LEXICOGRAPHIC APPROACH TO WELL PLACEMENT OPTIMIZATION FOR SHORT, MEDIUM AND LONG TERM INVESTMENT DECISIONS

BY

OSAMA MUTRIF SIDDIG ALI

A Thesis Presented to the
DEANSHIP OF GRADUATE STUDIES

KING FAHD UNIVERSITY OF PETROLEUM & MINERALS

DHAHRAN, SAUDI ARABIA

In Partial Fulfillment of the
Requirements for the Degree of

MASTER OF SCIENCE

In

PETROLEUM ENGINEERING

MAY 2014

KING FAHD UNIVERSITY OF PETROLEUM & MINERALS

DHAHRAN- 31261, SAUDI ARABIA

DEANSHIP OF GRADUATE STUDIES

This thesis, written by **Osama Mutrif Siddig** under the direction his thesis advisor and approved by his thesis committee, has been presented and accepted by the Dean of Graduate Studies, in partial fulfillment of the requirements for the degree of **MASTER OF SCIENCE IN PETROLEUM ENGINEERING.**

Dr. Abeeb A. Awotunde
(Advisor)

for Dr. Abdullah S. Sultan
Department Chairman

Dr. Hasan Y. Al-Yousef
(Member)

Dr. Salam A. Zummo
Dean of Graduate Studies

Dr. Abdullah S. Sultan
(Member)

14/7/14
Date

عمادة الدراسات العليا
DEANSHIP OF GRADUATE STUDIES

Dedication

To my loving, helpful and supportive parents and family

To the soul of my brotherly friends Wagid and Mazin

ACKNOWLEDGMENTS

The whole gratefulness is to the almighty Allah who supplies me with the will and strength, then to all who participate in the success of this work. Special thanks to my thesis supervisor Dr. Abeeb Awotunde for his support and dedication, and to the committee members Dr. Hasan Y. Al-Yousef and Dr. Abdullah S. Sultan for their great advices. Many thanks to all of the faculty and staff of Petroleum Engineering department at King Fahd University of Petroleum and Minerals who helped me very much throughout my Master program.

I would like also to express my appreciation to all of my friends, relatives and colleagues in Saudi Arabia and to the whole Sudanese community in the university campus. Special thanks to my roommate Ashraf and my cousins Mohammed and Siddig.

I which to acknowledge the endless support and carefulness of my father, mother, brothers, sister, fiancé, grand parents and friends without their encouragements this effort could not see the light.

TABLE OF CONTENTS

DEDICATION IV

ACKNOWLEDGMENTS V

TABLE OF CONTENTS VI

LIST OF TABLES IX

LIST OF FIGURES X

LIST OF ABBREVIATIONS XII

ABSTRACT XV

ملخصالرسالة XVII

CHAPTER 1 INTRODUCTION 1

1.1 Problem Statement and Thesis Objectives 2

1.2 Summary of the Research Work 4

CHAPTER 2 LITERATURE REVIEW 6

2.1 Different Optimization Algorithms and Helper Methods 6

2.1.1 Stochastic (Non-Gradient) Methods 6

2.1.2 Gradient Based Methods 11

2.2 Dealing with Uncertainty in Well Placement Optimization 14

2.3 Well Indexing in Well Placement Problem 17

2.4 Joint Optimization of Well Placement and Control 19

2.5 Application of Well Placement Optimization in Gas Injection and Gas Reservoirs 19

2.6 Objective Functions in Well Placement Optimization Problem 20

2.7 Adding Constraints to Well Placement Problem 21

2.8 Initialization of Well Placement Optimization (Initial Population) ... 22

2.9 Well Placement for Horizontal and Multilateral Wells ... 22

CHAPTER 3 THEORETICAL BACKGROUND ... 24

3.1 The Optimization Problem ... 24

3.2 Multi-Objective Optimization ... 25

3.3 Lexicographic Approach ... 28

3.4 CMA-ES ... 29

3.5 Different Investment Terms and Detailed Cases ... 31

3.6 Constrained Optimization ... 32

3.7 Penalty Method ... 33

3.8 Reservoir Simulator ... 36

3.9 Objective Function ... 36

3.10 Parameters to be Optimized ... 37

3.11 Reservoir Examples ... 38

3.11.1 Reservoir Example 1 ... 38

3.11.2 Reservoir Example 2 ... 38

CHAPTER 4 WELL PLACEMENT OPTIMIZATION FOR DIFFERENT INVESTMENT OPTIONS ... 42

4.1 Relationship between the Three Investment Terms ... 42

4.2 Effect of Objective Function Used ... 46

4.2.1 Unconstrained Optimization ... 46

4.2.2 Constrained Optimization ... 50

4.3 Reservoir Performance ... 53

4.4 Well placement ... 57

4.4.1 Unconstrained optimization ... 57

4.4.2 Constrained Optimization ... 64

4.5 Effect of Adding Constraints ... 69

4.6 Optimization Progress **72**

CHAPTER 5 LEXICOGRAPHIC APPROACH TO WELL PLACEMENT OPTIMIZATION **75**

5.1 Lexicographic Optimization Progress **75**
5.1.1 NPV Results 76
5.1.2 Reservoir Performance 80
5.1.3 Well Placement 83

5.2 Comparison between the Results of Single and Lexicographic Multi Objective Well Placement Optimization **96**
5.2.1 NPV Results 96
5.2.2 Reservoir Performance 100

CHAPTER 6 CONCLUSIONS AND RECOMMENDATIONS **103**

6.1 Conclusions **103**

6.2 Recommendations **104**

REFERENCES **105**

APPENDEX A RESERVOIR SIMULATION MODEL **109**

APPENDEX B CMA-ES OPTIMIZATION PARAMETERS **114**

VITAE **115**

LIST OF TABLES

Table 1.1: Range of the simulation time used in well placement optimization problem 3
Table 2.1: Stochastic optimization algorithms used in well placement optimization 7
Table 3.1: Details of cases used in the research...32
Table 3.2: Parameters used in NPV calculation...37
Table A.1: Properties for reservoir simulation model...110
Table B.1: CMA-ES parameters 114

LIST OF FIGURES

Figure 2.1: The pseudo wells around the original well 13
Figure 2.2: Different well indexing scheme 18
Figure 3.1: Multi-objectives optimization methods 27
Figure 3.2: Lexicographic process for Case 3a 35
Figure 3.3: Permeability distribution of the reservoir in Example 1 39
Figure 3.4: Porosity distribution of the reservoir in Example 1 40
Figure 3.5: Permeability distribution of the reservoir in Example 2 41
Figure 4.1: The relationship between the three terms NPVs for Example 1 44
Figure 4.2: The relationship between the three terms NPVs for Example 2 45
Figure 4.3: The effect of objective function used in the three terms NPVs for unconstrained optimization in Example 1 47
Figure 4.4: The effect of objective function used in the three terms NPVs for unconstrained optimization in Example 2 49
Figure 4.5: The effect of objective function used in the three terms NPVs for constrained optimization in Example 1 51
Figure 4.6: The effect of objective function used in the three terms NPVs for constrained optimization in Example 2 52
Figure 4.7: Oil production profile for the best results in Example 1 54
Figure 4.8: Oil production profile for the best results in Example 2 56
Figure 4.9: Well locations obtained from the best ST-NPV for non-constrained optimization in Example 1 X-coordinates 58
Figure 4.10: Well locations obtained from the best MT-NPV for non-constrained optimization in Example 1 59
Figure 4.11: Well locations obtained from the best LT-NPV for non-constrained optimization in Example 1 60
Figure 4.12: Well locations obtained from the best ST-NPV for non-constrained optimization in Example 2 62
Figure 4.13: Well locations obtained from the best MT-NPV & LT-NPV for unconstrained optimization in Example 2 63
Figure 4.14: Well locations obtained from the best ST-NPV for constrained optimization in Example 1 65
Figure 4.15: Well locations obtained from the best MT-NPV and LT-NPV for constrained optimization in Example 1 66
Figure 4.16: Well locations obtained from the best ST-NPV for constrained optimization in Example 2 67
Figure 4.17: Well locations obtained from the best MT-NPV and LT-NPV for constrained optimization in Example 2 68
Figure 4.18: The NPVs of the three terms for both constrained and unconstrained optimization in Example 2 70

Figure 4.19: The NPVs of the three terms for both constrained and unconstrained optimization in Example 2 71
Figure 4.20: Optimization progress for the best realizations in Example 1 73
Figure 4.21: Optimization progress for the best realizations in Example 2 74
Figure 5.1: NPVs of Case 3a and Case 3b in Example 1 77
Figure 5.2: NPVs of Case 3a and Case 3b in Example 2 79
Figure 5.3: Production profiles results of Case3 in Example 1 81
Figure 5.4: Production profiles results of Case3 in Example 2 82
Figure 5.5: Well placement obtained from the first step of Case 3a in Example 1 84
Figure 5.6: Well placement obtained from the second step of Case 3a in Example 1.....85
Figure 5.7: Well placement obtained from the third step of Case 3a in Example 1 86
Figure 5.8: Well placement obtained from the first step of Case 3a in Example 2 87
Figure 5.9: Well placement obtained from the second step of Case 3a in Example 2.....88
Figure 5.10: Well placement obtained from the third step of Case 3a in Example 2 89
Figure 5.11: Well placement obtained from the first step of Case 3b in Example 1 91
Figure 5.12: Well placement obtained from the second step of Case 3b in Example 1...92
Figure 5.13: Well placement obtained from the third step of Case 3b in Example 1......93
Figure 5.14: Well placement obtained from the first step of Case 3b in Example 2 94
Figure 5.15: Well placement obtained from the second and third step of Case 3b in Example 2...95
Figure 5.16: Comparison between the results of single and lexicographical multi objective optimization in Example 1 97
Figure 5.17: Comparison between the results of single and lexicographical multi objective optimization in Example 2 99
Figure 5.18: Production profile obtained from single and lexicographical multi objective optimization in Example 1 101
Figure 5.19: Production profile obtained from single and lexicographical multi objective optimization in Example 2 102
Figure A.1: Dead oil PVT data 111
Figure A.2: Relative permeability curve 112
Figure A.3: Permeability values range for Example 2 113

LIST OF ABBREVIATIONS

NPV	:	Net present value
ST-NPV	:	Short term net present value
MT-NPV	:	Medium term net present value
LT-NPV	:	Long term net present value
CAPEX	:	Capital expenditures
OPEX	:	Operating expenditures
STB	:	Stock tank barrel
MSCF	:	Thousand standard cubic feet
Min	:	Minimize
CMA-ES	:	Covariance matrix adaption- evolutionary strategy
GA	:	Genetic algorithm
HGA	:	Hybrid genetic algorithm
FDG	:	Finite difference gradient
SPSA	:	Simultaneous perturbation stochastic approximation
VFSA	:	Very fast simulated annealing
NPSO	:	Niche particle swarm optimization

RO	:	Retrospective optimization
DE	:	Deferential evolution
VRR	:	Volumetric replacement ratio
PInum	:	Numerical productivity index
PIfield	:	Field productivity index
BHP	:	Bottomhole pressure
FVF	:	Formation volume factor
PVT	:	Pressure, volume and temperature data
PVDO	:	PVT data for dead oil
PIfield	:	Field productivity index
$\mathbf{K_h}$	:	Horizontal permeability
$\mathbf{K_v}$	:	Vertical permeability
$\mathbf{K_{ro}}$	:	Oil relative permeability
$\mathbf{K_{rw}}$	:	Water relative permeability
$\mathbf{S_w}$	:	Water saturation
Pb	:	Bubble point pressure
psi	:	Pound per square inch

mD	:	Milli-Darcy
cP	:	Centi-poise
$\mathbf{N_{well}}$	:	Number of wells to be optimized
N	:	Optimization problem size
Xstart	:	Initial point variables
$\mathbf{u_x}$	:	Optimization variable upper limit
$\mathbf{l_x}$	:	Optimization variable lower limit
σ	:	Standard deviation
$\mathbf{F_{eval}}$	:	Number of function evaluations
$\mathbf{N_p}$	:	Population size
$\mathbf{N_t}$	:	Number of iterations
$\boldsymbol{\mu}$	:	parent number
cs	:	Cumulation constant for step-size

ABSTRACT

Full Name : Osama Mutrif Siddig

Thesis Title : Lexicographic Approach to Well Placement Optimization for Short, Medium And Long Term Investment Decisions

Major Field : Petroleum Engineering

Date of Degree : May, 2014

This thesis presents an investigation of the effect of production time in well placement optimization as well as the effect of adding well spacing constraints, and the use of lexicographical multi objective approach considering short, medium and long term net present values (NPV) as different objectives.

Adding minimum well spacing constraints to the optimization problem is necessary although it affects the results. We found this effect is varying from negligible to more noticeable depending on the density of wells to be completed in the reservoir.

The results of the study showed that well placement optimization results in short, medium and long term are affected by changing the simulated period. When short period NPV is used as the objective function the optimum results for medium and long term are not guaranteed.

We proposed the use of lexicographic approach in well placement optimization to simultaneously optimize the NPVs for different suggested project life times. The results of this approach compared to the regular single objective optimization found to achieve a well configuration that ensures better results in short, medium and long term investment

scenarios. A drawback of this approach is that it involves sequential optimization which requires more function evaluation and therefore more time and computational cost.

ملخص الرسالة

الاسم الكامل:اسامة مطرف صديق

عنوان الرسالة: المبدا الليكسكوقرافي في عملية الاختيار الامثل لمواضع الابار علي المستوي الزمني القريب, المتوسط و البعيد للاستثمار

التخصص: هندسة النفط

تاريخ الدرجة العلمية:مايو 2014

هذا البحث يقدم تحقيق عن تاثير مدة الانتاج و تاثير اضافة شرط المساحة الادنى على عملية الاختيار الامثل لمواقع الابار بالاضافة الى استخدام المبدا الليكسكوقرافي لعملية التحسين متعدد الاهداف باعتبار ثلاث خيارات استثمارية كاهداف مختلفة و هي الخيار الاستثماري قصير, متوسط و طويل المدة.

اضافة شرط المساحة الادنى للبئر ضروري رغم انها تؤثر علي نتائج عملية الاختيار. هذا التاثير يتراوح ما بين تاثير طفيف لا يلاحظ الي تاثير حقيقي و ذلك حسب عدد الابار بالنسبة لمساحة المكمنز

اظهرت الدراسة ان نتائج عملية تحسين مواقع الابار تاثرت بتغير مدة المشروع. عندما يتم استخدام المدة القصيرة كدالة هدففإن الحصول على مواقع الابار الامثل للمدى المتوسط او الطويل غير مضمون.

اقترحنا في هذا العمل استخدام المبدا الليكسكوقرافي في عملية اختيار مواقع الابار بحيث يتم الاختيار المناسب على المدى القصير، المتوسط و الطويل في آن واحد. بمقارنة نتائج استخدام هذا المبدا مع نتائج طريقة الهدف الواحد المعهودة، وجدنا ان هذه الطريقة يمكن ان تؤدي الي مواقع ابار افضل لكل الخيارت سواء القصير او المتوسط او الطويل. عيب هذا المبدا انه عملية التحسين فيه تسلسلية مما يعني زيادة في عمليات تمثيل المكمن التي تؤدي بدورها الي زيادة الوقت المطلوب.

CHAPTER 1

INTRODUCTION

The development of new fields is expensive and complicated operation, so the best profitable plans need to be considered. Well placement optimization is one of the field planning tasks that can improve the reservoir performance and the economic value of the project by increasing the total production. Proper wells locations enhance the sweep efficiency of water flooding and increase the recovery factor and thus the net present value (NPV).

Optimization is a process of finding and comparing feasible solutions until no better solution can be achieved. Direct optimization with common stochastic optimization algorithms using numerical reservoir simulator as evaluation tool and NPV as objective function has been used for well placement problems. The optimization process requires thousands of function evaluations and in the case of well placement thousands of reservoir simulation runs are needed. This process is computationally expensive however, the computational power of clusters are improving and thus optimization methods in well placement becomes more feasible.

Different optimization methods have been used in well placement problems, one of these optimization methods is a stochastic method using randomized search algorithm called Covariance Matrix Adaption- Evolutionary Strategy (CMA-ES). Generally stochastic optimization algorithms have some advantages over gradient based methods because no special formulation for the objective function to have derivatives is required and they are more likely to find the global optima (Andersson 2000). While the gradient based methods require calculating the gradient vector which is a vector contains the derivatives of the objective function with respect to the parameters to be optimized. Other problem with the gradient based methods is that they are searching for the local optima rather than the global optima.

Well placement optimization has been covered in the literature regarding the algorithms to use or how to deal with the uncertainty in the data. However, one of the issues that remains is that reservoir asset managers are routinely faced with the problem of deciding the life cycle of field development projects. This life cycle, often categorized into short, medium or long term, is very crucial in ensuring that the most benefit is obtained from the hydrocarbon field. Several external factors such as politics, uncertainty and safety often dictate which of these terms a company adopts. For instance, while a national oil company operating in a very stable society may benefit from a long-term project investment; a foreign company operating in politically volatile environments might consider short or medium term investment as its best option. Yet, perceived risks might fade away and companies might eventually operate their fields for long terms and vice versa. The problem thus becomes that of optimizing field development primarily based on the favored project duration (short, medium or long term) and secondarily based on other less favored project terms.

1.1 Problem Statement and ThesisObjectives

Well placement is one of the critical tasks in field development planning; proper well placement can significantly improve the reservoir performance and the economic gain from the field. Most of the previous studies that are related to well placement optimization have focused on the optimization algorithms performance and some helper methods or how to deal with geological uncertainty in well placement problems. However, one of the issues that remains is that reservoir asset managers are routinely faced with the problem of deciding the life cycle of field development projects.

Optimization of well placement requires objective function calculation and each function evaluation requires coupling the optimization tool with numerical reservoir simulator. In literatures researchers have used different simulation times to do their investigations.Table1.1 shows the various simulation times used for well placement optimization problems. These times range from a couple of years to tens of years.

Table1.1: Range of the simulation time used in well placement optimization problem

Simulation time	Authors
2.19 years	(Ozdogan and Horne 2006)
4.6 years	(Gǚyagǚler, et al. 2000)
5.48 years	(Bangerth, et al. 2006)
6 years	(Bellout, et al. 2012)
20 years	(Awotunde and Sibaweihi 2014)
23 years for water injection project and 5 and 10 years for gas injection	(Badru and Kabir 2003)
up to 50 years	(Wang, et al. 2007)

Some authors reported that the project anticipated time will affect the result of the well placement problem, however they did not make an investigation of different simulation times (Badru and Kabir 2003; Forouzanfar, et al. 2010)

As with any project, oil companies plan for their fields for the period that they are expecting to stay and operate based on the contracts, but some times and unexpectedly due to some political instability or lack of security, companies may decline from the projects earlier or reversely some companies may have renewal of the ongoing contracts. Therefore companies should take into account more than one scenario when they are planning for the field development.

The use of multi objective optimization in well placement problems has not been reported in the literature except using weighted summation of the different objectives. To the best of our knowledge Lexicographical multi objective optimization method has not been used before in well placement optimization.

The main objectives of this research are to study the effect of project life time on well placement optimization problem and to investigate the use of lexicographic multi objective optimization to simultaneously improve the economics considering different reservoir life periods. The research has been designed also to study the effects of adding minimum well spacing constraints to the optimization problem.

1.2 Summary of theResearch Work

As mentioned in the previous section the main objectives of this research are to study the effect of production time on well placement optimization problem, and to investigate the use of lexicographic approach for different scenarios well placement problem. Details about the objective function, reservoir examples and the different cases in this work are presented in Chapter 3.

Three different project periods were defined; short term, medium term and long term, and so three objective functions used; short term NPV (ST-NPV), medium term NPV (MT-NPV) and long term NPV (LT-NPV) for each of the mentioned terms respectively.

Three cases were considered in this work each has sub-cases, all of it will be applied for the two reservoir examples. Single objective optimization was used in the first two cases unlike the third case in which lexicographic multi objective optimization was used. In the first case no constraints were applied while in the second case a minimum well spacing was defined.

Two synthetic heterogeneous reservoir examples were used the first is channel reservoir and the other is reservoir with a distributed permeability field. CMA-ES coupled with numerical reservoir simulator was used as an optimization tool.

CHAPTER 2

LITERATURE REVIEW

Well placement optimization has been studied by many researchers and they covered different aspects, using different optimization algorithms with numerical reservoir simulators as evaluation tool. The use of different algorithms, optimization techniques and helper methods has been studied by different authors. Also, the effect of the uncertainties in the well placement optimization has been studied and different approaches to deal with geological uncertainties have been suggested in the literature.

Different ways to initialize the optimization have been investigated by researchers, and different objective functions have been used in the literatures as well. Some authors have investigated joining control optimization with the well placement optimization and others applied constraints on the optimization. Different ways of well indexing in well placement optimization problems have been studied by scholars. Optimization of location of vertical, horizontal and multilateral wells has been covered in the literatures. Following are the literature review in each of these topics.

2.1 Different Optimization Algorithms and Helper Methods

2.1.1 Stochastic (Non-Gradient) Methods

Table 2.1displays some of the stochastic optimization algorithms used in well placement optimization by different researchers.

Table 2.1: Stochastic optimization algorithms used in well placement optimization

Authors	Optimization algorithm
(BecknerB. and Song 1995; Norrena and Deutsch 2002)	Simulated Annealing (SA)
(Bittencourt and Horne 1997; Bukhamsin, et al. 2010; Emerick, et al. 2009; Guyaguler and Horne 2000; Morales, et al. 2010; Yeten, et al. 2003)	Genetic Algorithm (GA)
(Bangerth, et al. 2006)	Simultaneous perturbation stochastic approximation (SPSA), finite difference gradient (FDG), and very fast simulated annealing (VFSA) algorithms
(Bouzarkouna, et al. 2010; Ding 2008)	Covariance Matrix Adaptation – Evolution Strategy (CMA-ES)
(Onwunalu and Durlofsky 2010; Wang, et al. 2011)	Particle swarm optimization
(Cheng, et al. 2012)	Niche Particle Swarm Optimization (NPSO)
(Awotunde and Sibaweihi 2014)	Differential evolution and CMA-ES

Bittencourt and Horne (Bittencourt and Horne 1997)showed that the performance of the GA optimization improved when it is hybridized with polytope algorithm and tabu search and they called this technique Hybrid Genetic Algorithm.

Pan and Horne (Pan and Horne 1998)investigated the use of multivariate interpolation algorithms, Least Squares and Kriging, as proxies to reservoir simulations for well placement optimization problems.

Güyagüler et al.(Gǔyagǚler, et al. 2000)proposed a hybrid genetic algorithm (HGA) in which the genetic algorithm (GA) is hybridized with polytope algorithm, kriging algorithm and neural networks. The investigation of the performance of this technique was done by optimizing the placement of injection wells in Pompano field in the Gulf of Mexico. Well placement and injection rate were optimized with net present value of the waterflooding project as the objective.

From the experiments the authors found that the number of function evaluation required to find optimal placement was reduced significantly using the proposed technique, HGA reduced the required simulation runs to less than half compared to the simple GA.

Montes et al. (Montes, et al. 2001)studied the effects of different optimization parameters on the performance of the Genetic Algorithm. The parameters studied include population size, elitism and mutation rate.

Ozdogan et al. (Ozdogan, et al. 2005) used the HGA (Bittencourt and Horne 1997) in order to develop a methodology to place wells on specified patterns called Fixed Pattern Approach.

Bangerth et al.(Bangerth, et al. 2006)analyzed the performance of several optimization algorithms for the well placement problem. These algorithms are finite difference gradient (FDG), simultaneous perturbation stochastic approximation (SPSA), and very fast simulated annealing (VFSA) algorithms.

The authors used three main performance indicators for comparison of the convergence properties of algorithms, these indicators are:

1- The effectiveness; which reflects how close the algorithm gets to the global optimum on average.
2- The efficiency; which means the quantity of function evaluations required to reach the solution.
3- The reliability; which means how often the algorithm reach the global optimum or close solution.

Different conclusions were reached for single and multiple well placement. For the first case the authors observed that the SPSA algorithm was the most efficient algorithm in finding good solutions and VFSA can find even better solutions but it requires significantly more time to do so.

For multiple well placement, the authors found that both SPSA and VFSA were better than the FDG algorithm and were more likely to find good solution. The SPSA was more efficient in finding good positions in fewer function evaluations, while VFSA obtained better solution but required more function evaluations.

Ding(Ding 2008) presented the first use of Covariance Matrix Adaptation – Evolution Strategy (CMA-ES) in well placement problem. The author presented the application of CMAES to the problem of unconventional well placement optimization by comparing the CMAES to GA. The author also studied the impacts of model parameters such as population size and discretization steps in the optimization of well placement.

CAMES results were found not to be very good when the population size was small. However, when the population size becomes larger, significant improvements were obtained. Although CMAES provided generally higher values in objective function than the genetic algorithm, it usually requires more evaluations. The author also stated that possible well configurations are very limited in genetic algorithm. While in CMAES, well configurations are more various and he explained that it's because CMAES is a continuous approach. The results showed that algorithm parameters might have a great impact on the optimization; CMAES can be potentially improved with good choices of algorithm parameters.

Bouzarkouna et al.(Bouzarkouna, et al. 2010)tied CMA-ES with a local regression based meta-model in order to reduce the computational cost. Partially separated meta-models were built to utilize the partial separability of the objective function, so different meta-models were built for each well or set of wells, that results in a more accurate modeling. The aim of using the meta-model is to replace the true objective function evaluation which requires reservoir simulation by cheap approximate model built based on the true objective function evaluations and use it throughout the optimization process to save evaluations time on the expensive original objective function.

According to their results this approach cut the total number of reservoir simulations required to reach good results by 19- 25%. The use of the partial separability of the objective function resulted into a significant reduction of the reservoir simulation runs needed to find the optimal well placement by around 60% compared to the regular CMA-ES.

Cheng et al. (Cheng, et al. 2012) investigated the use of Niche Particle Swarm Optimization (NPSO) for well placement problem. The idea of NPSO is to cluster the whole particle swarm into smaller particle swarm group then the particles of the subgroup conduct the evolution to achieve the target of the optimal particle in this smaller group. The results showed the advantage of NPSO algorithm over the Particle Swarm Optimization algorithm, by having earlier convergence and higher ability to find the global optimum solution.

2.1.2 Gradient Based Methods

Gradient based optimization algorithms have better computational efficiency although they have less probability of reaching the global optimum, since they can get stuck in the local optimum solution. Many approaches have been suggested to handle well placement optimization problems using gradient based methods. The following are a summary of some of the work done in this area.

The first attempt to consider gradient-based optimization algorithm for optimization of well placement was made by Handels et al. 2007 (Handels, et al. 2007), in which the concept of pseudo wells has been used. This concept uses eight imaginary wells called "pseudo-wells" in the grid blocks around the grid block that contain the actual well (see Figure 2.1), this pseudo-wells have very small injection/production rates so that they have negligible effect on the NPV. To have the new location for the wells the gradient of the NPV with respect to all the pseudo-well rates is calculated and the wells in the next iteration should move toward the largest positive gradient of the all eight direction which should increase the NPV.

Wang et al.(Wang, et al. 2007) presented a different idea of gradient-based well placement optimization. In their work the optimization is initialized with an injector well at each grid block that does not contain a producer well (their work was to optimize the location of injectors while the producer location was fixed). Subsequently, the optimization was made by changing the injector rate to improve the NPV, if the injection rate of any injector in the optimization process went to zero the cost of this well will not be considered in NPV calculation (as it does not exist). Therefore, at the end of the optimization, some wells will be eliminated and optimal well locations and number will be obtained. The authors made two simple cases for water injectors' placement in homogeneous and heterogeneous reservoirs to test their approach in which they used a steepest ascent as optimization algorithm.

