A MODIFIED GENETIC ALGORITHM APPLIED TO HORIZONTAL WELL PLACEMENT OPTIMIZATION IN GAS CONDENSATE RESERVOIRS

A Thesis

by

ADRIAN NICOLAS MORALES

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

December 2010

Major Subject: Petroleum Engineering

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Approved by:

Co-Chairs of Committee,	Hadi Nasrabadi
	Ding Zhu
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ABSTRACT

A Modified Genetic Algorithm Applied to Horizontal Well Placement Optimization in Gas Condensate Reservoirs. (December 2010)

Adrian Nicolas Morales, B.S., University of Houston

Co-Chairs of Advisory Committee: Dr. Hadi Nasrabadi
Dr. Ding Zhu

Hydrocarbon use has been increasing and will continue to increase for the foreseeable future in even the most pessimistic energy scenarios. Over the past few decades, natural gas has become the major player and revenue source for many countries and multinationals. Its presence and power share will continue to grow in the world energy mix. Much of the current gas reserves are found in gas condensate reservoirs. When these reservoirs are allowed to deplete, the pressure drops below the dew point pressure and a liquid condensate will begin to form in the wellbore or near wellbore formation, possibly affecting production.

A field optimization includes determining the number of wells, type (vertical, horizontal, multilateral, etc.), trajectory and location of wells. Optimum well placement has been studied extensively for oil reservoirs. However, well placement in gas condensate reservoirs has received little attention when compared to oil. In most cases involving a homogeneous gas reservoir, the optimum well location could be determined as the center of the reservoir, but when considering the complexity of a heterogeneous reservoir with initial compositional variation, the well placement dilemma does not produce such a simple result.

In this research, a horizontal well placement problem is optimized by using a modified Genetic Algorithm. The algorithm presented has been modified specifically for gas condensate reservoirs. Unlike oil reservoirs, the cumulative production in gas reservoirs does not vary significantly (although the variation is not economically negligible) and there are possibly more local optimums. Therefore the possibility of finding better production scenarios in subsequent optimization steps is not much higher than the worse case scenarios, which delays finding the best production plan. The second modification is developed in order to find optimum well location in a reservoir with geological uncertainties. In this modification, for the first time, the probability of success of optimum production is defined by the user.

These modifications magnify the small variations and produce a faster convergence while also giving the user the option to input the probability of success when compared to a Standard Genetic Algorithm.

DEDICATION

For my mother, Aleida Salinas and father, Nicolás Morales

Para mi madre, Aleida Salinas y mi padre, Nicolás Morales

ACKNOWLEDGEMENTS

I would like to thank my committee co-chairs, Dr. Nasrabadi and Dr. Zhu. Thank you for all of your help and patience. I feel you have tried to teach me beyond academics and, hopefully I have been able to understand and make those lessons part of who I am.

I also wish to thank the sponsor of this study: Qatar's National Research Fund under grant NPRP 28-6-7-33 for the financial support provided.

Lastly, I want to thank my parents for their patience and love.

NOMENCLATURE

CAPEX = Capital Expenditures

EOS = Equations of State

GA = Genetic Algorithm

HGA = Hybrid Genetic Algorithm

μ = Mean of Original Population

μ_o = Mean of Standard Normal Distribution Population

MiniVar = Minimal Variance Modification

MMSCF = Million Standard Cubic Feet

MSCF = Thousand Standard Cubic Feet

MSTB = Thousand Stock Tank Barrel

N = Number of Functions in the Probability of Success Modification

N_p = Number of Individuals in the Population

NPV = Net Present Value

p_s = Probability of Success

PUNQ3 S3 = European Community Production Forecasting with Uncertainty Quantification

σ = Standard Deviation of the Original Population

σ_o = Standard Deviation of the Standard Normal Distribution Population

SGA = Standard Genetic Algorithm

STB = Stock Tank Barrel

w_i = Individual Realization Weights

$x(i)$ = Original Fitness of Individual i

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CHAPTER I

INTRODUCTION

Well placement in reservoirs is one of the most important steps in field development. Depending on the reservoir geological and fluid properties, the production strategy could be to optimize gas production, maximize condensate production or find an economic balance between the fluids for gas condensate reservoirs. Some gas condensate reservoirs, besides heterogeneity in reservoir properties such as permeability, porosity, etc., have variation in initial fluid composition. Over the production lifetime of the reservoir, the composition, condensate and gas production will change, affecting both the near wellbore and wellbore flow conditions. The economic benefits of condensate production can be higher than crude oil production when compared on a per barrel basis, but the well planning for a horizontal gas well which unexpectedly encounters condensate production can lead to wellbore blockage and decreased gas production. Vertical wells are more vulnerable to the negative wellbore effects of condensate blockage than horizontal wells (Miller et al. 2010). With most of the proven natural gas reserves classified as associated or wet gas (D.O.E./E.I.A. 2010. *Natural Gas Reserves Summary*, by E.I.A.), it is crucial to consider condensate production and try to find the right balance between gas and condensate production.

This thesis follows the style of *SPE Journal*.

In well placement optimization, an efficient algorithm is essential for computational feasibility. The algorithm must also be able to find global optima or a set of optimums, while avoiding getting stuck on a set of local extrema. This requires a stochastic, as opposed to a deterministic, approach to the problem. The global optima requirement generally cancels all calculus-based, hill-climbing methods as the main solvers. Also, the algorithm must be a generalized answer to the problem to allow a wide variety of applications. The generalization characteristic of the algorithm requires the ability to handle varying types and numbers of parameters.

An algorithm which can satisfy the constraints of a complex reservoir model but still be flexible enough to thrive in a multi nodal domain, eliminates practically all hill climbing techniques. This leaves stochastic and non-deterministic techniques for consideration. In this research, the Standard Genetic Algorithm (SGA) was considered as a starting point due to its robustness and flexibility (Goldberg 1989).

Application of Genetic Algorithms in Petroleum Engineering

Genetic algorithms have been used within the petroleum industry for a long time with many varying applications. Production scheduling was among the first problems approached with evolutionary algorithms. Drilling schedule and well location in an oil reservoir was optimized by using a simulated annealing approach (Beckner and Song 1995). Gas storage and production has also been studied and optimized by Standard Genetic Algorithms (Gűyagűler and Gümrah 1999). The objective of these initial applications was to optimize the production from individual wells in order to maximize the Net Present Value (NPV) of a given scenario, Pan and Horne (1998) also used Genetic Algorithms to determine scheduling and well placement (Harding et al. 1998). After almost a decade, gas production and scheduling optimization is still a very active research topic (Park et al. 2006; Park et al. 2010). Genetic algorithms have also been used to estimate the dew point pressure of a gas condensate reservoir with positive results (Shokir 2008). Another application, which not only optimized gas production scheduling, but also determined the production strategy; the number of wells, type and location has also been done (Nogueira and Schiozer 2009). Evolutionary algorithms have been used in a vast area of expertise within the petroleum industry, with the previously mentioned research only being a small portion of articles published.

Literature Review of Genetic Algorithms for Well Placement Optimization

One of the first studies conducted in well placement optimization by evolutionary algorithms was conducted by Bittencourt and Horne (1997). Their algorithm optimized the location of various new wells in an existing field and optimized the final economic value based on a work proposal already presented. Their results had a 6 % increase in profit compared to the original scenario proposed by the company. They used a Hybrid Genetic Algorithm (HGA), which refers to any Standard Genetic Algorithm (SGA) which has been modified or customized to certain problems. Field cases for the North Sea have also been done by using a Standard Genetic Algorithm, Ekofisk and Smørbukk fields were studied and a Standard Genetic Algorithm was concluded to be a robust tool capable of finding the optimum case in large scenarios (Santellani et al. 1998). Well locations as well as injection rates for a water flooding project, by using a HGA to optimize NPV has also been studied (Gűyagűler et al. 2000). Other studies have focused on the sensibilities of several parameters within the well placement context, but also highlighted the difficulty of having absolute convergence or a reliable stopping criteria (Montes et al. 2001).

Optimization of nonconventional wells in complex oil reservoirs has also been reported. This study included the possibility of several wells or multilateral wells being optimized by a Hybrid Genetic Algorithm (Yeten et al. 2003). Badru and Kabir (2003) also used a similar HGA to optimize and maximize the NPV of an oil reservoir in comparison to “engineering judgment” case. Their approach offers a different kind of stopping mechanism but it does not guarantee to find the global optimum.

The use of a neuro-fuzzy proxy in conjunction with a HGA was used to reduce the total run time of the algorithm by estimating production from a set of data points within an internal database (Zarei et al. 2008).

Some of the more recent research includes well placement optimization with nonlinear constraints instead of using penalty functions (Emerick et al. 2009). In the study, NPV was maximized by optimizing the number, location, length and trajectory of producer and injector wells in an oil reservoir.

Plenty of research has been done concerning well placement optimization within oil reservoirs but the industry is still lacking on studies in gas and gas condensate reservoirs.

Literature Review of Well Placement in Presence of Geological Uncertainty

The last part of this research is done with the purpose of having not only a robust algorithm, but an algorithm that can handle environmental uncertainties. In a typical reservoir there will be different kinds of data; seismic, logs, cores, etc. All of these different data must be analyzed and a concise model is created. This undertaking has been compared to mapping out the streets of London, at night from a bird's eye view, using only several street lamps. Invariably, this will lead to different maps by different people or interpretations. In order to finalize this research several methods to include geological uncertainty were examined and implemented.

Some of the research has used a combination of history matching a theoretical case put forward by the European community, PUNQ3 S3 (production forecasting with uncertainty quantification). This artificial case was created and presented with 'historical' data, the researchers then create history matching models and allow a Genetic Algorithm to optimize the well placement scheme (Soleng 1999). Several other researchers have conducted similar studies, each with a slightly different approach towards uncertainty, some consider equally probable reservoir realizations (Santellani et al. 1998), while others manipulate the fitness value depending on the standard deviation of several realizations, and the risk the user is able to admit (Yeten et al. 2003). Well placement optimization in an existing field with historical data is arguably a solid approach (Özdogan and Horne 2004).

Still other researchers define the uncertainty by a utility function which does not consider a whole gamut of realizations, but initially chooses a random realization and then a decision node will consider the next step based on the calculated fitness. This is controlled by a 'risk aversion coefficient' within the utility function, and depending on the user input, it can avoid certain reservoir areas if a conservative approach is defined (Gűyagűler and Horne 2004).

A Quality Map is a preliminary estimation of areas which can be considered more attractive than another. The definition can be a combination of several parameters such as absolute permeability with reservoir height, if both of these surpass a certain threshold, then the grid becomes a valid grid in the domain. Using this methodology for horizontal well placement in an oil reservoir reported positive results with a decrease in overall run time (Nakajima and Schiozer 2003). A field project was also considered and optimized by using a Genetic Algorithm in conjunction with a two dimensional Quality Map combining several reservoir properties (Maschio et al. 2008). The Quality Map approach creates a two dimensional object which will tell the algorithm where a well can be placed, it does not determine the possibility of producing the amount of hydrocarbon calculated by the simulator.

The methodology used in this research is termed as Probability of Success. This approach is capable of taking various realizations, giving each individual weights, and based on the collective fitness outcomes, report a final fitness based on a user defined Probability of Success (Chan and Sudhoff 2009). The method is covered in detail in Chapter II.

Research Objectives

The first objective of the research is to modify an already existing Standard Genetic Algorithm for a small reservoir into a larger domain (Carroll 2001; Gibbs 2009). It validates the expanded algorithm with several varying scenarios and demonstrates algorithm robustness has not been lost. The second objective is to migrate and customize the algorithm for a gas condensate reservoir by taking into account condensate production and implementing a Minimal Variance modification.

The last objective of the research is to develop the uncertainty section of the code. This section will allow the user to examine how risk adverse the results are allowed to be. Once the code is completed, several field cases related to Qatar’s North Field are presented with different algorithm modifications and the results compared.

CHAPTER II

THEORETICAL APPROACH

Introduction

By definition, a Genetic Algorithm relies on the mechanics of natural selection and genetics in order to find the optimum solution for a domain. They combine Darwin's idea of survival of the fittest with a certain amount of randomness by transferring and reproducing their codes in string format. While the small amount of randomness allows for the occasional jump out of the ordinary, the string method to transmit data ensures the algorithm will exploit historical data in order to determine new search points (Goldberg 1989).

A single peak function such as that presented in **Fig. 2.1** can be easily solved through calculus based methods. Hill climbing methods depend on the derivative or slope of the domain in order to determine if the algorithm should continue or halt. Real world problems inhabit multi nodal domains and cause calculus based methods to come to a dilemma when confronted with a complex domain as shown in **Fig. 2.2**. For this research application, the complexity of the solution domain is quite high, noisy and discontinuous as later results will demonstrate.

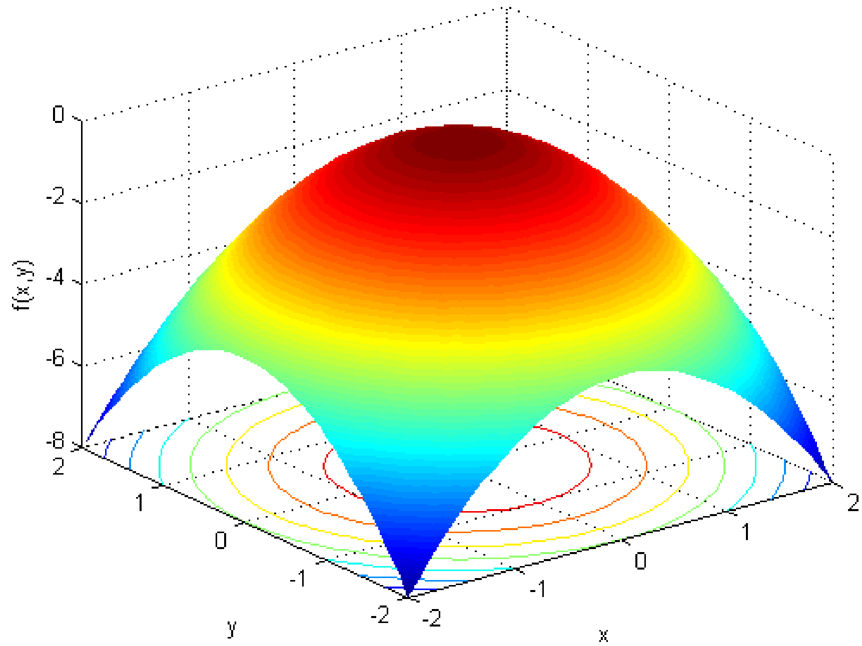


Figure 2.1 – Example of 3-D Single Peak Function.

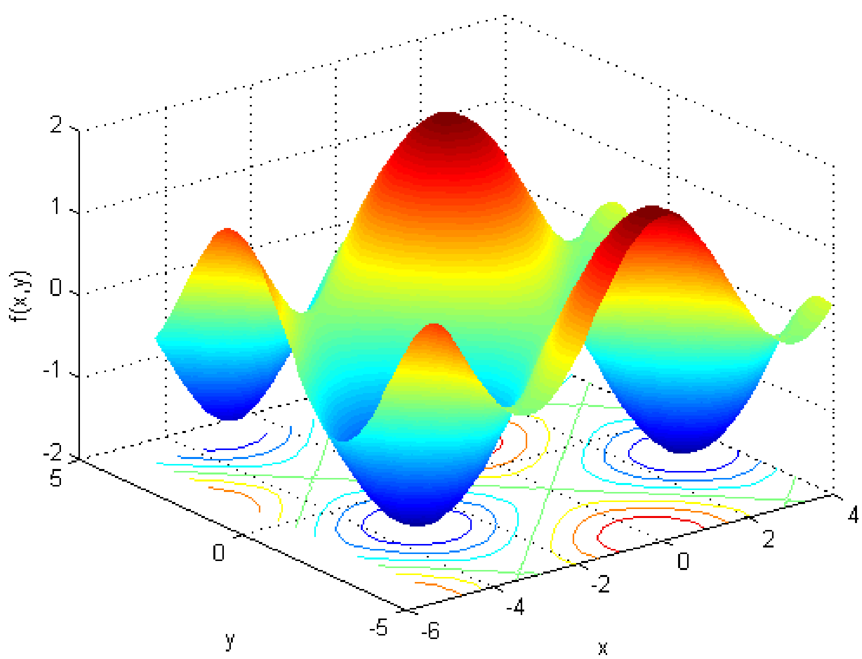


Figure 2.2 – Example of a Multi-Peak Function.

Genetic Algorithm Theory

At an arbitrary moment in time, in nature an initial set of individuals for a given species can be observed. This initial population is termed as Generation Zero. The individuals go about their lives and their success can be quantified by the number of offspring a certain individual was able to have. During this life time some individuals die off due to weakness or lack of survival techniques. At a second moment in time, Generation One can be identified. This population of individuals has traits from their ancestors, but most are uniquely different. As time progresses, stronger individuals will produce a higher number of offspring ensuring the survival of their DNA code, while the overall population improves.

Genetic Algorithms are made up by a binary (0 or 1) code which represents an individual's parameters. Probabilistic transition rules based on their overall performance over their lifetime instead of deterministic establish the population for the next generation.

There are three main operations for Standard Genetic Algorithms; reproduction, crossover and mutation (Goldberg 1989). Reproduction consists of determining the fitness function for each individual. Then the population undergoes either one of two basic parent selection criteria for the new generation; a tournament style selection or a roulette wheel selection process. The tournament selection process will compare the first two individuals and the one with the higher fitness is chosen as Parent # 1. The process is repeated using the next two individuals to select Parent # 2, thus ensuring every individual three chances for reproduction. Roulette wheel selection is based on each individual's contribution to the total fitness sum. If Individual # 1 has a considerably higher fitness value than the rest of the population, then there is a chance that Individual #1 will mate more than twice. Each method has its advantages, but in this research the later, Conventional/Roulette Wheel selection is used. The Roulette Wheel selection is better suited for the modifications presented in Chapter III. Detailed examples for these two selection methods are presented in **Appendix A** and **Appendix B**.

After selection and reproduction, the crossover operator will create a new string code from the parents selected in the previous operation. Based on the crossover probability, the parent strings are switched at a random location. This operation can be done in either of two methodologies; simple crossover or a multipoint crossover. **Fig. 2.3a** demonstrates a simple crossover on a randomly chosen integer, in this case the fourth integer is chosen. In contrast, **Fig. 2.3b** shows the multiple crossover operation done on the fourth and eighth integer. Within this study, a multipoint crossover was utilized.

1001 | 01001011 – Parent # 1	1001 | 0100 | 1011 – Parent # 1
0101 | 10001001 – Parent # 2	0101 | 1000 | 1001 – Parent # 2
1001 | 10001001 – Offspring	1001 | 1000 | 1011 – Offspring
(a)	(b)

Figure 2.3 – Crossover Operation (a) Simple Crossover (b) Multipoint Crossover.

The last operation is mutation, another random operator. Mutation is an essential part of a genetic algorithm. It allows for a random change in parameters. Ideally, the initial population is spread out over the entire domain and the mutation probability is low, close to zero. This is done in order to allow the algorithm early convergence on several optimums. After the individuals over several generations begin to homogenize, the mutation is one of the determining factors to allow strings to extend the search radius beyond the converged maximum by suddenly altering the parameters. In this research, mutation can happen in two forms; creep or jump mutation. The creep mutation will change the binary code from a zero to one or vice versa. **Fig. 2.4a** shows the random mutation operator on integer 10 of the binary code. This has the opportunity to affect a parameter on a varying degree, depending on the location of the mutated integer. A jump mutation will not only affect a single binary digit, instead it will affect the array of binary digits representing a specific parameter. A jump mutation could change the x-value of the horizontal well by one, but alter several binary digits representing that x-value, **Fig. 2.4b**. Within this research, the mutation was held constant at a low rate. An example of the reproduction and mutation operators is shown in **Appendix C**. These three basic operators presented make up the Standard Genetic Algorithm. The basic program flowchart for a Standard Genetic Algorithm is presented in **Fig. 2.5**.

1001 | 1000 | 1011 → 1001 | 1000 | 1111

(a)

1001 : x-value = 10   0010 : x-value = 9

1000 : y-value = 2 → 1000 : y-value = 2

1011 : z-value = 14   1011 : z-value = 14

(b)

Figure 2.4 – Mutation Operation (a) Creep Mutation (b) Jump Mutation.

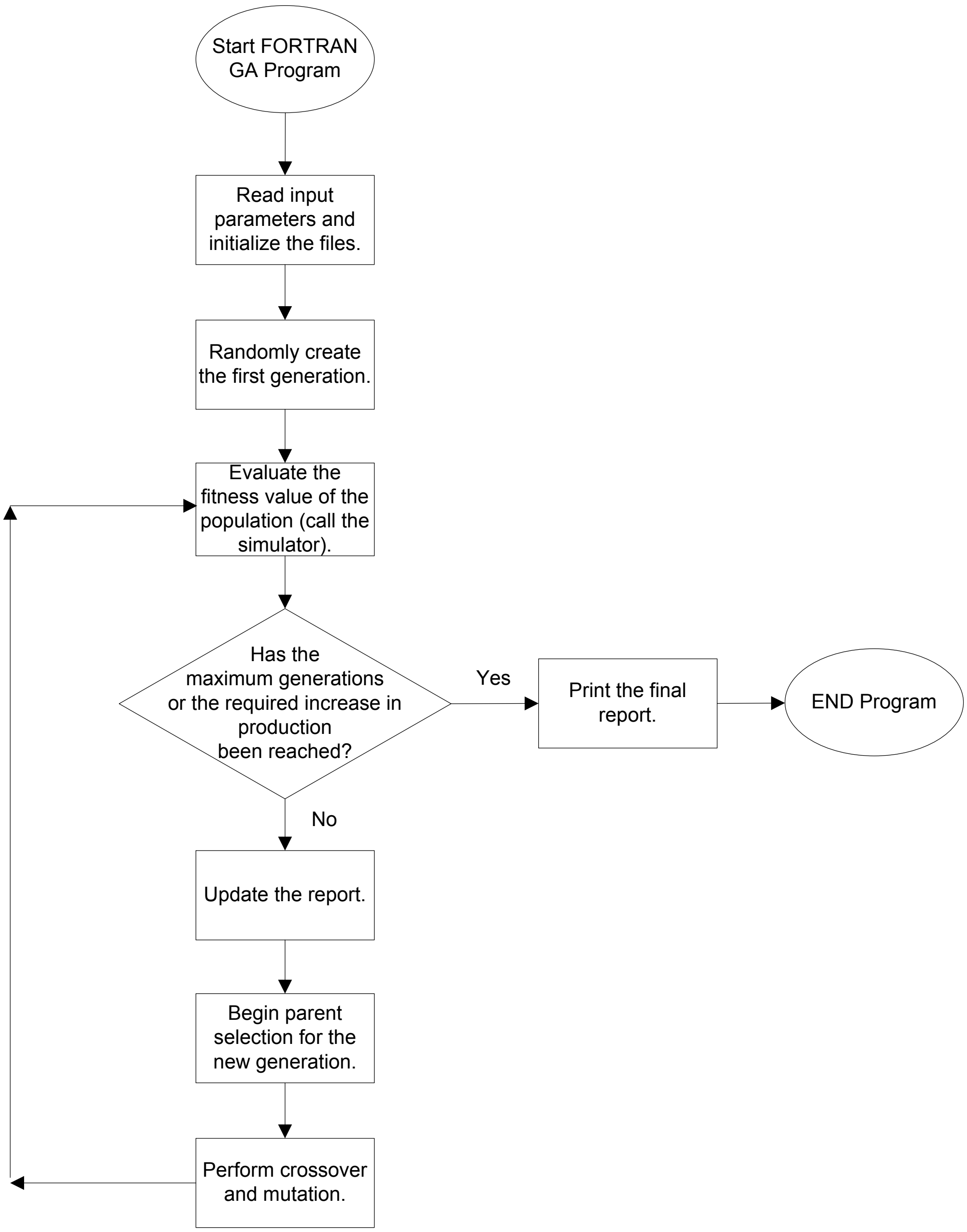


Figure 2.5 – Program Flowchart for a Standard Genetic Algorithm.

