSMISSIBILITIES BETWEEN THE CURRENT LAYER
--  AND THE LAYER BELOW.
--     ARRAY  VALUE     ------- BOX ------

INIT

GRIDFILE
1/

EQUALS
      'DX'    60      /
      'DY'    60      /
      'PORO'  0.2 /

      'TOPS' 8325       1 30 1 30 1 1/
      'DZ'    200        1  30  1  30  1  1  /
--      'MULTZ' 0.3  /
/       EQUALS IS TERMINATED BY A NULL RECORD
INCLUDE
        'reference.out'  /

-- THE Y AND Z DIRECTION PERMEABILITIES ARE COPIED FROM PERMX
--    SOURCE  DESTINATION  ------- BOX ------
COPY
--      'PERMX'    'PERMY'   1  50  1  1  1  50  /
--      'PERMX'    'PERMZ'   /
/

RPTGRID
1 1 1 1 1 1  0 0 1 1 0 1 1 0 1 1 1 /
PROPS    ===============================================================
-------- THE PROPS SECTION DEFINES THE REL. PERMEABILITIES, CAPILLARY
-------- PRESSURES, AND THE PVT PROPERTIES OF THE RESERVOIR FLUIDS
----------------------------------------------------------------------
-- WATER RELATIVE PERMEABILITY AND CAPILLARY PRESSURE ARE TABULATED AS
-- A FUNCTION OF WATER SATURATION.
```

```
--
--  SWAT   KRW   PCOW
SWFN
    0.12    0.0     0
    0.2899  0.0022 0
    0.3778  0.0180 0
    0.4667  0.0607 0
    0.5556  0.1438 0
    0.6444  0.2809 0
    0.7000  0.4089 0
    0.7333  0.4855 0
    0.8222  0.7709 0
    0.9111  1.0000 0
    1.0000  1.0000 0 /
-- FOR OIL-WATER AND OIL-GAS-CONNATE WATER CASES
--
--  SOIL     KROW
SOF2
   0        0
    0.18     0
    0.28     0.045
    0.38     0.091
    0.43     0.13
    0.48     0.18
    0.58     0.32
    0.63     0.425
    0.68     0.55
    0.76     0.756
    0.83     0.913
    0.86     0.965
    0.879    1
    0.88     1       /
-- PVT PROPERTIES OF WATER
--
--    REF. PRES. REF. FVF  COMPRESSIBILITY  REF VISCOSITY  VISCOSIBILITY
PVTW
       4014.7     1.029        3.13D-6           1            0 /

-- ROCK COMPRESSIBILITY
--
--    REF. PRES   COMPRESSIBILITY
ROCK
        14.7          3.0D-6          /

-- SURFACE DENSITIES OF RESERVOIR FLUIDS
--
--        OIL   WATER   GAS
DENSITY
         49.1   64.79  0.06054  /

-- PVT PROPERTIES OF DEAD OIL (NO DISSOLVED GAS)
-- WE WOULD USE PVDO TO SPECIFY THE PROPERTIES OF DEAD OIL
--
-- FOR EACH VALUE OF RS THE SATURATION PRESSURE, FVF AND VISCOSITY
-- ARE SPECIFIED. FOR RS=1.27 AND 1.618, THE FVF AND VISCOSITY OF
-- UNDERSATURATED OIL ARE DEFINED AS A FUNCTION OF PRESSURE. DATA
-- FOR UNDERSATURATED OIL MAY BE SUPPLIED FOR ANY RS, BUT MUST BE
-- SUPPLIED FOR THE HIGHEST RS (1.618).
--
--   POIL  FVFO  VISO
PVDO
     14.7  1.012 1.16
   10000   0.95   1.2/

SOLUTION ===============================================================
-------- THE SOLUTION SECTION DEFINES THE INITIAL STATE OF THE SOLUTION
-------- VARIABLES (PHASE PRESSURES, SATURATIONS AND GAS-OIL RATIOS)
-----------------------------------------------------------------------
-- DATA FOR INITIALISING FLUIDS TO POTENTIAL EQUILIBRIUM
--
--    DATUM  DATUM   OWC    OWC    GOC    GOC    RSVD   RVVD   SOLN
--    DEPTH  PRESS  DEPTH   PCOW  DEPTH   PCOG  TABLE  TABLE   METH
EQUIL
       8450   4800   8600    0     8200    0      1      0       0  /