Sarma and Chen (Sarma and Chen 2008) used the concept of pseudo-wells introduced by (Handels, et al. 2007) with different approach to obtain the gradient, the actual well rate is distributed between the well and its pseudo-wells based on their distance to the actual well location. They proposed to use continuous spatial domain (x, y) well locations instead of the discrete parameters (i, j) well location indices, and to obtain a continuous functional relationship between the objective function and the continuous well location parameters by numerical discretization of a modified PDE. As a result of this continuous functional relationship, adjoints and gradient-based optimizations algorithms can be applied to obtain the optimal well locations. The investigations on the efficiency and practical applicability of this approach were done on a few synthetic waterflood optimization problems.

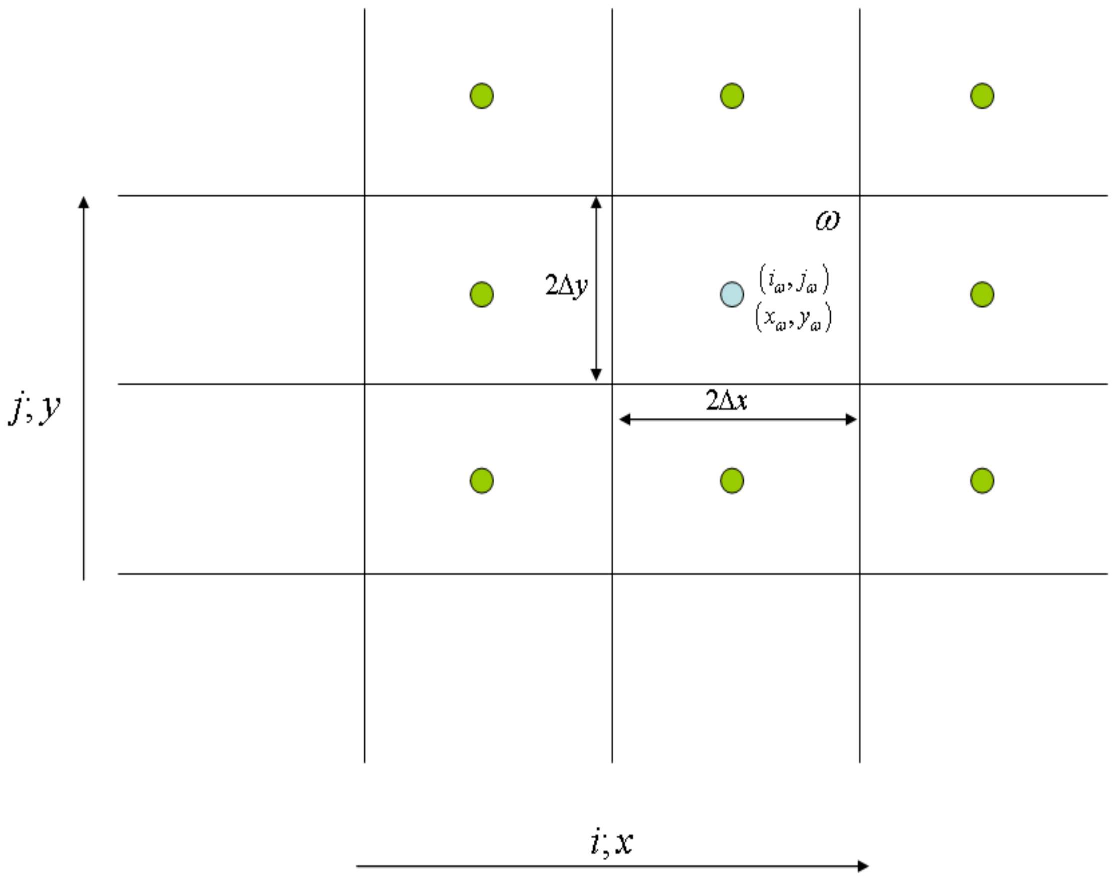

Figure 2.1: The pseudo wells around the original well

Forouzanfar et al.(Forouzanfar, et al. 2010)suggested some improvements on the basic approach introduced by (Wang, et al. 2007) so that it can be applied to more practical problems. i.e., three-dimensional three-phase (Wang et al.’s work was done for two dimensional problems) or problems that require optimization the location of both producers and injectors (Wang et al.’s optimization work was only for injector locations only). In addition they made constraints on wellbore pressures (maximum bottomhole pressure in water injection wells and minimum bottomhole pressure in producing wells).

In addition to the previously mentioned articles, other researchers proposed different approaches for well placement optimization using gradient-based optimization techniques. These include(Vlemmix, et al. 2009; Zandvliet, et al. 2008; Zhang, et al. 2010).

2.2 Dealing with Uncertainty in Well Placement Optimization

Subsurface geology is one of the information that has high level of uncertainty which has an impact on the well placement optimization. Following is a summary for some work done on optimization of well placement problem under uncertainty.

Badru and Kabir(Badru and Kabir 2003) investigated the impact of uncertainties in some variables such as the degree of communication between layers, k_h, k_v/k_h and perforation interval in well placement optimization problem.

Güyagüler and Horne (Güyagüler and Horne 2004)proposed an approach which can reflect the uncertainty in the data to uncertainty in the decision of well placement in terms of economic value. Their approach has the ability to consider the risk attitudes of the decision maker and they stated that it was computationally feasible.

A randomly selected realization of the reservoir properties is used whenever a specific well configuration was to be evaluated, and then numerical simulation with the selected realization is used to calculate the objective function value. Then the developed utility framework is used to evaluate the uncertainty in the performance forecasts when evaluating different well placement.

Ozdogan and Horne (Ozdogan and Horne 2006)developed an approach to reduce the uncertainty and to increase the economic value that focus on the value of time-dependent information. In this approach, recursive probabilistic history-matching steps were integrated with the well-placement optimization by using the concept of “pseudohistory” which is the expected response of the reservoir. The pseudohistory is generated using probabilistic forecasting model.

The authors tested their approach using an example of Sequential Well Placement with different realizations. In their work, the hybridized genetic algorithm introduced by (Gǚyagǚler, et al. 2000)was modified and used as the optimization tool.

The results of their study showed that the probabilistic reservoir performance obtained from the reservoir can improve the subsequent well-placement decisions. Using this approach the relative uncertainty reduced and so the economic value increased.

Morales et al.(Morales, et al. 2011) modified the genetic algorithm (GA) to optimize the well configuration under uncertainty in geological parameters. The acceptable risk level for the decision makers and the probable geological models is used as additional inputs.

The application was presented using a gas condensate reservoir in Qatar’s North Field as an example to optimize horizontal well placement. The authors used different permeability fields to express the uncertainty and different risk factors were defined as well. Different well configurations were obtained when different acceptable risk factors were used.

Wang et al.(Wang, et al. 2011)used retrospective optimization (RO) to handle the optimization problem under uncertainty for well placement. RO sequentially optimizes subproblems with increasing number of realizations. It does not solve all the realizations at every generation of the optimization algorithm, *k*-means clustering was used in selecting the realizations to be tested.

Particle swarm optimization and simplex linear interpolation based line search were used as the optimization tools to test three example cases of the suggested approach.

Their results confirmed the benefits of using the RO in comparison with comprehensive sampling. Within the use of RO procedure, the use of cluster sampling adds value over the random sampling and it is suitable for problems that contain large numbers of geological realizations. The authors claim that both RO and exhaustive optimization approach achieved the same results but RO requires much less number of simulation runs.

Bouzarkouna et al.(Bouzarkouna, et al. 2012)proposed an approach for well placement problem with uncertainty uses already simulated well configurations in the neighborhood of each well configuration for the objective function evaluation. Their proposed approach can be combined with any optimization algorithm. However, the authors combined it with CMA-ES.

This approach was compared to the reference approach using all the possible realizations for each well configuration. It is shown that the proposed approach is able to reduce significantly the number of reservoir simulations by more than 80% for the reservoir case in this study.

In addition to the summarized work this topic has been addressed by other authors such as (Onwunalu and Durlofsky 2010; V., et al. 2006; Yeten, et al. 2003) in which the optimization was performed on a fixed number of realizations.

2.3 Well Indexing in Well Placement Problem

Güyagüler (Güyagüler 2002)studied different indexing schemes as in Figure 2.2 for wells in well placement optimization and found that (i, j) indexing which represent x-y coordinates is the best way to handle this type of problem, because the other indexing schemes are discontinuous and thus make artificial noise.

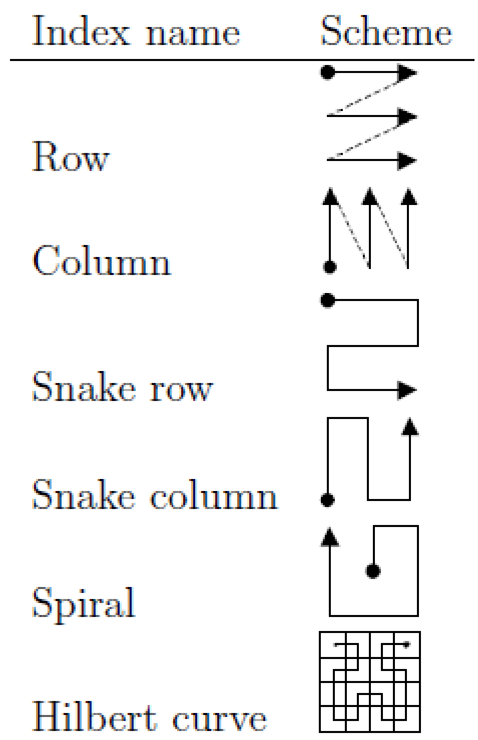

Figure 2.2: Different well indexing scheme

2.4 Joint Optimization of Well Placement and Control

Forouzanfar et al.(Forouzanfar, et al. 2010)attempted to eliminate the need to specify the oil production/water or gas injection rate and operational reservoir life ahead of the well placement optimization, by adding an initialization step to find out proper operating well rates for the particular operational life. After this initial stage another stage is needed in order to determine the optimal number of wells (including the number of producers and injectors), the best locations for the chosen wells and the optimal rates for these wells. In their work, a gradient based optimization algorithm was used. Analytical methods and adjoint method were used to calculate the gradient.

Bellout et al.(Bellout, et al. 2012)proposed a joint approach that performs well control optimization within the process to find the optimum well placement configurations, instead of sequential process. In this approach, the two different optimizations are considered in a nested fashion. The outer loop involves a well location optimization, while the inner loop consists of optimizing well controls for fixed well positioning.

In their findings, joint optimization yields a significant increase, of up to 20% in net present value, when compared to reasonable sequential approaches. The joint approach does, however, require about an order of magnitude increase in the number of objective function evaluations compared to sequential procedures.

2.5 Application of Well Placement Optimization in Gas Injection and Gas Reservoirs

Most of publications in well placement optimization have been done for oil reservoirs to optimize the location of oil producers/water injectors, but there is relatively small number of researches focused on gas/gas condensate reservoirs or gas injection project. Badru and Kabir (Badru and Kabir 2003) applied a hybrid GA to optimize the locations of wells in water injection project and gas injection project as well using both horizontal and vertical wells.

Morales et al.(Morales, et al. 2010)studied the well placement problem in gas condensate reservoirs to optimize the placement of horizontal wells. Their work was applied to the North Field located in Qatar. MiniVar (The Minimal Variation) modified genetic algorithm was used and its results compared with the conventional genetic algorithm.

The authors observed that unlike oil reservoirs the recovery factor in gas reservoirs does not vary significantly, and there is higher possibility of having local optimums. Therefore the optimum reservoir performance is not much better than the worse case scenario, that makes it more difficult to obtain the best field plan.

2.6 Objective Functions in Well Placement Optimization Problem

Most of the well placement optimization problems in the literature used the net present value NPV as objective function although other objective functions were used by researcher such as maximizing oil recovery (Badru and Kabir 2003; Castiñeira, et al. 2009), maximizing the numerical productivity index (PI_{num}) and the field productivity index (PI_{field})(Ding 2008).

The use of multi objective optimization was presented by Awotunde and Sibaweihi (Awotunde and Sibaweihi 2014) incorporating NPV and VRR in solving the well placement optimization problem. The authors conducted their study in three phases using NPV, VRR and weighted sum of the NPV and the VRR respectively as the objective function. The authors used a set of four weights in the third phase to describe the relative importance of the NPV and the VRR and they made comparison of how these weights affect the optimized NPV and VRR values is provided.

In their work two evolutionary-type algorithms: the covariance matrix adaptation evolutionary strategy (CMA-ES) and differential evolution (DE) were used to solve the optimization problem.

2.7 Adding Constraints to Well Placement Problem

Ozdogan et al.(Ozdogan, et al. 2005)were the first to introduce geometrical constraints to the well placement optimization problem in which non-uniform reservoir geometry was considered.

Emerick et al. (Emerick, et al. 2009)used the Genetic Algorithm to develop a tool for linear and nonlinear constrained well placement optimization. In this work the objective was to optimize the number, locations and trajectory of production and injection wells in complex model grids under set of constraints. The technique used to handle this problem is called Genocop III which is abbreviation for Genetic Algorithm for Numerical Optimization of Constrained Problems.

The constraints involved are minimum spacing for each well (minimum distance between wells), grid cell size and maximum length of the well. In addition to these constraints other conditions were imposed so that the wells would not be located in some user-defined regions or inactive grids.

2.8 Initialization of Well Placement Optimization (Initial Population)

Emerick et al.(Emerick, et al. 2009)studied two strategies to initialize the well placement optimization problem in order to generate the initial population of stochastic optimization algorithm. The first strategy is to define all the members of the initial population randomly, while the other approach is to use engineer's proposed well placement as part of the initial population.

Better results were achieved with the second technique, since it gave higher NPV when the engineer's proposed well locations were part of the in initial population compared to the randomly selected initial population.

Another approach to initialize the well placement optimization algorithm has been studied by Emerick et al. (2009) called "quality maps". The concept of quality maps which is a two-dimensional representation of the reservoir responses has been introduced to well placement problem by (Cruz, et al. 1999) and found to be helpful in choosing well locations with relatively small number of reservoir simulation runs. The result showed that quality map helps to indicate good areas for well location, and they suggest that the quality map can be used to locate the wells and the optimization can be completed to optimize the type and number of wells only. This approach is useful when there is no time to execute the complete well placement optimization procedure.

2.9 Well Placement for Horizontal and Multilateral Wells

Bittencourt and Horne 1997 (Bittencourt and Horne 1997)were the first attempt to optimize both vertical and horizontal wells in which Genetic Algorithm (GA) was used as an optimization tool.

Yeten et al.(Yeten, et al. 2003)used GA with some performance acceleration techniques to propose a methodology to optimize the location, type and trajectory of multilateral wells.

Badru and Kabir (Badru and Kabir 2003)used a hybrid GA proposed by (Güyagüler et al. 2000) to optimize the locations of vertical and horizontal wells. This optimization was applied in gas injection and water injection projects.

Ding(Ding 2008)used unconventional wells cases to investigate the use of CMA-ES in well placement optimization.

CHAPTER 3

THEORETICAL BACKGROUND

3.1 The Optimization Problem

Optimization is a process of finding and comparing feasible solutions until no better solution can be found. The general optimization problem can be formulated as following:

$$\min\ F = f(x_1, x_2, ..., x_n) \qquad (1)$$

Subject to *m* constraints $g_i(x) \leq 0$ i =1,2,…,m

where

f(x) is the objective function.

$x_1, x_2, ..., x_n$ are the *n* parameters that affect the objective function and are required to be optimized.

g(x) is the set of constraint functions.

In this work, net present value NPV was used as objective function and *i,j* indexing was used to describe wells locations, so that the well placement optimization problem can be expressed as:

$$\min\ \{-NPV\} = f(i_1, j_1, i_2, j_2, ..., i_N, j_N) \qquad (2)$$

Subject to

$$1 \le i_1, i_2, ..., i_N \le I$$
$$1 \le j_1, j_2, ..., j_N \le J$$

Where

N is the total number of wells

$i_{1}, i_{2}, \ldots, i_N$ are the N wells cells' index in X direction

$j_{1}, j_{2}, \ldots, j_N$ are the N wells cells' index in Y direction

I is the total number of cells in X direction

J is the total number of cells in Y direction

3.2 Multi-Objective Optimization

Real optimization problems may contain many conflicting objectives, giving rise to the need for multi-objective optimization. Multi-objective optimization has been available for about two decades, and its application in optimization problems is continuously increasing. There are different methods available to handle multi-objective optimization problems (Andersson 2000). Figure 3.1 illustrates the different ways to handle multi-objective problems with examples of the methods of each way.

Four different methods for optimizing different objectives simultaneously can be considered based on when the user prioritize the different objectives either before, after or during the optimization process or never articulate any preference. One of the most popular ways is to combine the different objectives using weighted summation and applying the regular optimization.

A multi-objective problem is formulated by the following equation

$$Min\ F\left(\vec{x}\right) = \left(f_1\left(\vec{x}\right),\ f_2\left(\vec{x}\right),\ldots\ldots,\ f_k\left(\vec{x}\right)\right)^T \qquad (3)$$

s.t.

$$\vec{x} \in S$$

$$\vec{x} = \left(x_1,\ x_2,\ldots\ldots,\ x_n\right)^T$$

where

$f_i(x)$ is the i^{th} objective function.

x_i is the i^{th} optimization parameter.

$S \in R^n$ is the parameter space

$F(x)$ is the vector containing all the objectives.

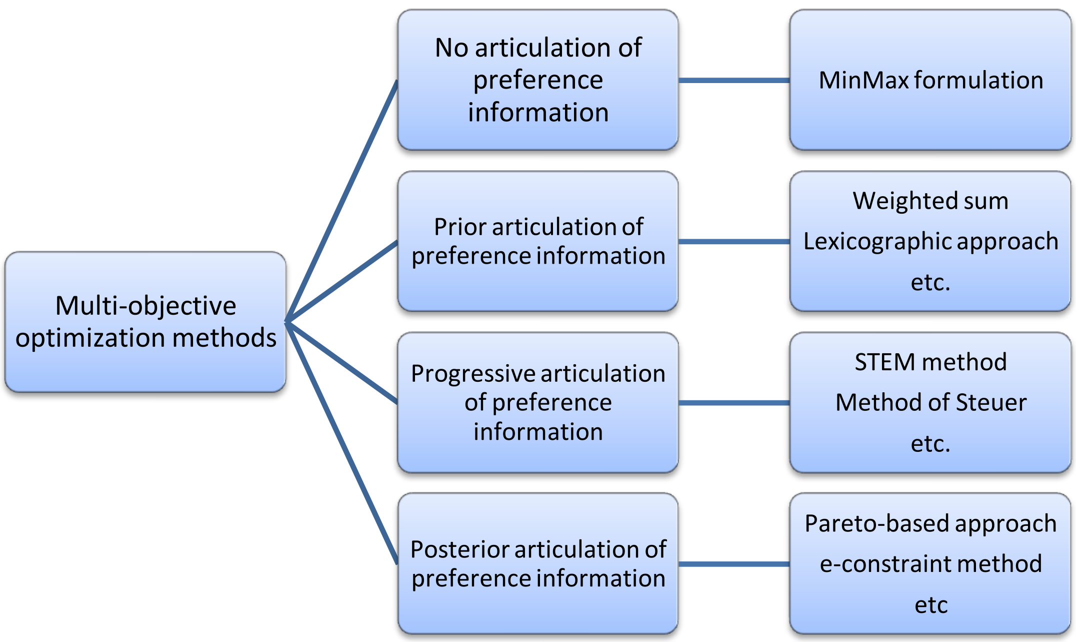

Figure 3.1: Multi-objectives optimization methods

3.3 Lexicographic Approach

One of the ways to conduct multiobjective optimization problems is by priori articulation of the decision maker's preferences. One of these methods is the lexicographic approach. In this approach the orders of the objective functions to be optimized have to be determined. These objectives have to be prioritize based on importance or the preferences, so that the optimization of the second objective should not negatively affect the results on first objective and so on. The drawback of this approach is that not all objectives might be considered because of the strict definition of preferences.

The lexicographic optimization can be formulated as (Marler and Arora 2004):

$$Min\ F_i\left(\vec{x}\right),\ \ \vec{x} \in S \qquad (4)$$

Subjected to

$$F_j\left(\vec{x}\right) \le F_j\left(\vec{x}_j^{\,*}\right),\ j = 1, 2, \ldots\ldots i-1,\ i > 1,\ i = 1, 2, \ldots\ldots, k$$

k is the total number of the objective functions.

i represents a function's position in the preference ranking.

$F_j\left(\vec{x}_j^{\,*}\right)$ represents the optimum solution of the j^{th} objective function which come before the i^{th} objective function and found in the j^{th} iteration.

Waltz (Waltz 1967)suggested another way for this approach in which the constraints are formulated as:

$$F_j(x) \le F_j(x_j^*) + \delta_j$$

Where,

δ_j is positive tolerance determined by the user to reduce the sensitivity of the solution of the j^{th}objective function when optimizing the less important objectives.

3.4 CMA-ES

In this work CMA-ES was used as optimization tool, CMA-ES has been used in well placement optimization by (Awotunde and Sibaweihi 2014; Bouzarkouna, et al. 2010; Ding 2008).

Covariance matrix adaptation –evolutionary strategy CMA-ES (Hansen and Ostermeier 2001) is a stochastic method for non-linear optimization problem that use Randomized search algorithms. In the CMA Evolution Strategy, a population of new search points (individuals, offspring) is generated by sampling a multivariate normal distribution. The basic equation for sampling the search points for generation number g +1 is:

$$x_k^{(g+1)} \sim m^{(g)} + \sigma^{(g)} \aleph\left(0, C^{(g)}\right) \text{ for k = 1, ……}\lambda \qquad (5)$$

Where

$\sim$ denotes the same distribution on the left and right side.

$\aleph\left(0, C^{(g)}\right)$is a multivariate normal distribution with zero mean and covariance matrix $C^{(g)}$.

$x_k^{(g+1)} \in R^n$ is the k-th offspring (individual, search point) from generation g + 1.

$m^{(g)} \in R^n$ is the mean value of the search distribution at generation g.

$\sigma^{(g)} \in \mathrm{R}+$ is the "overall" standard deviation at generation g.

$C^{(g)} \in R^{n \times n}$ is the covariance matrix at generation g.

$\lambda \geq 2$ is the population size.

The new mean $m^{(g+1)}$ of the search distribution is a weighted average of μ selected points from the sample $x_1^{(g+1)}, \ldots\ldots\ldots x_\lambda^{(g+1)}$ as given by:

$$m^{(g+1)} = \sum_{i=1}^{\mu} w_i x_{i:\lambda}^{(g+1)} \qquad (6)$$

while,

$$\sum_{i=1}^{\mu} w_i = 1 \ , \ w_1 \geq w_2 \geq \ldots\ldots\ldots \geq w_\mu > 0 \qquad (7)$$

where,

$\mu \leq \lambda$, is the parent population size, i.e. the number of selected points.

$w_{i=1,\ldots\mu} \in R^+$ is the positive weight coefficients for recombination.

$x_{i:\lambda}^{(g+1)}$ is th i^{th} best individual out of $x_1^{(g+1)} \ldots\ldots\ldots x_\lambda^{(g+1)}$

To re-estimate the covariance matrix $C^{(g+1)}$ using the sampled population $x_1^{(g+1)} \ldots\ldots\ldots x_\lambda^{(g+1)}$ the following equation can be used:

$$C_\lambda^{(g+1)} = \frac{1}{\lambda} \sum_{i=1}^{\lambda} \left(x_i^{(g+1)} - m^{(g)} \right) \left(x_i^{(g+1)} - m^{(g)} \right)^T \qquad (8)$$

In this work the total number of function evaluations was set at 6000 while the population size (λ) was determined using:

$$\lambda = floor(4 + 3\ \ln\ (N)) \qquad (9)$$

where,

N is the problem size (the number of parameters to be optimized).

Details about the CMA-ES parameters used in this work are available in Appendix 2.

3.5 Different Investment Terms and Detailed Cases

Many oil projects contracts range between 20 to 25 years (Bindemann 1999; News 2014), therefore we defined the investment term scenarios as following:

- Short term, 7 years of production/injection.
- Medium term, 25 years of production/injection.
- Long term, production until the reach of economical limit.

The economic constraints for wells and the field are the maximum allowed water cut and minimum allowed oil production per well or per field.

Three cases were considered in this work each has sub-cases, all of them were applied to the two reservoir examples and each optimization run contained 5 realizations (except the third case) to confirm the results and to insure the global optima. The first two cases use single objective optimization while the third case that will use multi objective optimization. In the first case, no constraints were used while in the second and the third cases a minimum well spacing of five acres was used. The followings are the details about the cases:

Table 3.1: Details of cases used in the research

<table>
<tr><td colspan="3">Case 1 (single objective optimization)</td><td colspan="3">Case 2 (single objective optimization with D_{min} constraint)</td></tr>
<tr><td>Sub case</td><td>Objective</td><td>Constraints</td><td>Sub case</td><td>Objective</td><td>Constraints</td></tr>
<tr><td>Case 1a</td><td>ST-NPV</td><td>None</td><td>Case 2a</td><td>ST-NPV</td><td>None</td></tr>
<tr><td>Case 1b</td><td>MT-NPV</td><td>None</td><td>Case 2b</td><td>MT-NPV</td><td>None</td></tr>
<tr><td>Case 1c</td><td>LT-NPV</td><td>None</td><td>Case 2c</td><td>LT-NPV</td><td>None</td></tr>
</table>

Case 3 (Lexicographic approach)				
Sub cases	First objective	Second objective	Third objective	Constraints
Case 3a	ST-NPV	MT-NPV	LT-NPV	yes
Case 3b	LT-NPV	MT-NPV	ST-NPV	yes

3.6 Constrained Optimization

In Case 2, a minimum well spacing (D_{min}) has been defined for constrained optimization, so additional condition should be added to Eq. 2. In this work, we used the penalty method to apply these constraints. We used the method presented by Awotunde and Naranjo(Awotunde and Naranjo 2014), the additional conditions added to Eq. 2:

$$\begin{cases} g_1(\vec{x}) = D_{\min}^2 - (x_2 - x_1)^2 - (y_2 - y_1)^2 \le 0, \\ g_2(\vec{x}) = D_{\min}^2 - (x_3 - x_1)^2 - (y_3 - y_1)^2 \le 0, \\ g_3(\vec{x}) = D_{\min}^2 - (x_3 - x_2)^2 - (y_3 - y_2)^2 \le 0, \\ \qquad\qquad \vdots \\ g_{N_c-1}(\vec{x}) = D_{\min}^2 - (x_{N_{wells}} - x_{N_{wells}-2})^2 - (y_{N_{wells}} - y_{N_{wells}-2})^2 \le 0, \\ g_{N_c}(\vec{x}) = D_{\min}^2 - (x_{N_{wells}} - x_{N_{wells}-1})^2 - (y_{N_{wells}} - y_{N_{wells}-1})^2 \le 0, \end{cases} \qquad \textbf{\textit{(10)}}$$

where

D_{min} is the required minimum distance between wellscan be and calculated from the 5 Acres minimum well spacing A_{min} as:

$$D_{\min} = \sqrt{\frac{43560 A_{\min}}{\pi}} \qquad (11)$$

$N_c$is the number of constraints computed as:

$$N_c = \frac{N_{wells}(N_{wells} - 1)}{2} \qquad (12)$$

$N_{wells}$is the number of wells

3.7 Penalty Method

Penalty method is one of the methods that are used for constrained optimization, in which a positive value called "penalty" is added to the objective function for solutions that violate the required constraints (Freund 2004). We can illustrate the concept of this method by the following optimization problem P:

$$P : \min\ f(\vec{x})\ s.t.\ g(\vec{x}) \le 0 \qquad (13)$$

To solve this constraint optimization problem with this method, we have to reformulate it as following:

$$P: \min\ f(\vec{x})\ +\ c\ p(\vec{x}) \qquad (14)$$

$$s.t.\ \begin{cases} p(\vec{x}) = 0 \text{ if } g(\vec{x}) \le 0 \\ p(\vec{x}) \ne 0 \text{ if } g(\vec{x}) > 0 \end{cases}$$

The function p(x) is called a penalty function and it has zero value when the constraints are satisfied and positive value for any violation on the constraints. c is called the penalty parameter and it is a scalar with positive value increasing with the iterations as the optimizations progresses.