Genetic Algorithm Applied to a Horizontal Well

Every horizontal well can be described by their location coordinates at the heel (x_0, y_0 and z_0), length and the orientation of the well. In this application the length of the horizontal well is constant, so there are a total of four variables describing (x_0, y_0, z_0, D) the system. The variables can then be translated into a binary code (values of 0 or 1) to create a string of a finite length. All of the possible individuals have maximum values, such as the X-axis location, (if the grid is 100 × 100, then you cannot have a well in the grid 105 × 25 because it is out of range) then these binary codes will have exactly the same length for any well within the system.

In order to apply these life concepts to the situation, the first generation is created by randomly assigning the string parameters (binary code) for each individual well. The newly created individual wells are allowed to produce gas independently from the other wells. At the end of the well lifetime, the individuals are assessed based on their cumulative gas production. A better production means that a particular well will have a better 'fitness' and higher chance of procreating and passing on its characteristics.

Once the wells have been appraised, the mating procedure begins. The individual wells are weighted and then using a roulette wheel probability, two mates are selected. The parent wells' DNA or binary string is then flipped or 'crossover' at a random location, creating an offspring similar to the parents but with its own unique characteristics for the next generation. Detailed examples for the selection and reproduction processes have been presented in **Appendix B** and **Appendix C** respectively. **Appendix D** demonstrates a detailed example for a simple reservoir; the same concepts are applied to a larger domain to validate and apply a field case to the algorithm.

Validation of Approach

Exhaustive Search

Before applying the genetic algorithm, a standard must be created upon which the results from the algorithm can be compared. This is done by making an exhaustive search for the validation case. The case for validation is 16 × 32 × 7 grids in dimension **(Fig. 2.6)**. At initial stages of validation, the well location varied along the X-Y plane while the wellbore location in the Z-direction was held constant. Since the well is eight grid blocks in length, there are certain well locations where one or more segments of the well would be outside of the grid domain. These cases were eliminated, and this led to a total number of 1,400 possible well locations per layer for the exhaustive. When the wellbore location was allowed to vary in all three dimensions, including different orientations, the possible well locations increased to almost 10,000 different combinations.

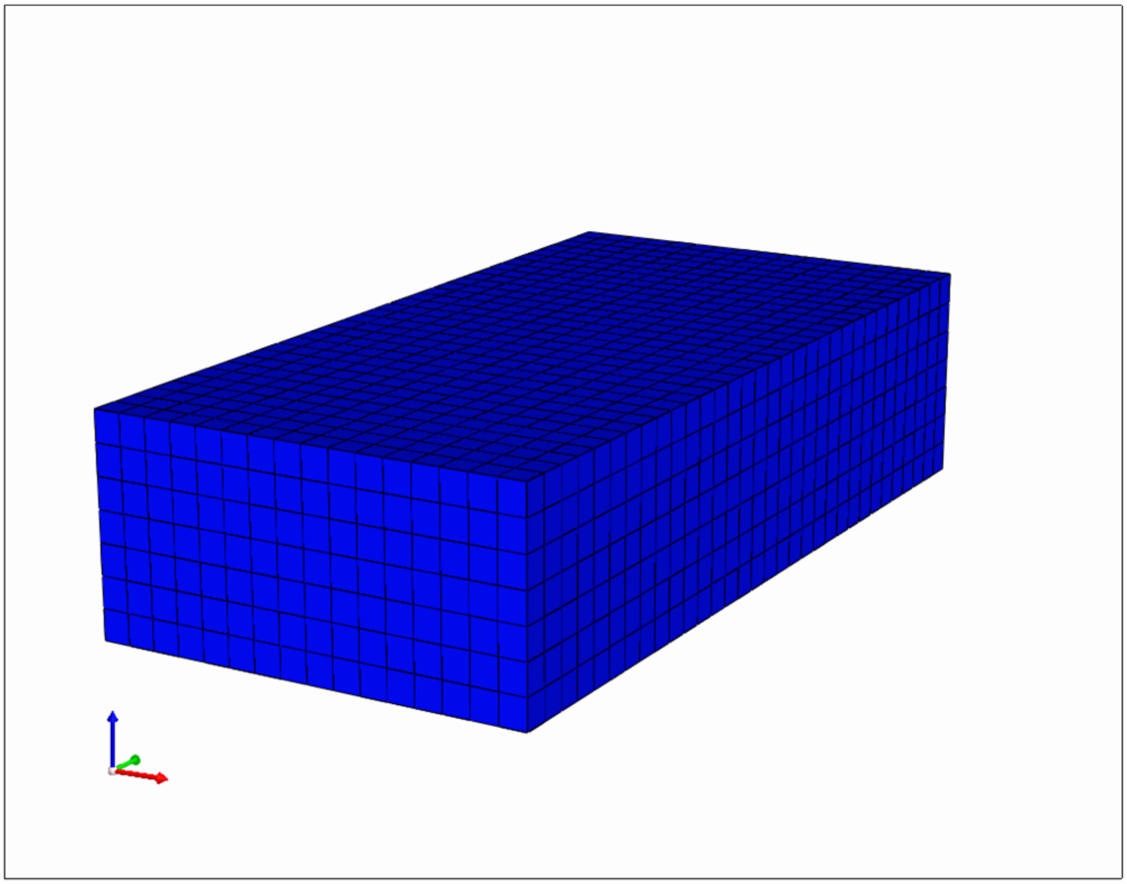


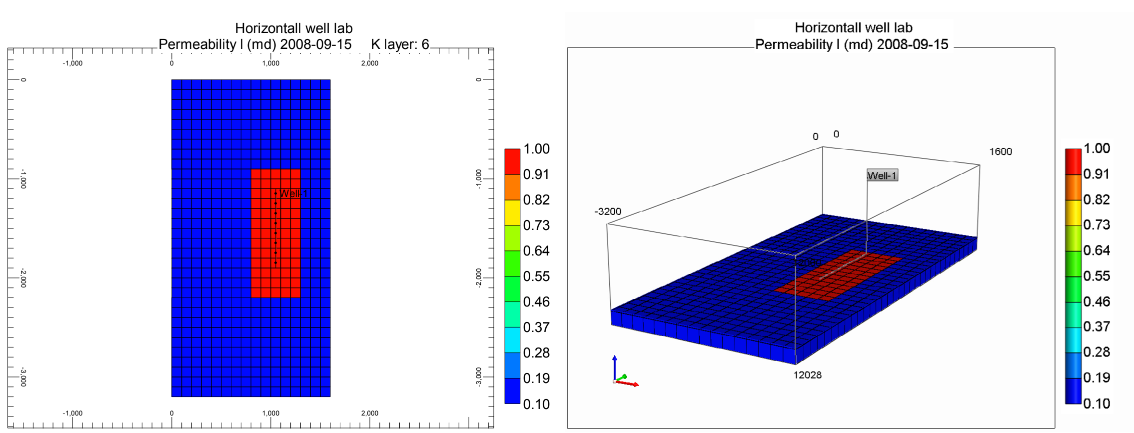
Figure 2.6 – Geometric Grid Layout for Model Validation.

Once the exhaustive run is completed, the algorithm is tested and the final solution is compared to the exhaustive run. After the initial model validation was confirmed, the complexity of the reservoir was gradually increased until we reached a model with permeability variation similar to the North Field case and confirmed that the algorithm could reproduce the same solution as the exhaustive run.

Genetic Algorithm Validation

A Standard Genetic Algorithm (Carroll 2001) was validated against the exhaustive search. The genetic algorithm was allowed to vary the location of the well in all three dimensions in order to test the wellbore placement in a three dimensional environment. A high permeability patch was created just below the center of the reservoir, and offset slightly to the right. The exhaustive search composes of 9,633 simulations while the genetic algorithm needed only 556 simulations to find the global optimum. **Fig. 2.7a** and **Fig. 2.7b** show the optimum well location determined by the genetic algorithm and confirmed by the exhaustive search.

The model validation has shown the genetic algorithm's potential for quick convergence on the global maximum. The total simulation runs required by the algorithm for convergence on the global optimum were less than 10% of the exhaustive run in all cases. The results are summarized in **Table 2.1**.



(a) (b)

Figure 2.7 – Optimum Well Placement (a) with an Off Centered High Permeability Patch in the 6th layer (b) 3-D View of the Off Centered Well.

Table 2.1 – Model Validation Results

	Exhaustive Search	Standard Genetic Algorithm
High Permeability Patch		
Well Location	(11, 12, 6) to (11, 19, 6)	(11, 12, 6) to (11, 19, 6)
Production (MMSCF)	2,830	2,830
Simulations to find the Maximum Production	9,633	556

Synthetic Cases

Case 1 – Application in a Heterogeneous Formation

After the confirmation of accurate well placement in a 3-D environment from the model validation, the next step was to increase the complexity of the reservoir and in turn the solution domain. The same grid structure as the model validation case was used ($16 \times 32 \times 7$), but instead of having a patch of high permeability, the reservoir was converted into a heterogeneous permeability distribution. The heterogeneity of the reservoir was created by assigning random permeabilities between 0.01 to 1.0 mD at different locations and then the rest of the reservoir was populated by running an ordinary Kriging estimation across the domain. The resulting heterogeneous reservoir is shown in **Fig. 2.8**.

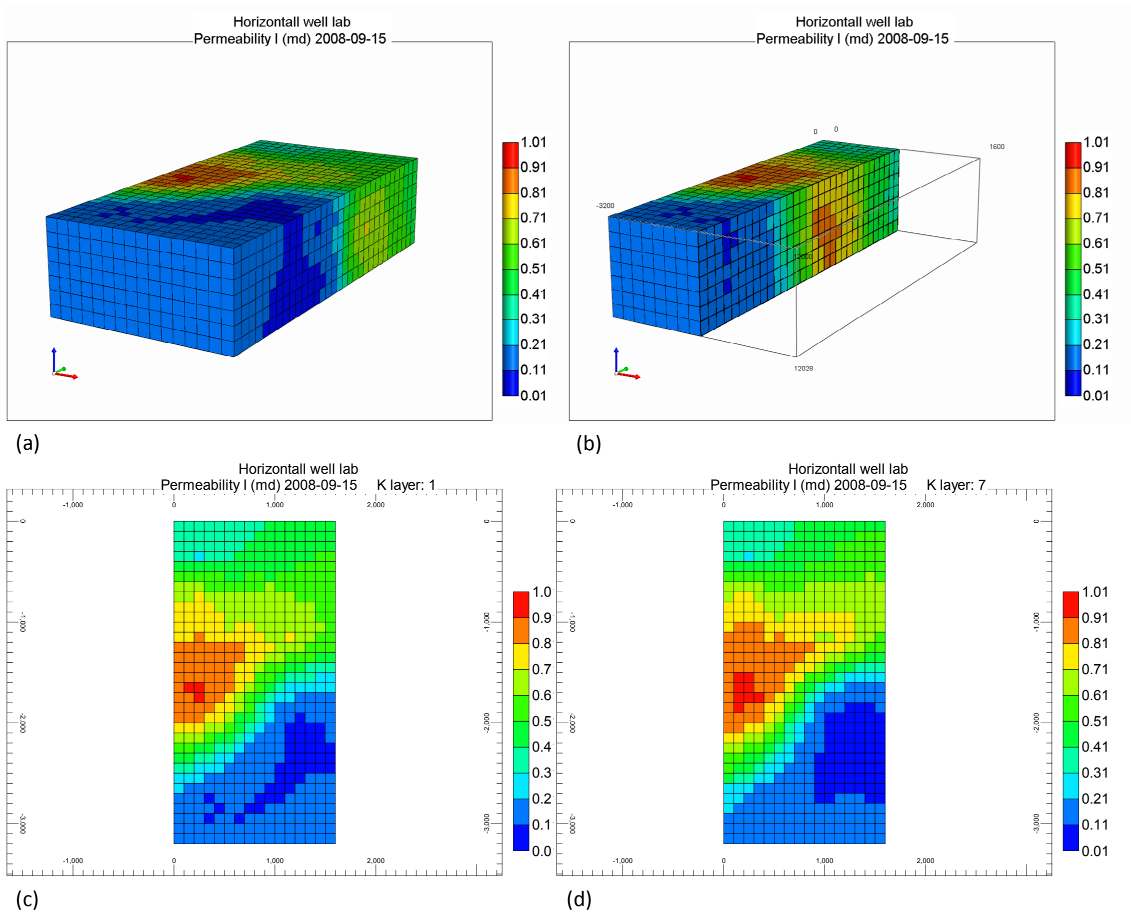


Figure 2.8 – Synthetic Case 1 Heterogeneous Reservoir Model (a) Lateral View of the 3-D Reservoir Model (b) Lateral View of the 3-D Reservoir, Sliced Vertically (c) Aerial View of the Top Layer of the Reservoir (d) Aerial View of the Bottom Layer of the Reservoir.

Since the geometric model and the reservoir composition is the same as the one used in model validation, an exhaustive run can be done for this system. Once the exhaustive model is done, the maximum cumulative production value (global maximum) is located and the parameters for that particular production, (X, Y, Z, and well direction) are plotted on a 3-D contour. For example, the optimum well location for Case 1 is from (X, Y, Z: 5, 14, 4) to (X, Y, Z: 5, 22, 4), so the optimum well location is located in the layer Z = 4 with a well in the direction of +Y. The cumulative production for all possible well locations for this specific scenario (Z = 4 and well direction +Y) are plotted in 3-D surface plot if the well were actually placed in that particular grid **(Fig. 2.9)**. From **Fig. 2.9**, it is then possible to hold the X- coordinate constant and produce a slice of the 3-D plot onto a 2-D plane. **Fig. 2.10** plots the production of a horizontal well by displacing the well one grid at a time in the Y- direction, while always maintaining the well direction (+Y), X- value and Z- value unchanged.

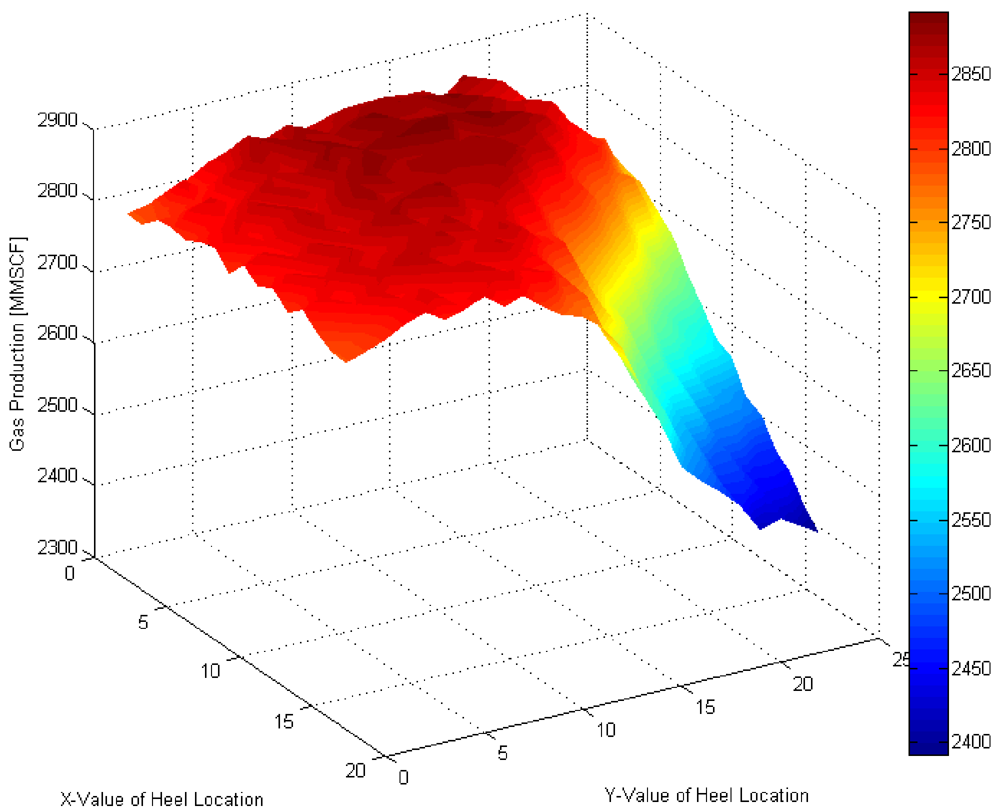


Figure 2.9 – Synthetic Case 1 – Production Contour Map, Z = 4.

Both **Fig. 2.9** and **Fig. 2.10** show plenty of local optimum points and one local optimum very close to the global maximum. The genetic algorithm took 920 simulations in order to find the global maximum while the exhaustive run needed 9,633 runs. This case showed that the algorithm had the ability to find the global optimum even when it is surrounded by local minima.

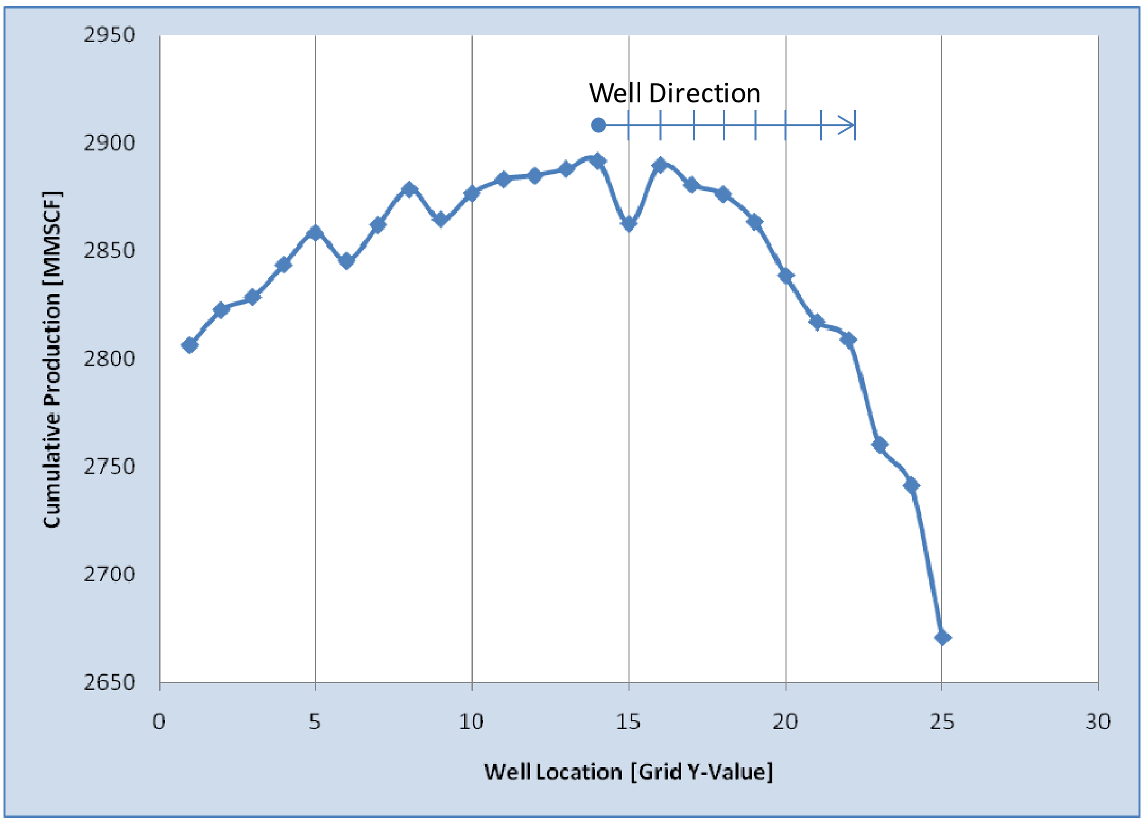


Figure 2.10 – Cumulative Production, X = 5, Z = 4 and +Y Well Direction.

Case 2 – Severe Permeability Variation

The next step in testing the algorithm would be to introduce a greater change in permeability. The main characteristic of this case is the sharp changes of permeability from the middle of the reservoir to the edges, which in some cases can be by a factor of 3. In this case the permeability was allowed to vary between 0.1 to 100 mD. Another important factor in this case is the radical change of the solution domain; **Fig. 2.11** shows the permeability variation.

The solution for this case is as expected, a complex one. The optimum solution was located in the 6th layer of the reservoir. In the layer above the optimum solution, the production contour map has numerous peaks **(Fig. 2.12a)**. The optimum solution was surrounded by local minimums and the global minimum as well in layer 6 **(Fig. 2.12b)**. Below it, in layer 7 the surface solution is a smooth bell shaped curve **(Fig. 2.12c)**. **Fig. 2.12d** shows an aerial view of **Fig. 2.12b**.

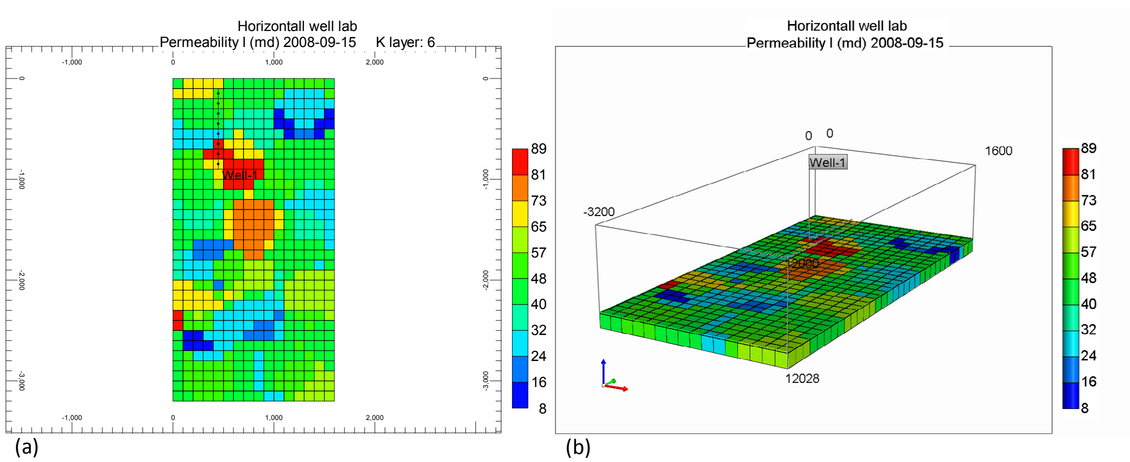


Figure 2.11 – Synthetic Case 2 Severe Permeability Variation, Permeability Contour Map (a) Aerial View of Layer 6 with the Optimum Well Placement (b) 3-D Lateral View with a 6th Layer Horizontal Cut.