-- OUTPUT CONTROLS (SWITCH ON OUTPUT OF INITIAL GRID BLOCK PRESSURES)
```

```
RPTSOL
   1  11*0  /

SUMMARY  ==============================================================
-------- THIS SECTION SPECIFIES DATA TO BE WRITTEN TO THE SUMMARY FILES
-------- AND WHICH MAY LATER BE USED WITH THE ECLIPSE GRAPHICS PACKAGE
-----------------------------------------------------------------------

--REQUEST PRINTED OUTPUT OF SUMMARY FILE DATA
INCLUDE
        'RUNSUM.INC'  /
SCHEDULE ==============================================================
-------- THE SCHEDULE SECTION DEFINES THE OPERATIONS TO BE SIMULATED
-----------------------------------------------------------------------
-- CONTROLS ON OUTPUT AT EACH REPORT TIME
RPTRST
  'BASIC=2'
/
-- SET 'NO RESOLUTION' OPTION
DRSDT
      0  /

-- SET INITIAL TIME STEP TO 1 DAY AND MAXIMUM TO 6 MONTHS
TUNING
0.01 365
/
/
/
--0.001 0.15 3.0 0.3 0.01

INCLUDE
        'WELSPECS.INC'  /

INCLUDE
        'COMPDAT.INC'  /
INCLUDE
        'WCONINJ.INC'  /
INCLUDE
        'WCONPROD.INC'  /
INCLUDE
        'WCONPROD2.INC'  /
END     ================================================================
```

where

WELSPECS.INC contains

```
WELSPECS
   'WELL_1'  'G' 23 4 8450 'OIL'/
  'WELL_2'  'G' 17 10 8450 'WATER'/
  'WELL_3'  'G' 23 18 8450 'OIL'/
  'WELL_4'  'G' 27 5 8450 'OIL'/
/
```

COMPDAT.INC contains

```
COMPDAT
   'WELL_1'  23 4 1 1 'OPEN' 0 -1 0.5/
  'WELL_2'  17 10 1 1 'OPEN' 0 -1 0.5/
  'WELL_3'  23 18 1 1 'OPEN' 0 -1 0.5/
  'WELL_4'  27 5 1 1 'OPEN' 0 -1 0.5/
/
```

WCONPROD.INC contains

```
WCONPROD
  'WELL_1' 'OPEN' 'ORAT' 15000 4* 4000/
  'WELL_3' 'SHUT' 'ORAT' 15000 4* 4000/
```

```
  'WELL_4' 'SHUT' 'ORAT' 15000 4* 4000/
/
TSTEP
20*10
/
```

WCONPROD2.INC contains

```
WCONPROD
  'WELL_3' 'OPEN' 'ORAT' 15000 4* 4000/
/
TSTEP
20*10
/
WCONPROD
  'WELL_4' 'OPEN' 'ORAT' 15000 4* 4000/
/
TSTEP
50*10
/
TSTEP
10*10
/
```

WCONINJ.INC contains

```
WCONINJ
  'WELL_2' 'WATER' 'OPEN' 'BHP' 30000  3* 5500/
/

RUNSUM
SEPARATE
FOPT
FWIT
FWPT
```

A.2. Preparation of HGA keywords file

In this step, the limits and the precision of the optimization parameters are specified within the HGA keywords file. Only some basic parts in the keyword file need to be changed. The parts that need to be changed are written in blue.