In this work, we used the penalty method for two purposes; to apply minimum well spacing constraints and to conduct the lexicographic approach for multi-objective. Figure 3.2 displays how the penalty method has been used in the lexicographic multiobjective optimization process for Case3a (in which STNPV was set as the most preferred objective). The following equations have been used to estimate the penalty function to apply the minimum well spacing constraint.

$$p(\vec{x}) = \sum g_{a,b} \qquad (15)$$

where

$D_{a,b}$ is the distance between well a and well b. and $g_{a,b}$can be calculated from:

$$g_{a,b} = \begin{cases} D_{\min}^2 - D_{a,b}^2\ ,\ if\ \ D_{a,b} < D_{\min} \\ 0\ ,\ if\ \ D_{a,b} \ge D_{\min} \end{cases} \qquad (16)$$

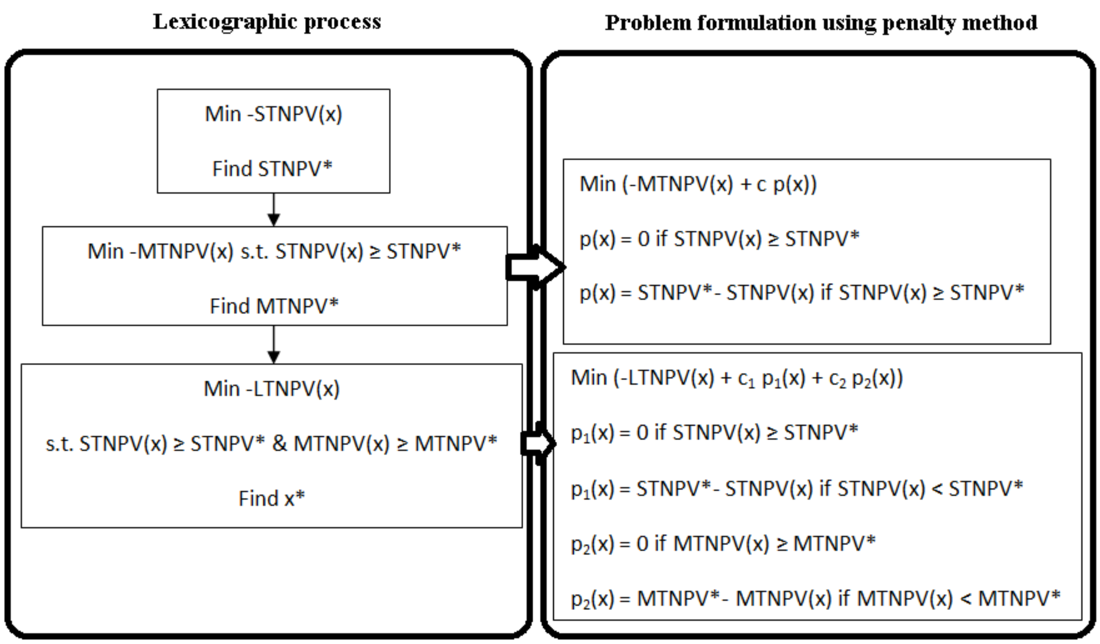

Figure 3.2: Lexicographic process for Case 3a

3.8 Reservoir Simulator

Eclipse 100 reservoir simulator has been used as evaluation tool to predict the reservoir performance for every suggested wells placement. ECLIPSE 100 is a “fully-implicit, three phases, three dimensional, general purpose black oil simulator with gas condensate options”.

3.9 Objective Function

Generally, NPV has been used as objective function.Different project life times have been used to calculate NPVsfor short, medium and long term. Each of these NPVs were used as different objective functions. NPV is one of the economic yardsticks that are widely used to evaluate the projects and to compare them, and it represents the discounted net value of money that comes from a project. Table 3.2displays the parameters used in NPV calculations using the following formula:

$$NPV = \sum_{i=0}^{n} \frac{revenue_i - CAPEX_i - OPEX_i}{(1+r)^n} \qquad (17)$$

where

$$revenue_i = oil\ price \times oil\ yearly\ production_i \qquad (18)$$

CAPEX is the capital expenditures (eg. Drilling and facilities cost)

OPEX is the operating expenditures (eg. Maintenance and lifting cost)

r = discount rate

n = project life time

The following abbreviations will be used for different terms NPVs

- ST-NPV for short term NPV.
- MT-NPV for medium term NPV.
- LT-NPV for long term NPV.

Table 3.2: Parameters used in NPV calculation

Parameter	**value**	**unit**
Drilling cost	2.5	MM$/well
Facility cost	50	MM$
Water production cost	5	$/STB of produced water
Water injection cost	10	$/STB of injected water
Operational cost	8	$/STB of oil
Oil price	105	$/STB of oil
Discount rate	6	%

3.10 Parameters to be Optimized

Well placement optimization problem uses the well index as the parameter to be optimized and it has been stated in the literature that the best well indexing system for optimization is the i,j indexing (Güyagüler 2002) which represents the well x-y coordinates.

The size of the optimization problem is defined by the total number of parameters which is in this case twice the total number of wells. In order to have various well spacing we used different number of wells in each example. In Example 1 there were 50 wells (30 producers and 20 injectors) and all their locations were optimized so the number of parameters will be 100. While in Example 2, five wells (three producers and two injectors) out of 25 wells (15 producers and 10 injectors) were considered as pre-project drilled and the rest were optimized with total number of parameters of 40.

3.11 Reservoir Examples

To investigate the mentioned cases two synthetic reservoirs were used, the first is channel reservoir and the other is reservoir with a distributed permeability field. Detailed description of the reservoir simulation models including the fluid properties and rate control is in Appendix 1.

3.11.1 Reservoir Example 1

This example is a channelized heterogeneous reservoir with an area of 3955 acres and 200 ft thickness, discretized into 75×75×4 cells. For Example 1, all of the wells locations were optimized which are 30 producers and 20 injectors. Figure 3.3displays the permeability distribution for the four layers while Figure 3.4shows the porosity distribution.

3.11.2 Reservoir Example 2

Example 2 is a heterogeneous reservoir with an area of 3761 acres and 225 ft thickness, discretized into 64×64×3 cells. For this reservoir example, five wells (three producers and two injectors) were considered as pre-project drilled and the rest were optimized. Of the 25 wells in this example, only 20 will be optimized (12 producers and 8 injectors). Figure 3.5displays the permeability distribution for the three layers in this reservoir.

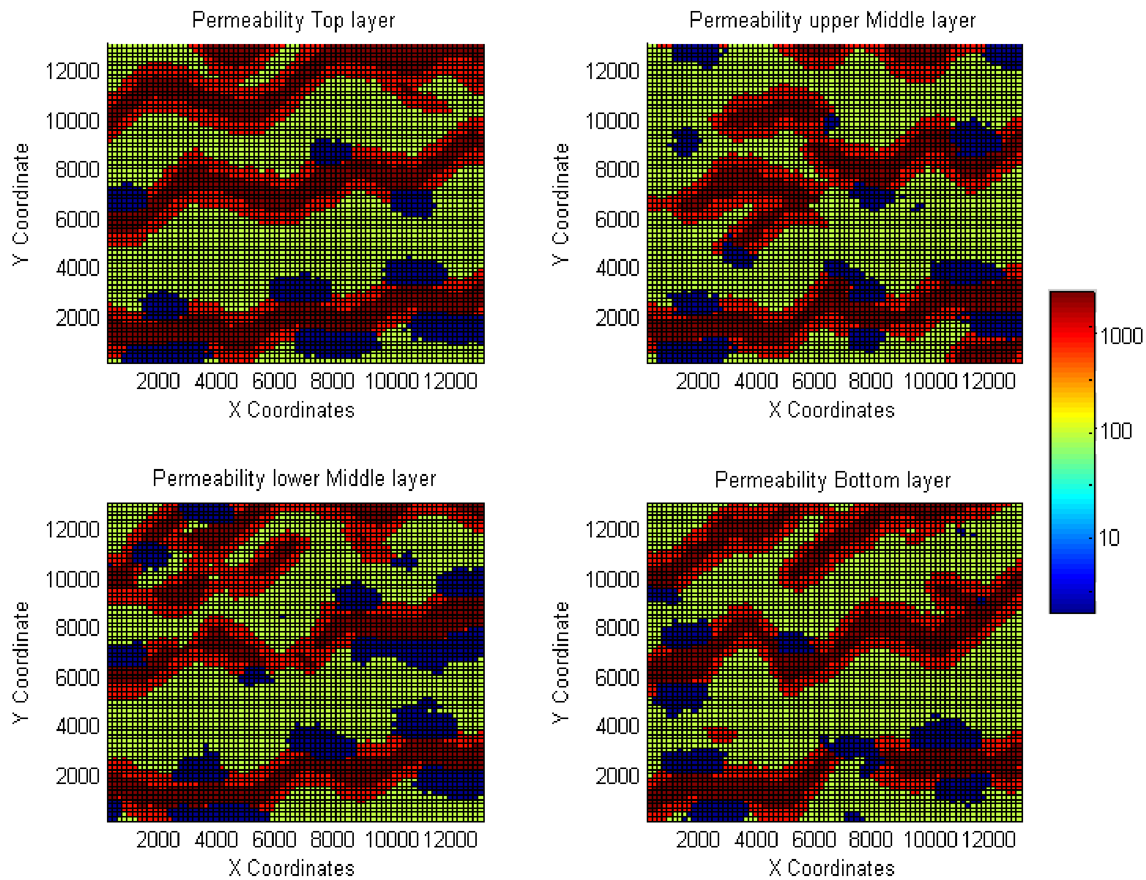

Figure 3.3:Permeability distribution of the reservoir in Example 1

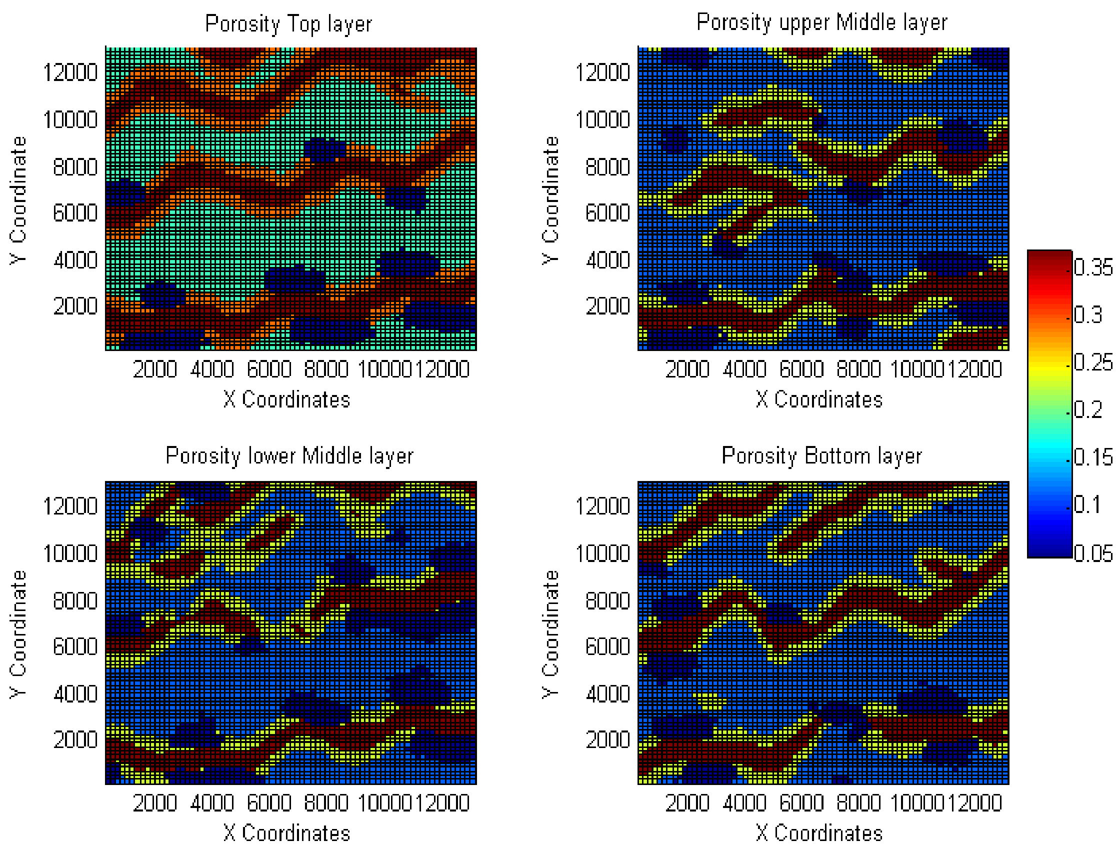

Figure 3.4: Porosity distribution of the reservoir in Example 1

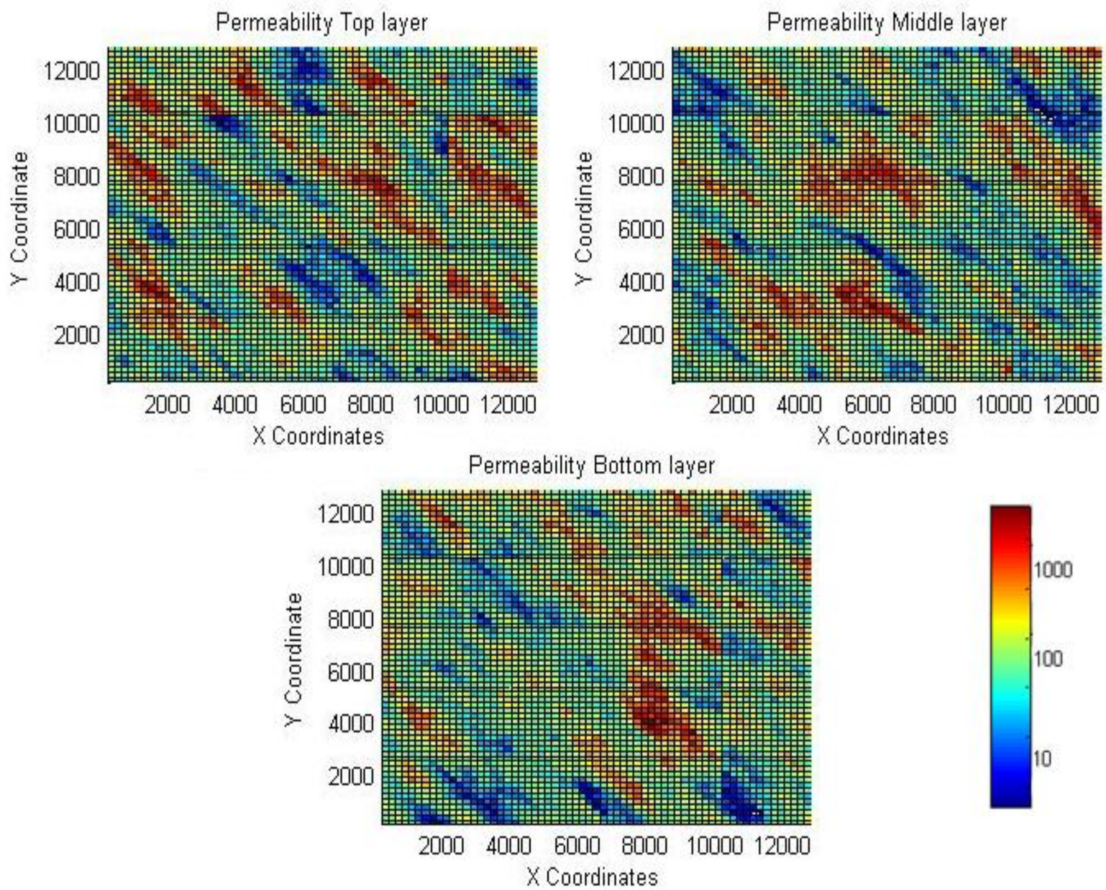

Figure 3.5: Permeability distribution of the reservoir in Example 2

CHAPTER 4

WELL PLACEMENT OPTIMIZATION FOR DIFFERENT INVESTMENT OPTIONS

In this chapter we study the effect of project life length on the well placement optimization problem. As described in Chapter 3, three definitions of reservoir life time have been used as short, medium and long term investment options and two example reservoirs were used. In the first case (Case 1), no constraints have been made on the optimization, while in the second case a five acres minimum well spacing has been used to constrain the problem.

4.1 Relationship between the Three Investment Terms

This section is to answer the question is the best well placement for a particular project life time is also the best for a different period?Figure 4.1 and Figure 4.2illustrates the relationship between the different investment terms.

Figure 4.1 a and Figure 4.2a shows the plots of the MT-NPV and LT-NPV versus ST-NPV, while the plots in Figure 4.1 b and Figure 4.2bshowsthe ST-NPV and LT-NPV versus MT-NPV. InFigure 4.1 c and Figure 4.2 c, the ST-NPV and MT-NPV are plotted versus the LT-NPV.

Example1

In Example 1, the MT-NPV and LT-NPVare highly correlated as it is observed in the Figure 4.1 b and 4.1 c, while their relation with ST-NPV is arbitrary. That means when optimizing the ST-NPV the MT-NPV and LT-NPV are not necessarily optimized, butoptimizing the MT-NPV will most probably results in optimized LT-NPV and vice versa. Due to the relatively high number of wells and the discounting factor on the NPV, the MT-NPV and the LT-NPV have very close values which is obvious in the top plot of the figure.

Example 2

Figure 4.2shows that the NPVs for medium and long term are highly related. This is similar to our observation in Example 1.The short term NPV is not related to NPVs of the medium and long terms investment options. That means, that optimizing the ST-NPVdoes notnecessarily mean that MT-NPV and LT-NPV are optimized.However, optimizing the MT-NPV will most probably results in optimized LT-NPV and vice versa.

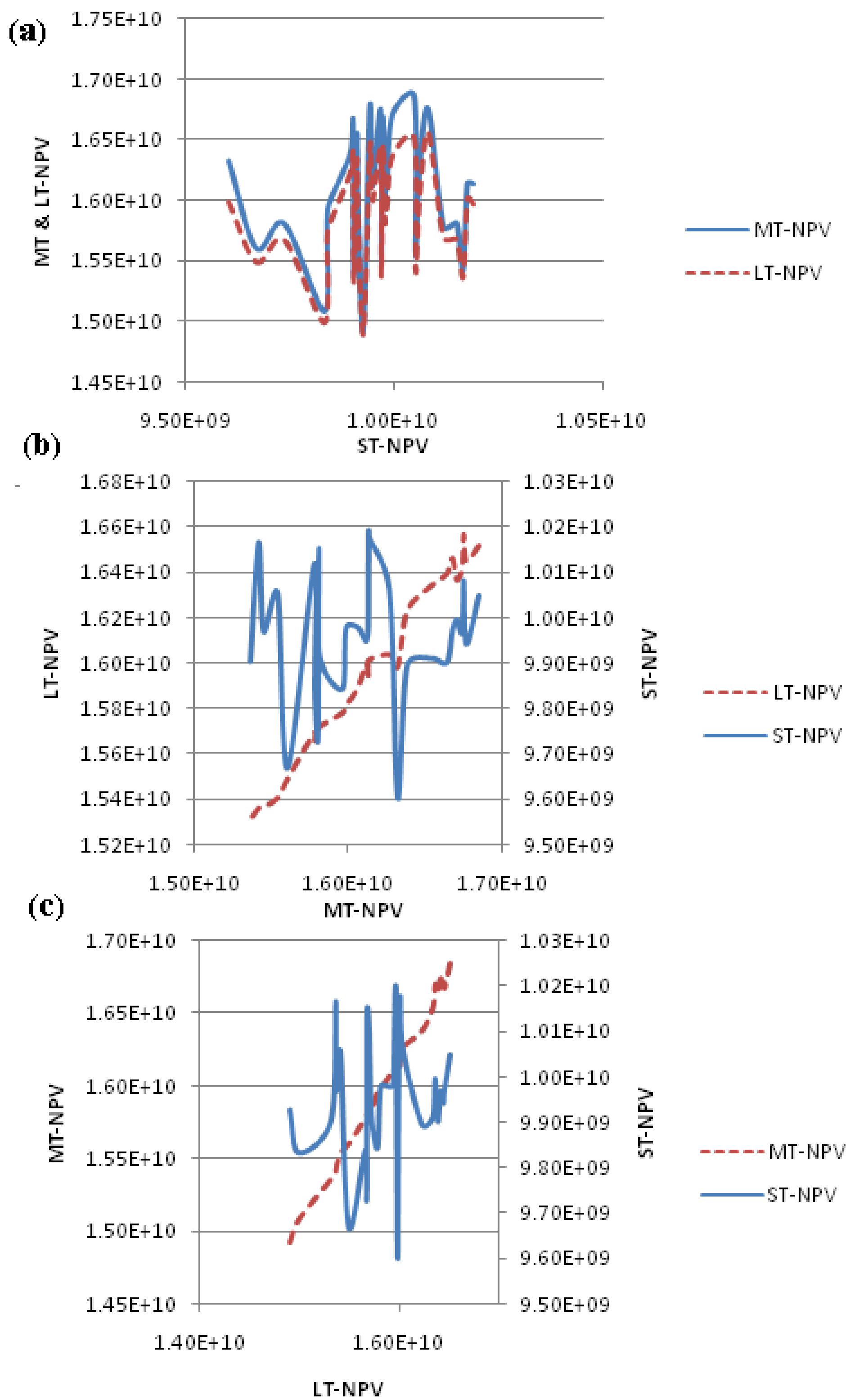

Figure 4.1: The relationship between the three terms NPVs for Example 1

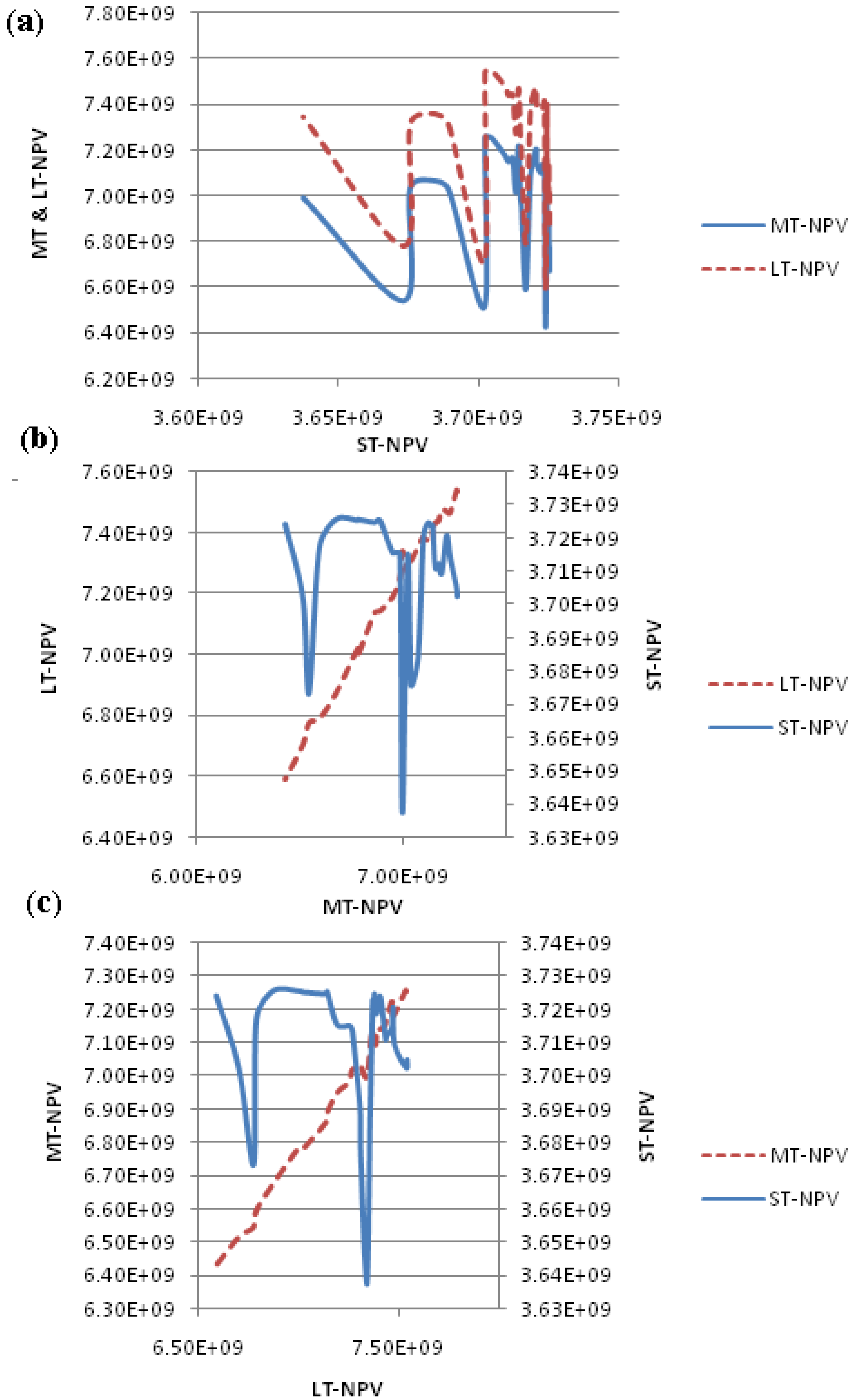

Figure 4.2: The relationship between the three terms NPVs for Example 2

4.2 Effect of Objective Function Used

In this section we discuss how changing the objective function affected the optimization results in each term, and we examined whether it possible to generalize an objective function to be the best for all terms.

4.2.1 Unconstrained Optimization

First we discuss the results of unconstrained optimization (Case 1) of the two examples. In this case three objective functions were used ST-NPV (Case 1a), MT-NPV (Case 1b) and LT-NPV (Case 1c). In each of these cases five realizations were made or in other words five different optimization runs. The range of the results of the realizations on different terms NPVs when different terms were used as objective function are shown in Figure 4.3 and Figure 4.4 for Example 1 and 2 respectively.

Figure 4.3 a and Figure 4.4 a show the range of ST-NPVs while Figure 4.3 b and Figure 4.4 bpresent the range ofMT-NPVs and the resulted LT-NPVs range are presented in Figure 4.3 c and Figure 4.4 c.

Example1

As evident from Figure 4.3 the best NPVs for short term were obtained when we used short term as an objective function (Case 1a), the best medium term NPVs were obtained when we used it as an objective function (Case 1b) and the best long term NPVs were also obtained when we used the long term as an objective function. The values of ST-NPV were high in Case 1a but lower in Case 1b and Case 1c.However, Case 1b and Case 1c resulted in close results in MT-NPV and LT-NPV. This shows that the MT-NPV and LT-NPV are related.