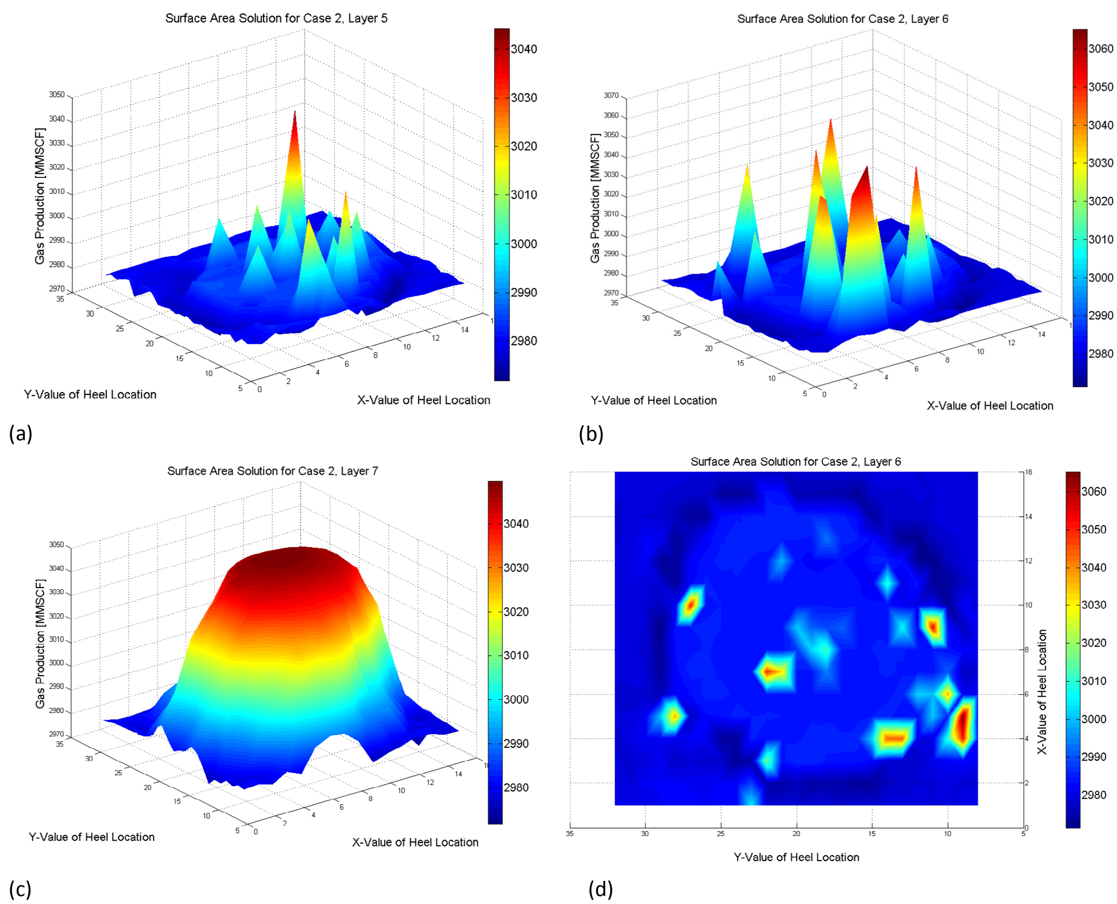


Figure 2.12 – Synthetic Case 2 Cumulative Production Contour Map (a) Cumulative Production for a Well Located in Layer 5 (b) Cumulative Production for a Well Located on Layer 6 (c) Cumulative Production for a Well Located on Layer 7 (d) an Aerial View of Layer 6 showing the Global Maximum in the Lower Right surrounded by Local Minimums.

Most numerical solvers will have problems converging upon the global optimum for a case like this because most solvers rely on hill climbing methods or Newton-Raphson derivative approach methodologies. These methodologies are based on the changing slope to find an optimum location. In this case, the global solution is surrounded by local minimums and the global minimum. Converging upon the global solution in this case is very difficult since the numerical solver's tendency would be to steer away the highly negative sloping region and miss the global maximum altogether.

Even though the case was a very complex, the genetic algorithm successfully found the global maximum production point in 2,644 simulations, which was corroborated by an exhaustive run. The optimum well location is presented in **Fig. 2.11**. The genetic algorithm proved to be a reliable tool for wellbore placement in the synthetic cases. The results for these two cases are reported in **Table 2.2**.

Table 2.2 – Synthetic Case Results

	Exhaustive Search	Standard Genetic Algorithm
Case 1 – Heterogeneous Formation		
Well Location	(5, 14, 4) to (5, 22, 4)	(5, 14, 4) to (5, 22, 4)
Production (MMSCF)	2,892.1	2,892.1
Simulations to find the Maximum Production	9,633	920
Case 2 – Severe Permeability Variation		
Well Location	(5, 9, 6) to (5, 2, 6)	(5, 9, 6) to (5, 2, 6)
Production (MMSCF)	3,065.2	3,065.2
Simulations to find the Maximum Production	9,633	2,644

General Code Modifications

During the course of the research, the original code (Gibbs 2009) underwent several code modifications which were done to customize the genetic algorithm for gas and gas condensate reservoirs. These modifications were the result of observed phenomena with the intention of applying the final algorithm to a complex field case.

Increase Model Complexity

The first modification needed was to increase the domain complexity. The starting algorithm could handle a domain size of 16 × 32 × 7 grids; this would result in a 3,584 grid system. The grid size was increased to 30 × 30 × 11 which contains a total of 9,900 grids, limited by the current simulator's research license (10,000 grids).

In order to capture some of the complexities of the North Field, the reservoir size has to be large enough to represent the subtle permeability changes of the middle layers as well as the compositional gradient that may be present.

Check List

Multi-component reservoirs in large domains require considerable greater run time than a small, single component reservoir. The run time for a simple case is a little less than 3 seconds. Assuming the user has defined a hard stop at 200 generations with 25 individuals per generation, the total run time is 15,000 seconds or about 4 hours.

The usual runtime for a 24 component simulation in the same domain as the previously stated is between 40-50 minutes. Completing the simulation with the same parameters as the previous example, this would take between 4 and 6 months for a complete run.

As the algorithm progresses, some results begin to repeat themselves over several generations, and towards the end of the algorithm run time, the repetition rate is over 80%. An internal check list was created to take advantage of this generational convergence. Before each binary code is decoded and sent to the reservoir simulation, an internal database is checked for previous runs. If that particular code has been run, then the value is taken from the database and the simulation is skipped. Alternatively, if the simulation has not occurred, the reservoir simulation proceeds and the result is recorded in the database for future reference. This slight modification greatly reduced total run times, in some cases from an estimated 2 months to slightly less than 1 month.

Penalty Function Elimination

Genetic algorithms in unconstrained objective functions assume that any combination of parameters within the domain is an acceptable location and will determine a fitness value. In a reservoir certain points may not be feasible, such as a cap rock or a grid point outside of the main grid representation. This means that the application of a genetic algorithm to a reservoir is by definition a constrained objective function. It is constrained by the boundaries and the fixed length of the horizontal well.

In certain cases a binary code may represent an unfeasible situation. For example, a horizontal well location with a predetermined length (in this example, 8 grids) is placed with coordinates ($x = 25$, $y = 25$, $z = 5$) and the reservoir domain is $30 \times 30 \times 11$, then a well placed at (25, 25, 5) can have either have a negative x-direction or negative y-direction, otherwise a segment of the well will be outside of the domain.

Previously this situation would have been handled by a penalty function and assigned a fitness value of zero. If a penalty function is used, there should be a determined methodology to determine the amount of penalty applied to the fitness value (Goldberg 1989). In the case of a horizontal well, the penalty function would be applied to a well which has part of its horizontal section outside of the reservoir domain. Since it is assumed no reservoir information is available for these areas, the harsh penalty function of zero was replaced with a new approach which also works better with the Minimal Variance modification presented in the next section.

The penalty function was eliminated and two separate subroutines created; a "check" subroutine which would analyze the binary code and a "repair" subroutine which would confirm a location and repair if necessary.

The binary code would first be sent to the "check" subroutine where it will validate the location. If the binary code represents an invalid location, the "repair" subroutine would be called to change the binary digits representing the well orientation. There are two binary digits that represent the well orientation, and are located at the end of a 14 digit code, ensuring minimal change to the overall structure and maintaining core stability which maintains code stability (Goldberg 1989).

Probability Selection Process

The initial inherited code (Gibbs 2009) operated on a tournament selection process. It was crucial to have a probability selection process such as that presented in **Appendix B** which would take advantage of the Minimal Variance (MiniVar)

Modification presented in the following section. This selection method combined with the Minimal Variance (MiniVar) Modification provided increased convergence rates, especially in complex environments.

Modified Fitness Value

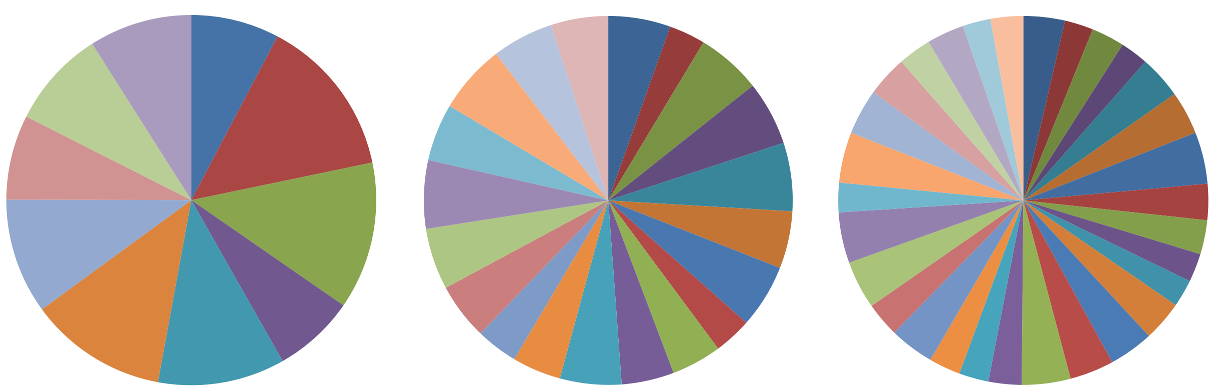
The reported fitness value was the last modification needed in order to estimate gas condensate reservoir performance. Initially the model validation and synthetic cases were applied to single component (methane) reservoirs. When applying the algorithm to a gas condensate reservoir such as Qatar's North Field, it is equally important to consider the condensate production as well as the gas production.

Gas condensate was included to the fitness value by creating an "economic" subroutine. This subroutine would take into consideration both the gas and condensate production by assigning a monetary value per unit of production. At the time of this research it was determined that 4 dollars per MSCF of gas and 80 dollars per barrel of condensate an appropriate estimation.

This last subroutine was left open for the user to input as many variables and create a Net Present Value (NPV) economic model. For the purpose of this research the revenue from sales is considered the fitness value. It is important to note that this research does not encompass a detailed economic plan and thus, H_2S production was not taken into account for the final fitness value, although it can easily increase CAPEX significantly.

Minimal Variance Modification

After the individuals of an entire generation are simulated and a fitness value reported, the next step is to conduct the mating procedure. Normally this would include a tournament or probability selection process. The two mating methods presented are suitable for small populations, or for populations whose fitness values have a high degree of variability. As the number of individuals per generation increase, the probability of selecting a good individual as opposed to a bad individual begin to converge with a probability equal to the inverse to the population size, **Fig. 2.13**. This convergence is more prominent when the individuals have a similar fitness value and the global maximum might only be a few fractions of the total order of magnitude higher than a typical individual.



(a) (b) (c)

Figure 2.13 – Effect of Increasing Individuals per Generation on the Probability of Mating with Random Fitness Values between 50 and 100. Mean of 75, Standard Deviation of 15 (a) N_p = 10 (b) N_p = 20 (c) N_p = 30.

If we keep this in mind when applying the genetic algorithm to naturally prolific natural gas reservoirs, it is obvious that this can become a problem and hinder the performance of the algorithm as the model grows in complexity. A typical gas reservoir will produce amply for a number of years, if the wellbore is placed away from the best location in a simulator; the gas reservoir will still produce handsomely but not quite as much as the global maximum. This small variation between locations chokes the effectiveness of a conventional genetic algorithm when applied to a gas reservoir.

In complex systems such as a reservoir, a large population is required in order to give the next generation larger variability, but as the population size increases, the efficiency of a normal mating process decreases.

In this modification, small variations in fitness values are magnified. In order to apply the Minimal Variation (MiniVar) Modification, first a generation is allowed to complete its run, and the fitness values assigned to their corresponding individuals (in this case the production can be considered to be the raw fitness value). First the mean and variance of the raw fitness data is calculated, and then a standard normal distribution is created. The standard normal distribution consists of a population with a mean equal to zero and variance equal to one,

$$y(i) = \frac{x(i) - \mu}{\sigma} \tag{1}$$

$$i = 1,2, \dots\ N_p,$$

where $x(i)$ represents the original fitness for the i individual, μ and σ represent the mean and standard deviation of the original population fitness, and N_p represents the population number. After this, a cumulative distribution is done based on the new standard distribution population.

$$y'(i) = \frac{1}{2}\left[1 + erf\left(\frac{y(i) - \mu_0}{\sqrt{2\sigma_0^2}}\right)\right] \tag{2}$$

$$i = 1,2, \dots N_p,$$

where μ_0 represents the mean and σ_0 represents the standard deviation of the standard normal distribution. Then the probability of the resulting population fitness is calculated and that is used as the actual fitness of each individual. This manipulation will ensure that the small differences in the original fitness values are magnified, resulting in higher probabilities for the better individuals than they would have without any statistical manipulations. At the same time, individuals which originally had a slightly lower raw fitness are not completely discarded, but will have a significantly lower chance of mating than a conventional genetic algorithm. When comparing the traditional probability method, **Fig. 2.14a** to the MiniVar method **Fig. 2.14b**, the advantages become clear. A detailed example of the process is presented in **Appendix E**.

The MiniVar process presented is easily applicable to groups of populations with a large variability as well. As the fitness values of a given population becomes more erratic and the standard deviation increases, the proportional weights given to each individual will approach the conventional probability selection process, **Fig. 2.15**. As **Fig. 2.14** and **Fig. 2.15** show the MiniVar modification can improve the mating procedure by adapting to either small or large population variance.

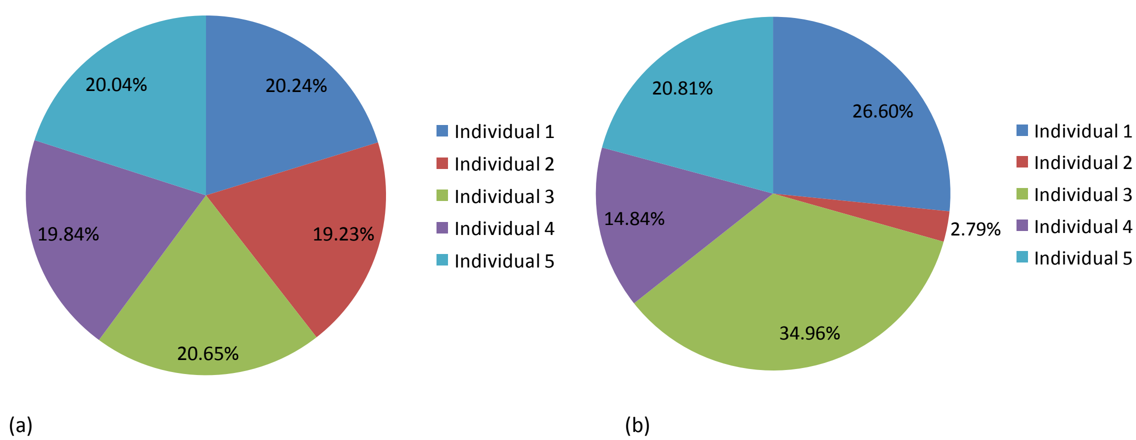


Figure 2.14 – Comparison of the Conventional Probability and MiniVar Method with a Small Standard Deviation. Fitness Values are 100 for Individual #1, 95 for Individual #2, 102 for Individual #3, 98 for Individual #4 and 99 for Individual #5, with a Mean of 98.8 and Standard Deviation of 2.59 (a) Conventional Probability Method (b) MiniVar Probability.

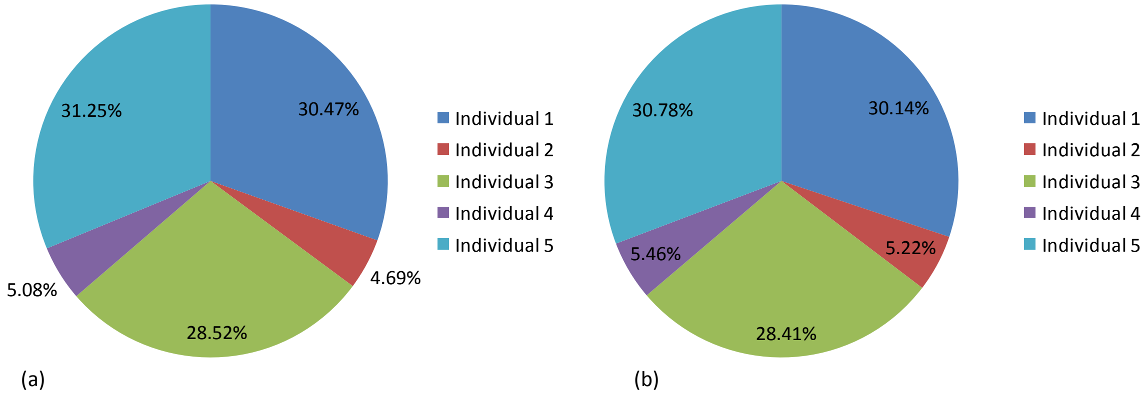


Figure 2.15 – Comparison of the Conventional Probability and MiniVar Method with a Large Standard Deviation. Fitness Values are 78 for Individual #1, 12 for Individual #2, 73 for Individual #3, 13 for Individual #4 and 80 for Individual #5, with a Mean of 51.2 and Standard Deviation of 35.4(a) Conventional Probability Method (b) MiniVar Probability.

The MiniVar addition significantly reduced simulation run time. The modified code was tested on Case 1 from the model validation section which resulted in finding the optimum well location in 552 simulations which represents a 40 % simulations reduction from the Standard Genetic Algorithm and 94 % of the Exhaustive Search. The results are compared in **Fig. 2.16**.

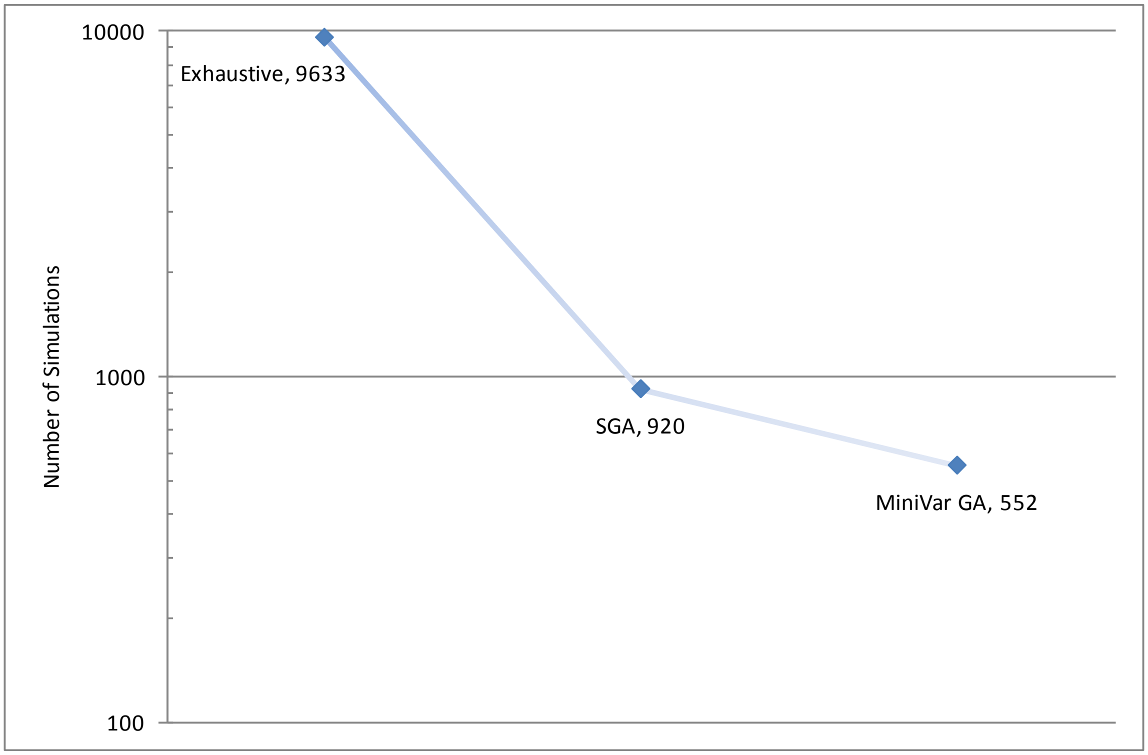


Figure 2.16 – Simulations Required to Find Global Optimum for Synthetic Case 1, using Exhaustive Search, Standard Genetic Algorithm and a Genetic Algorithm with MiniVar Modification.

Probability of Success Modification

In order to have a robust and practical model, reservoir uncertainty needed to be included in the model. The last modification gives the already modified genetic algorithm the flexibility to determine optimum well location with a specified uncertainty. This uncertainty can be parameters such as compositional gradient across the reservoir, permeability distribution, reservoir porosity, among others. The uncertainty is created by having several reservoir realizations. Each realization should be a unique model with any combination of uncertainty parameters. For this research, only permeability is presented as the uncertain parameter and will be discussed in detail in Chapter III.

The methodology applied is reported by Chan and Sudhoff (2009). It consists of several domains, each with a specific weight. In the petroleum industry, this can be translated as having more confidence in a specific realization over the others, so it is advantageous to give it a higher weight over other realizations. A user defined probability of success, p_s, is the principal input parameter for this method and it is defined as the probability that the optimized design will produce the fitness value reported. The modification will then create a fitness array, $\tilde{F}$,

$$\tilde{F} = \frac{1}{\tilde{\tilde{N}}} \sum_{j=1}^{\tilde{N}} F_{sort}\,(j) \tag{3}$$

$$\widetilde{N} = p_s N$$

where N denotes the function evaluations, F_{sort} is a vector consisting of fitness values F_i sorted in descending order. This approach will consider the number $\widetilde{N}$ of the best fitness solutions, if a low probability of success is input, the algorithm will return a higher fitness value than a low risk, high probability of success case. This method allows the user to have control over the robustness of the solution by modifying the probability of success, p_s accordingly. A detailed example can be reviewed in **Appendix F**.

Validation Test of the Probability of Success Modification

The example presented is done for a black oil reservoir model similar to what is expected to find in the North Field **(Fig. 2.17a)**. The permeability distribution is presented in **Fig. 2.17**. The first realization is done by Kriging approximation based on six random permeabilities ranging from 28 to 32 mD, **Fig. 2.17b**. The other four realizations are done by a Gaussian distribution based on the same random permeabilities, **Fig. 2.17c**, **Fig. 2.17d**, **Fig. 2.17e** and **Fig. 2.17f**. The simulations are relatively fast due to the single component nature of the test case and a detailed study on the effectiveness can be carried out.