```
HYBRIDGENETICALGORITHM
{
  DOPOLYTOPE               1
  DOKRIGING                1
  DOKRIGINGERRORANALYSIS   1
  KRIGINGRECURSIVEFILENAME SAME
  POLYTOPETYPE             { 2 }
  CLOSESTSCALINGFACTOR   0.9
  CONVERGENCECRITERIA      0
  CONVERGENCETOLERANCE   0
  CONVERGENCEVALUE         0
  FITNESSSCALINGFACTOR     1
  MAXNUMEVALUATIONS        1000000
  MAXNUMITERATIONS         20
  MAXTIME                  1000000
  NEIGHBORHOODRANGE        3
  NUMPOPULATION            1
  NUMTOURNAMENT            1
  NUMRUN                   1
  OUTPUTFILES              1
  PCROSSOVER               0.8
  PMUTATION                0.25
  PMUTATIONNEIGHBORHOOD    1
  RANDOMSEED               0
```

```
RUNDESCRIPTION          Optimization
RUNNAME                 opti_1
SELECTIONTYPE           1
USECLOSESTDATA          1
USEDATABASE             1
USEELITISM              1
POPULATION
{
  UNIFORMINITIALIZATION   0
  POPULATIONNAME          Injectors
  POPULATIONSIZE          20
  ALPHABETSIZE          {  30   30  30  30  }
  MAXVALUE  {  30  30   30  30   }
  MINVALUE  {  1    1    1   1   }
  PRECISION  {  1    1    1    1   }
  VALUENAME  {  i    j    i    j   }
}
POLYTOPEALGORITHM
{
  CLOSESTSCALINGFACTOR    0.9
  CONTRACTIONCOEFFICIENT  0.5
  CONVERGENCECRITERIA     0
  CONVERGENCETOLERANCE    0
  CONVERGENCEVALUE        0
  EXPANSIONCOEFFICIENT    2
  REFLECTIONCOEFFICIENT   1
  MAXIMUMNUMCONTRACTION   2
  MAXNUMEVALUATIONS       100
  MAXNUMITERATIONS        1
  MAXTIME                 500
  OUTPUTFILES             1
  USECLOSESTDATA          1
  USEDATABASE             1
  RUNDESCRIPTION          Polytope Pompano 1 Well Placement Optimization
  RUNNAME                 Polytope_Pompano_1Well
  INITIALSOLUTION       {  30   1   1  30  }
  MAXVALUE              {  30  30  30  30  }
  MINVALUE              {  1    1   1   1  }
}
KRIGINGALGORITHM
{
  VARIOGRAMA              1.5
  VARIOGRAMC              1
  NUMKRIGDATA             -1
  VARIOGRAMTYPE           3
  OUTPUTFILES             0
  RUNNAME                 Kriging
}
}
```

PMUTATION **_value_**

value should be equal to the 1/number of parameters to be optimized

POPULATIONSIZE **_value_**

value should be integer closest to n1+n2+n3

where

n1=log(par1_maximum-par1_minimum)/log2

n2=log(par2_maximum-par2_minimum)/log2

n3=log(par3_maximum-par3_minimum)/log2

MAXVALUE { **_Value1 Value2 Value3_** }

Value1 is the maximum number of grid blocks in x-direction

`Value2` is the maximum number of grid blocks in y-direction

`Value3` is the maximum number of grid blocks in x-direction

`Value4` is the maximum number of grid blocks in y-direction

`MINVALUE { Value1 Value2 Value3 }`

`Value1` is the minimum number of grid blocks in x-direction

`Value2` is the minimum number of grid blocks in y-direction

`Value3` is the minimum number of grid blocks in x-direction

`Value4` is the minimum number of grid blocks in y-direction

`PRECISION {  Value1 Value2 Value3    }`

`Value1` is the precision of grid blocks in x-direction

`Value2` is the precision of grid blocks in y-direction

A.3. Preparation of Active Mask

In this section, the active mask is prepared for the producers and /or injectors.

A.4 Comments and Recommendations

- The precision of the optimized parameters should be examined. If the precision is kept at a high level, it can cause HGA to bypass some of the existing solutions.
- If the algorithm can not find the input files to MPH, the run will stop and output a warning like

  “`WARNING, Could not find the input file: active_mask.txt`”
- To use the pseudohistory first, you should make optimize option 1. If you do not make it 1, the program will not use the pseudohistory unless the option is set to 3 in which case the approach will use the database.