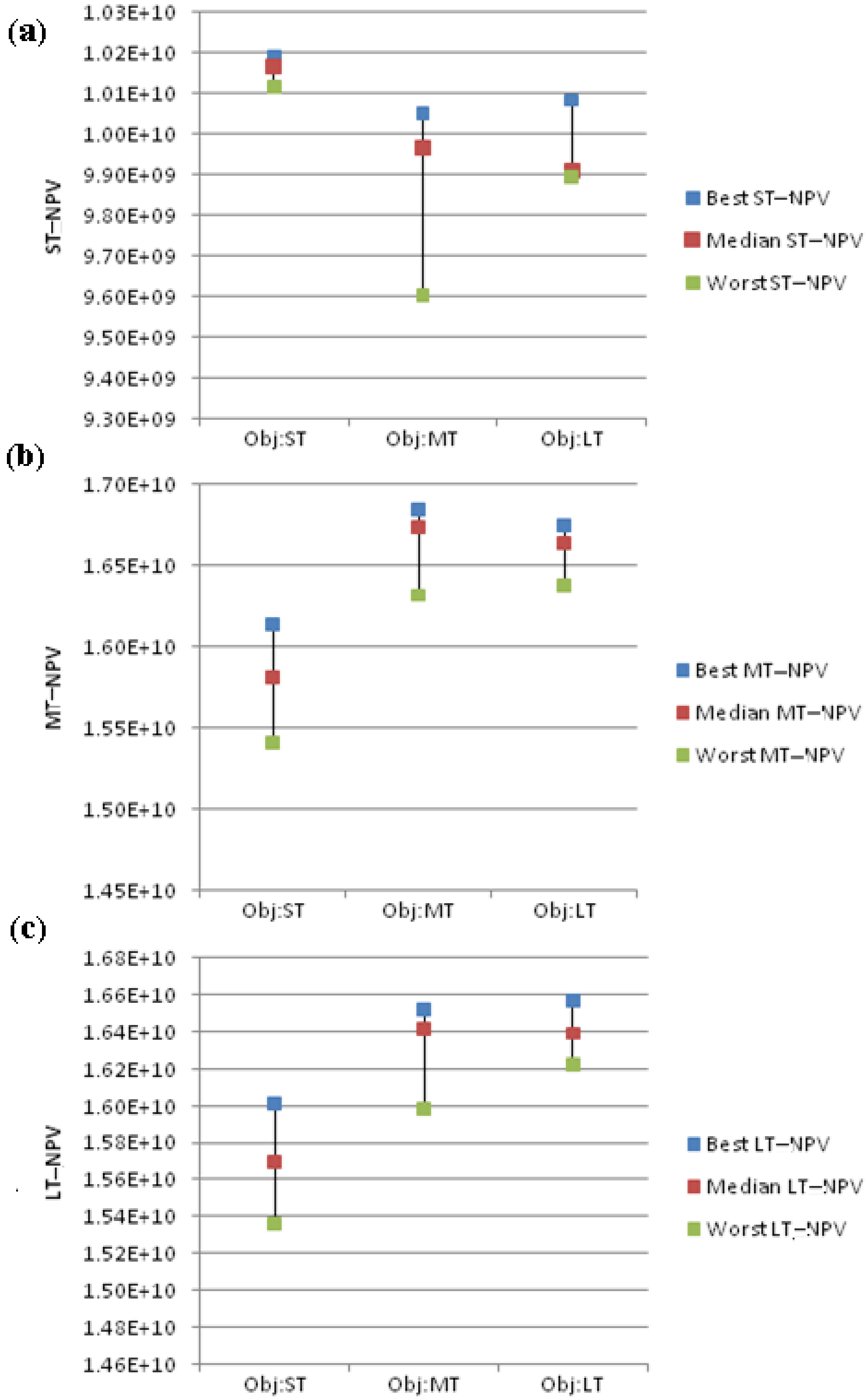

Figure 4.3: The effect of objective function used in the three terms NPVs for unconstrained optimization in Example 1

Example 2

In this example, all the three objectives resulted in almost similar range of ST-NPVs.However, the best value was obtained when ST-NPV used as objective. The range of MT-NPVs and LT-NPVs were almost similar when medium and long terms were used as the objective while the short term as objective resulted in lower values of MT-NPVs and LT-NPVs as observed in Figure 4.4.

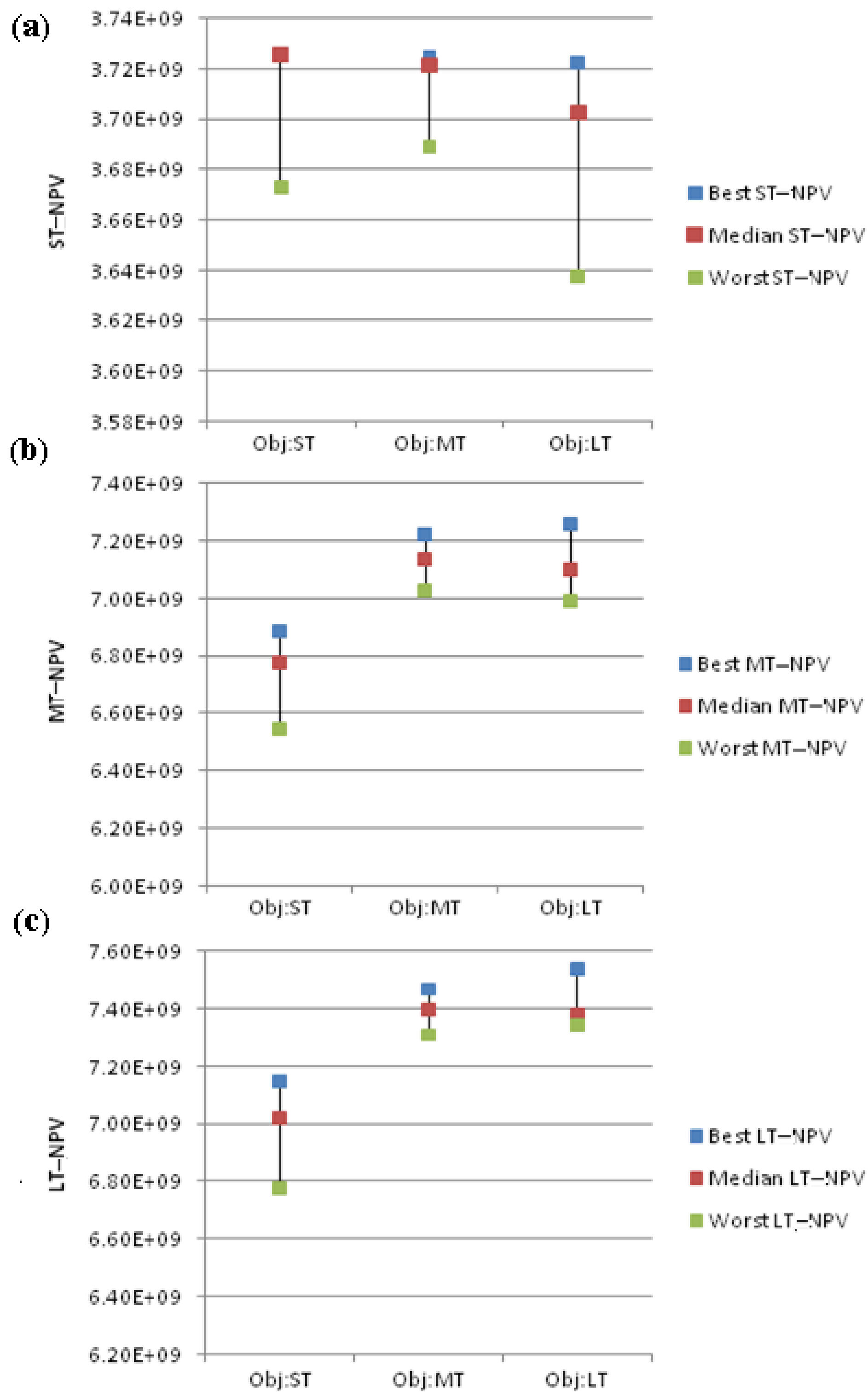

Figure 4.4: The effect of objective function used in the three terms NPVs for unconstrained optimization in Example 2

4.2.2 Constrained Optimization

In this section, we present the results of constrained optimization (Case 2) for the two examples considered. Three objective functions were used ST-NPV (Case 2a), MT-NPV (Case 2b) and LT-NPV (Case 2c). In each of these cases, five realizations were made. The ranges of the results of the runs from different terms of NPV for different objective functions areshown in Figure 4.5 and Figure 4.6. Figure 4.5 a and Figure 4.6. a show the range of ST-NPVs while Figure 4.5 b and Figure 4.6. b present the range of MT-NPVs and the resulted LT-NPVs range are presented in Figure 4.5 c and Figure 4.6. c.

Example1

It can be seen from Figure 4.5that all the three objectives resulted in almost similar range of ST-NPVs, although when ST-NPVwas used as objective the results of NPVs of medium and long terms werelower than when the other two terms were used as the objectives. The range of MT-NPVs and LT-NPVs when the medium term was used as the objective was close to the values when the long term was used.

Example 2

The results of this case were very similar to the unconstrained case (Case 1) as shown in Figure 4.6. All the three objectives resulted in very close range of ST-NPVs while the best value was obtained when ST-NPVwas used as objective. The range of MT-NPVs and LT-NPVs were almost similar when medium and long terms were used as the objective while short term as objective resulted in lower values of MT-NPVs and LT-NPVs.

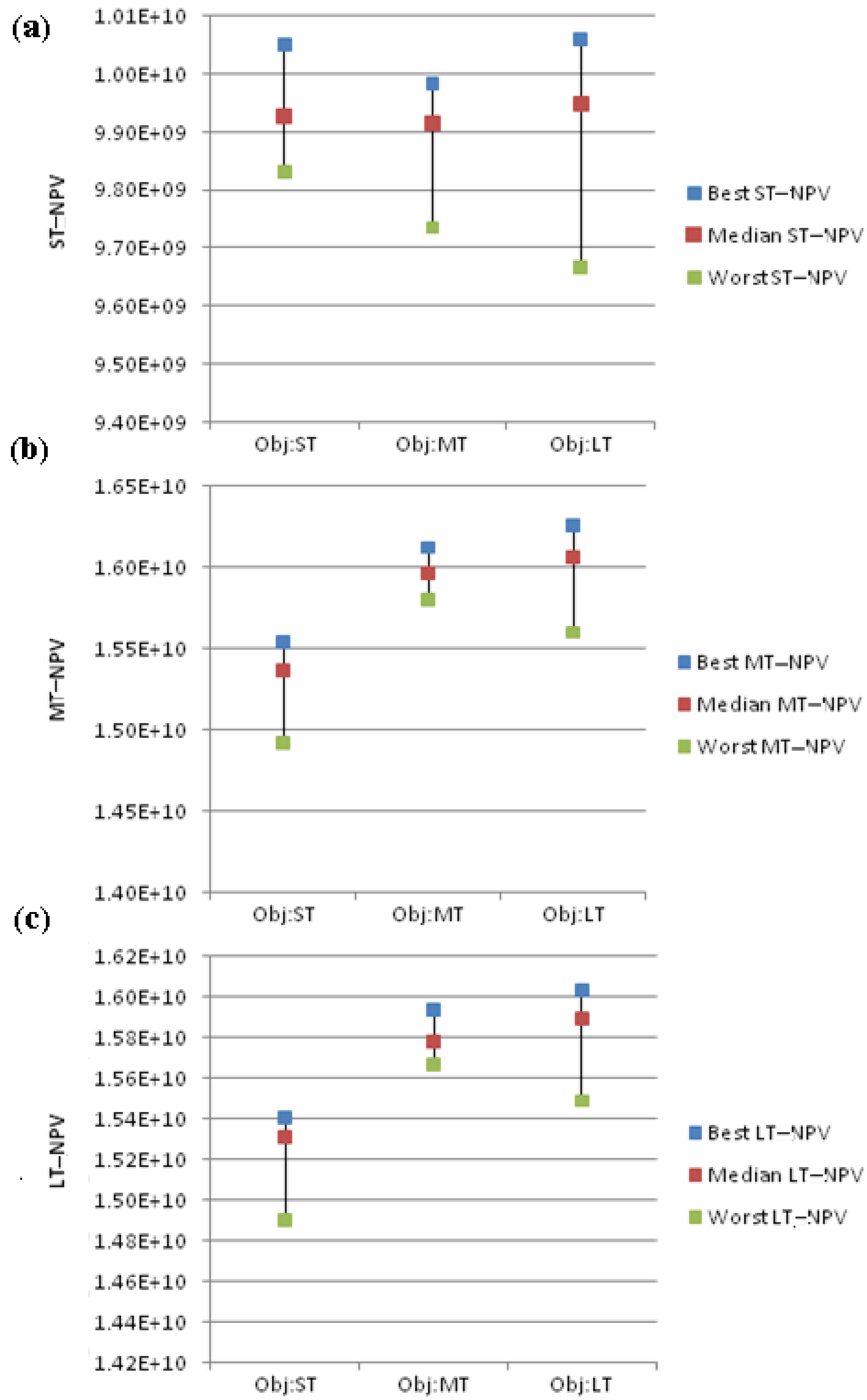

Figure 4.5: The effect of objective function used in the three terms NPVs for constrained optimization in Example 1

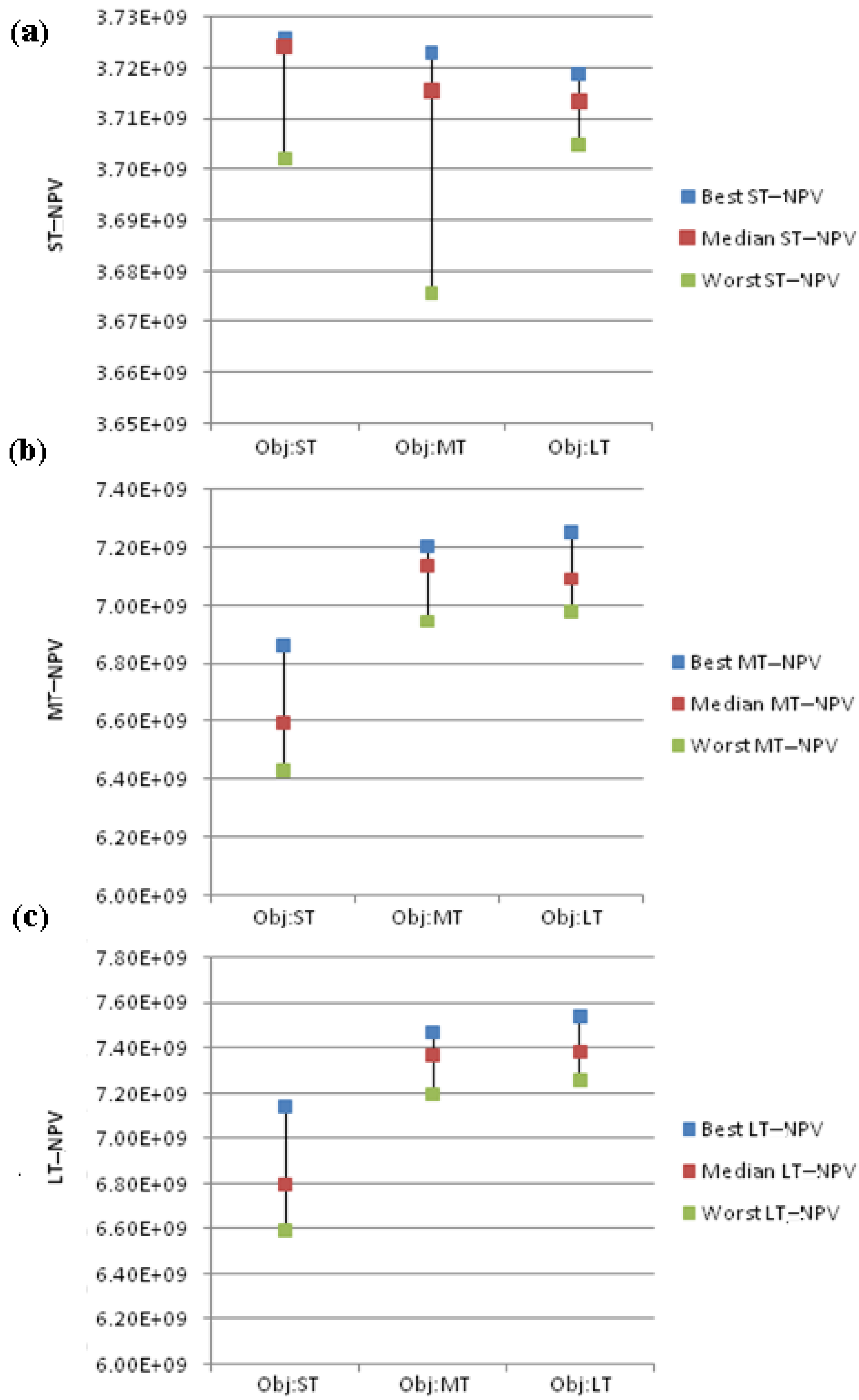

Figure 4.6: The effect of objective function used in the three terms NPVs for constrained optimization in Example 2

4.3 Reservoir Performance

In this section, we discuss the oil production profile for the best well placement results from different objectives for both the unconstrained and constrained cases and for each of the two reservoir examples. Figure 4.7 and Figure 4.8 show the reservoir performance results for Example 1 and Example 2 respectively.Figure 4.7 a and Figure 4.8a are for the unconstrained case while Figure 4.7 b and Figure 4.8 bare for the constrained case.

Example1

Figure 4.7 a shows the oil production profile for the unconstrained case (Case 1), while Figure 4.7 bshows the constrained case (Case 2). In both cases and for all the results, the production profile started with high production rate that fell rapidly from the beginning then the production stabilized for several years and declined afterward. This because at the first period the total production rate was higher than the total injection rate, thus the pressure could not stabilized till the production declined to a rate close to the injection rate.

In the two cases the stabilized production period was longer for the well placement that resulted in the best LT-NPV than the one of the best ST-NPV. This period is longer in the unconstrained case (Figure 4.7 a) than in the constrained case (Figure 4.7 b).

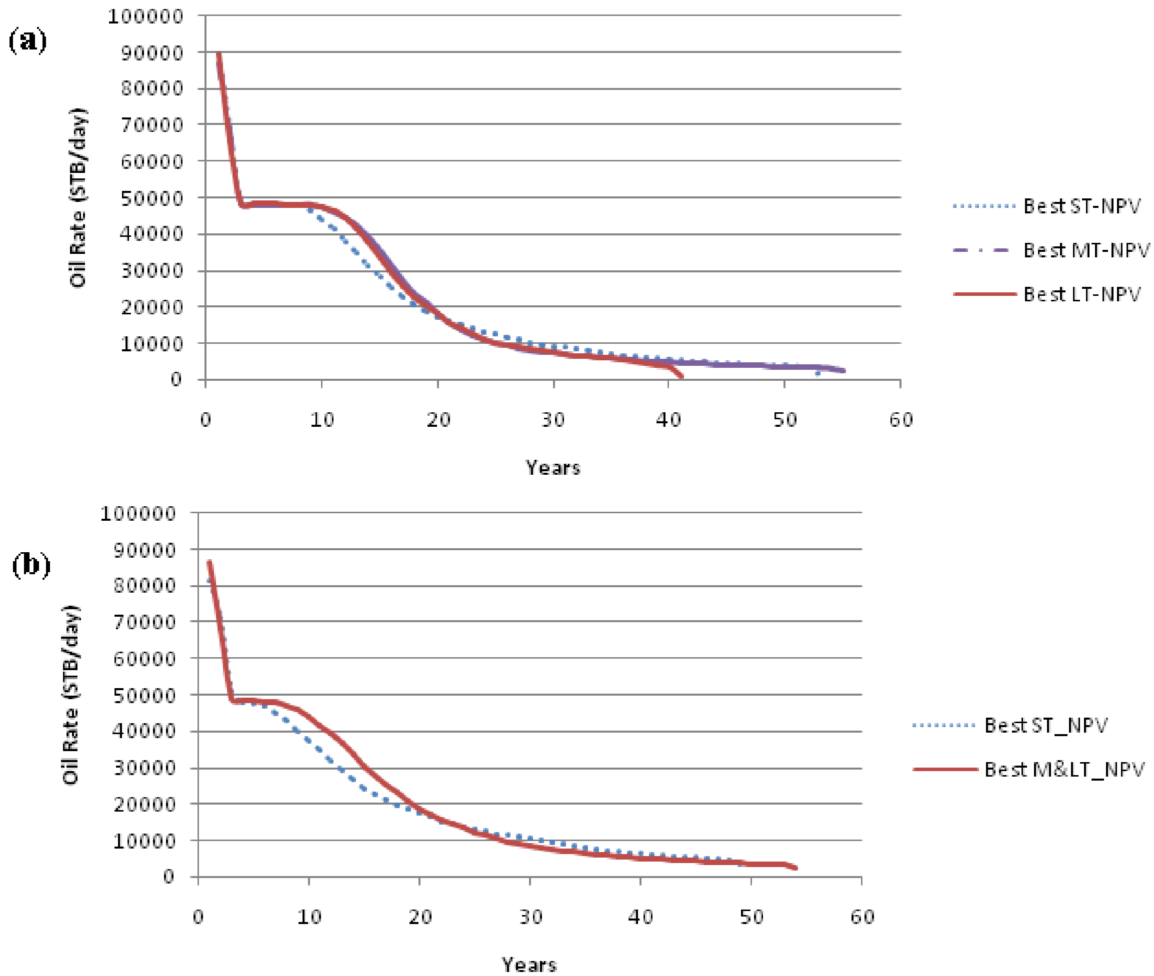

Figure 4.7: Oil production profile for the best results in Example 1

Example 2

In Figure 4.8 a which is for the unconstrained case (Case 1) the wells placement in which the best ST-NPV was obtained resulted in seven years of plateau phase of production (constant production rate), while this phase was durable for five years for the wells placement of the best MT-NPV and LT-NPV which illustrate why the results of ST-NPVs was not very far when ST-NPV was used as objective and when MT-NPV and LT-NPV were used. Although the well placement of the best ST-NPV resulted in longer plateau phase, the production decline was more rapid in this case, that’s why it has lower MT-NPV and LT-NPV.

The second case (Case 2) which is represented in Figure 4.8b has the same behavior of Case 1. Compared to the well placement that resulted in the best MT-NPV and LT-NPV, the well placement that resulted in the best ST-NPV has longer plateau phase of production and more rapid decline afterward.

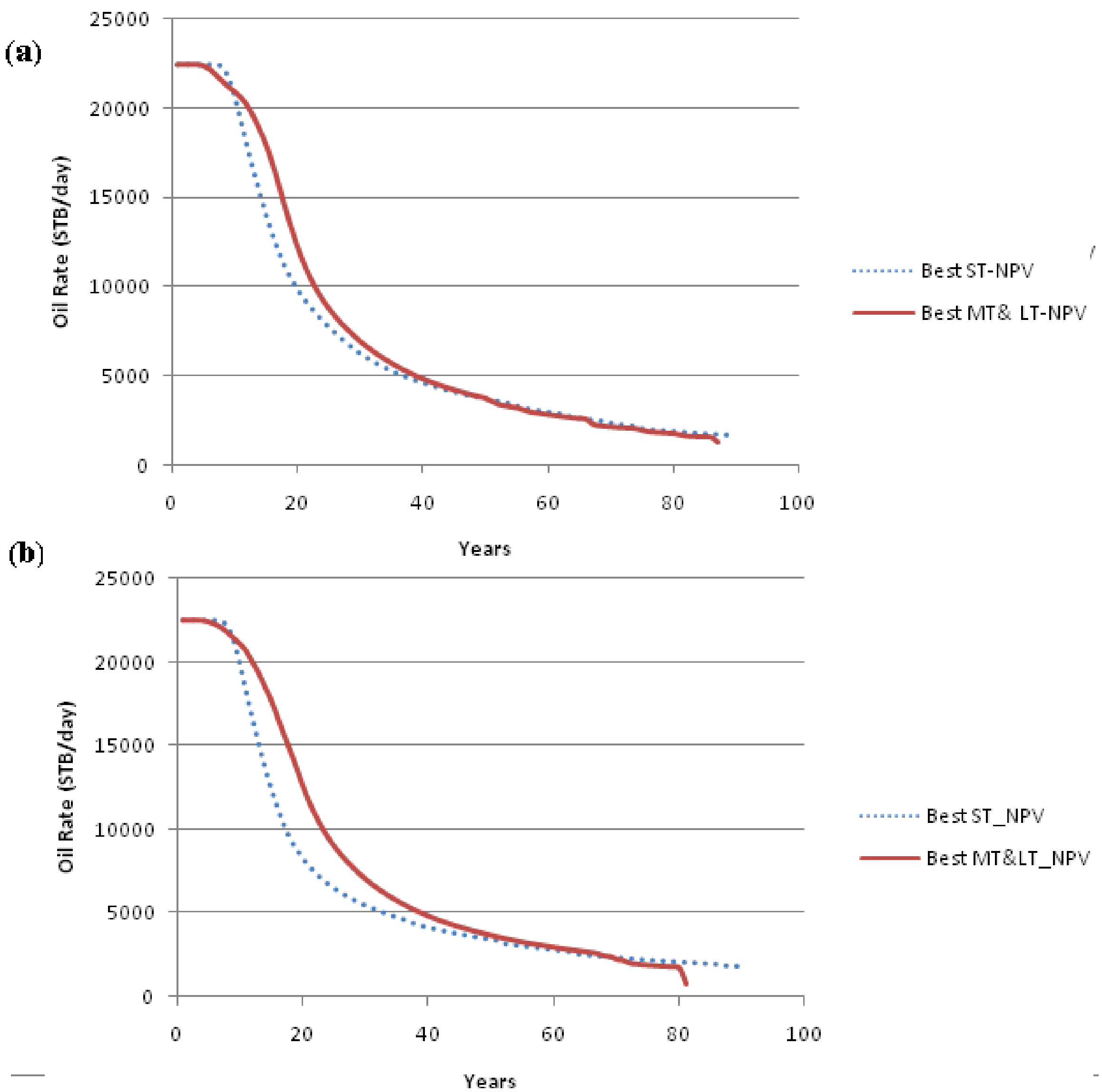

Figure 4.8: Oil production profile for the best results in Example 2

4.4 Well placement

The Different well placements obtained from the results of the investment options are presented in this section for each of the reservoir examples for the unconstrained and constrained cases, respectively. Figure 4.9 to Figure 4.17 show the production and injection wells locations for the best optimization results of the different realization. The background of these figures is the permeability distribution of the top layer in the reservoir examples.

4.4.1 Unconstrained optimization

We start by displaying the well placement for the unconstrained case (Case 1), and it can be noticed in Figure 4.9 to Figure 4.13 that the locations of some producers/injectors are close to each other.

Example1

Figure 4.9 to Figure 4.11 show the well locationsobtained from the best ST-NPV, MT-NPV and LT-NPV in Example 1. It is observed that, in Figure 4.9 some injectors were completed inside the channels and some producers completed outside the channels, while in Figure 4.10 and Figure 4.11 the numbers of injectors completed inside the channels and producers completed outside the channels were smaller. It is also observed from these figures that the locations of some producers/injectors are close to each other.