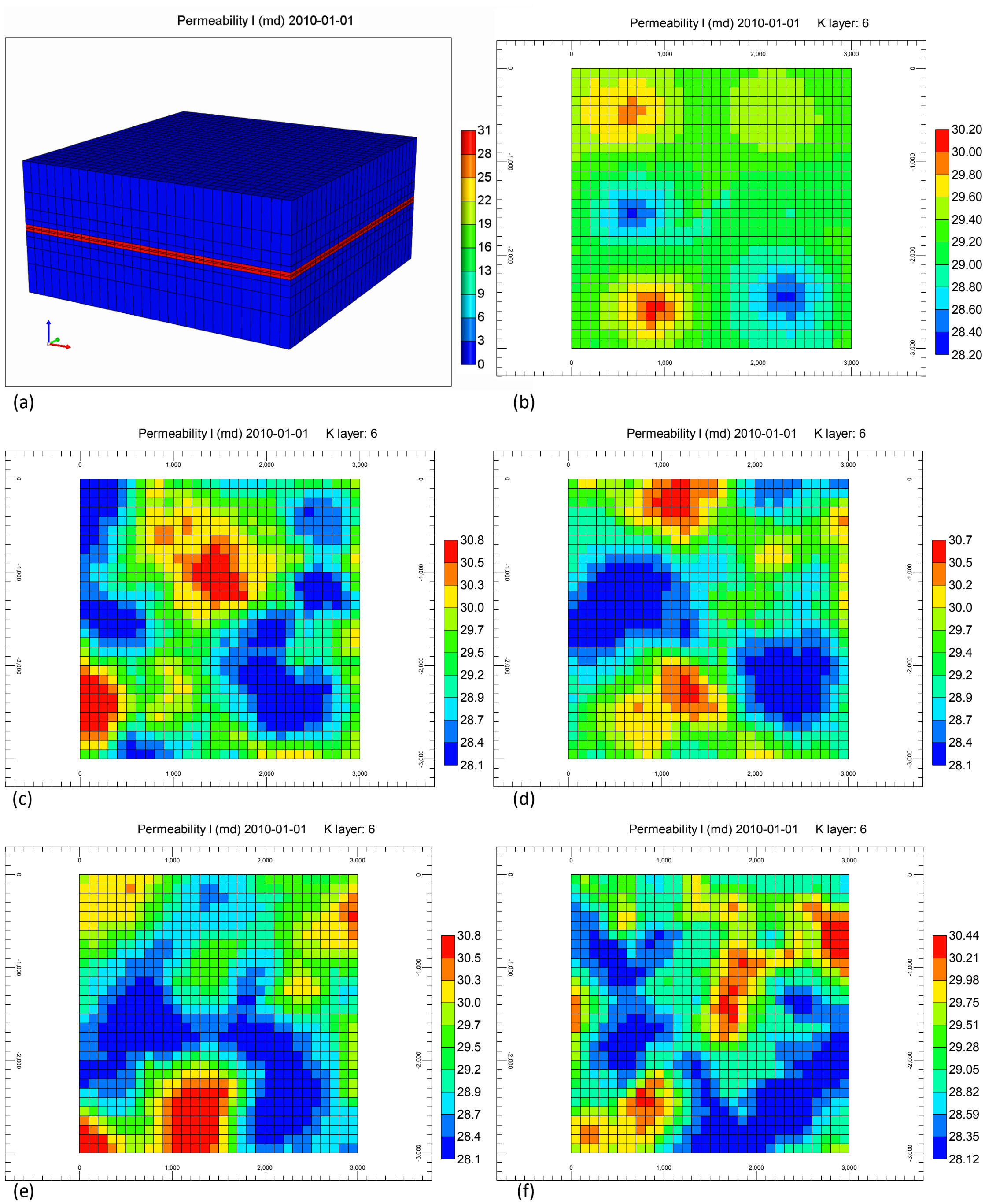


Figure 2.17 – Case 3, Testing the Probability of Success (a) General View of the Reservoir Domain (b) Realization # 1, Ordinary Kriging (c) Realization # 2, Gaussian Distribution (d) Realization # 3, Gaussian Distribution (e) Realization # 4, Gaussian Distribution (f) Realization # 5, Gaussian Distribution.

The modified genetic algorithm as well as an exhaustive search is run individually for each realization, the results are presented in **Table 2.3**. Then the modified genetic algorithm with probability of success was run for several values of probability of success. The results are presented in **Table 2.4**.

Table 2.3 – Individual Reservoir Realizations Compared to Exhaustive Search

	Exhaustive Search	Modified Genetic Algorithm
Realization 1		
Well Location	(15, 18, 5) to (15, 11, 5)	(15, 18, 5) to (15, 11, 5)
Production (MMSCF)	30,189.0	30,189.0
Realization 2		
Well Location	(15, 13, 5) to (15, 20, 5)	(15, 13, 5) to (15, 20, 5)
Production (MMSCF)	31,185.0	31,185.0
Realization 3		
Well Location	(13, 15, 5) to (20, 15, 5)	(13, 15, 5) to (20, 15, 5)
Production (MMSCF)	30,198.0	30,198.0
Realization 4		
Well Location	(12, 15, 5) to (19, 15, 5)	(12, 15, 5) to (19, 15, 5)
Production (MMSCF)	30,236.0	30,236.0
Realization 5		
Well Location	(15, 19, 5) to (15,12, 5)	(15, 19, 5) to (15,12, 5)
Production (MMSCF)	30,252.0	30,252.0

Table 2.4 – Results for Several Probabilities of Success Using a Modified Genetic Algorithm

	Modified Genetic Algorithm with Probability of Success
Probability of Success = 20 %	
Well Location	(15, 18, 5) to (15, 11, 5)
Production (MMSCF)	30,245.25
Probability of Success = 50 %	
Well Location	(15, 18, 5) to (15, 11, 5)
Production (MMSCF)	30,212.1
Probability of Success = 80 %	
Well Location	(15, 18, 5) to (15, 11, 5)
Production (MMSCF)	30,200.45

As expected, with the increasing probability of success, the allowed risk is lowered and the production decreased. Likewise, with the smaller probability of success, the risk and potential production increase, **Fig. 2.18**.

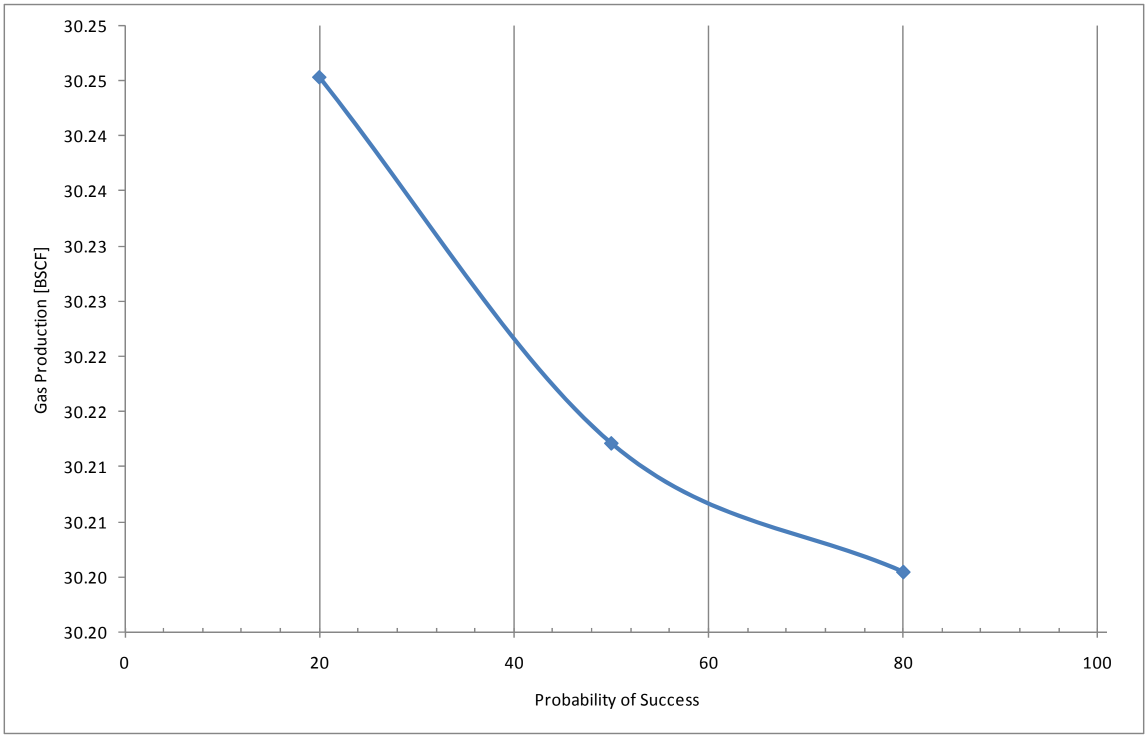


Figure 2.18 – Results for Several Probabilities of Success Using a Modified Genetic Algorithm.

CHAPTER III

QATAR'S NORTH FIELD: HORIZONTAL WELL PLACEMENT OPTIMIZATION USING A MODIFIED GENETIC ALGORITHM

Introduction

The modifications presented have been developed with the purpose of directly applying the modified genetic algorithm to a gas condensate reservoir. This new methodology will be applied to the North Field located in Qatar. It is estimated that the North Field holds approximately 890 TSCF of proven reserves, making it the largest non associated gas field in the world (D.O.E./E.I.A. 2010. *Natural Gas Reserves Summary*, by E.I.A.). This single field holds about 15% of the total world reserves and thrusts Qatar into third place among countries with natural gas reserves, behind Russia and Iran. Well placement could have a gigantic effect of total recoverable fluids in this colossal field.

North Field is a gas condensate reservoir. As the reservoir pressure falls below the saturation pressure, condensates begin to form and results in a potential of wellbore blockage and reduced production.

North Field Case Development

Published data for the Qatar's North Field is very limited. The reservoir is an extension of the Khuff formation, and it is widely accepted that the reservoir is composed of four main layers called K1, K2, K3 and K4. Each of these layers contains a highly permeable layer sandwiched between two low permeability sections, **Fig. 3.1**. The thick black lines represent the high permeability area in each zone (Miller et al. 2010). In this work, horizontal permeability variation was introduced by assigning random permeability at several points in the reservoir, and then performing a Kriging distribution to populate the rest of the domain, but the main characteristics of a high permeability center is maintained as shown in **Fig. 3.2**.

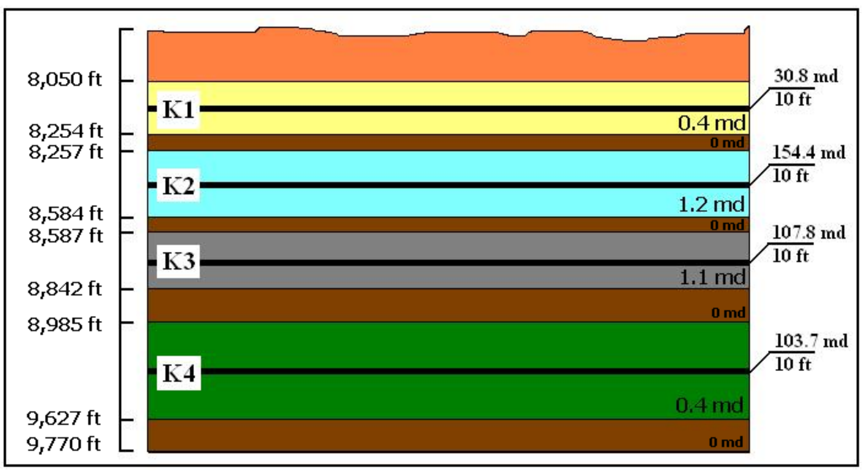


Figure 3.1 – North Field Formation Layers (Miller et al. 2010).

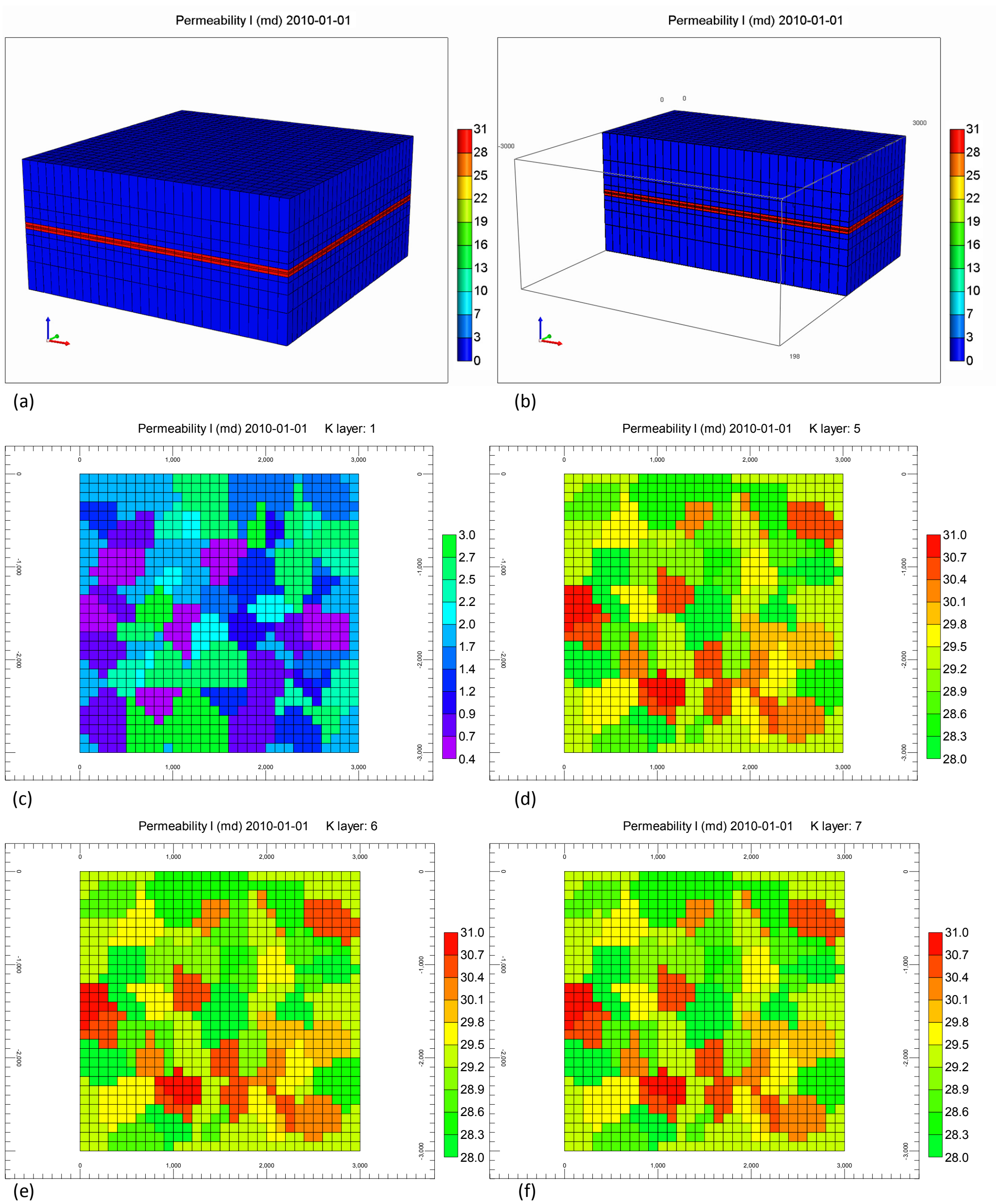


Figure 3.2 – North Field Reservoir Model Permeability Variation (a) 3-D lateral View, Permeability Scale Range is 0.4 – 31 mD (b) 3-D Lateral View with a Vertical Slice, Permeability Scale Range is 0.4 – 31 mD (c) Aerial View of Layer 4, Permeability Scale Range is 0.4 – 3.0 mD (d) Aerial View of Layer 5, Permeability Scale Range is 28.1 – 30.8 mD (e) Aerial View of Layer 6, Permeability Scale Range is 28.1 – 30.8 mD (f) Aerial View of Layer 7, Permeability Scale Range is 28.1 – 30.8 mD.

For the model creation, only one of these layers, the K1 layer, is used. The reservoir model was constructed in CMG with a dimension of 3,000 ft × 3,000 ft × 200 ft which is represented by a 30 × 30 × 11 gridding system. This is only about 0.8 km^2 of the North Field's total surface area of 6,000 km^2, a miniscule amount, but a large enough drainage area for one horizontal well. The top of the reservoir is located at a depth of 8,050 ft and an initial pressure of 5,315 psia (**Table 3.1** and **Table 3.2**). Initial composition of the reservoir is presented in **Table 3.3** (Whitson and Kuntadi 2005).

Table 3.1 – Geometric Model Description for the North Field Application K1 Layer

Surface Area, ft	3,000 × 3,000
Cartesian Gridding	30 × 30 × 11
Total Size of Reservoir, ft	3,000 × 3,000 × 200

Table 3.2 – North Field Reservoir Properties (Whitson and Kuntadi 2005)

Rock and Fluid Properties	
Porosity	0.10
Ky = Kx	
Low Permeability (mD)	0.4
High Permeability (mD)	30.8
Kz = 0.1Kx = 0.1Ky	
Rock Compressibility (1/psi)	5.00E-06
Reservoir Temperature (F)	220.0
Water Compressibility (1/psi)	2.64E-06
Water FVF (rb/stb)	1.0375
Water Density (lbs/cuft)	62.37
Water Viscosity (cp)	0.65
Depth to Top of Formation (ft)	8,050
Initial Conditions	
Initial Pressure (psia)	5,315
Dew Point Pressure (psia)	5,135
Relative Permeability	
Connate Water Saturation (Swc)	0.2
Residual Oil Saturation to Water (Sorw)	0.2
Residual Oil Saturation to Gas (Sorg)	0.2
Critical Gas Saturation (Sgc)	0.1
Water Relative Permeability at Sw=1-Sorw, Sg=0 (krwro)	0.5
Gas Relative Permeability at Sw=Swc, So=Sorg (krgro)	0.33
Oil Relative Permeability at Sw=Swc, So=0 (krocw)	0.9

Table 3.3 – North Field Compositional & EOS Data (Whitson and Kuntadi 2005)

Component	% moles	MW	Pcrit (psia)	Tcrit (R)	Acentric Factors	Parachors	Volume Shift	Zcrit
N2	3.349	28.014	492.84	227.16	0.037	59.1	-0.0009	0.29178
H2S	0.529	34.082	1299.97	672.12	0.09	80.1	0.1015	0.28292
CO2	1.755	44.01	1069.51	547.42	0.225	80	0.2175	0.27433
C1	83.265	16.043	667.03	343.01	0.011	71	-0.0025	0.2862
C2	5.158	30.07	706.62	549.58	0.099	111	0.0589	0.27924
C3	1.907	44.097	616.12	665.69	0.152	151	0.0908	0.2763
iC4	0.409	58.123	527.94	734.13	0.186	188.8	0.1095	0.28199
nC4	0.699	58.123	550.56	765.22	0.2	191	0.1103	0.27385
iC5	0.280	72.15	490.37	828.7	0.229	227.4	0.0977	0.27231
nC5	0.280	72.15	488.78	845.46	0.252	231	0.1195	0.26837
C6	0.390	82.319	491.32	924.21	0.23726	232.57	0.1341	0.27034
C7	0.486	95.357	457.18	988.34	0.27142	263.86	0.1429	0.26589
C8	0.361	108.772	422.82	1043.92	0.30936	296.05	0.1522	0.2614
C9	0.266	121.895	389.97	1094.09	0.35002	327.55	0.1697	0.25713
C10	0.201	134.784	361.66	1138.55	0.38996	358.48	0.1862	0.25334
C11	0.153	147.589	336.96	1178.85	0.42946	389.21	0.2018	0.24986
C12	0.116	160.302	315.31	1215.63	0.4684	419.72	0.2165	0.2466
C13	0.089	172.914	296.27	1249.41	0.50673	449.99	0.2302	0.24352
C14	0.068	185.422	279.43	1280.57	0.54442	480.01	0.243	0.24056
C15	0.052	197.823	264.48	1309.45	0.58144	509.77	0.2548	0.2377
C16	0.040	210.113	251.14	1336.33	0.6178	539.27	0.2657	0.23493
C17-19	0.073	233.389	229.29	1383.11	0.68566	595.13	0.2843	0.22981
C20-29	0.063	299.514	184.61	1493.68	0.87122	753.83	0.3239	0.2161
C30+	0.011	477.341	167.56	1616.94	1.04107	1180.62	0.1154	0.20582

The original fluid composition is made up of a 24 component system. In order to reduce the complexity of the system and decrease the simulation run time, the fluid compositional model was lumped into 13 components, with six pseudo components. The regression results for the original data are presented in **Fig. 3.3** and the lumped regression results are presented in **Fig. 3.4**. The initial composition of the reservoir using the lumped system is presented in **Table 3.4**.

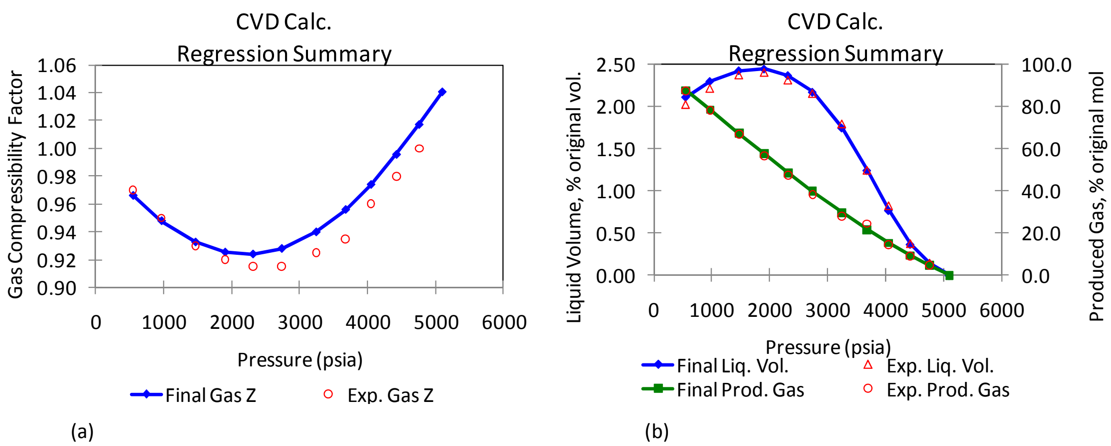


Figure 3.3 – Regression Results for the Original 24 Component System (a) Gas Compressibility Regression (b) Produced Liquids and Saturation Pressure Regression.

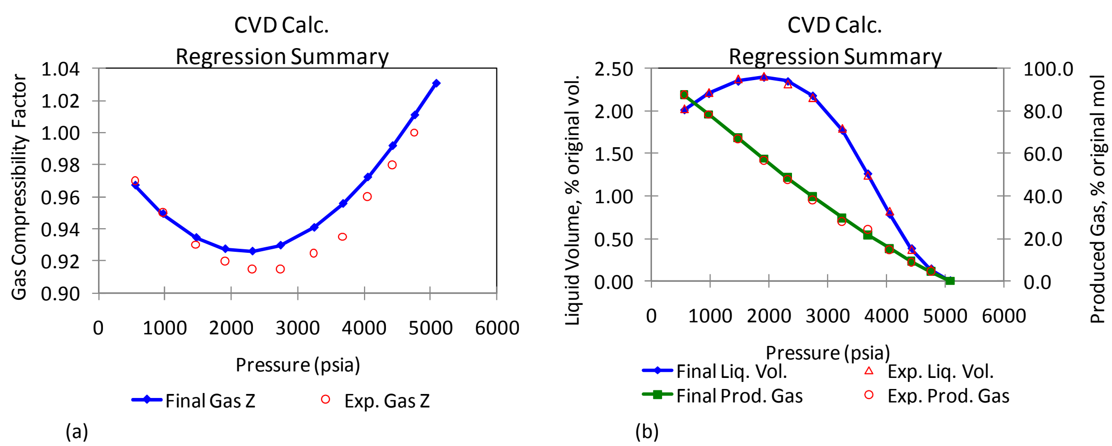


Figure 3.4 – Regression Results for the Lumped 13 Component System (a) Gas Compressibility Regression (b) Produced Liquids and Saturation Pressure Regression.

Table 3.4 – North Field Lumped Compositional & EOS Data

Component	% moles	MW	Pcrit (psia)	Tcrit (R)	Acentric Factors	Parachors	Volume Shift	Zcrit
N2	3.349	28.014	492.84	227.16	0.040	59.1	-0.0009	0.28952
H2S	0.529	34.082	1299.97	672.12	0.100	80.1	0.1015	0.28368
CO2	1.755	44.010	1069.51	547.42	0.225	80.0	0.2175	0.27414
C1	83.265	16.043	667.03	343.01	0.008	71.0	-0.0025	0.28737
C2	5.158	30.070	706.62	549.58	0.098	111.0	0.0589	0.28465
C3	1.907	44.097	616.12	665.69	0.152	151.0	0.0908	0.28029
C4	1.109	58.123	542.98	753.81	0.187	190.2	0.1100	0.27725
C5	0.559	72.150	490.25	836.97	0.239	229.2	0.1087	0.26660
C6	0.390	82.319	477.16	913.50	0.275	232.6	0.1318	0.26813
C7 to C10	1.314	110.450	447.67	1100.58	0.397	300.1	0.2504	0.26032
C11 to C15	0.477	166.211	263.37	1263.35	0.479	433.9	0.2007	0.21401
C16 to C19	0.113	225.176	199.82	1265.31	0.617	575.4	0.1956	0.21101
C20+	0.075	327.366	198.62	1380.37	0.956	820.7	2.0751	0.25924

The wellbore constraints are presented in **Table 3.5**. The saturation pressure compared with a nearby grid (30,30,6) pressure over time is presented in **Fig. 3.5** and shows how the reservoir pressure near the wellbore will quickly drop below the dew point pressure and create condensate in the wellbore vicinity. The same comparison is done for the furthest grid block (1,1,1), **Fig. 3.6**, and shows the same trend.

The two compositional models are run with the same well location and a period of five years. The difference in production and run time are presented in **Table 3.6**.

Table 3.5 – Simulation Well Constraints

Parameter	Value
Maximum Surface Gas Rate	50 MMSCF per day
Minimum Bottom Hole Pressure	800 psi

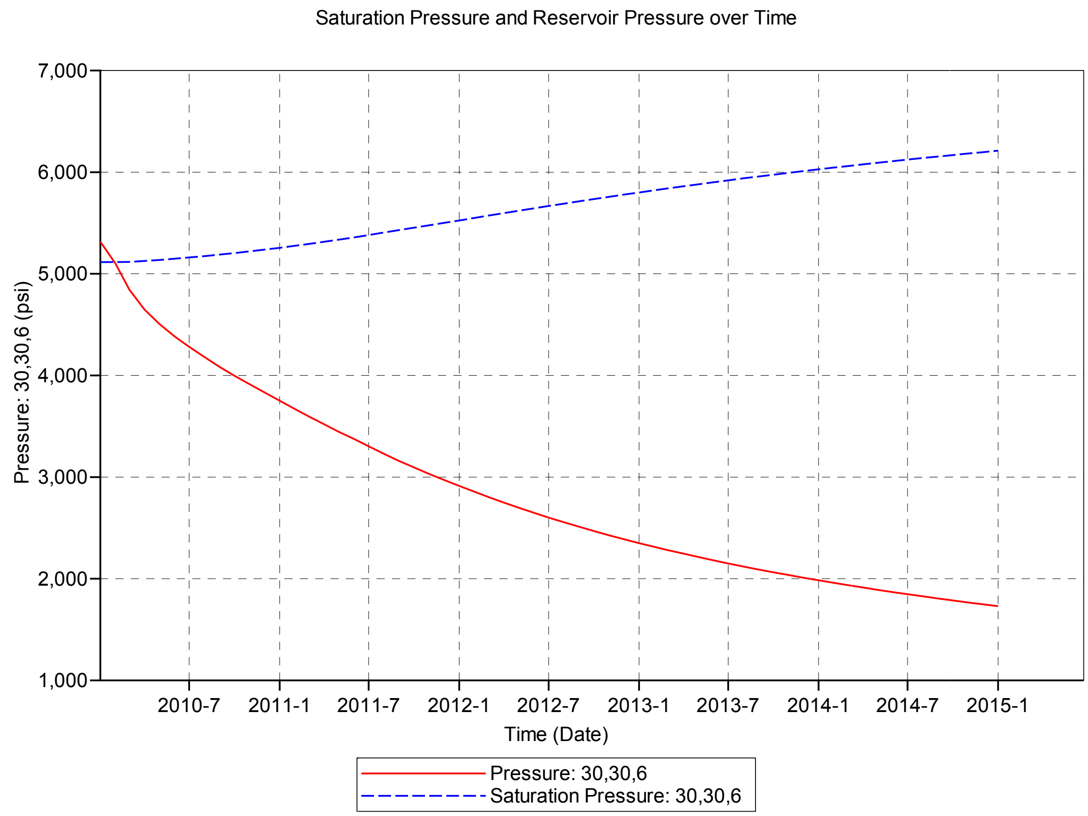


Figure 3.5 – Grid Reservoir Pressure and Saturation Pressure near the Wellbore.

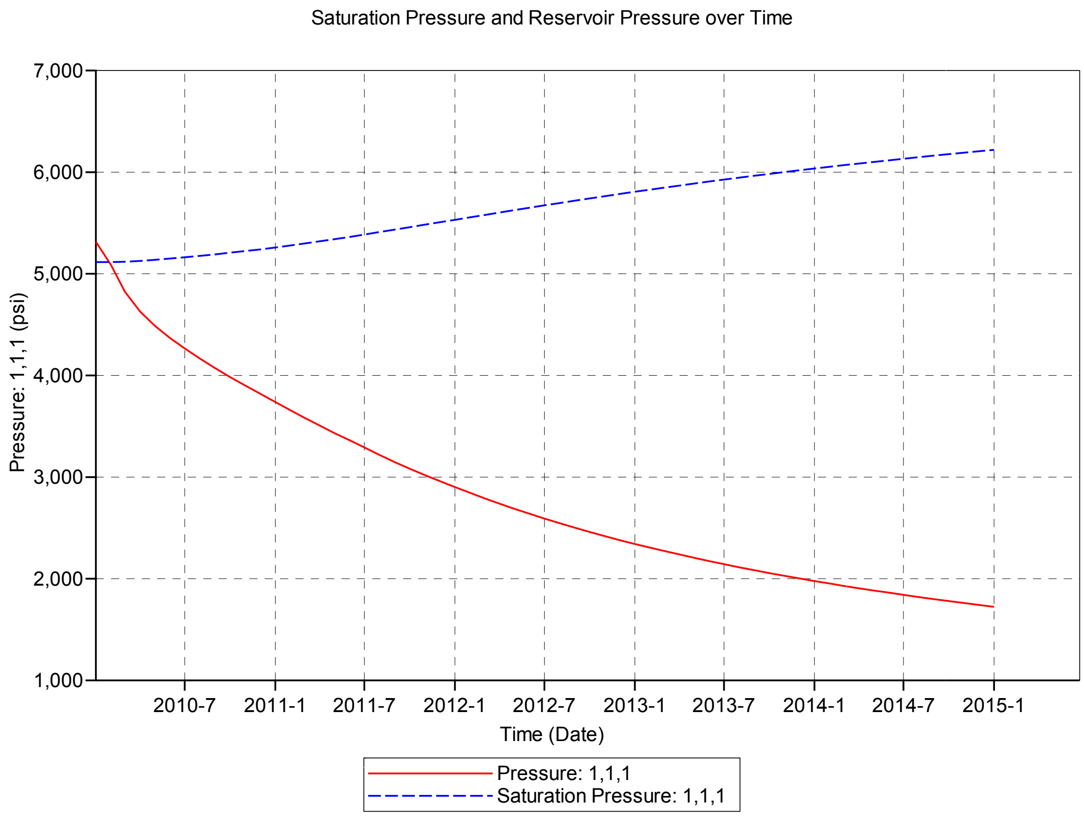


Figure 3.6 – Grid Reservoir Pressure and Saturation Pressure at the Reservoir Boundary.

Table 3.6 – Comparison of Results for Original and Lumped EOS

	Well Location	**Gas Production (MMSCF)**	**Oil Production (MSTB)**	**Run Time (seconds)**
Original	(12, 15, 6) to (19, 15, 6)	23,343	242.32	254.4
Lumped	(12, 15, 6) to (19, 15, 6)	23,312	268.82	86.4
Difference		-0.13 %	10.94 %	-66.04 %

North Field Case with Minimal Variance Modification

As the cases increase in complexity, the exhaustive search option is no longer feasible. This case will compare the performance of a standard genetic algorithm with that of a customized genetic algorithm with the Minimal Variance (MiniVar) modification. The search parameters for both cases are maintained the same, except for the parent selection mechanism, and are presented in **Table 3.7**. This case utilizes the North Field permeability distribution presented in the previous section. The results for both the SGA and modified GA are presented in **Table 3.8**. The general program flow chart, excluding the probability of success modification, used is presented in **Fig. 3.7**.

Both SGA and the modified GA, demonstrated that neither gas nor condensate production was maximized for the sake of the other. There were certain well locations that produced more gas or condensate than the optimized solution, but at the penalty of a lower overall fitness value. This demonstrates that the optimum solution in a complex domain is a balance between condensate and gas production.

Table 3.7 – Genetic Algorithm Search Parameters for the North Field Case

	Standard Genetic Algorithm	Modified Genetic Algorithm with MiniVar
General		
Generations	200	200
Population Size	25	25
Optimized Parameters	4	4
Probabilities		
Mutation	5 %	5 %
Creep Mutation	3.3 %	3.3 %
Crossover	60 %	60 %
Selection & Reproduction		
Elitist Reproduction	Yes	Yes
Parent Selection	Standard Tournament	MiniVar with Roulette
Fitness Value		
Price for Oil	80 Dollars per Barrel	80 Dollars per Barrel
Price for Gas	4 Dollars per MSCF	4 Dollars per MSCF

Table 3.8 – Results Comparison for SGA and Modified GA with MiniVar

	Well Location	Gas Production (MMSCF)	Oil Production (MSTB)	Fitness (MMDollars)	Simulations Required
Standard Genetic Algorithm	(17, 25, 7) to (17, 18, 7)	27,085	274.92	130.3	2,025
Modified Genetic Algorithm with MiniVar	(17, 25, 7) to (17, 18, 7)	27,085	274.92	130.3	350
Difference		none	none	none	-82.72%

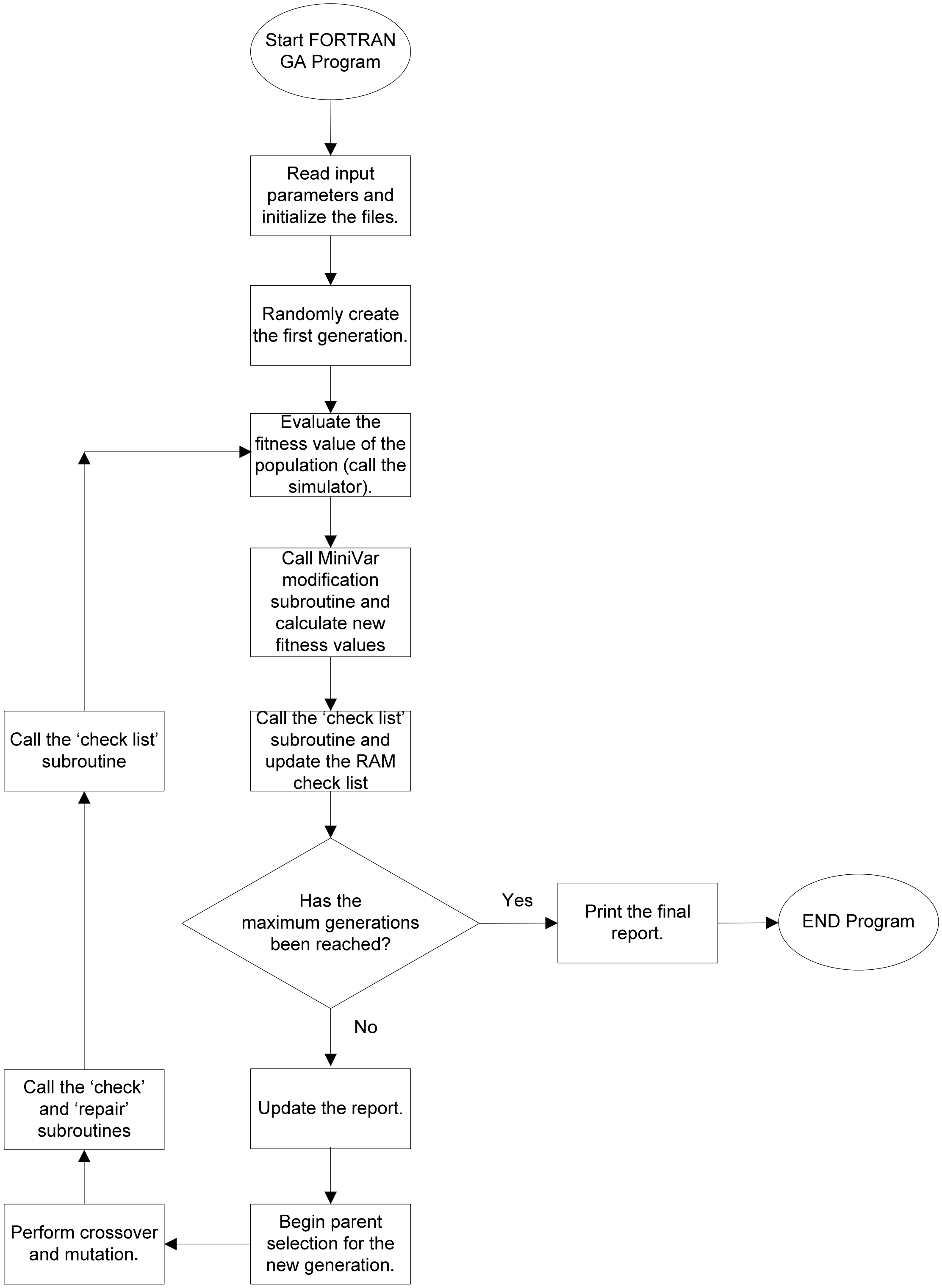


Figure 3.7 – Modified Genetic Algorithm Program Flow Chart, Without Probability of Success.

North Field Case with Initial Compositional Variation

The importance of the North Field has been made clear as well as the importance to find a balance between gas and liquids production. Another important factor to consider is the field's compositional variation. Compositional variation has been reported in many fields. An obvious mechanism behind compositional variation; gravity, where there is an increase in molecular weight with increasing depth. Depending on the well location, the immediate section can be condensate rich, sour gas, or dry gas. The normal range of variation reported for Khuff reservoirs is between 0 and 5 mole percent variation for H_2S (Temeng et al. 1998), and 1 to 4.5 mole percent variation for C_{6+} components, and C_1 variation lies between 65 to 85 mole percent (Whitson and Kuntadi 2005). The general trend for the variations is that C_1 thru C_6 decrease in composition and H_2S, N2, CO2 and C7+ composition increases with depth (Temeng et al. 1998). For the following cases, the same permeability distribution as the one presented in Minimal Variance case is used and the simulation parameters are presented in **Table 3.7**.

Case 1 – Multi-Component Horizontal Compositional Variation

This case will vary all 13 components presented in **Table 3.4**. Random well data was placed on either side of the reservoir, and then a Kriging Distribution was performed for the middle ground. The main characteristics of the reservoir are; increasing C_1 from 77 to 83 mole percent, decreasing C_{6+} from 4.5 to 1 mole percent and decreasing H_2S from 6 to 1 mole percent in the south to north direction, **Fig. 3.8**.

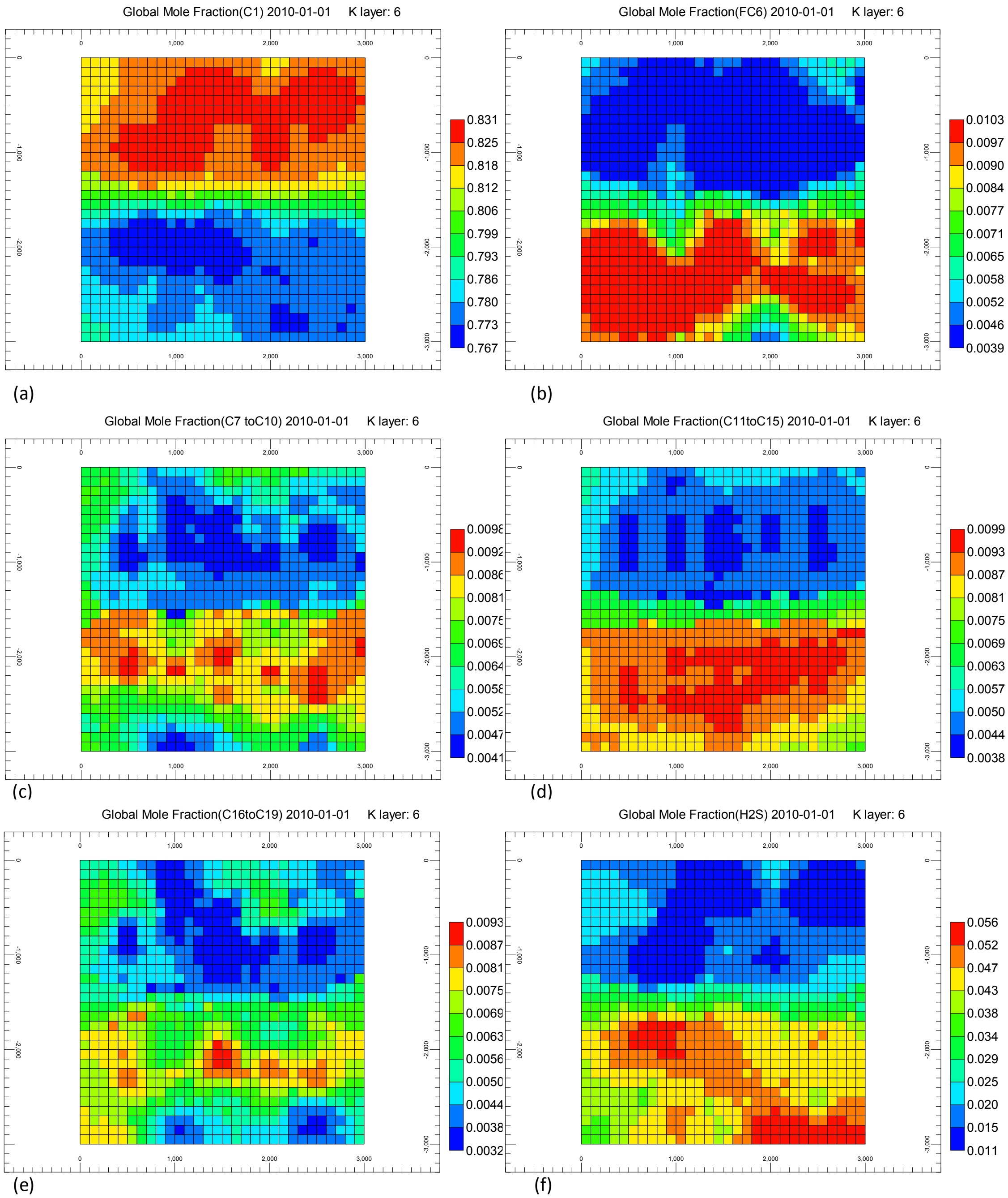


Figure 3.8 – Compositional Variation Case 1 (a) C_1 Composition, Layer = 6 (b) C_6 Composition, Layer = 6 (c) C_7 to C_{10} Composition, Layer = 6 (d) C_{11} to C_{15} Composition, Layer = 6 (e) C_{16} to C_{19} Composition, Layer = 6 (f) H_2S Composition, Layer = 6.

Case 2 – Multi-Component Diagonal Compositional Variation

This case will vary all 13 components presented in **Table 3.4**. Random well data was placed on the top north and bottom south of the reservoir, and then a Kriging Distribution was performed for the middle ground. The main characteristic for the case is increasing C_1 from 75 to 85 mole percent from the top north layer to the bottom south layer in a diagonal fashion. Inversely to the light hydrocarbons, C_{6+} and H_2S will decrease from 4.5 to 1 mole percent and 6 to 1 mole percent in the same direction. The complete compositional gradients are shown in **Fig. 3.9** thru **Fig. 3.12**.

The optimum well locations are presented in **Fig. 3.13**, and the results summarized in **Table 3.9**. For the horizontal compositional variation case, the majority of the wellbore is located in the southern section of the reservoir. This southern section is condensate rich and the optimum location shows a balance between gas and condensate production. In the second case, diagonal variation, the optimum location is very near the center of the reservoir, but in layer 5, the top most of the high permeability region.

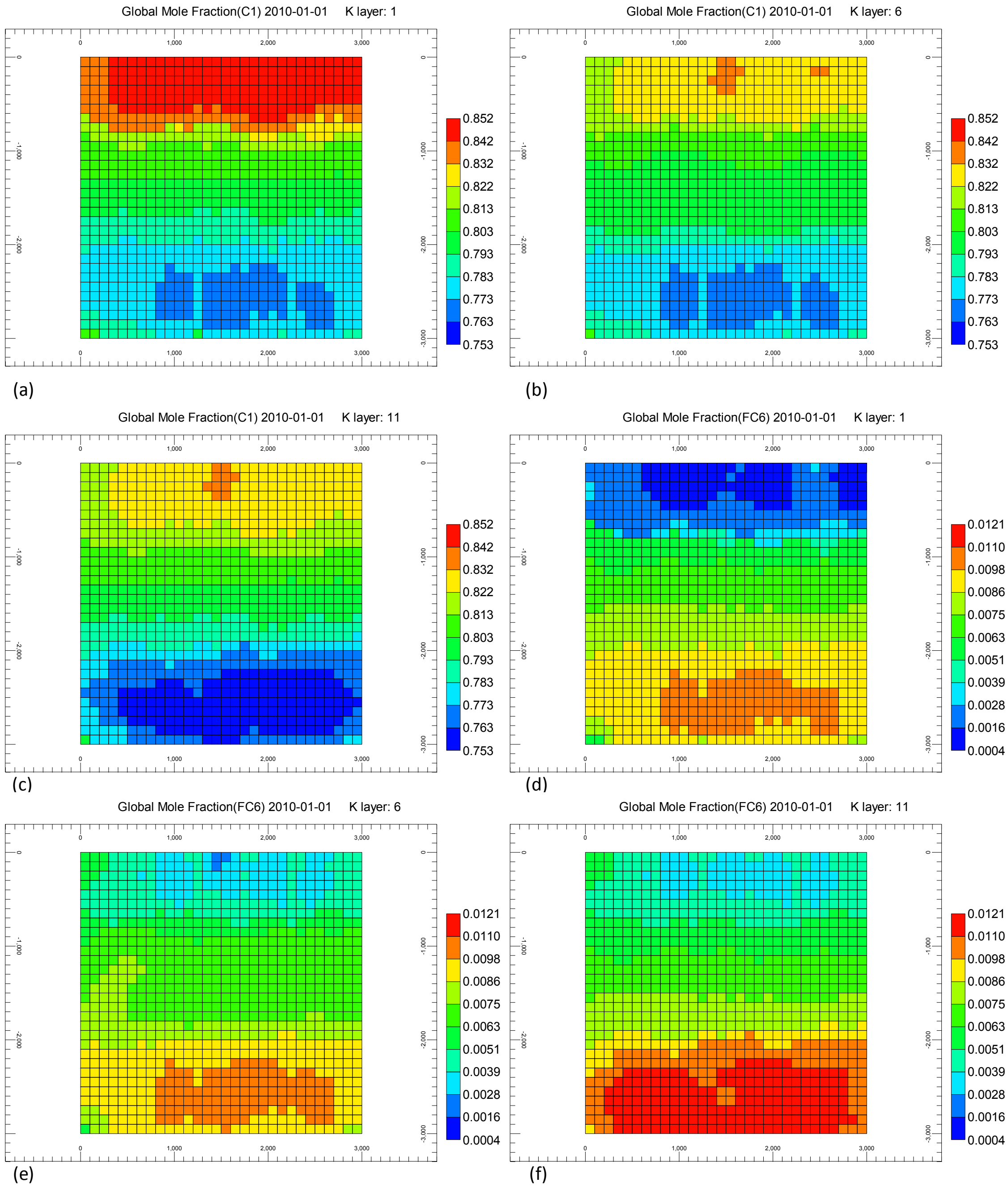


Figure 3.9 – Compositional Variation Case 2 (a) C_1 Composition, Layer = 1 (b) C_1 Composition, Layer = 6 (c) C_1 Composition, Layer = 11 (d) C_6 Composition, Layer = 1 (e) C_6 Composition, Layer = 6 (f) C_6 Composition, Layer = 11.