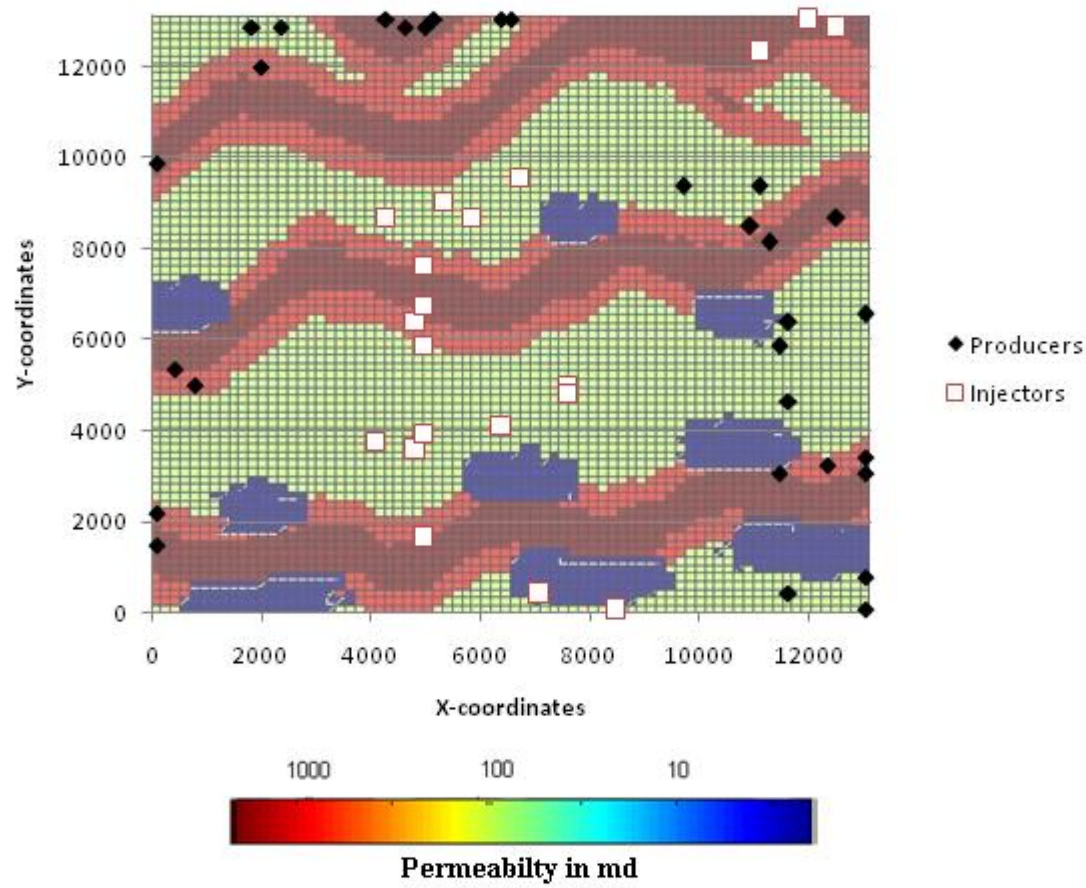

Figure 4.9: Well locations obtained from the best ST-NPV for non-constrained optimization in Example 1X-coordinates

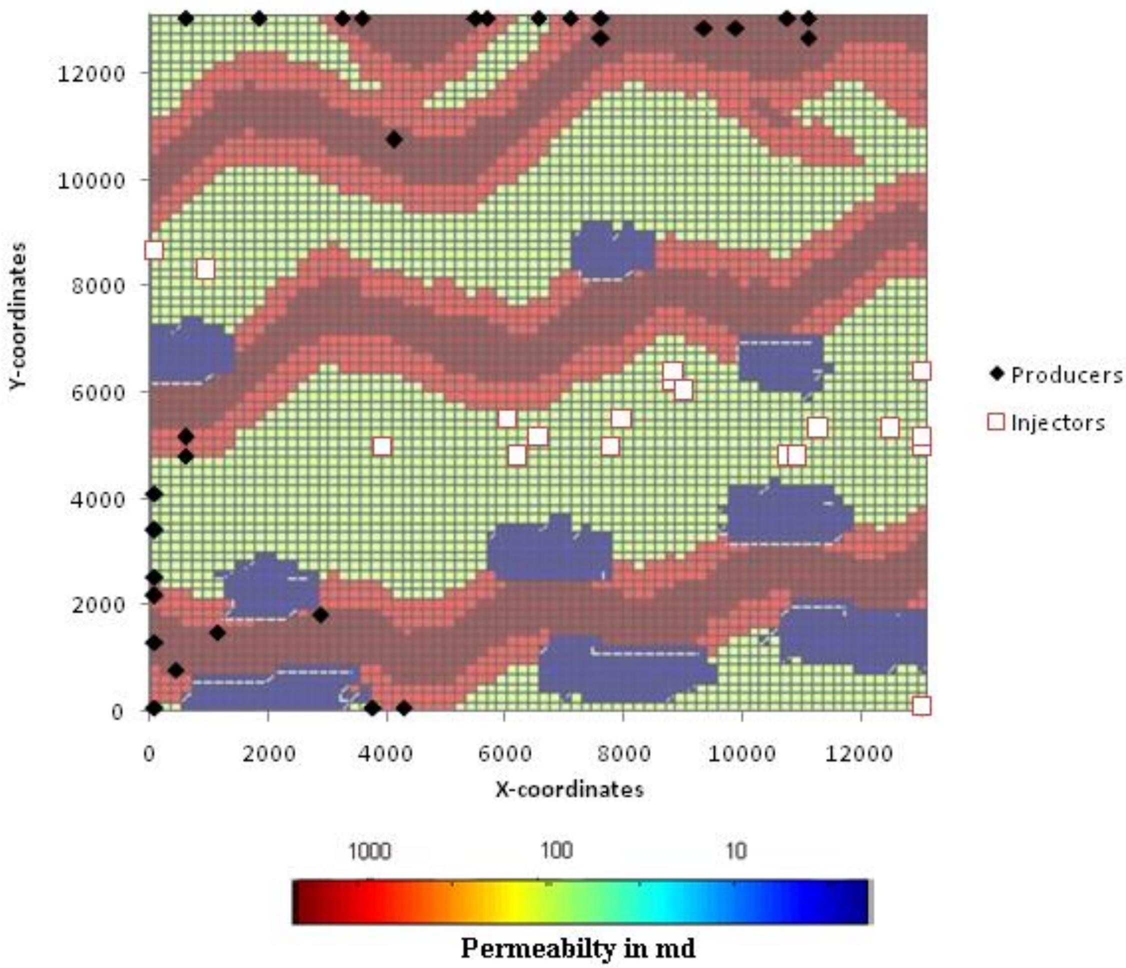

Figure 4.10: Well locations obtained from the best MT-NPV for non-constrained optimization in Example 1

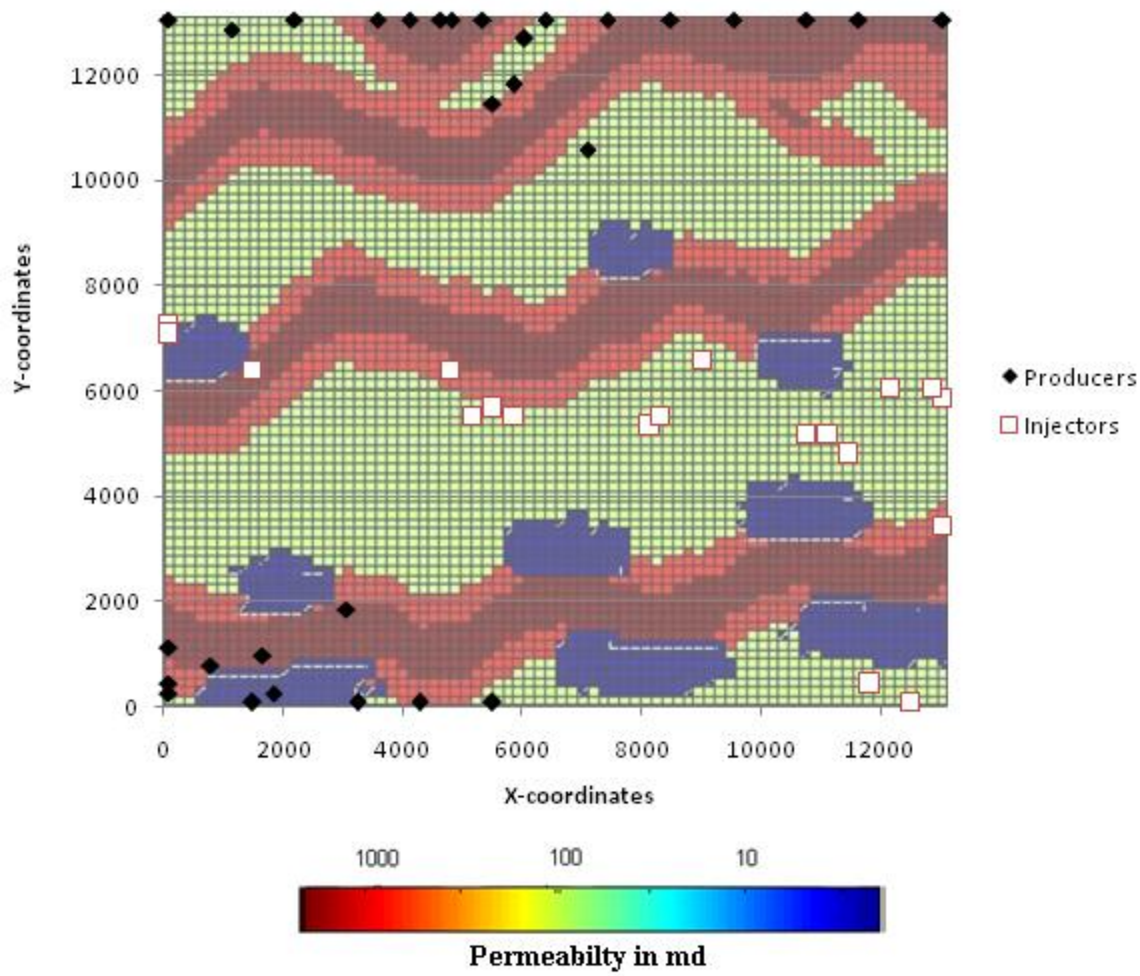

Figure 4.11: Well locations obtained from the best LT-NPV for non-constrained optimization in Example 1

Example 2

Figure 4.12 shows the well locationsobtained from the best ST-NPV and Figure 4.13 show the well locationsobtained from the best MT-NPV and LT-NPV in unconstrained optimization of Example 2. The background of this figure is the permeability distribution for the top layer out of three layers.This permeability distribution is different in the other layers. In these figures, also it can be seen that the locations of some producers/injectors are too close to each other and in Figure 4.13 many of injectors fall in the same grid cell of the reservoir model.

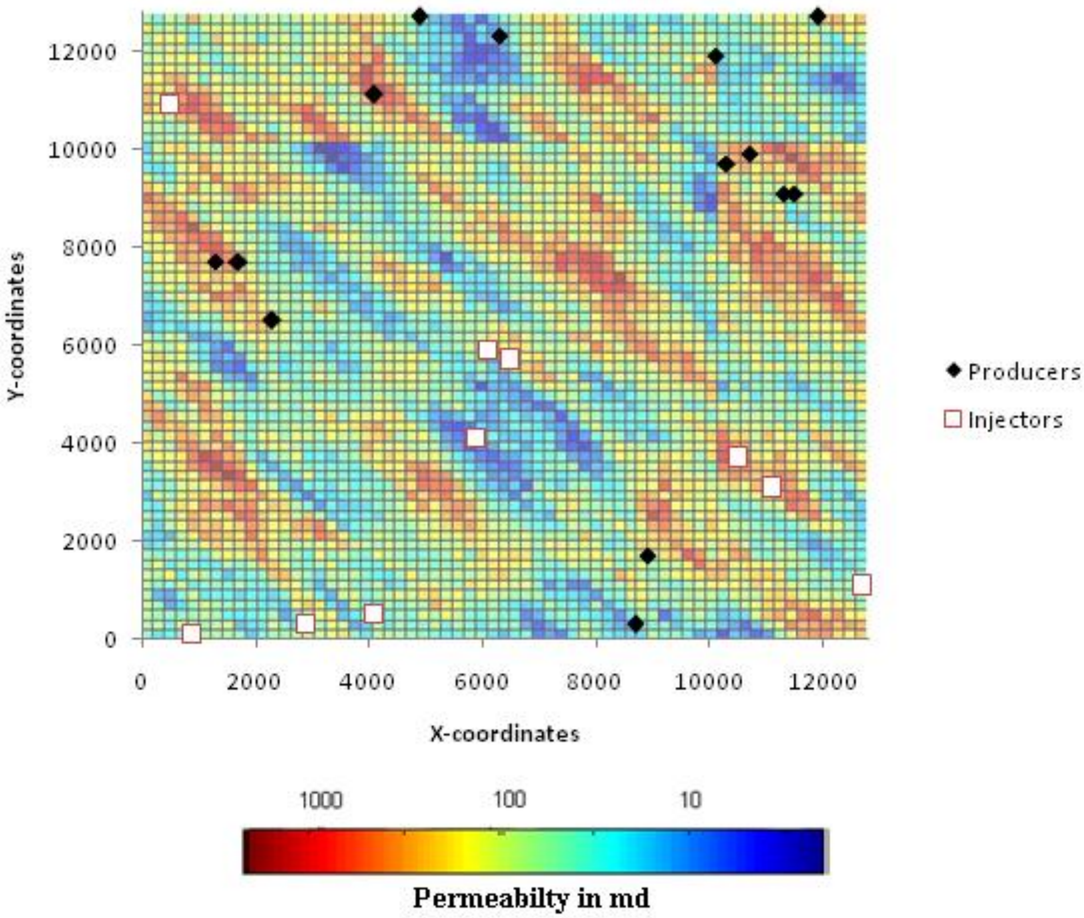

Figure 4.12: Well locations obtained from the best ST-NPV for non-constrained optimization in Example 2

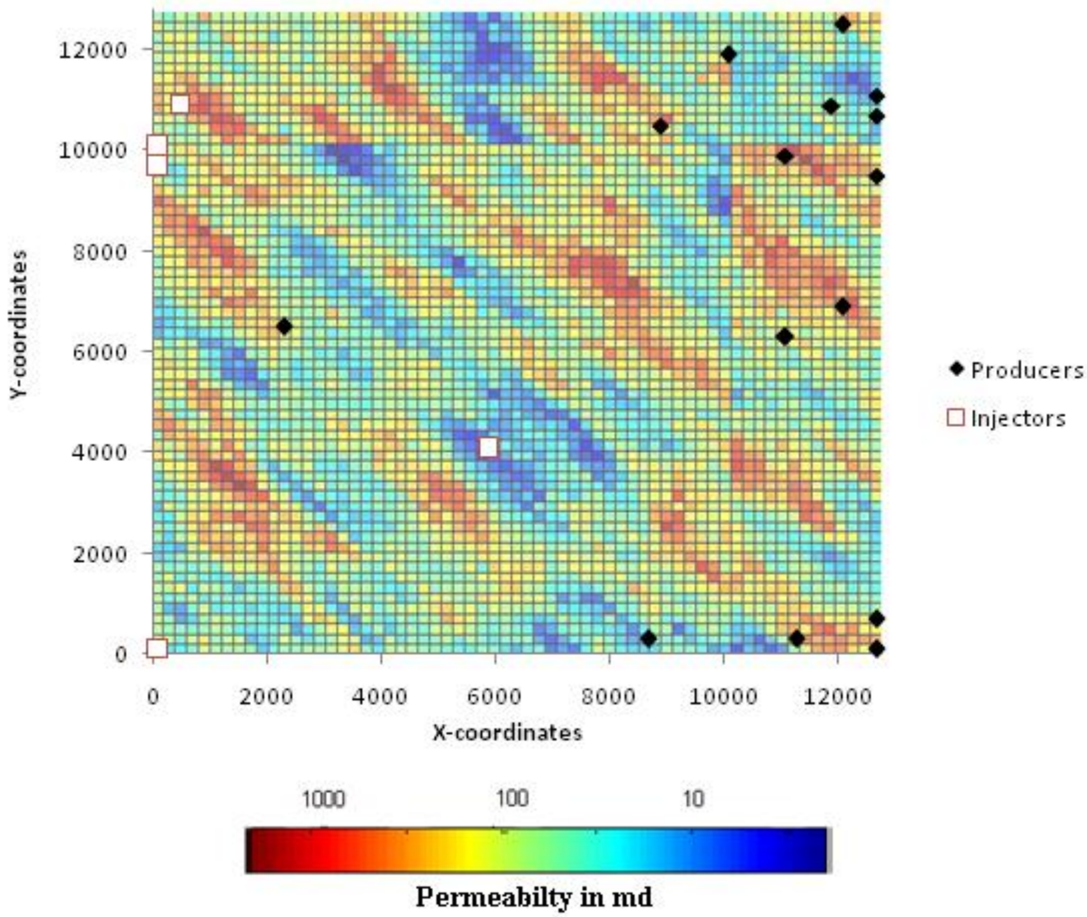

Figure 4.13: Well locations obtained from the best MT-NPV&LT-NPV for unconstrained optimization in Example 2

4.4.2 Constrained Optimization

In this part, we presentthe results for the well placement for the constrained case (Case 2). Figure 4.14 to Figure 4.17show that the distances between the wells are larger than those in the unconstrained case (Case 1).

Example1

The well placement corresponding to the best ST-NPVis shown in Figure 4.14, while the corresponding to the best MT-NPV and LT-NPVis shown in Figure 4.15. In both figures, most of the producers are located on the right side of the reservoir while most of the injectors are located on the left side. It is observed that the distance between the wells is bigger than those in the unconstrained case.

Example 2

Figure 4.16 shows the well locationsobtained from the best ST-NPV and Figure 4.17 shows the well locationsobtained from the best MT-NPV and LT-NPV in the constrained optimization of Example 2. Again these figures do not give the whole picture of wells pattern because the permeability distribution for the top layer is different from the other layers. In these figures also it can be seen that the distances between the wells are bigger than those in the unconstrained case.For example while some injectors fall in the same grid cell in Case 1 (Figure 4.13), this did not happened in this case.

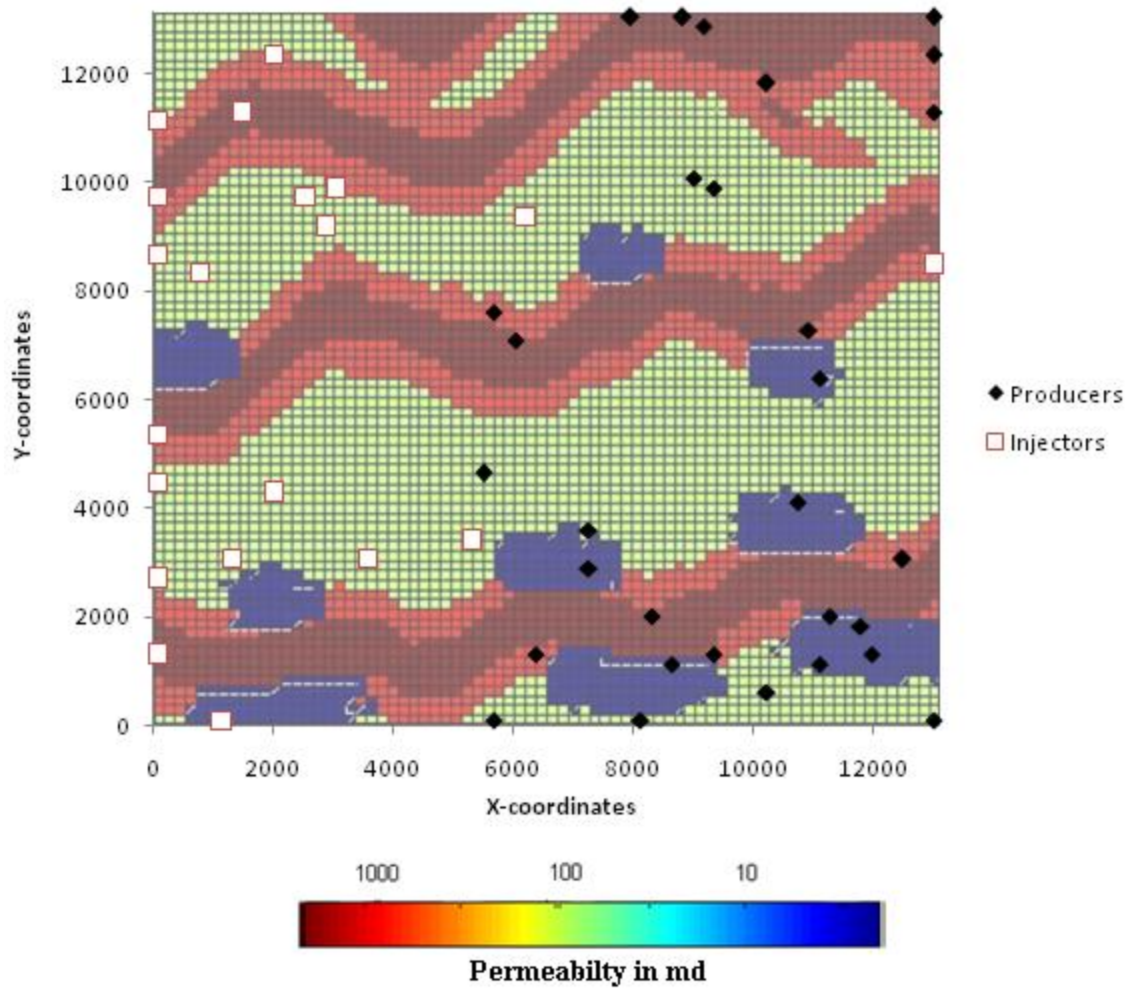

Figure 4.14: Well locations obtained from the best ST-NPV for constrained optimization in Example 1

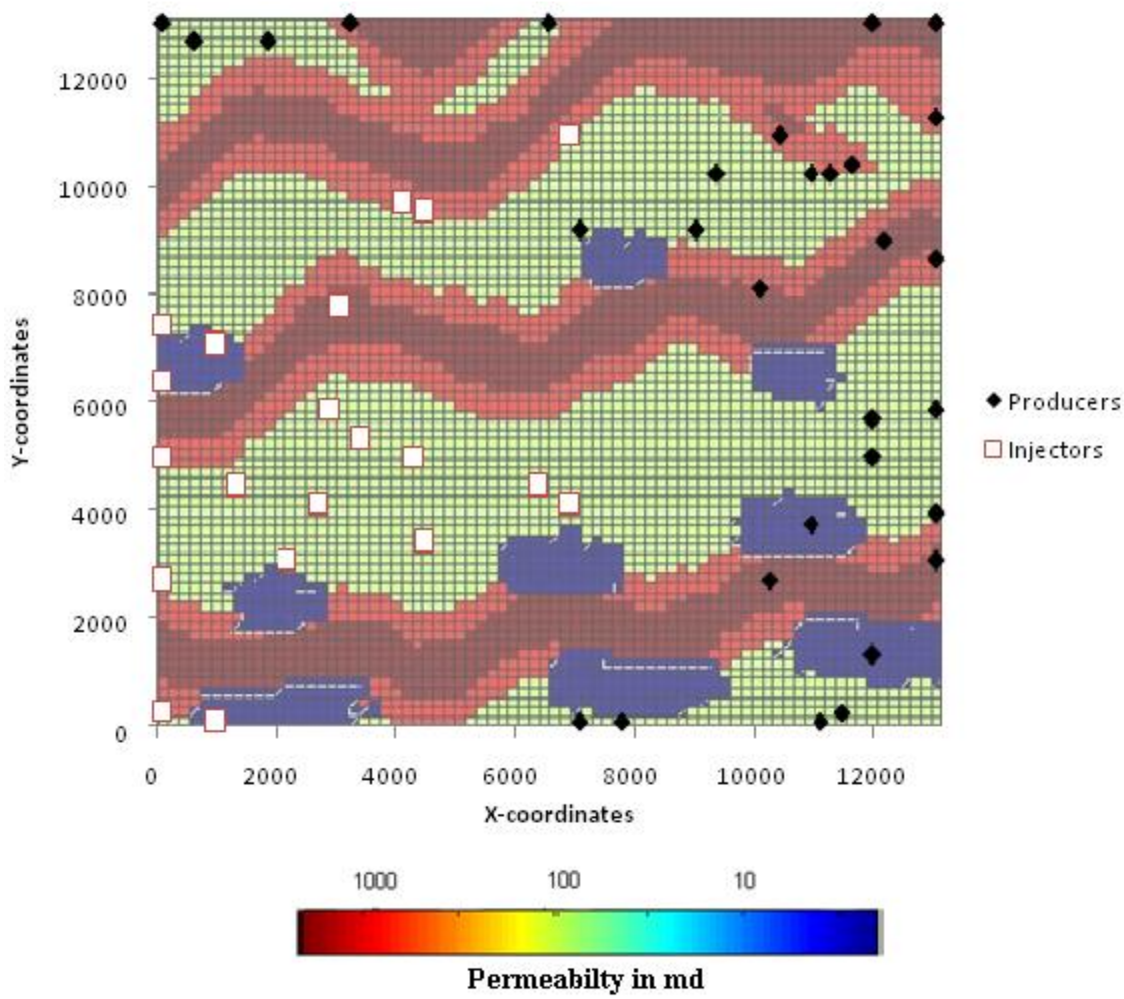

Figure 4.15: Well locations obtained from the best MT-NPV and LT-NPV for constrained optimization in Example 1

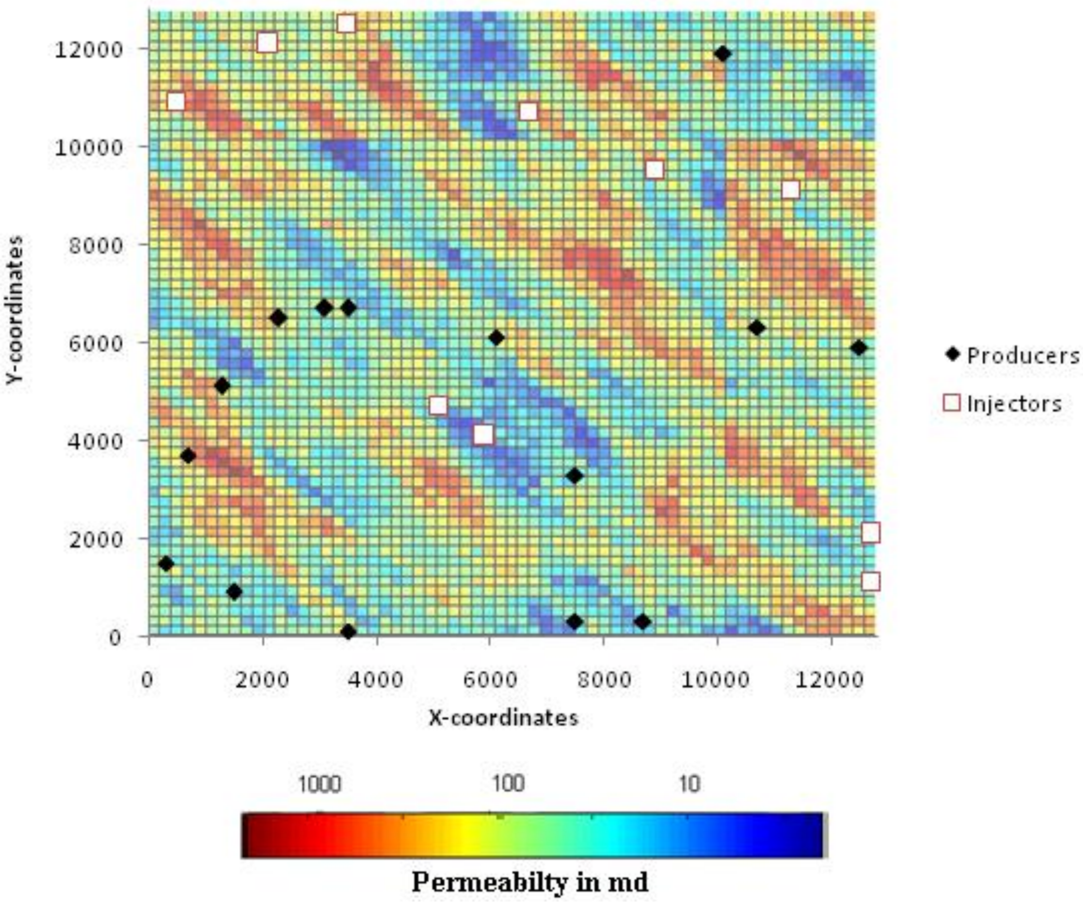

Figure 4.16: Well locations obtained from the best ST-NPV for constrained optimization in Example 2

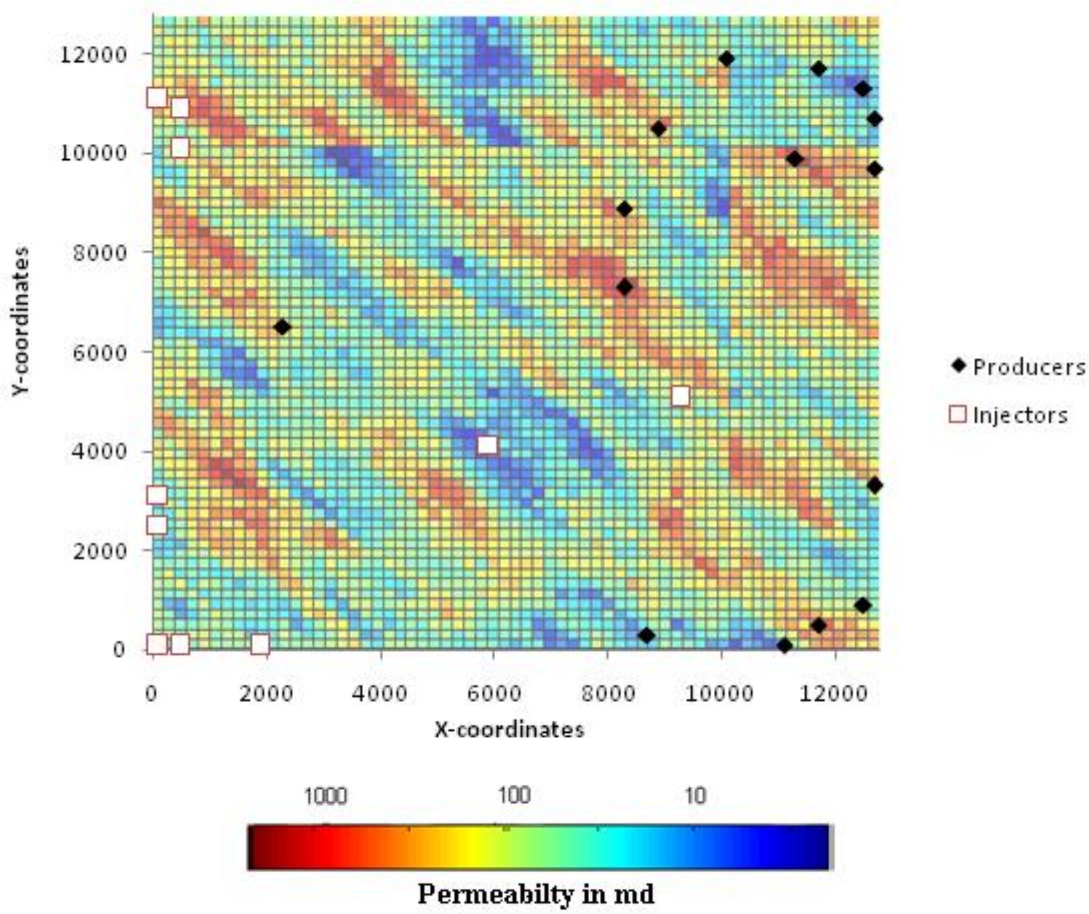

Figure 4.17: Well locations obtained from the best MT-NPV and LT-NPV for constrained optimization in Example 2

4.5 Effect of Adding Constraints

Figure 4.18 and Figure 4.19shows the NPVs range for different realization when different investment options were used as objectives in the optimization. In addition, these figures contain results from both the unconstrained and constrained cases.