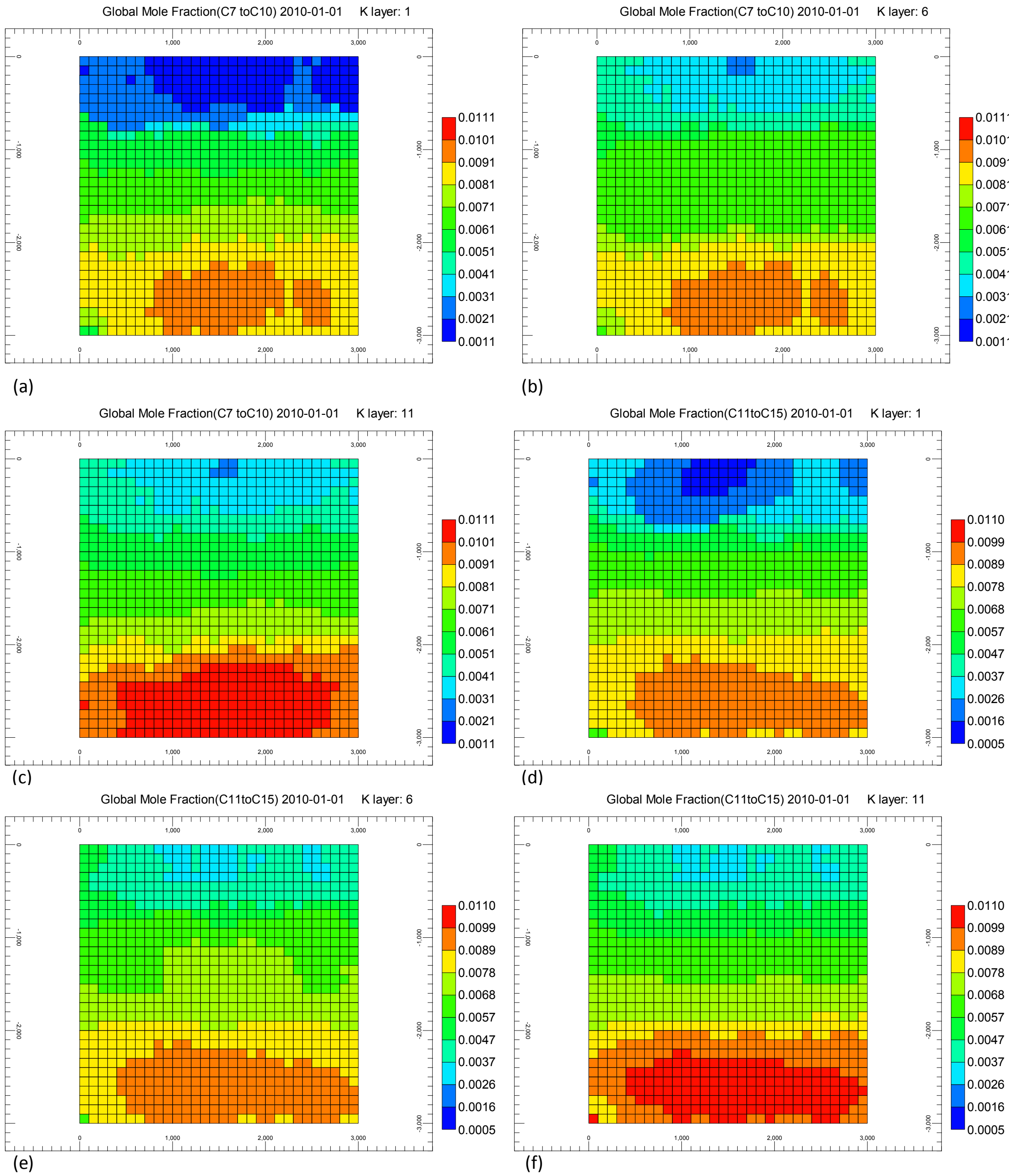


Figure 3.10 – Compositional Variation Case 2 (a) C_7 to C_{10} Composition, Layer = 1 (b) C_7 to C_{10} Composition, Layer = 6 (c) C_7 to C_{10} Composition, Layer = 11 (d) C_{11} to C_{15} Composition, Layer = 1 (e) C_{11} to C_{15} Composition, Layer = 6 (f) C_{11} to C_{15} Composition, Layer = 11.

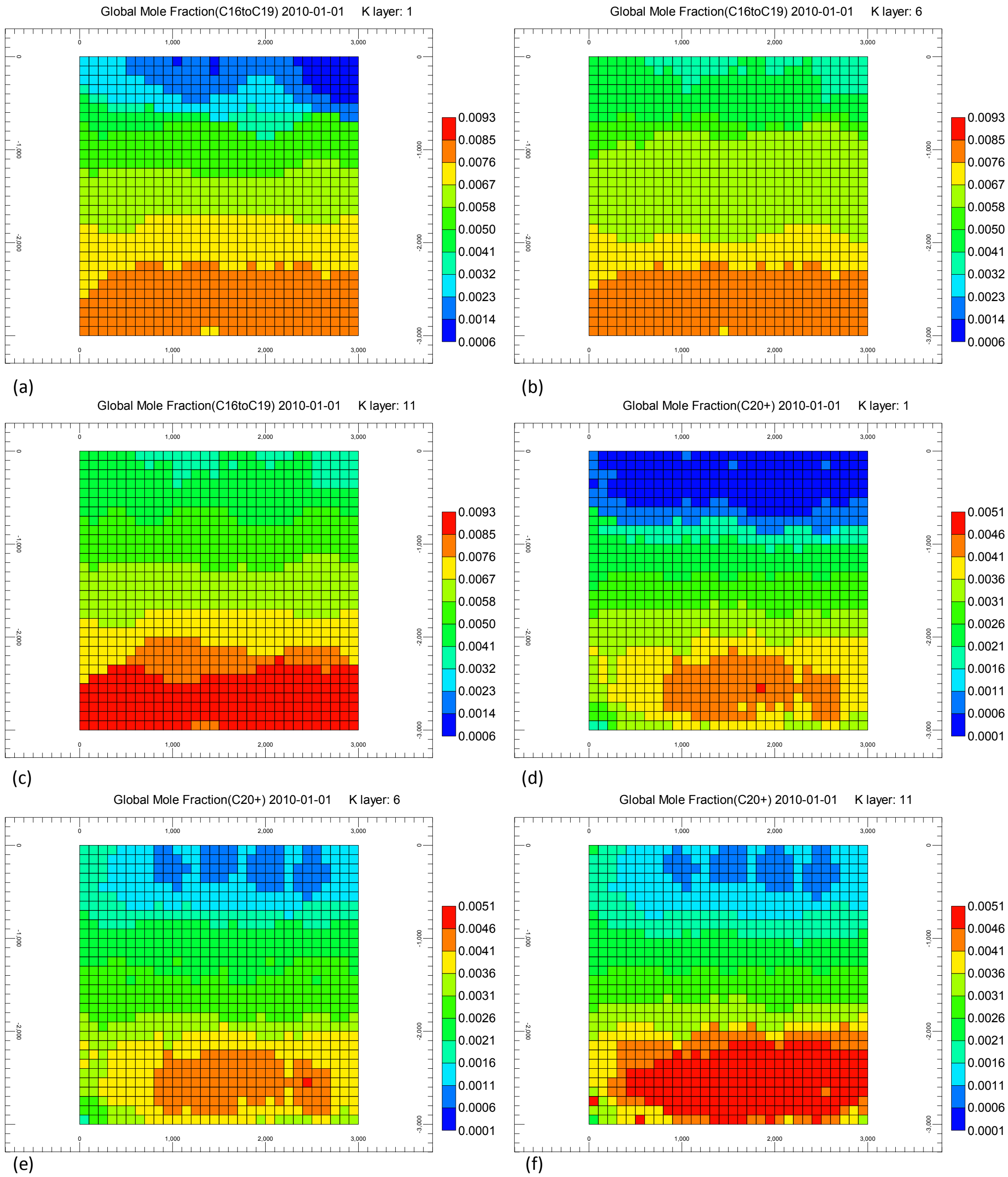


Figure 3.11 – Compositional Variation Case 2 (a) C_{16} to C_{19} Composition, Layer = 1 (b) C_{16} to C_{19} Composition, Layer = 6 (c) C_{16} to C_{19} Composition, Layer = 11 (d) C_{20+} Composition, Layer = 1 (e) C_{20+} Composition, Layer = 6 (f) C_{20+} Composition, Layer = 11.

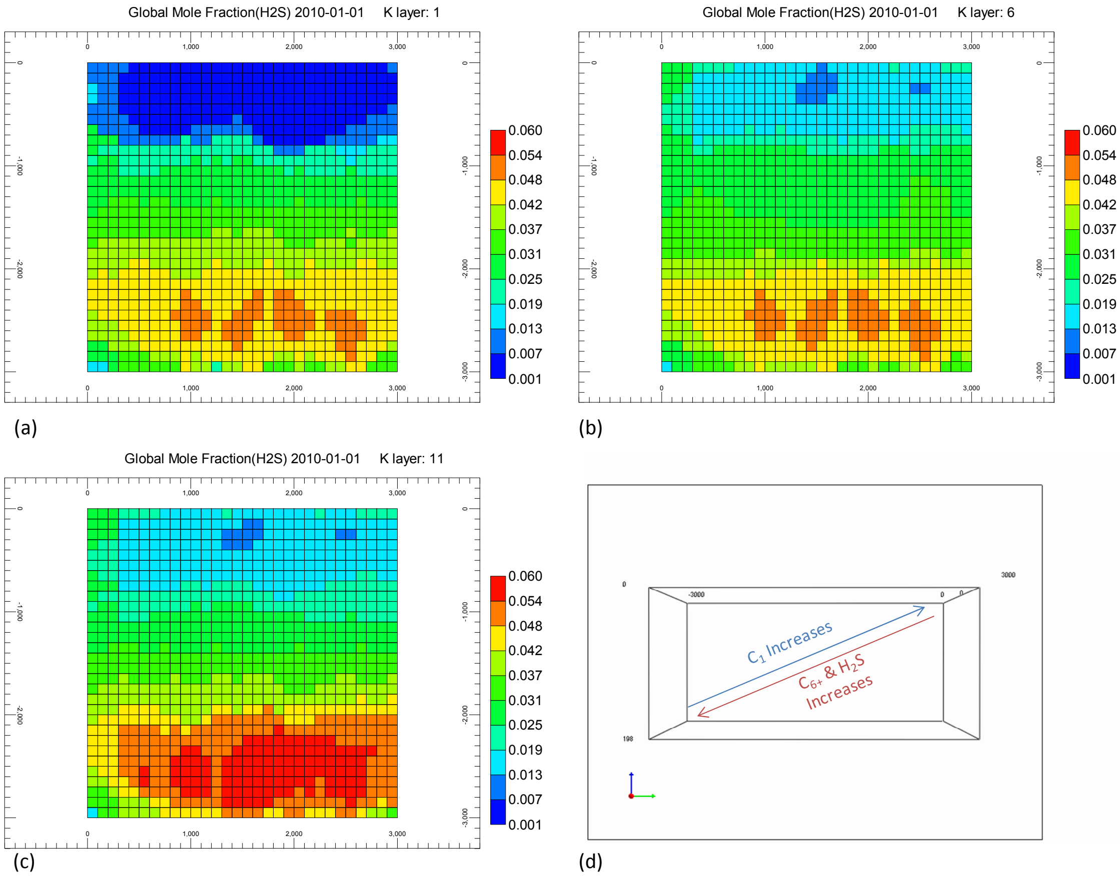


Figure 3.12 – Compositional Variation Case 2 (a) H_2S Composition, Layer = 1 (b) H_2S Composition, Layer = 6 (c) H_2S Composition, Layer = 11 (d) General Composition Trend.

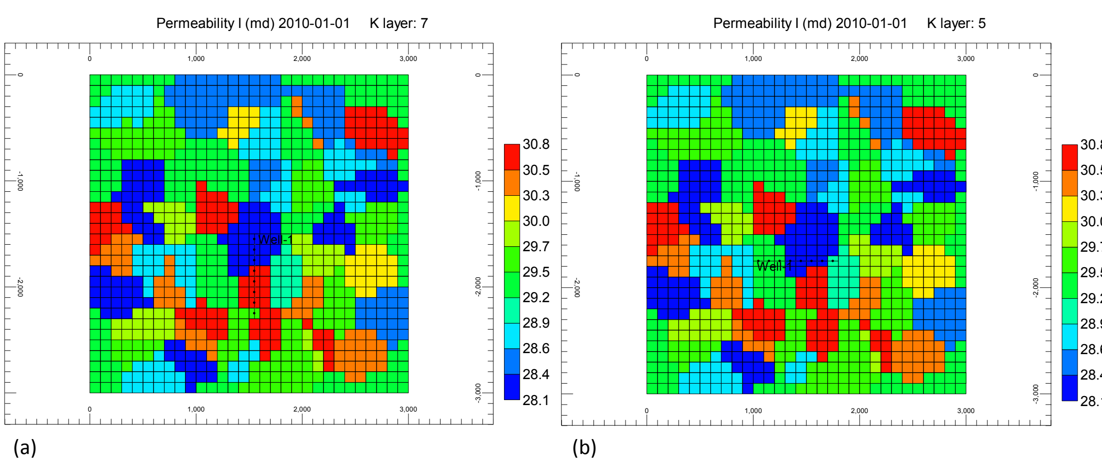


Figure 3.13 – Optimum Well Location for Initial Composition Variation (a) Case 1, Horizontal Variation (b) Case 2, Diagonal Variation.

Table 3.9 – North Field Compositional Variation Results

	Well Location	Gas Production (MMSCF)	Oil Production (MSTB)	Fitness (MMDollars)
Case 1, Horizontal Variation	(16, 16, 7) to (16, 23, 7)	27,304	217.21	126.6
Case 2, Diagonal Variation	(11, 18, 5) to (18, 18, 5)	27,000	233.49	126.7

North Field Case with Probability of Success Modification

In this research, the main uncertainty parameter is the permeability distribution. Any combination of parameters, including compositional variation, can be assigned as the uncertainty parameters, but for simplicity, only permeability is considered.

Each permeability realization is based on the same initial well parameters. The permeability distribution is created on the first realization by an ordinary Kriging distribution. The other three realizations are done by creating a Gaussian distribution based from the same initial parameters used in the first realization. The four realizations are presented in **Fig. 3.14**. Each realization has kept the main characteristics of certain high permeability regions such as the southwest region. These permeability distributions have a small spread from 28 to 31 mD, and each realization has a different weight. The individual weights are presented in **Table 3.10**.

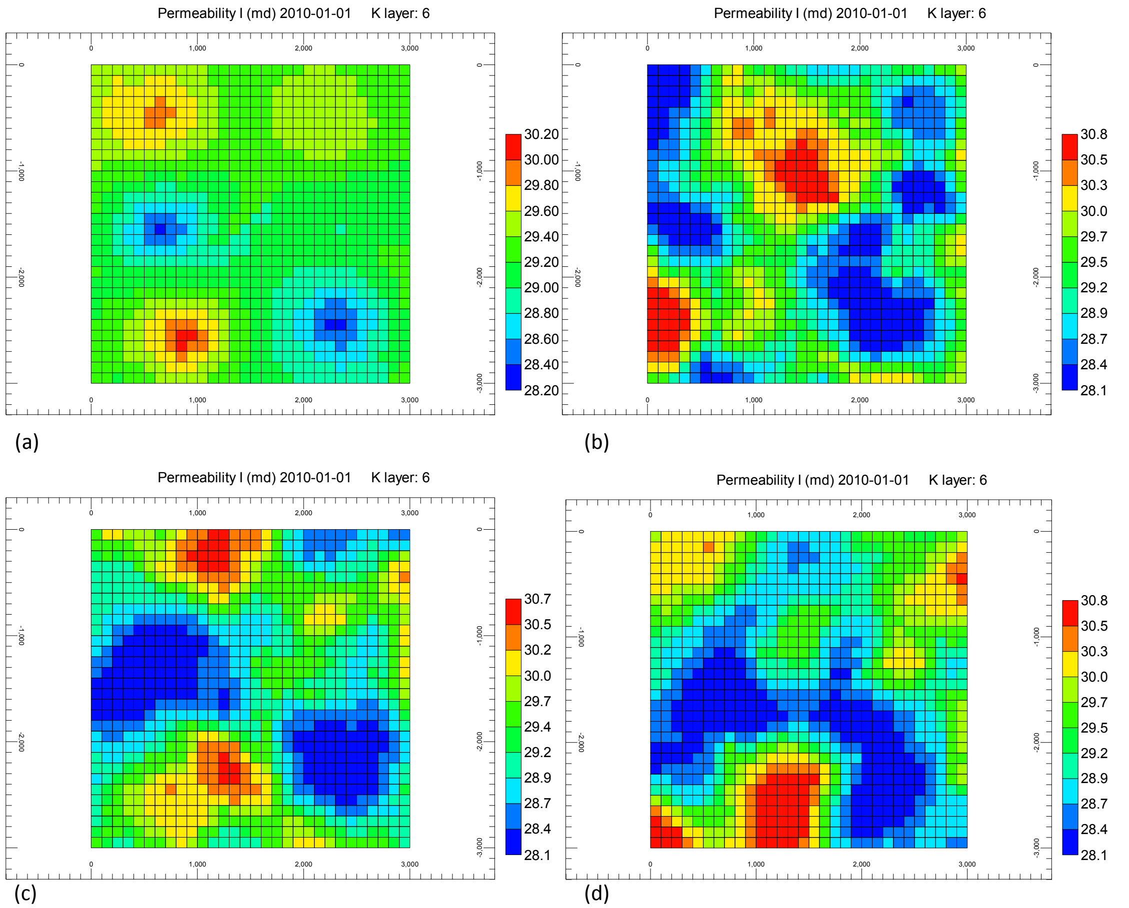


Figure 3.14 – Uncertainty Permeability Realizations (a) Realization #1, Ordinary Kriging Distribution (b) Realization #2, Gaussian Distribution (c) Realization #3, Gaussian Distribution (d) Realization #4, Gaussian Distribution.

Table 3.10 – Realization Weights for Probability of Success

	Weight
Realization 1	0.4
Realization 2	0.2
Realization 3	0.3
Realization 4	0.1

The probability of success of 10 % (P10), 50 % (P50), 75 % (P75) and 90 % (P90) are presented here. When the probability of success is set at 10 % this means that the user is willing to take a high risk attitude towards the well location optimization. Conversely, when the user is only willing to take a very low risk attitude towards the well location optimization, the probability of success is set at 90 %. The other values presented (P50 and P75) are presented in order to study how the algorithm performs at intermediate values. This case is done using the modified genetic algorithm which has been built up to this point.

The results for several Probability of Success values are reported in **Table 3.11**. The trend shown is expected, as the user specifies a higher risk bias, the fitness value increases. The general trend is shown in **Fig. 3.15**. The general program flow chart, including the probability of success modification, used is presented in **Fig. 3.16**.

Table 3.11 – Probability of Success Results

	Well Location	Gas Production (MMSCF)	Oil Production (MSTB)	Fitness (MMDollars)
Case 1, Ps = 10	(9, 12, 5) to (16,12,5)	26,212	254.00	125.2
Case 2, Ps = 50	(12, 12, 5) to (12, 19, 5)	26,030	254.29	124.5
Case 3, Ps = 75	(12, 12, 5) to (12, 19, 5)	25,990	253.73	124.3
Case 3, Ps = 90	(13, 15, 5) to (13, 22, 5)	25,977	253.38	124.2

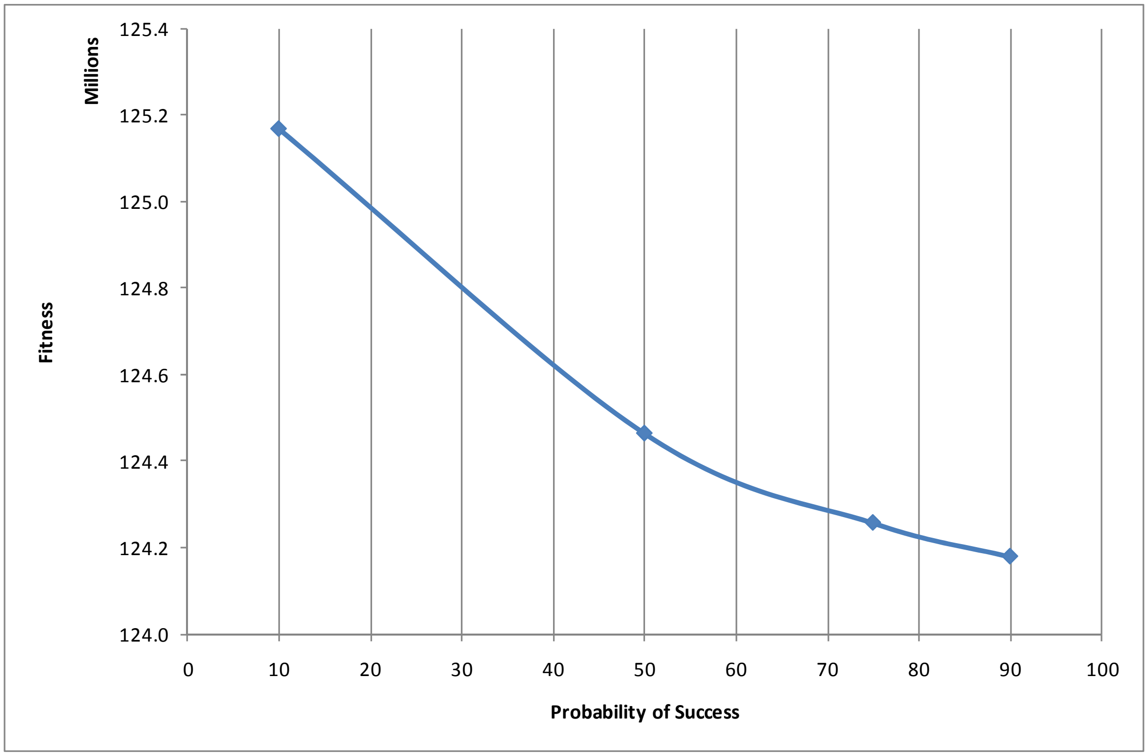


Figure 3.15 – Fitness Trend with Increasing Probability of Success.