Example1

From the Figure 4.18 it is obvious that adding constraints affects the results negatively especially in the medium and long term (Figure 4.18 b and Figure 4.18 c), even though it's necessary to give applicable results to well placement problem. This effect is up to around 4% of the NPV of the best results.

Example 2

In this example the effect of adding constrained to the optimization problem was not severe especially in short term.This may be due to the fact that number of wells is relatively small or because the minimum well spacing defined can be achieved easily. But generally, the NPVs of the unconstrained case (Case 1) are slightly higher than the NPVs of the constrained case (Case 2) as evident in Figure 4.19.

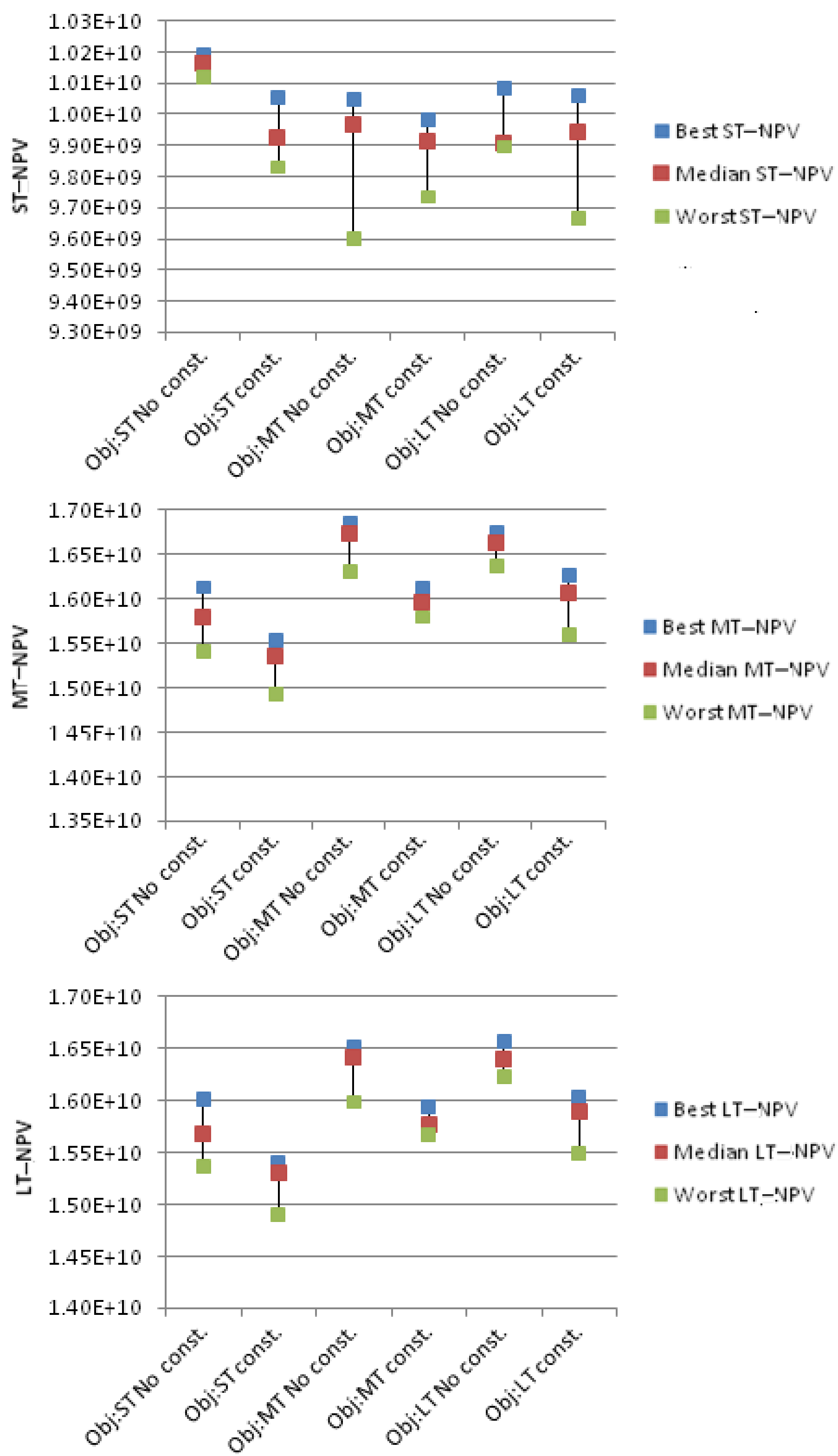

Figure 4.18: The NPVs of the three terms for both constrained and unconstrained optimization in Example 2

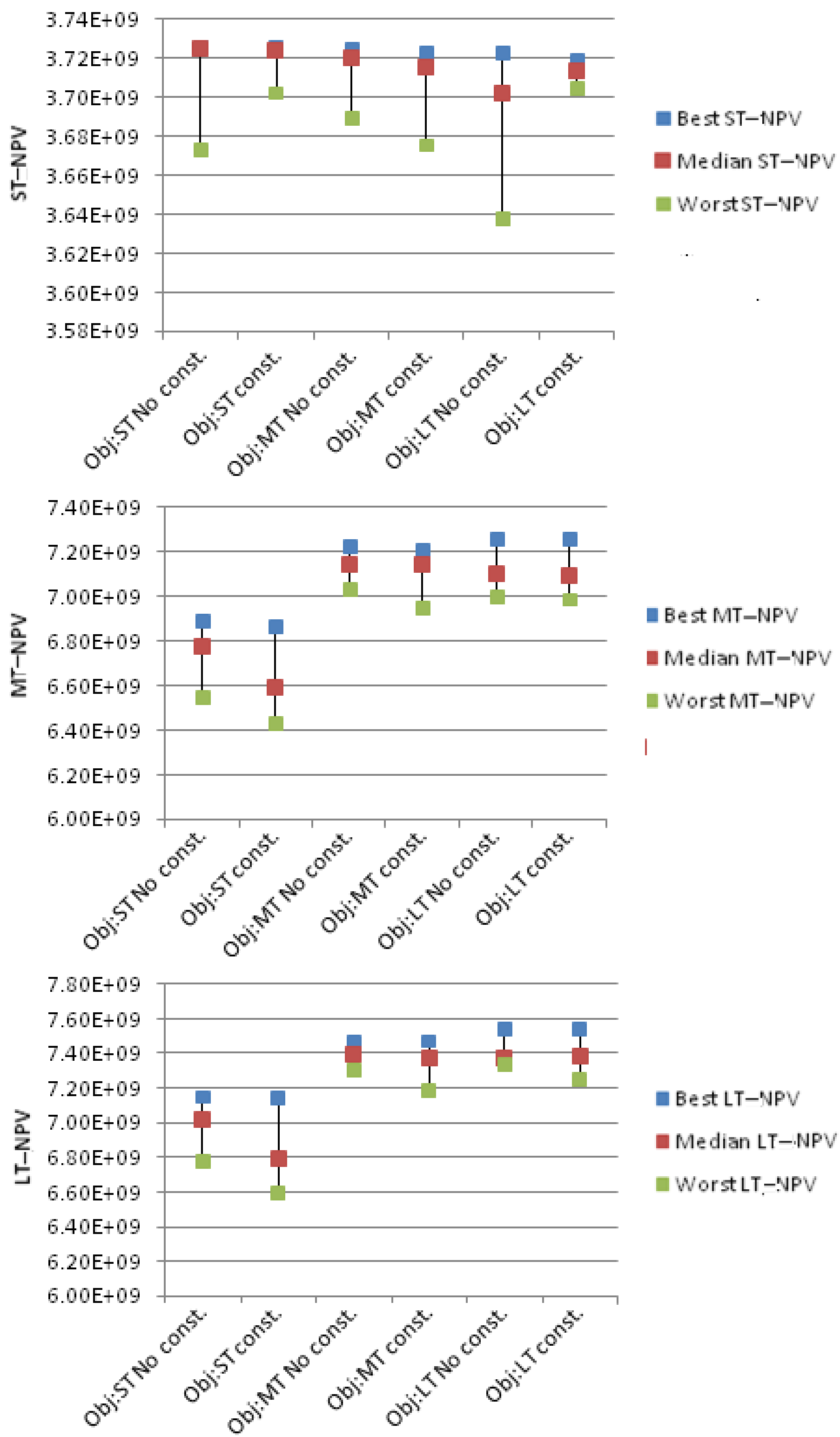

Figure 4.19: The NPVs of the three terms for both constrained and unconstrained optimization in Example 2

4.6 Optimization Progress

Figure 4.20 and Figure 4.21 show the progress of the optimization for the best realizations in Example 1 and Example 2, respectively. Figure 4.20 a and Figure 4.21a is for the unconstrained case (Case 1), whileFigure 4.20 b and Figure 4.21 b is for the constrained case (Case 2).

Studying the optimization progress figures we observed that in Example 1 more function evaluations are required to achieve the solution compared to Example 2. This may be due to the larger dimension of the problem, the size of the problem in Example 1 is 100 (50 wells) and in Example 2 is 40 (20 wells).

The optimization of ST-NPVrequired fewer function evaluations to find the optimum than the optimization of MT-NPVorLT-NPV.

(a)

(b)

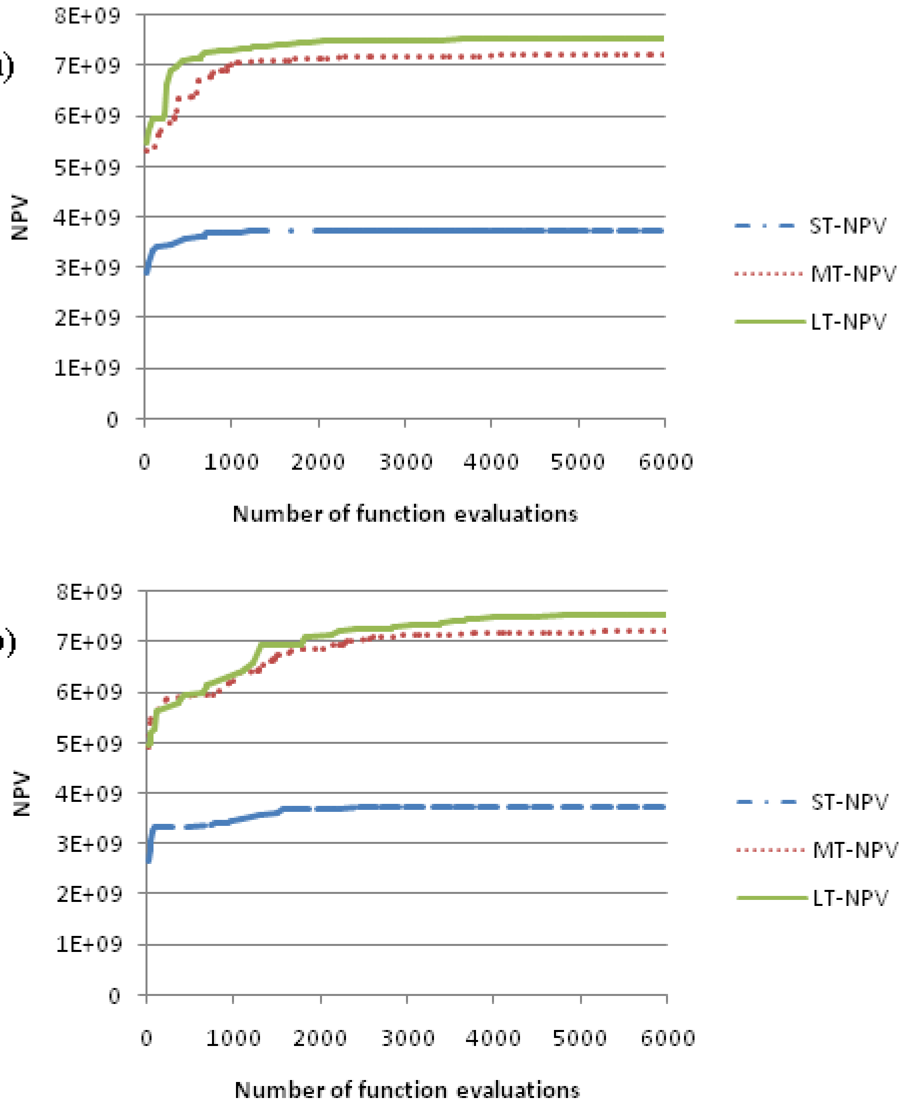

Figure 4.20: Optimization progress for the best realizations in Example 1

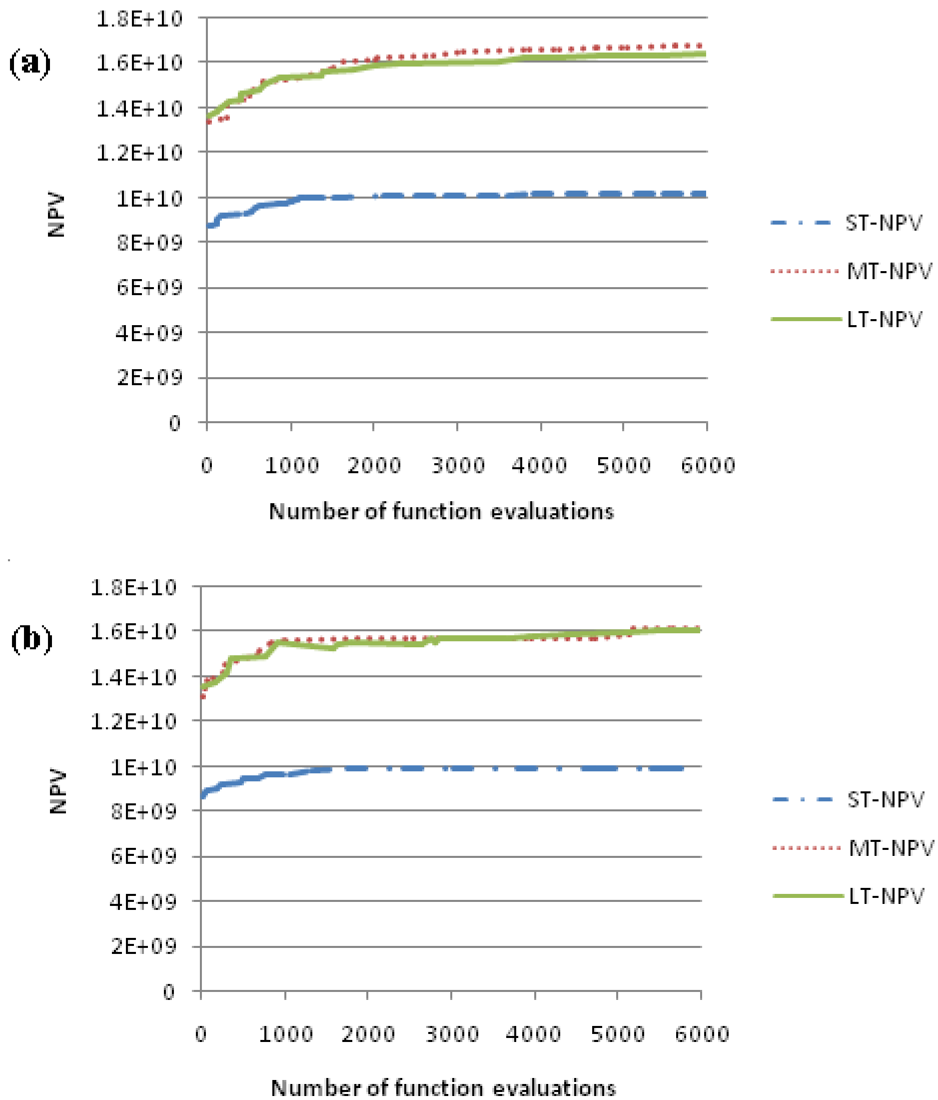

Figure 4.21: Optimization progress for the best realizations in Example 2

CHAPTER 5

LEXICOGRAPHIC APPROACH TO WELL PLACEMENT OPTIMIZATION

In this chapter, the results of using lexicographic multiobjective on well placement optimization to simultaneously optimize the NPV for different investment terms are discussed. In lexicographical approach, the objectives should be ranked based on the priority of the decision makers.Here we used two different rankings, inthe first ranking (Case 3a) the most-desirable objective function is the ST-NPV, followed by MT-NPVthenLT-NPV. This ranking has been reversed in Case 3b so that the LT-NPV is the most-desirable objective and ST-NPV is the least-desirable objective function. These cases have been applied to the two reservoir examples and a minimum well spacing of 5 acres was used as constraint.

5.1 Lexicographic Optimization Progress

As discussed in chapter 3, the lexicographic approach is a sequential optimization approach with more than one step depending on the number of the objectives. In this research we have three objectives as stated above, so the optimization in Case3 will have three steps. In the first step, the optimization is made on the first objective, then in the second step the optimization is made on the second objective so that the value of the first objective should not be worse than what was acquired in the first step.In the third step, the optimization is made on the third objective such that the values of the first two objectives should not be worse than what were acquired in the first two steps.

5.1.1 NPV Results

The progress of the lexicographic multi objective optimization in terms of NPVs of the short, medium andlong terms is described in this section. Figure 5.1 and Figure 5.2 show the NPVs of the three steps for Example 1 and Example 2, respectively.Figure 5.1 a and Figure 5.2a are for the case in which the ST-NPV is the first objective (Case 3a), whileFigure 5.1 b and Figure 5.2 b are for the case whenLT-NPVwas used as the first objective (Case 3b).

Example 1

It can be seen in Figure 5.1a (Case 3a) that the ST-NPV almost reached its maximum value in the first step because it is the first objective while the MT-NPV improved in Step 2 and remained constant in Step 3. The LT-NPV improvement in Step 3 is unnoticeable.This is mainly because when MT-NPV is optimized the LT-NPV is optimized as well, as we discussed in Chapter 4.

In Case 3b, although the first objective is the LT-NPV, the LT-NPV has been improved in Step 2 as the MT-NPV is optimized. Also the ST-NPV increased in Step 2. Generally, no significant improvement is seen in Step 3 because the NPVs of all the terms reached high values in Step 2.

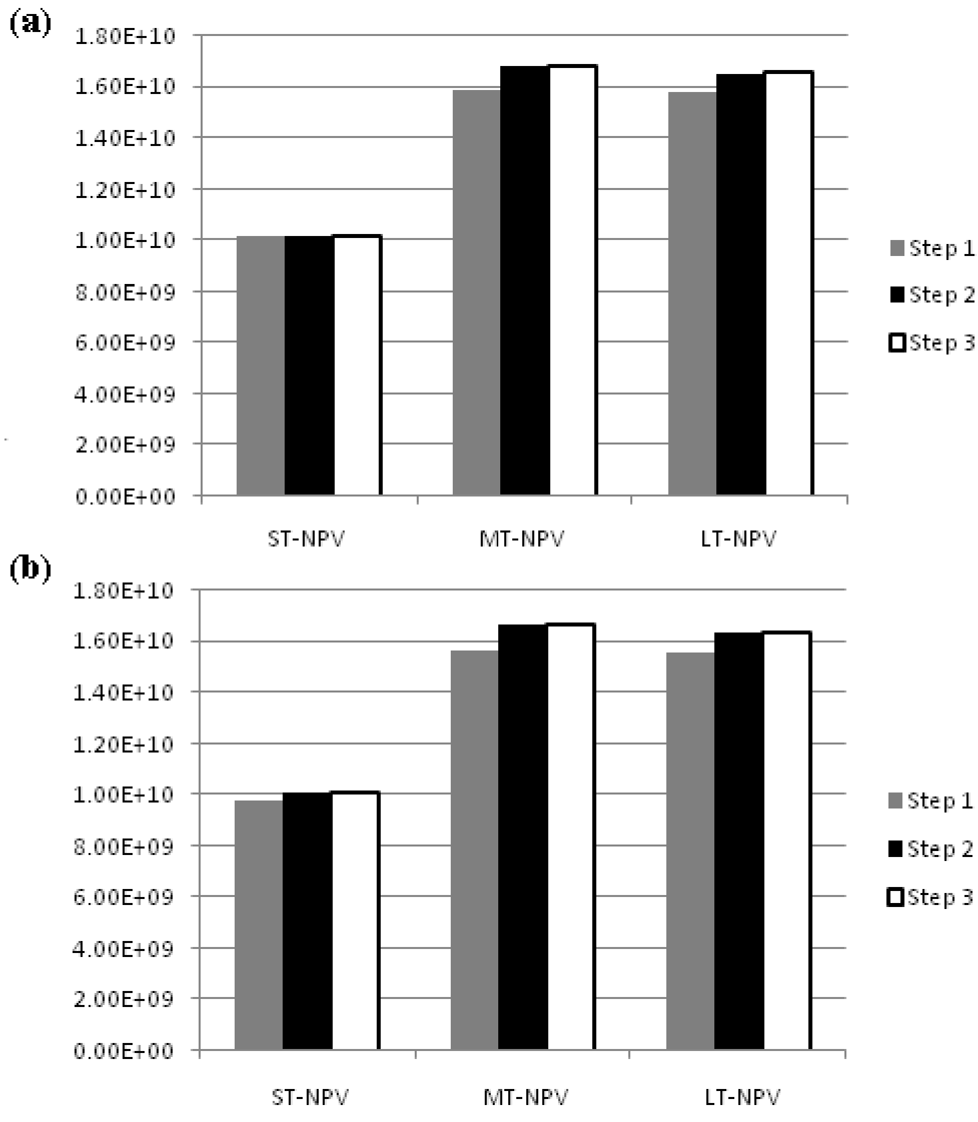

Figure 5.1: NPVs of Case 3a and Case 3b in Example 1

Example 2

In Case 3a, the ST-NPV achieved its optima from the first step as can be seen in Figure 5.2a because it is the first objective. MT-NPV and LT-NPV improved in the second step. In Case 3b, there was no noticeable improvement through the steps.The optimization of LT-NPV in the first step resulted in near-optimalST-NPV that couldn't be increased in the further steps. This is observed in Chapter 4 that the range of ST-NPVsobtained from optimizationof different NPV terms was not significantly different.

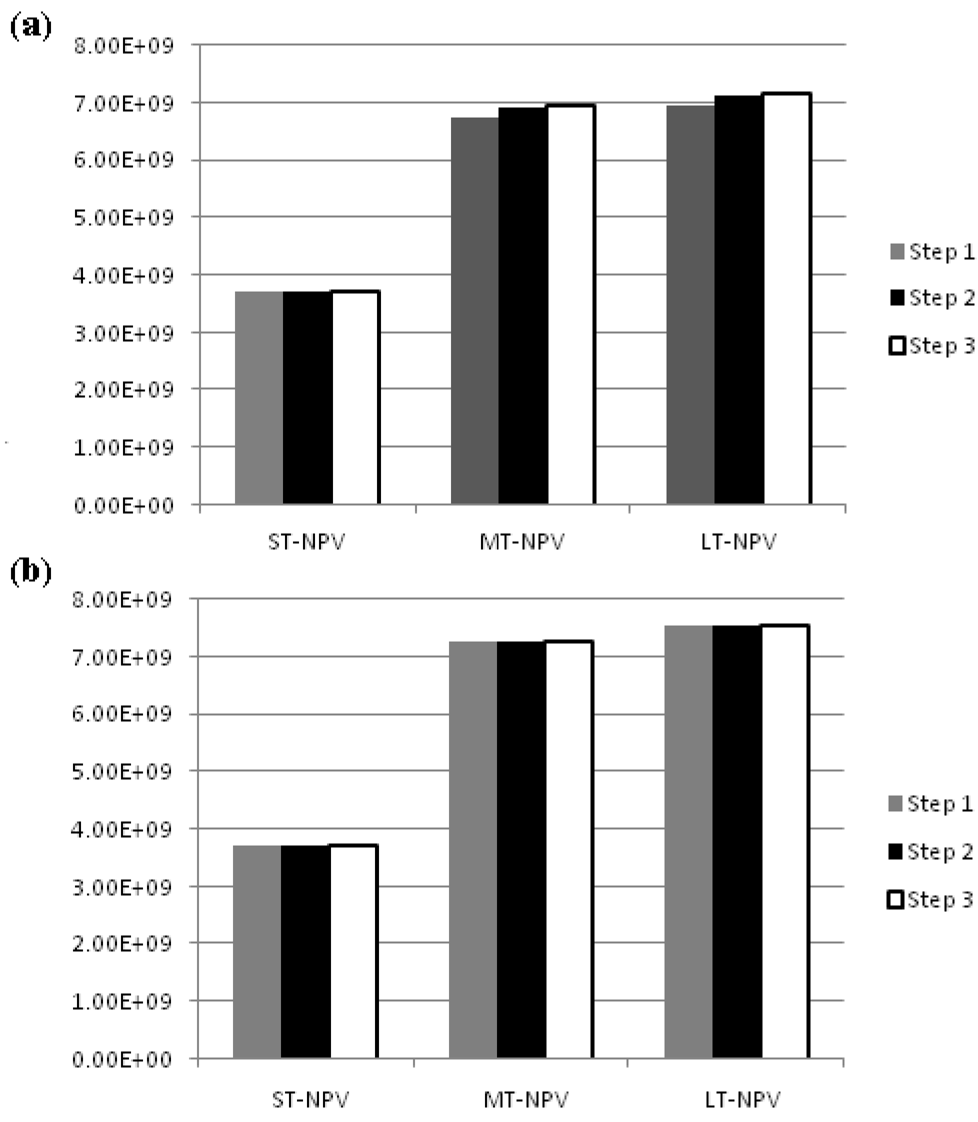

Figure 5.2: NPVs of Case 3a and Case 3b in Example 2

5.1.2 Reservoir Performance

In this section, we present the oil production profile obtained from the different steps of lexicographic multi objective well placement optimization. Figure 5.3 and Figure5.4 show the reservoir performance results for Example 1 and Example 2, respectively.Figure 5.3 a and Figure5.4a are for Case 3a in which the short term is used as the first objective, while Figure 5.3 b and Figure5.4 b are for Case 3b that has the long term as the first objective.