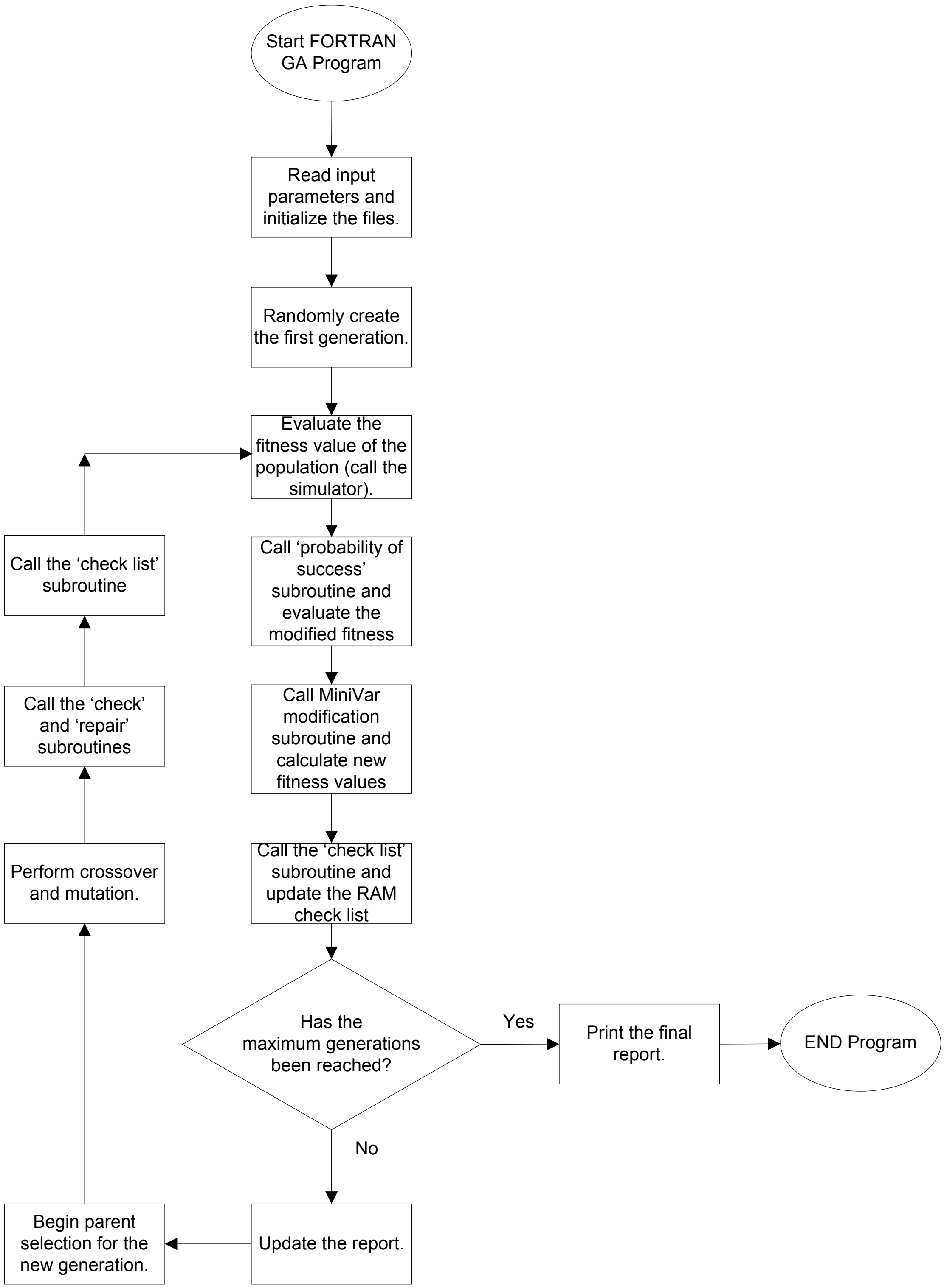


Figure 3.16 – Modified Genetic Algorithm Program Flow Chart.

CHAPTER IV

CONCLUSIONS AND FUTURE WORK

Conclusions

The initial problem statement presented an array of possibilities and different areas which could have been examined. Several of these problems were looked at and developed. The initial code was designed for a horizontal well in a small reservoir; this was expanded into a large domain. The addition of a compositional simulation instead of a black oil engine was incorporated to represent Qatar's North Field. Then several code modifications including the Minimal Variance and Probability of Success were incorporated into the code and the performance analyzed. The following conclusions have been made based on the study:

- When working with genetic algorithms, it is important to correctly adjust several algorithm parameters in order to have a fast convergence and not get prematurely entrapped within a set of solutions. This is done by adjusting the probabilities of mutation, individuals per generation, parent selection method and the stopping mechanism.
- The Minimal Variance (MiniVar) modification proved to be a valuable tool for evolutionary algorithms which need to compare large fitness populations with small variance. This technique can also be easily adapted to any other optimization techniques involving comparison among large populations. The

MiniVar modification can easily self adapt to populations with small variance or large. This makes it a very flexible tool for a variety of situations and scenarios.

- The increased convergence speed by applying the MiniVar modification is quite significant and more apparent as the optimized cases increase in complexity.
- The addition of uncertainty makes the genetic algorithm a robust tool able to identify well targets with a degree of uncertainty within any set of parameters.
- Initial composition variation affects the amount of produced condensate and in turn, the wellbore blockage. It is important to take into account condensate estimates, because as shown in the results, small variation with heavier components can significantly affect wellbore placement when compared to a compositionally homogeneous reservoir.
- The combination of heterogeneities presented make intuitive horizontal well placement a difficult, if not impossible task. The wide range of heterogeneities presented demonstrated that small variations in permeability or composition have a noticeable effect on the well location, total recovered hydrocarbons and economic fitness.

Future Work

- Parallelization of the code from a linear to a cluster format or supercomputer format can decrease the total run time by orders of magnitude. The total simulations required will not change, but the run time would be drastically reduced.

- Adding more complexity to the system by including multilateral wells or several wells within a reservoir will create the model into a truly robust solution methodology.
- Adding more degrees of freedom for well trajectory. In this research, four well directions were considered, but a whole range of trajectories can be studied by changing the well orientation reference from a one dimensional into a multi dimensional array describing location, length and angle for the well trajectory.

REFERENCES

Badru, O. and Kabir, C.S. 2003. Well Placement Optimization in Field Development. Paper SPE 8419 presented at the SPE Annual Technical Conference and Exhibition, Denver, Colorado, 10/05/2003.

Beckner, B.L. and Song, X. 1995. Field Development Planning Using Simulated Annealing: Optimal Economic Well Scheduling and Placement. Paper SPE 30650-MS presented at the SPE Annual Technical Conference and Exhibition, Dallas, Texas, 10/22/1995.

Bittencourt, A.C. and Horne, R.N. 1997. Reservoir Development and Design Optimization. Paper SPE 38895-MSpresented at the SPE Annual Technical Conference and Exhibition, San Antonio, Texas, 10/05/1997.

Carroll, D. Genetic Algorithm Driver, 2001. http://www.cuaerospace.com/carroll/ga.html.

Chan, R.R. and Sudhoff, S.D. 2009. An Evolutionary Computing Approach to Robust Design in the Presence of Uncertainties. *IEEE Transactions on Evolutionary Computation* (99): 1-1.

D.O.E./E.I.A. 2010. *Natural Gas Reserves Summary*, by E.I.A. http://www.eia.gov/dnav/ng/ng_enr_sum_dcu_NUS_a.htm.

Emerick, A.A., Silva, E., Messer, B. et al. 2009. Well Placement Optimization Using a Genetic Algorithm with Nonlinear Constraints. Paper SPE 118808 presented at the SPE Reservoir Simulation Symposium, The Woodlands, Texas, 02/02/2009.

Gibbs, T. 2009. Horizontal well placement optimization in gas reservoirs using genetic algorithms. M.Sc., Texas A&M University, College Station, Texas.

Goldberg, D.E. 1989. *Genetic Algorithms in Search, Optimization & Machine Learning*. Reading, Indiana: Addison Wesley.

Gűyagűler, B. and Gümrah, F. 1999. Comparison of Genetic Algorithm with Linear Programming for the Optimization of an Underground Gas Storage Field. *In-Situ* **23** (2): 131.

Gűyagűler, B. and Horne, R.N. 2004. Uncertainty Assessment of Well-Placement Optimization. *SPE Reservoir Evaluation & Engineering* **7** (1): 24-32. DOI: 10.2118/87663-pa.

Gűyagűler, B., Horne, R.N., Rogers, L., Rosenzweig, J.J. 2000. Optimization of Well Placement in a Gulf of Mexico Waterflooding Project. Paper SPE 63221-M presented at the SPE Annual Technical Conference and Exhibition, Dallas, Texas, 10/01/2000.

Harding, T.J., Radcliffe, N.J., and King, P.R. 1998. Hydrocarbon Production Scheduling with Genetic Algorithms. *SPE Journal* **3** (2): 99-107. DOI: 10.2118/36379-pa.

Maschio, C., Nakajima, L., and Schiozer, D.J. 2008. Production Strategy Optimization Using Genetic Algorithm and Quality Map. Paper SPE 113483-MS presented at the Europec/EAGE Conference and Exhibition, Rome, Italy, 06/09/2008.

Miller, N., Nasrabadi, H., and Zhu, D. 2010. On Application of Horizontal Wells to Reduce Condensate Blockage in Gas Condensate Reservoirs. Paper SPE 130996-

MS presented at the International Oil and Gas Conference and Exhibition in China, Beijing, China, 06/08/2010.

Montes, G., Bartolome, P., and Udias, A.L. 2001. The Use of Genetic Algorithms in Well Placement Optimization. Paper SPE 69439-MS presented at the SPE Latin American and Caribbean Petroleum Engineering Conference, Buenos Aires, Argentina, 03/25/2001.

Nakajima, L. and Schiozer, D.J. 2003. Horizontal Well Placement Optimization Using Quality Map Definition. Paper PETSOC-2003-053 presented at the Canadian International Petroleum Conference, Calgary, Alberta, 06/10/2003.

Nogueira, P.D.B. and Schiozer, D.J. 2009. An Efficient Methodology of Production Strategy Optimization Based on Genetic Algorithms. Paper SPE 122031-MS presented at the Latin American and Caribbean Petroleum Engineering Conference, Cartagena de Indias, Colombia 05/31/2009.

Özdogan, U. and Horne, R.N. 2004. Optimization of Well Placement with a History Matching Approach. Paper SPE 90091-PA presented at the SPE Annual Technical Conference and Exhibition, Houston, Texas 09/26/2004.

Pan, Y. and Horne, R.N. 1998. Improved Methods for Multivariate Optimization of Field Development Scheduling and Well Placement Design. Paper SPE 49055-MS presented at the SPE Annual Technical Conference and Exhibition, New Orleans, Louisiana, 09/27/1998.

Park, H.-J., Lim, J.-S., Kang, J.M., Roh, J., Min, B.-H. 2006. A Hybrid Artificial Intelligence Method for the Optimization of Integrated Gas Production System.

Paper SPE 100997-MS presented at the SPE Asia Pacific Oil & Gas Conference and Exhibition, Adelaide, Australia, 09/11/2006.

Park, H.-J., Lim, J.-S., Kang, J.M., Roh, J., Min, B.-H. 2010. Production-System Optimization of Gas Fields Using Hybrid Fuzzy/Genetic Approach. *SPE Journal* **15** (2): pp. 417-425. DOI: 10.2118/100179-pa.

Santellani, G., Hansen, B., and Herring, T. 1998. "Survival of the Fittest": An Optimized Well Location Algorithm for Reservoir Simulation. Paper SPE 39754-MS presented at the SPE Asia Pacific Conference on Integrated Modeling for Asset Management, Kuala Lumpur, Malaysia, 03/24/1998.

Shokir, E.M.E.-M.B. 2008. Dewpoint Pressure Model for Gas Condensate Reservoirs Based on Genetic Programming. Paper SPE 114454-MS presented at the CIPC/SPE Gas Technology Symposium 2008 Joint Conference, Calgary, Canada, 06/19/2008.

Soleng, H.H. 1999. Oil Reservoir Production Forecasting with Uncertainty Estimation Using Genetic Algorithms. *Proceedings of the 1999 Congress on Evolutionary Computation*, **1222:1223**.

Temeng, K.O., Al-Sadeg, M.J., and Al-Mulhim, W.A. 1998. Compositional Grading in the Ghawar Khuff Reservoirs. Paper SPE 49270-MS presented at the SPE Annual Technical Conference and Exhibition, New Orleans, Louisiana, 09/27/1998.

Whitson, C.H. and Kuntadi, A. 2005. Khuff Gas Condensate Development. Paper SPE 10692-MS presented at the International Petroleum Technology Conference, Doha, Qatar, 11/21/2005.

Yeten, B., Durlofsky, L.J., and Aziz, K. 2003. Optimization of Nonconventional Well Type, Location, and Trajectory. *SPE Journal* **8** (3): 200-210. DOI: 10.2118/86880-pa.

Zarei, F., Daliri, A., and Alizadeh, N. 2008. The Use of Neuro-Fuzzy Proxy in Well Placement Optimization. Paper SPE 112214-MS presented at the Intelligent Energy Conference and Exhibition, Amsterdam, The Netherlands, 02/25/2008.

APPENDIX A

TOURNAMENT STYLE SELECTION PROCESS

Table A-1 – Standard Genetic Algorithm Using Tournament Selection, Generation 1

Individual	Generation 1 Binary Code	Fitness
1	1001011101	100.00
2	0011010110	95.00
3	1100101011	102.00
4	1011010101	98.00
5	0011110010	99.00

Using tournament selection, the first parent for the first individual of Generation 2 is chosen by comparing the first two individuals.

1	1001011101	100.00	Individual 1 has a higher fitness and is chosen as the first parent.
2	0011010110	95.00	

Then the second parent is chosen by comparing the second individual with the third individual.

2	0011010110	95.00	Individual 3 has a higher fitness and is chosen as the second parent.
3	1100101011	102.00	

So for the first individual of Generation 2, the binary code will come from Individual 1 and Individual 3 of Generation 1. A random crossover is performed (it is assumed mutation did not occur in this example for sake of simplicity).

1	100101|1101	100.00	1001011011, will be the code for Individual 1, Generation 2.
3	110010|1011	102.00	

The process is then repeated starting from the second binary code of Generation 1 in order to find the second individual for Generation 2 and the whole process repeats itself until the new Generation is populated.

Table A-2 – Genetic Algorithm Using Tournament Selection, Generation 2

Individual	Generation 2 Binary Code	Parents from Previous Generation
1	1001011011	1 and 3
2	1100101011	3 and 3 – Elite Reproduction
3	1100101010	3 and 5
4	0011011101	5 and 1
5	1011010101	4 and 1*

* Once the cycle has been completed, the individuals are randomly shuffled and the process repeated once for the last individual.

APPENDIX B

ROULETTE STYLE SELECTION PROCESS

Table B-1 – Standard Genetic Algorithm Using Roulette Selection, Generation 1

Generation 1

Individual	Binary Code	Fitness	% of Sum
1	1001011101	100.00	20.24 %
2	0011010110	95.00	19.23 %
3	1100101011	102.00	20.65 %
4	1011010101	98.00	19.84 %
5	0011110010	99.00	20.04 %
	Sum	494.00	100.00 %
	Average	98.80	

Based on the fitness and their weighted average, the roulette wheel or probability method of mating is initiated. The chart below shows how similar the probabilities actually are. This method will have a hard time differentiating between small changes in the fitness value.

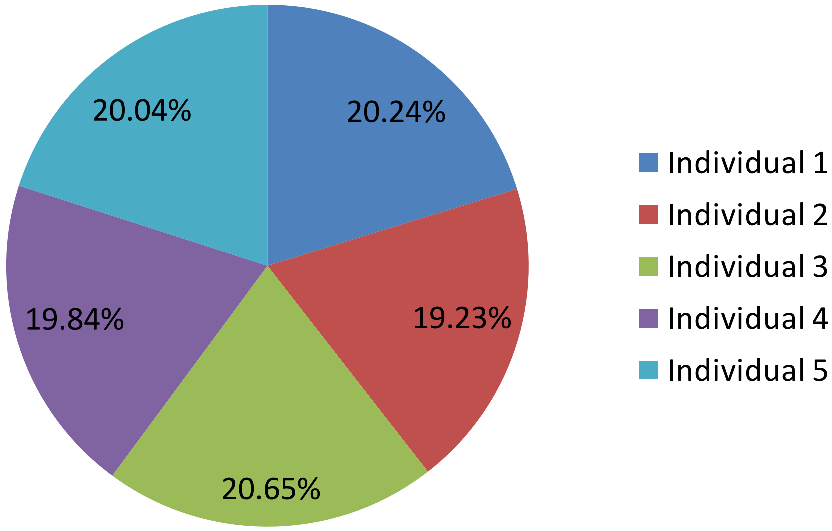


Figure B-1 – Initial Weights for Probability Mating in Generation 1.

The next step for reproduction would be to 'spin the wheel' or generate a random number between zero and one. After the two random numbers are generated, the parents for the new individual in Generation 2 would be determined.

Random Number 1 = 0.15

Random Number 2 = 0.62

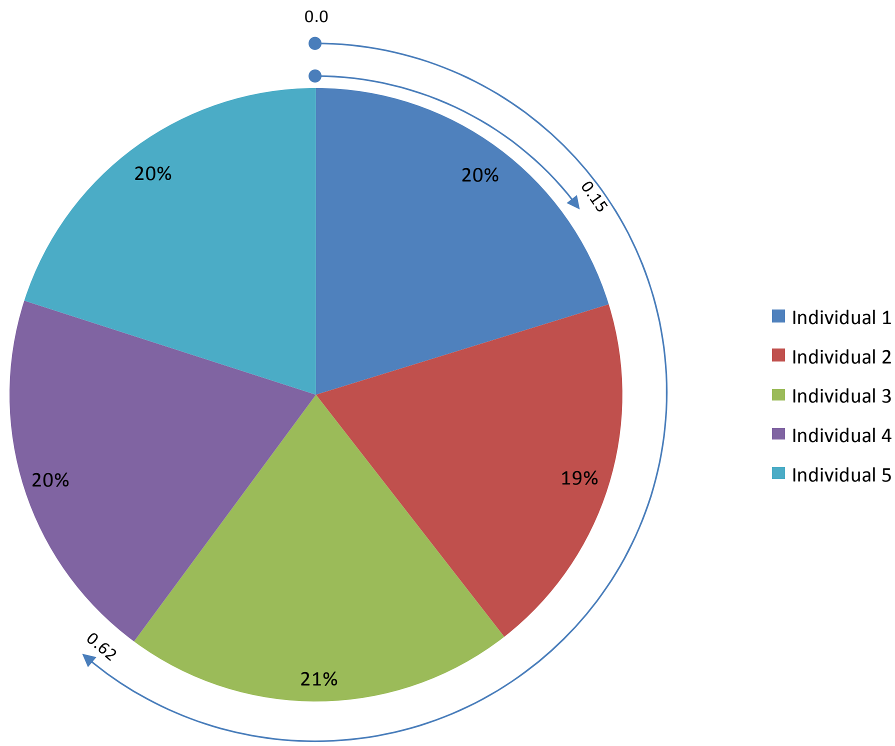


Figure B-2 – Randomly Chosen Parents from Original Population.

In this case Individual 1 and Individual 4 would be chosen to mate for the creation of Individual 1 in Generation 2. This process is repeated until the new generation has been populated.

Table B-2 – Standard Genetic Algorithm Using Roulette Selection, Generation 2

Individual	Generation 2 Binary Code	Parents from Previous Generation
1	1001010101	1 and 4
2	0011110010	2 and 5
3	1100101011	4 and 3
4	0011011101	2 and 1
5	1100101101	3 and 1

APPENDIX C

REPRODUCTION AND MUTATION PROCESS

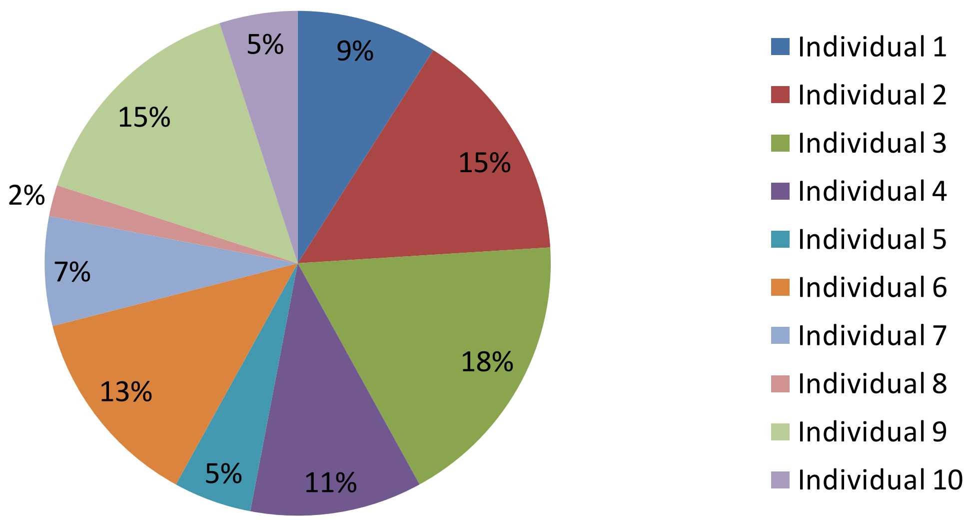


Figure C-1 – Individual Weighted Fitness.

The pie chart above represents the weighted fitness for 10 individuals from an arbitrary generation. The percentage values sum up to 100. In other words, "Individual 1", has a fitness of 9, and also a 9% chance to become a "Parent" for the next generation.

In the following example, two "Parents" are chosen randomly and their binary code is switched or "crossover" to produce a new unique code. Then the offspring's code undergoes a random mutation to finally produce a truly unique offspring.

Individual 3 Chosen as a Parent, Binary:
101001101
Individual 2 Chosen as a Parent, Binary:
011100110

Code / DNA Switch at Random Point (6):
10100|1101
01110|0110

Offspring Code:
10100|0110

Random Mutation (performed on the underlined bit):
10100|0110 ⟶ 10110|0110

Mutated Offspring Code:
10110|0110

APPENDIX D

A STANDARD GENETIC ALGORITHM APPLIED TO A HORIZONTAL WELL

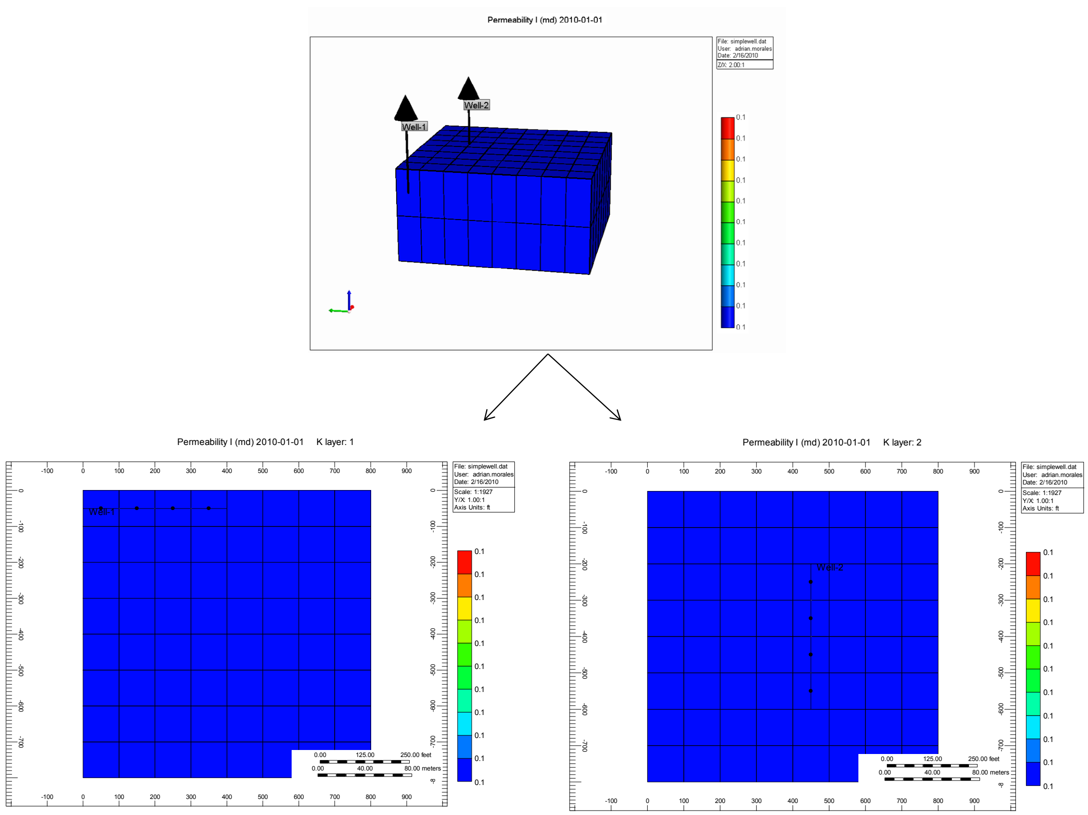


Figure D-1 – Two Horizontal Wells in a Simple Reservoir.

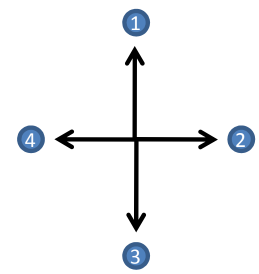
The first thing that the genetic algorithm must do is to create a dimensionalized work space. It reads the possible variable locations. In the horizontal well placement case, this means the reservoir dimensions.