Example 1

Figure 5.3shows the reservoir production profile obtained from the different steps of Case 3a (Figure 5.3 a) and Case 3b (Figure 5.3 b) in Example 1. In both cases, the later steps have longer stabilized production period compared to the first step but the decline afterward is larger. It is obvious there were no significant change in the reservoir performance in the third step.

Example 2

The reservoir production profile obtained from the different steps of Case 3a and Case 3b in Example 2 are shown in Figure 5.3 b and Figure5.4 b, respectively. It can be observed that the production did not improve significantly through the steps especially in Case 3b.

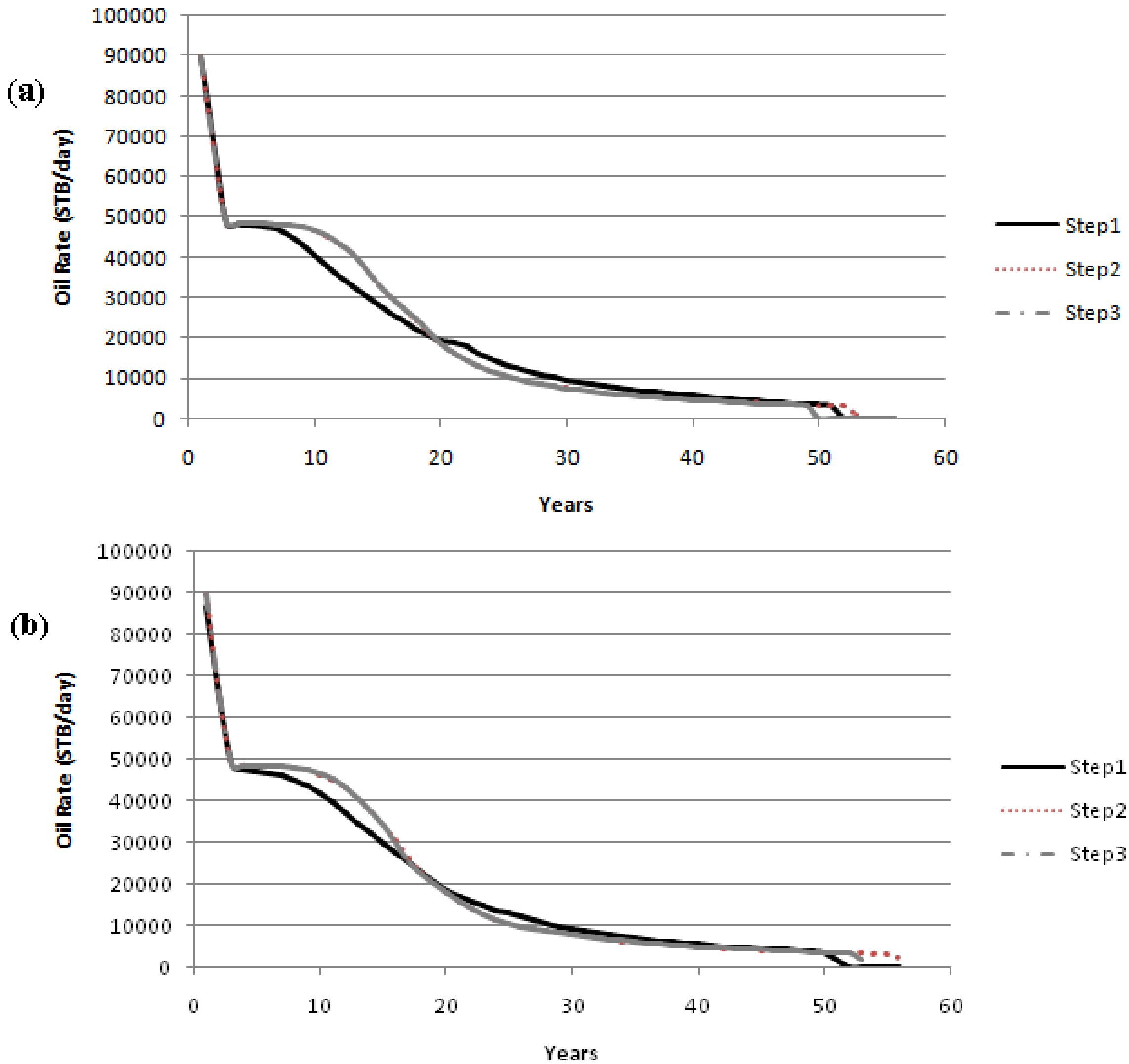

Figure 5.3: Production profiles results of Case3 in Example 1

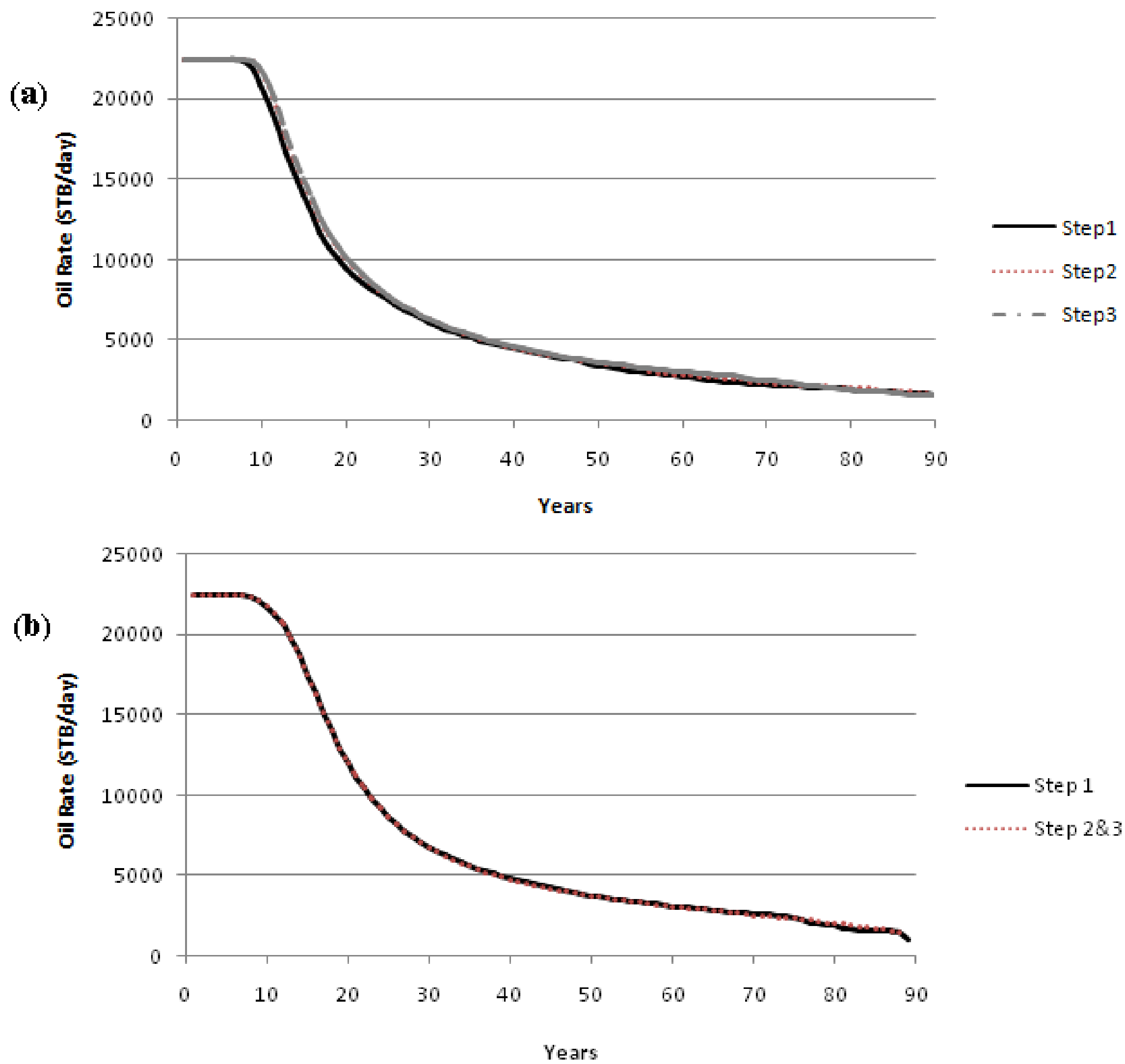

Figure5.4: Production profiles results of Case3 in Example 2

5.1.3 Well Placement

The well placements for the various steps of the lexicographical optimization are presented in this section for each of the reservoir examples. Figure 5.5 to Figure 5.15 show the locations of production and injection wells obtained from the optimization in the different steps. The backgrounds of these figures are the permeability distributions of the top layers in the reservoir examples.

Case 3a:

In this case, the short term is optimized first followed by the medium and then the long term. Figure 5.5 to Figure 5.10show the well placements obtained from this case in the two reservoir examples. It is observed that the wells maintain the minimum distance because the minimum well spacing constraint is applied in all Case 3 examples.

Example 1

Figure 5.5 to Figure 5.7 show the well placements obtained from Example 1 in the first, second and third steps of Case 3a, respectively.

Example 2

The well placements obtained from the first, second and third step of Case 3a in Example 1 are displayed in Figure 5.8 to Figure 5.10 respectively. These figures do not give the whole picture about the pattern of wells related to the permeability distribution because the permeability distribution is different for different layers and the background of these figures is that of the permeability distribution of the top layer only.

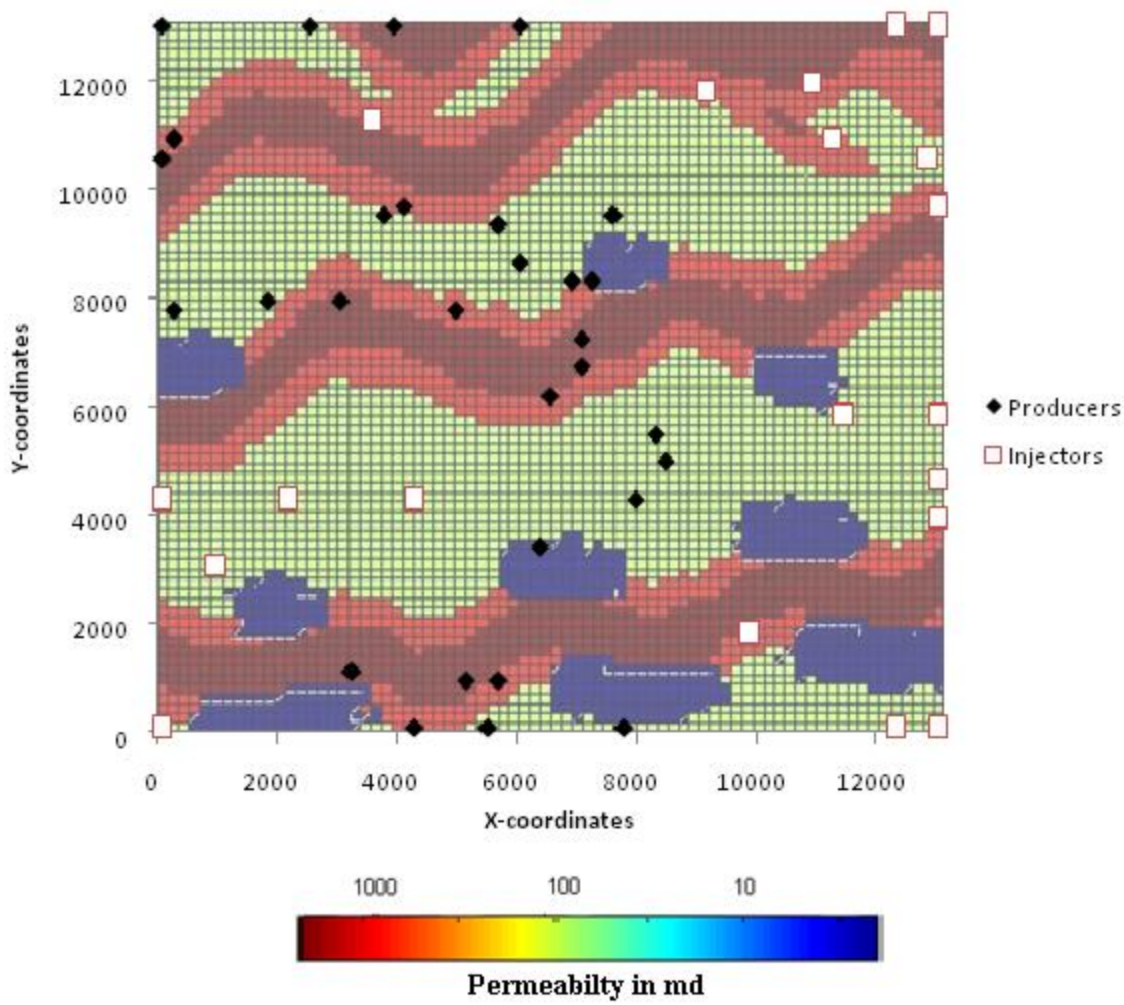

Figure 5.5: Well placement obtained from the first step of Case 3a in Example 1

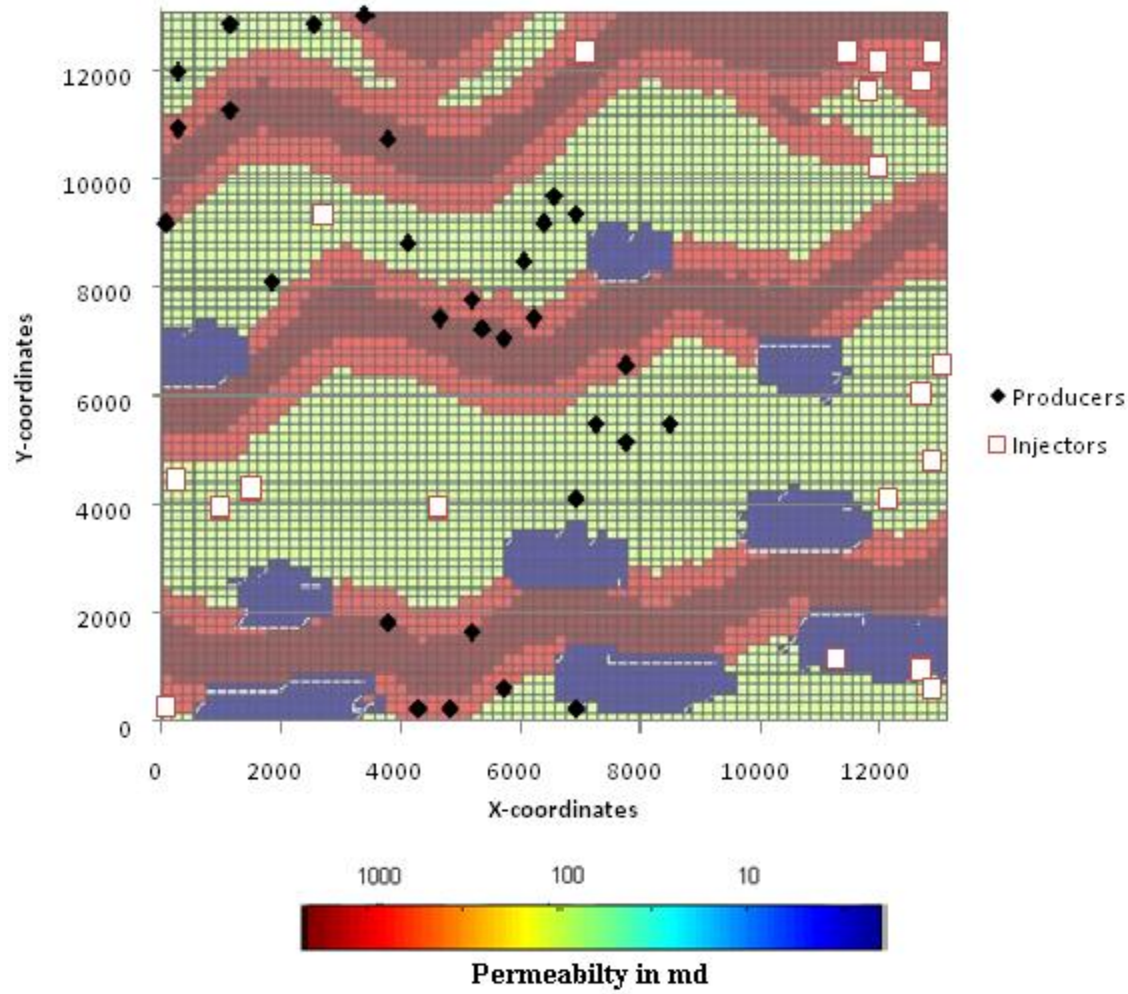

Figure 5.6: Well placement obtained from the second step of Case 3a in Example 1

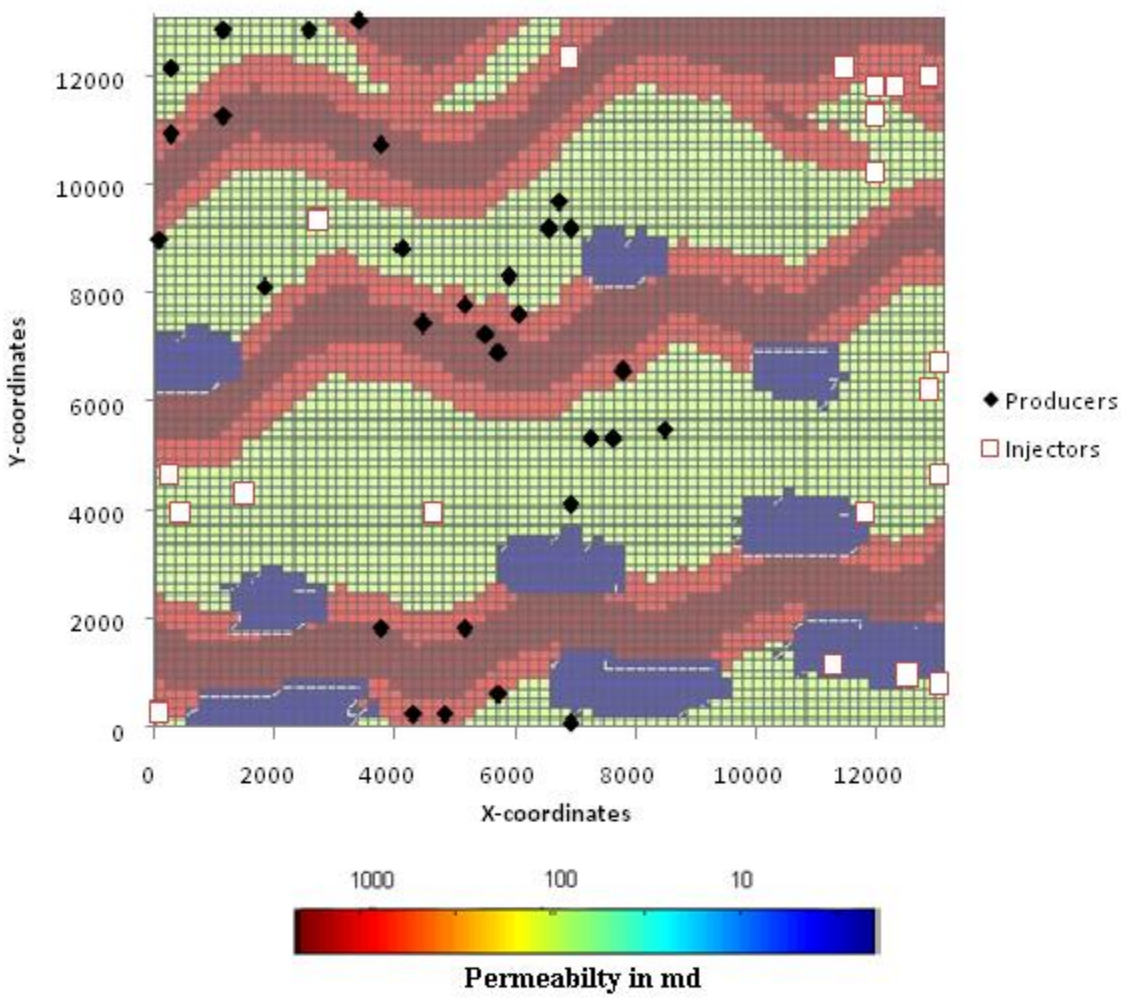

Figure 5.7: Well placement obtained from the third step of Case 3a in Example 1

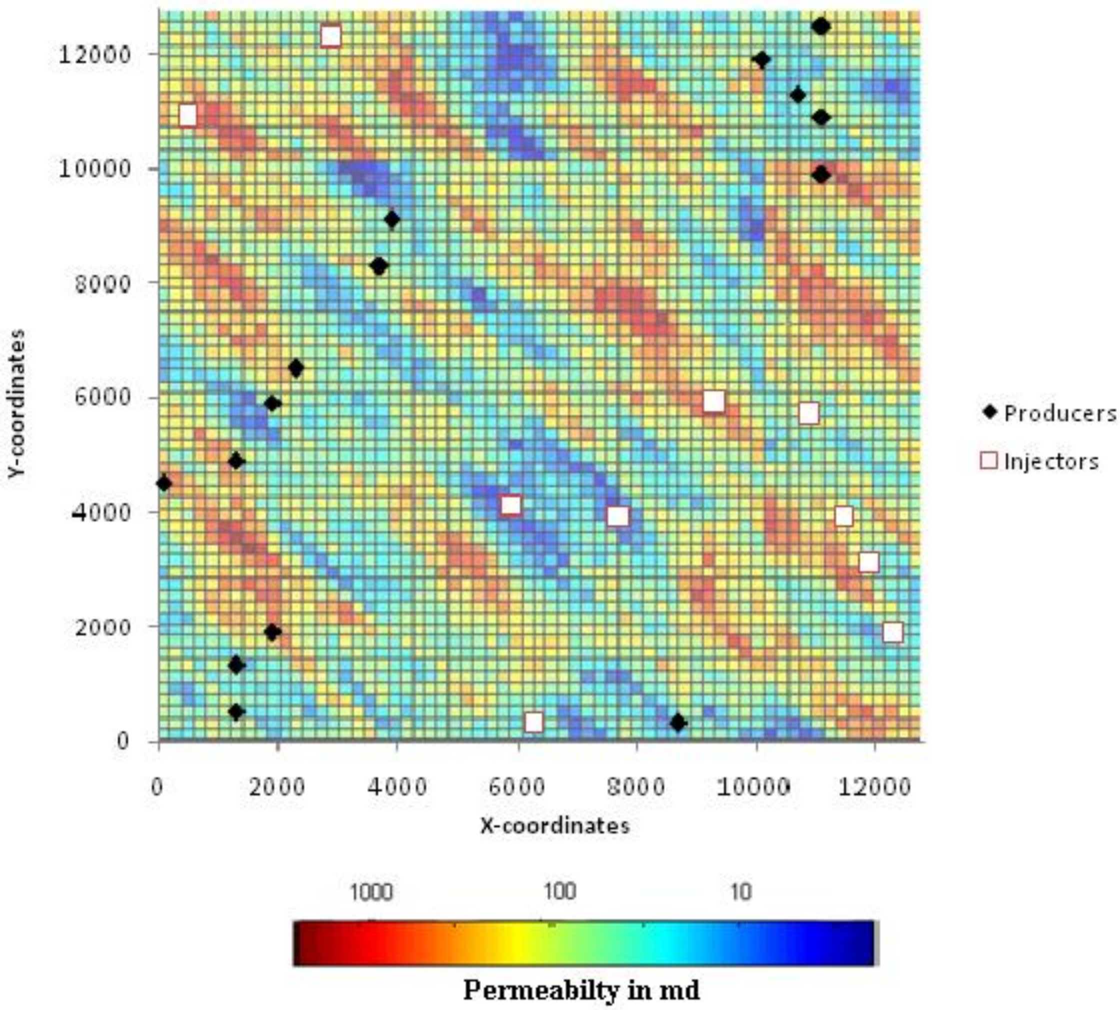

Figure 5.8: Well placement obtained from the first step of Case 3a in Example 2

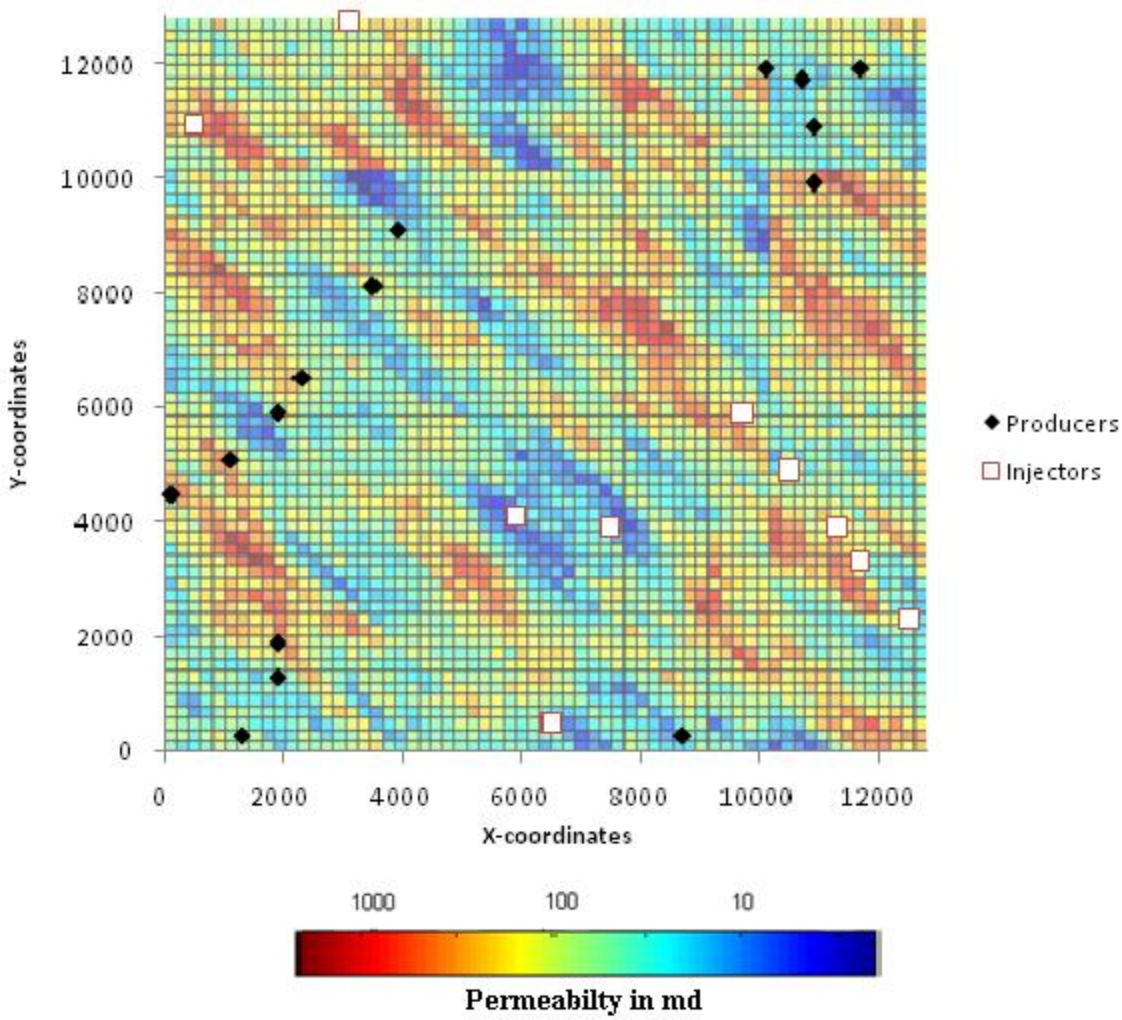

Figure 5.9: Well placement obtained from the second step of Case 3a in Example 2

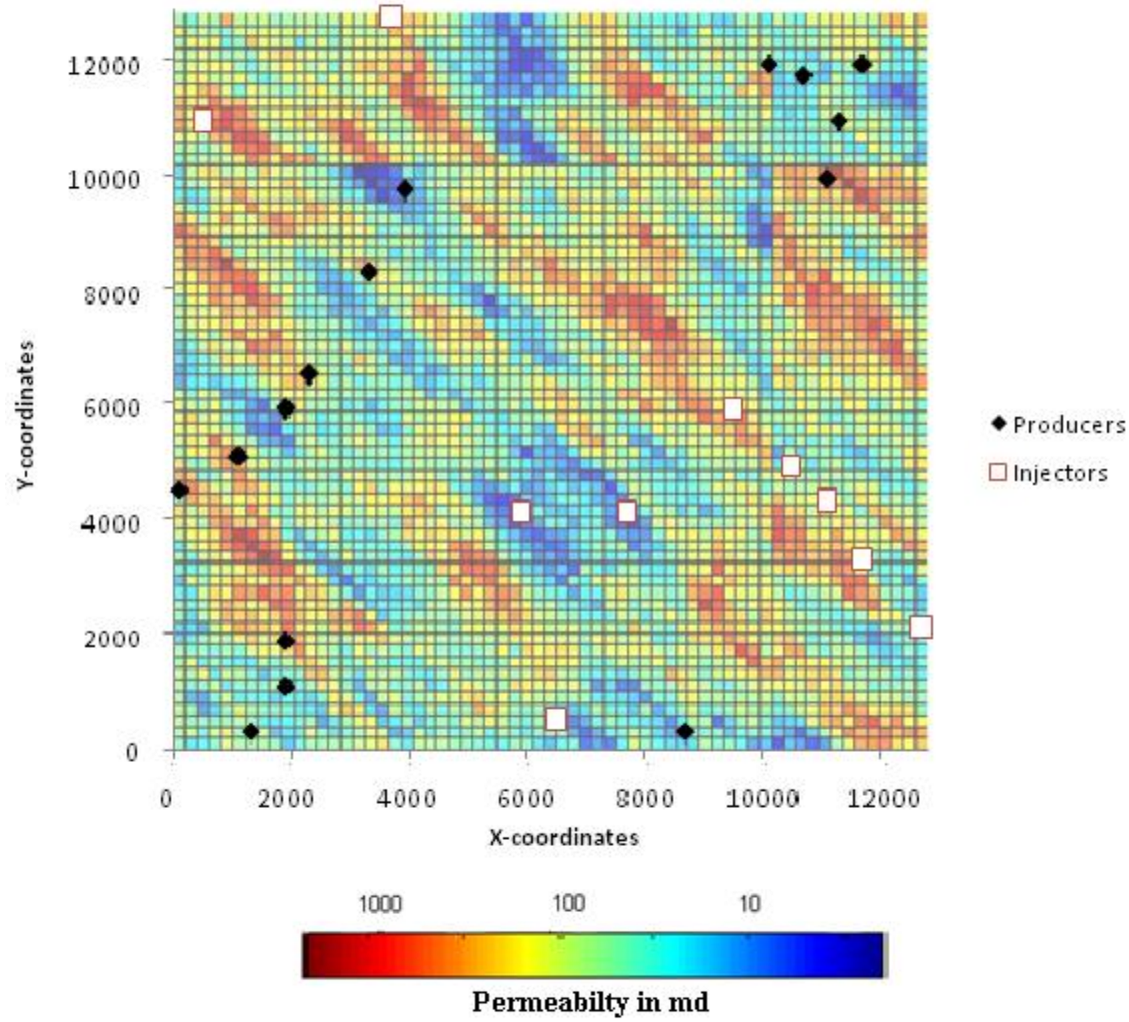

Figure 5.10: Well placement obtained from the third step of Case 3a in Example 2

Case 3b:

Example 1

Figure 5.11 to Figure5.13 indicate the well locationsobtained from the optimization in Example 1 in the first, second and third steps of Case 3b, respectively. It is observed that most of oil producers are located inside the channels while most of the water injectors are located in the moderate permeability areas.