Data Handling

Well – 1 Coordinates (X,Y,Z,D): (1, 1, 1, 2)
Well – 2 Coordinates (X,Y,Z,D): (5, 3, 2, 3)

Possible X-locations: 8
Possible Y-locations: 8
Possible Z-locations: 2
Possible D-orientations: 4

Well Directions



After the algorithm reads in the dimension parameters, it will calculate the necessary binary digits required to describe a location in that domain.

Binary Code Builder
X-Value Binary Digits: $2^3 = 8$
Y-Value Binary Digits: $2^3 = 8$
Z-Value Binary Digits: $2^1 = 2$
D-Value Binary Digits: $2^2 = 4$

$\underbrace{000}_{X}\ \underbrace{000}_{Y}\ \underbrace{0}_{Z}\ \underbrace{00}_{D}$, Need a 9 digit code

For the first generation, the wells are randomly created. Assuming our generations contain only four individuals, we randomly create the following binary codes (only two are shown).

Transformations

Well – 1 Code: 000000010

Well – 2 Code: 001010101

The next part in the algorithm will decode the binary code into real parameters.

Well – 1 Decoding Procedure:

The X-Binary code is the first three digits:

X-Binary = 000, $X = 0*2^0 + 0*2^1 + 0*2^2 = 0$

The Y-Binary code is the second three digits:

Y-Binary = 000, $Y = 0*2^0 + 0*2^1 + 0*2^2 = 0$

The Z-Binary code is the seventh digit:

Z-Binary = 0, $Z = 0*2^0 = 0$

The D-Binary code is the last two digits:

D-Binary = 10, $D = 1*2^0 + 0*2^1 = 1$

It is important to remember that when transforming a code into a parameter, the minimum value must be added. This happens because multiples of 2^n return values starting from zero, but there is no grid "0".

Well – 1 Decoding Procedure, add the minimum values:

X-Value = 0 + 1 = 1

Y-Value = 0 + 1 = 1

Z-Value = 0 + 1 = 1

D-Value = 1 + 1 = 2

Well – 1 Coordinates: (1, 1, 1, 2)

The same procedure is done for Well – 2:

Well – 2 Decoding Procedure:

X-Binary = 001, $X = 0*2^0 + 0*2^1 + 1*2^2 = 4$

Y-Binary = 010, $Y = 0*2^0 + 1*2^1 + 0*2^2 = 2$

Z-Binary = 1, $Z = 1*2^0 = 1$

D-Binary = 01, $D = 0*2^0 + 1*2^1 = 2$

Well – 2 Decoding Procedure, add the minimum values:

X-Value = 4 + 1 = 5

Y-Value = 2 + 1 = 3

Z-Value = 1 + 1 = 2

D-Value = 2 + 1 = 3

Well – 2 Coordinates: (5, 3, 2, 3)

After the wells are decoded the coordinates are evaluated using a simulator. In this case we will assume Well – 2 has a production value or fitness value of 70, while Well – 1 has a fitness of 50. So the first generation would look like this:

Table D- 1 – Standard Genetic Algorithm Applied to Horizontal Well, Generation 1

		Generation 1			
Binary Code	X-Value	Y-Value	Z-Value	Direction	Fitness
000000010	1	1	1	2	50
001010101	5	3	2	3	70
010001101	3	5	2	3	40
110001111	4	5	2	4	60

<u>Mating</u>

In this case Well – 1 has the higher chance of mating because the fitness value is higher than any other wells. In the following example, two "Parents" are chosen randomly and their binary code is switched or "crossover" to produce a new unique code. Then the offspring's code undergoes a random mutation to finally produce a truly unique offspring.

Individual 2: 0010|10101

Individual 4: 1100|01111

Offspring 1: 0010|01111

In this case, the mutation turned out to be zero so the offspring's code stays intact.

The same process is repeated for each new offspring while assuring elitist reproduction of the best fitness value producing a new generation:

Table D- 2 – Standard Genetic Algorithm Applied to Horizontal Well, Generation 2

Generation 2					
Binary Code	X-Value	Y-Value	Z-Value	Direction	Fitness
001010101	5	3	2	3	70
001001111	5	5	2	4	65
000001111	1	5	2	4	40
110001101	4	5	2	3	50

The process continues until the program reaches the stopping mechanism.

APPENDIX E

MINIMAL VARIANCE MODIFICATION

Table E-1 – Minimal Variance Modification, Original Generation

Individual	Generation 1 Binary Code	Fitness
1	1001011101	100.00
2	0011010110	95.00
3	1100101011	102.00
4	1011010101	98.00
5	0011110010	99.00
	Average	98.80
	Std Dev	2.59

Starting with the original population, the average and standard deviation is calculated from the raw fitness value. Then a standard normal distribution is performed by,

$$y(i) = \frac{x(i) - \mu}{\sigma} \tag{1}$$

$$i = 1,2, \ldots\ N_p$$

Table E-2 – Minimal Variance Modification, Step 1

Individual	Generation 1 Fitness	Std. Normal Distribution
1	100.00	0.464
2	95.00	-1.468
3	102.00	1.236
4	98.00	-0.309
5	99.00	0.055
Average	98.80	1.07E-15
Std Dev	2.59	1.00

After the standard normal distribution, a cumulative distribution is performed by,

$$y'(i) = \frac{1}{2}\left[1 + erf\left(\frac{y(i) - \mu_0}{\sqrt{2\sigma_0^2}}\right)\right] \tag{2}$$

$$i = 1,2, \ldots\ N_p$$

If the value of $\left(\frac{y(i)-\mu_0}{\sqrt{2\sigma_0^2}}\right)$ is negative, the cumulative distribution function becomes,

$$y'(i) = \frac{1}{2}\left[1 - erf\left|\frac{y(i) - \mu_0}{\sqrt{2\sigma_0^2}}\right|\right] \tag{4}$$

$$i = 1,2, \ldots\ N_p$$

Table E-3 – Minimal Variance Modification, Step 2

	Generation 1		
Individual	Fitness	Std. Normal Distribution	Cumulative Dist.
1	100.00	0.464	0.679
2	95.00	-1.468	0.071
3	102.00	1.236	0.892
4	98.00	-0.309	0.379
5	99.00	0.055	0.531
Average	98.80	1.07E-15	0.510
Std Dev	2.59	1.00	0.310

The final step is to do a weighted average of the cumulative distribution, which will be the new fitness. Then a roulette wheel selection is performed based on the new probabilities.

Table E-4 – Minimal Variance Modification, Step 3

		Generation 1		
Individual	Fitness	Std. Normal Dist.	Cumulative Dist.	Weighted Prob.
1	100.00	0.464	0.679	26.60 %
2	95.00	-1.468	0.071	2.79 %
3	102.00	1.236	0.892	34.96 %
4	98.00	-0.309	0.379	14.84 %
5	99.00	0.055	0.531	20.81 %
Average	98.80	1.07E-15	0.510	
Std Dev	2.59	1.00	0.310	

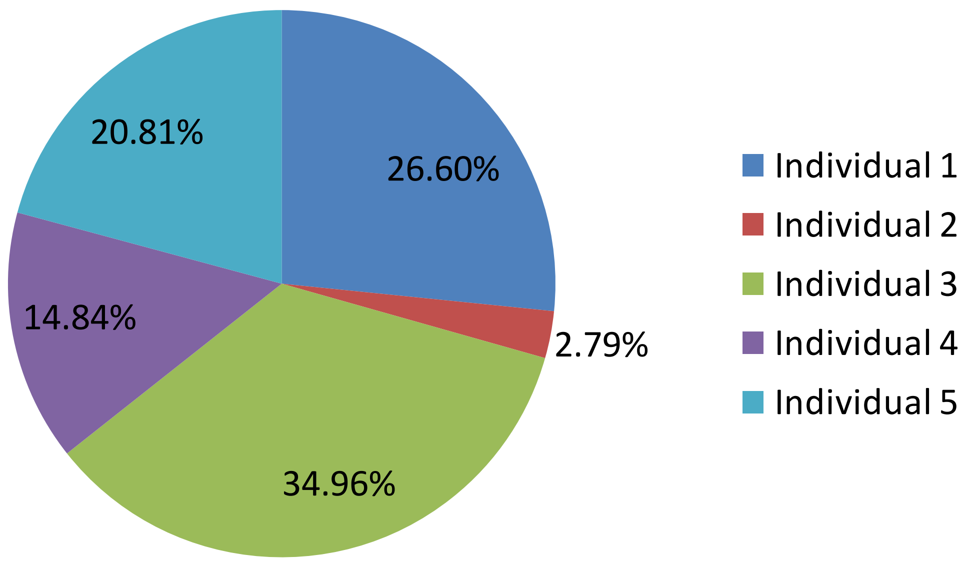


Figure E-1 – Modified Probability for Mating in Generation 1.

The next step for reproduction would be to ‘spin the wheel’ or generate a random number between zero and one. After the two random numbers are generated, the parents for the new individual in Generation 2 would be determined.

Random Number 1 = 0.15

Random Number 2 = 0.62

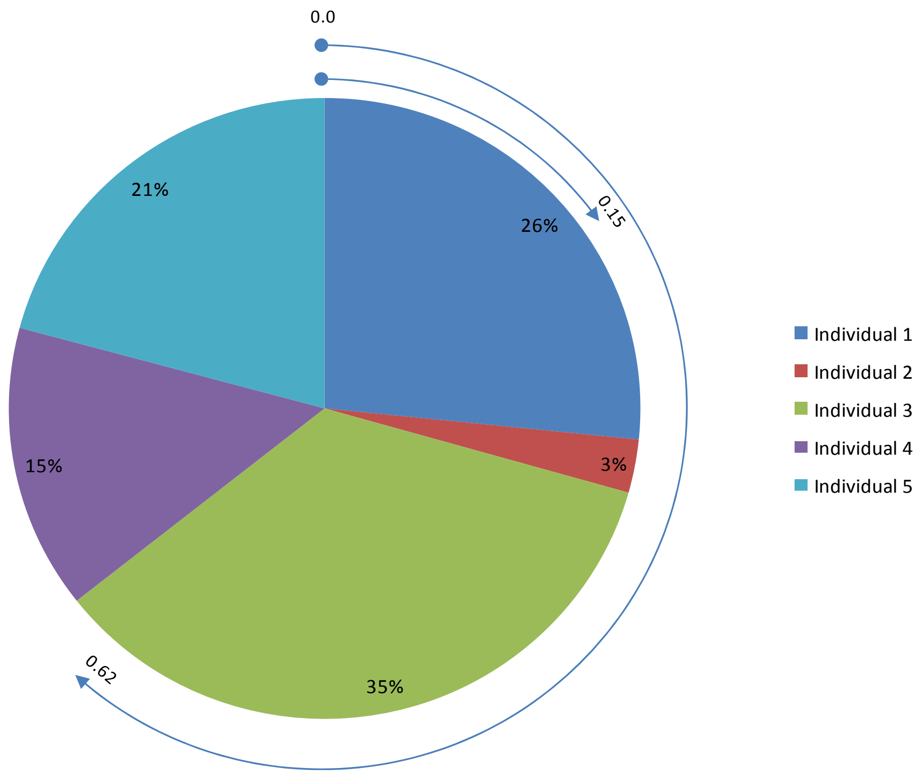


Figure E-2 – Randomly Chosen Parents from Modified Probability.

In this case Individual 1 and Individual 3 are chosen to be the parent strings for the first individual of Generation 2.

Table E-5 – Minimal Variance Modification, Generation 2

	Generation 2	
Individual	Binary Code	Parents from Previous Generation
1	1001010101	1 and 3
2	0011110101	5 and 1
3	1011011011	4 and 3
4	1101011101	3 and 1
5	0011010101	2 and 4

The rest of the new generation is populated in the same fashion as the first individual, and it becomes clear that the modified methodology will produce a greater variability by giving fitter individuals a much higher chance of mating than a pure probability or tournament selection. The advantages become more evident as the number of individuals per generation increases.

APPENDIX F

PROBABILITY OF SUCCESS MODIFICATION

User input parameters:

$$p_s = 0.9$$

$$N = 10$$

$$w_1 = 0.3, w_2 = 0.3, w_3 = 0.2, w_4 = 0.1, w_5 = 0.1,$$

where, p_s is the probability of success, N is the number of functions and w_i is the individual realization weight. This example consists of permeability uncertainty with five realizations. The objective is to determine the production with 90% confidence. The first step is to specify a well location: (12, 21, 6) with North direction. The following figures show the well in each realization.

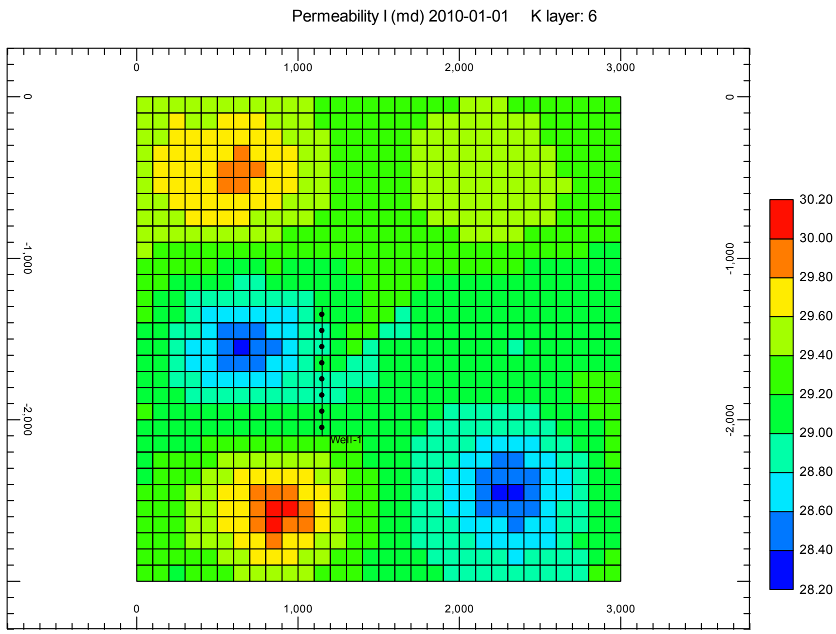


Figure F-1 – Realization 1 for Probability of Success.

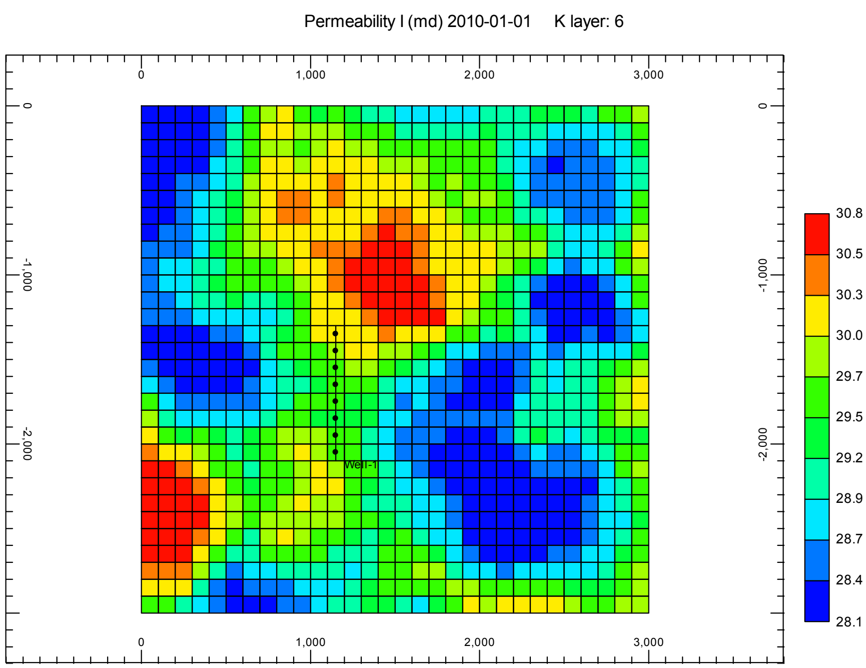


Figure F-2 – Realization 2 for Probability of Success.

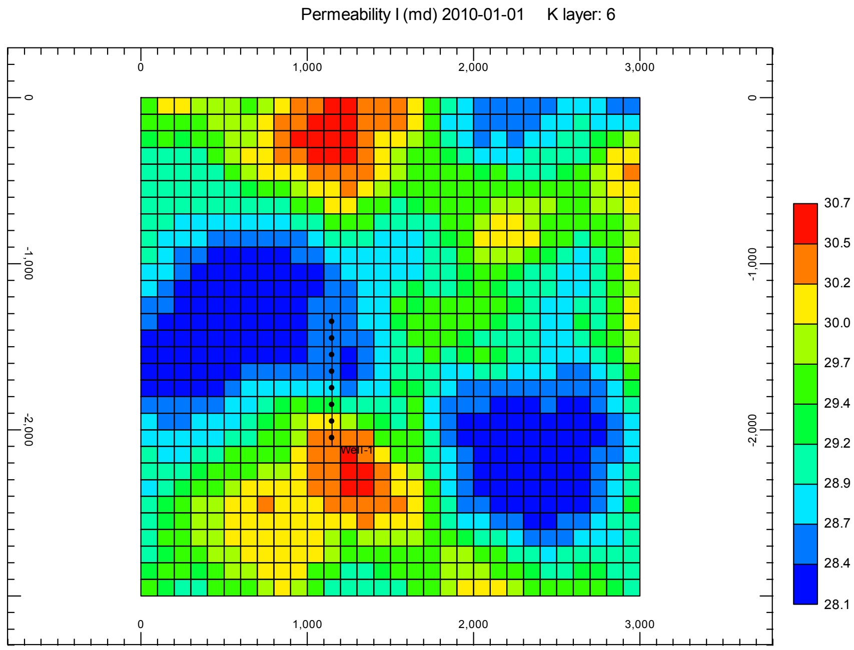


Figure F-3 – Realization 3 for Probability of Success.

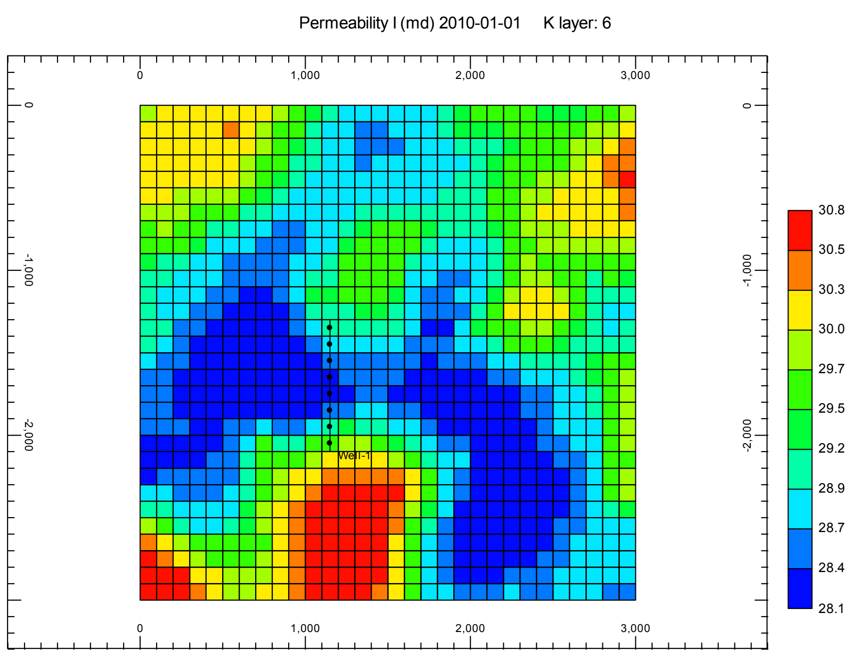


Figure F-4 – Realization 4 for Probability of Success.

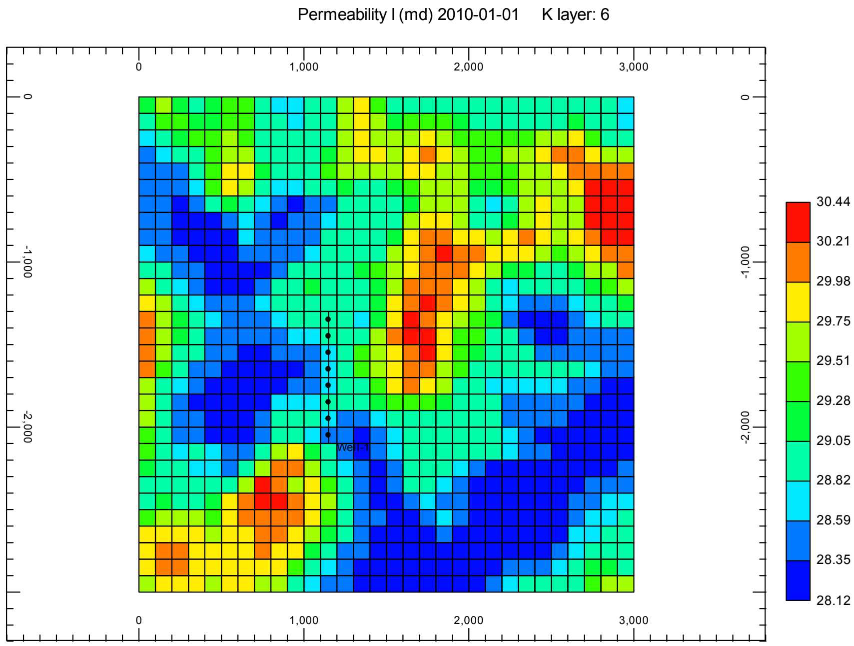


Figure F-5 – Realization 5 for Probability of Success.

After the wells are placed, the algorithm then calls on the commercial simulator and the production for each case is reported.

$$F_1 = 28{,}971, F_2 = 29{,}031, F_3 = 28{,}988, F_4 = 28{,}980, F_5 = 28{,}963$$

The next part will create the fitness array by taking into account the individual weights for each realization.

$$wt_i = w_i N \tag{5}$$

where wt_i represents the number of times fitness i will be repeated in the fitness array.

$$\widetilde{\boldsymbol{F}} = \begin{bmatrix} 28971 \\ 28971 \\ 28971 \\ 29031 \\ 29031 \\ 29031 \\ 28988 \\ 28988 \\ 28980 \\ 28963 \end{bmatrix} \xrightarrow{\text{The array is then sorted in descending order}} F_{sort} = \begin{bmatrix} 29031 \\ 29031 \\ 29031 \\ 28988 \\ 28988 \\ 28980 \\ 28971 \\ 28971 \\ 28971 \\ 28963 \end{bmatrix}$$

Then the resulting fitness is calculated based on the probability of success.

$$\tilde{F} = \frac{1}{\tilde{\tilde{N}}} \sum_{j=1}^{\tilde{N}} F_{sort}\,(j) \tag{3}$$

$$\tilde{N} = p_s N \tag{6}$$

$$\tilde{F} = \frac{1}{9} \sum_{j=1}^{9} \begin{bmatrix} 29031 \\ 29031 \\ 29031 \\ 28988 \\ 28988 \\ 28980 \\ 28971 \\ 28971 \\ 28971 \\ 28963 \end{bmatrix} = 28995.8$$

The calculated fitness for well location (12, 21, 6) North direction, with a probability of success of 90% is 28,995.8.

VITA

Adrian Morales received his Bachelor of Science degree in chemical engineering from the University of Houston in December 2006 with an honor's thesis entitled, "A Comparative Study of Four Sea-Going Transportation Methods for Natural Gas." After working as a process engineer for two years, he began his graduate studies in petroleum engineering at Texas A&M University in College Station. After completing one semester, he transferred to Texas A&M University at the Qatar campus to complete his research over the next year and a half, and graduated with his M.S. in December 2010.

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