Example 2

In Example 2, the well placement obtained from the first step of Case 3b is shown in Figure 5.14. In this example, the NPV could not be improved in the third step because high NPV for long term was obtained in the second step. Figure 5.15 shows the well placement for the second step which maintained in the third step as well.

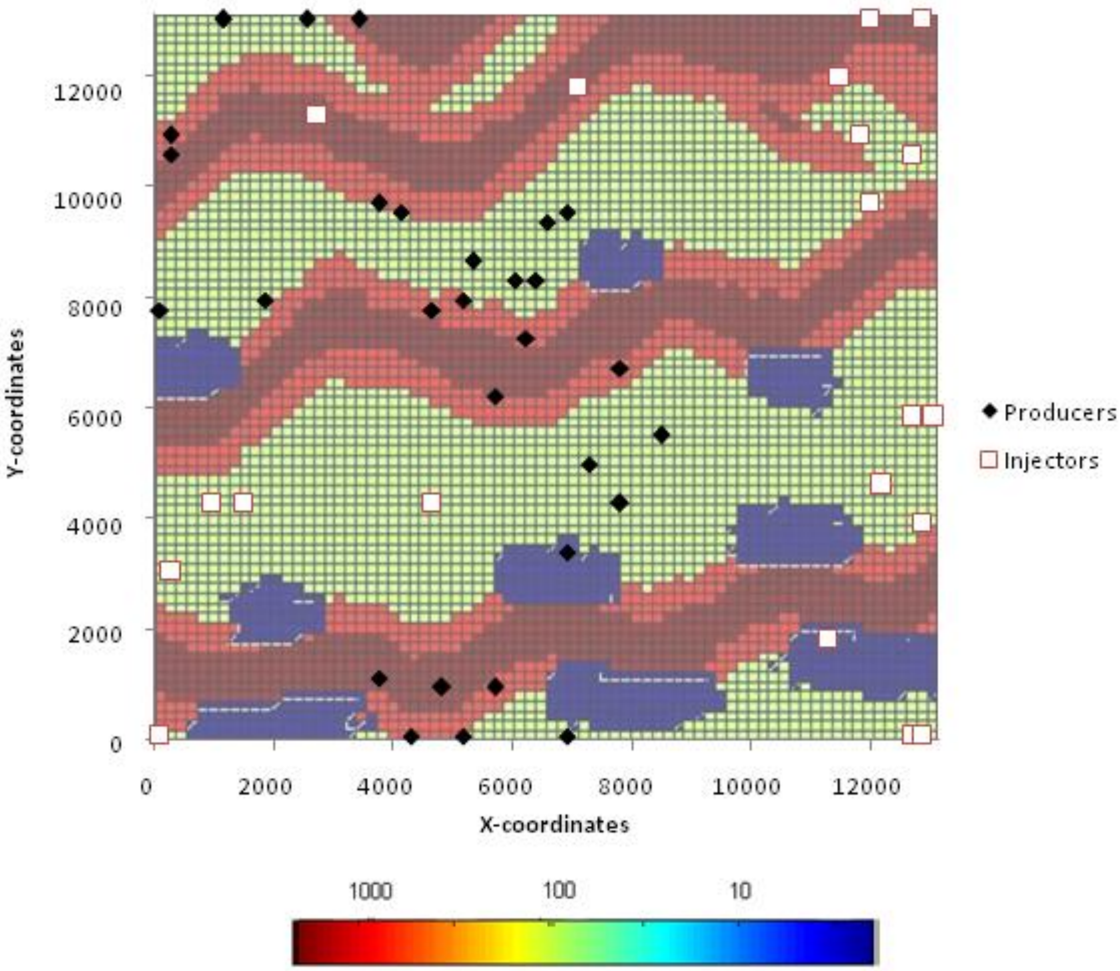

Figure 5.11: Well placement obtained from the first step of Case 3b in Example 1

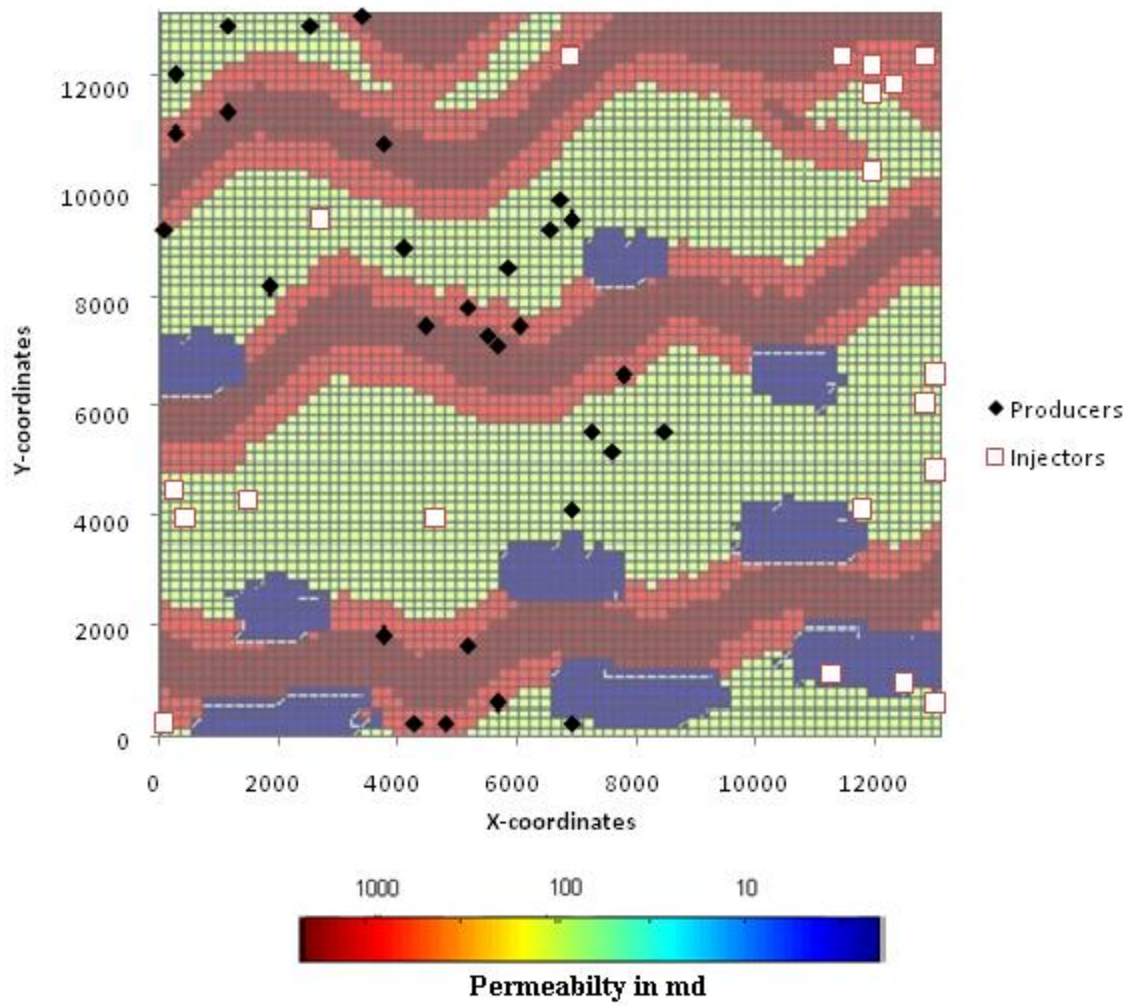

Figure 5.12: Well placement obtained from the second step of Case 3b in Example 1

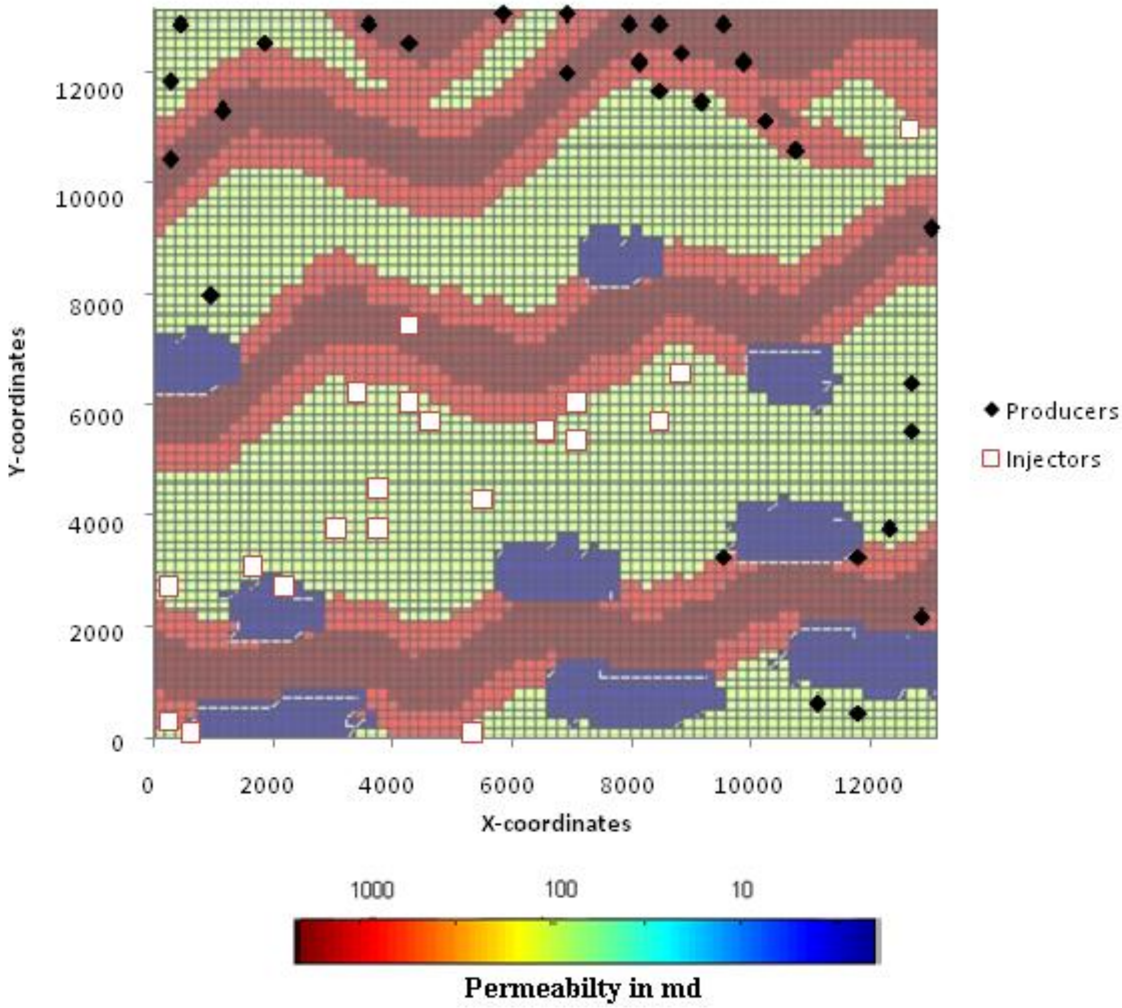

Figure5.13: Well placement obtained from the third step of Case 3b in Example 1

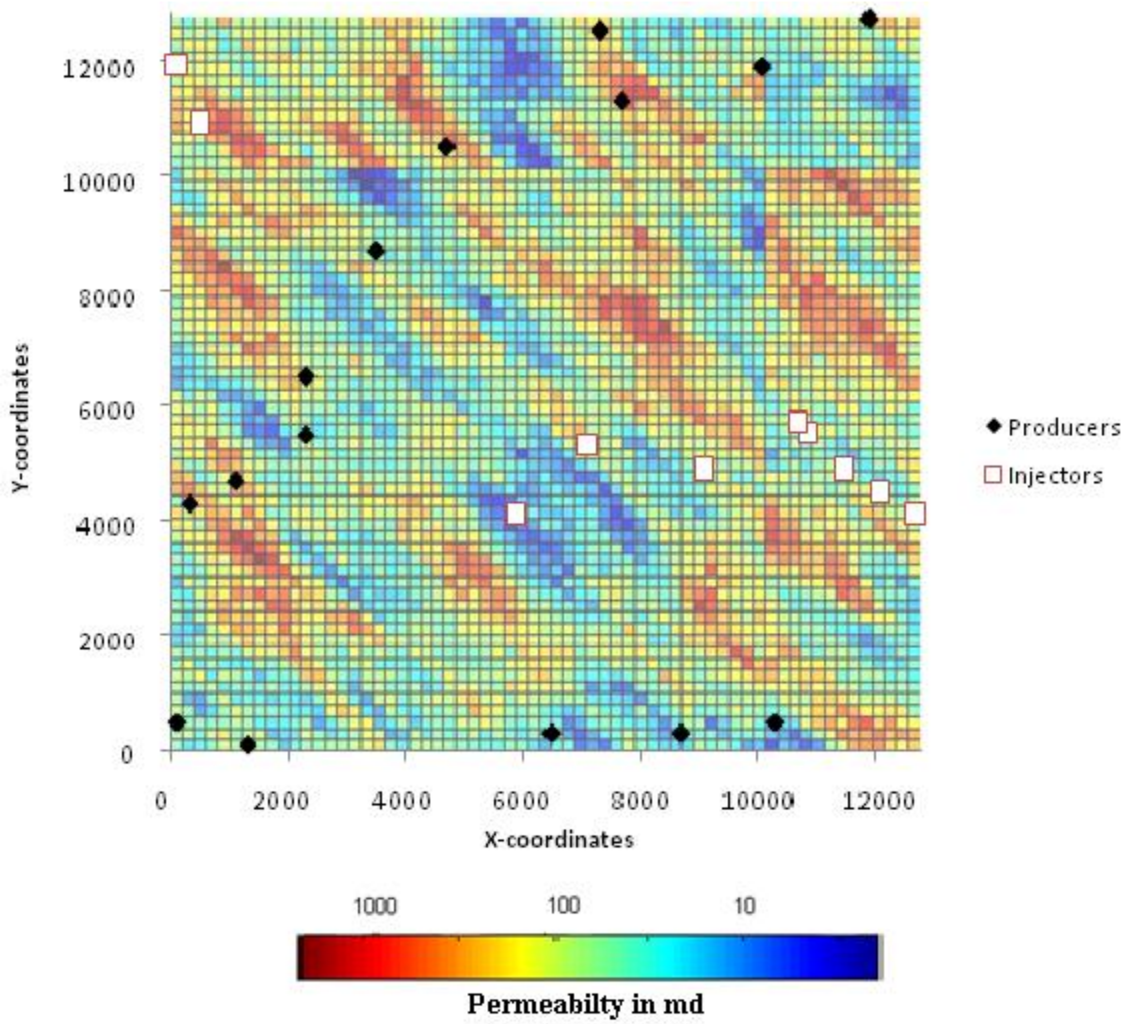

Figure 5.14: Well placement obtained from the first step of Case 3b in Example 2

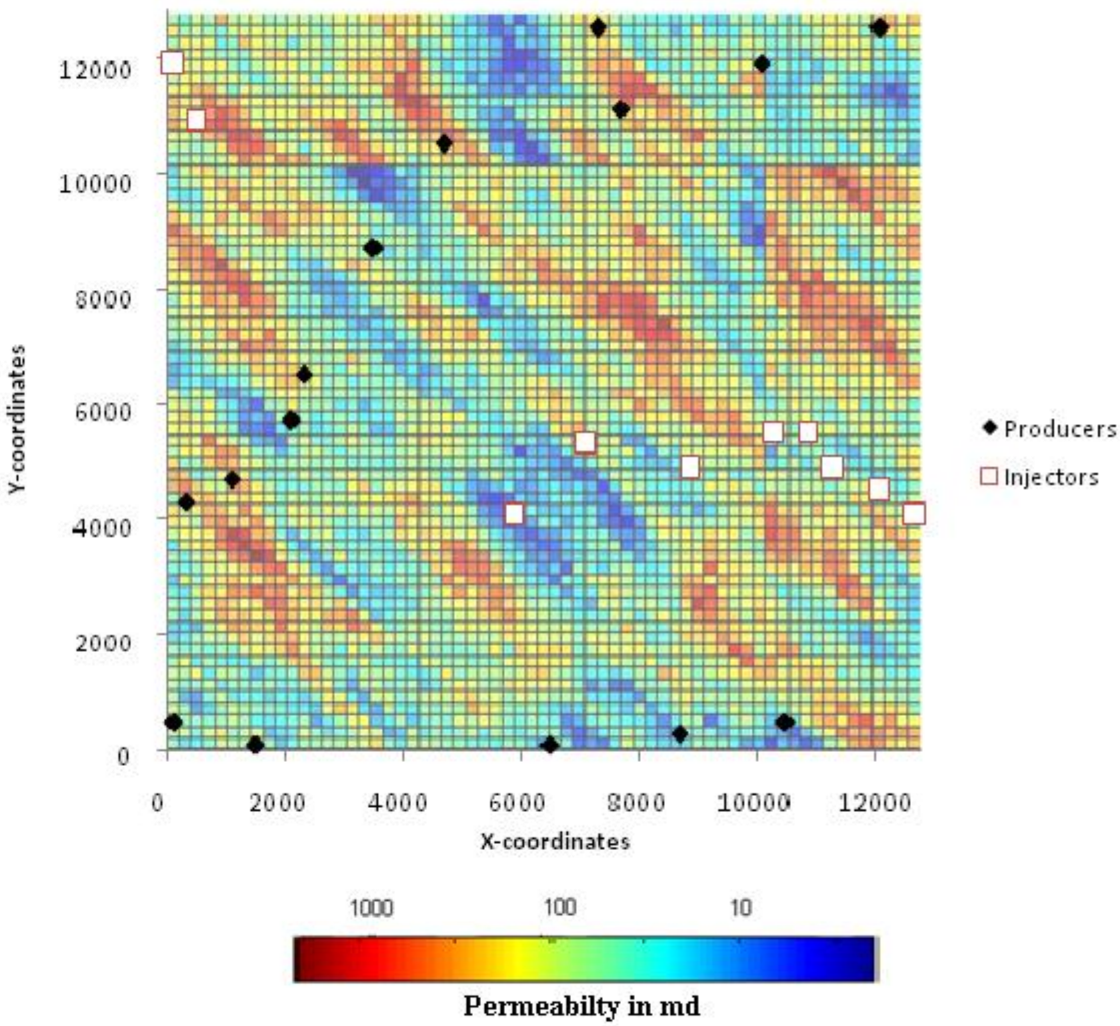

Figure 5.15: Well placement obtained from the second and third step of Case 3b in Example 2

5.2 Comparison between the Results of Single and Lexicographic Multi Objective Well Placement Optimization

In this section we compare the results of lexicographic multi objective optimization (Case 3) with the best results obtained in the constrained single objective case (Case 2). Case 3a withST-NPV as first objective is compared to Case 2a in which ST-NPV is the only objective, while Case 3b in which the LT-NPV is the first objective is compared to Case 2c that has the LT-NPV as the only objective.

5.2.1 NPV Results

Figure 5.16 and Figure 5.17show a comparison between the NPVs obtained from the lexicographical and the single objective optimization in Example 1 and Example 2 respectively. Figure 5.16 a and Figure 5.17 a represent the comparison between Case 3a and Case 2a, whileFigure 5.16 b and Figure 5.17 b are to compare Case 3b with Case 2c, Figure 5.16 c and Figure 5.17 ccontain all of the above.

Example 1

The use of ST-NPV as first objective followed by optimizing the other terms (Case 3a) gave higher MT-NPV and LT-NPVthan the use of ST-NPV as the only objective (Case 2a), while the value for ST-NPVremained the same as it can be seen in Figure 5.16 a. Optimizing MT-NPV after LT-NPV (Case 3b) led to higher values of the two terms compared to optimizing onlyLT-NPV (Case 2c) as shown in Figure 5.16 b. Figure 5.16 c illustrates that both Case 3a and Case 3b are better solutions in all terms than any of the single objective cases.

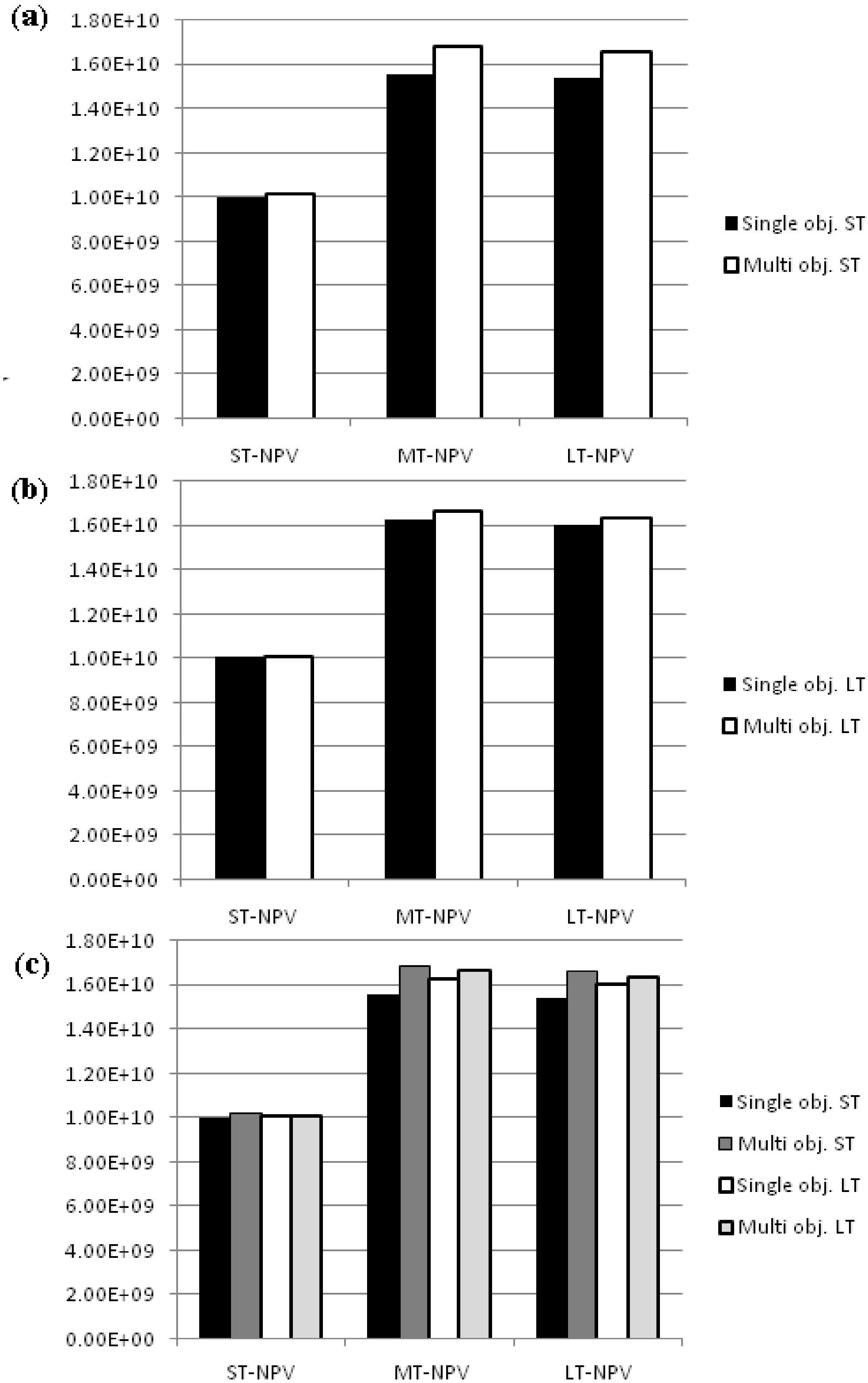

Figure 5.16: Comparison between the results of single and lexicographical multi objective optimization in Example 1

Example 2

In Example 2, Case 3a gave higher MT-NPV and LT-NPVthan Case 2a while the optimum value of ST-NPV is maintained as shown in Figure 5.17 a. Case 2c gave near-optimal NPVs for all the three terms.That is why there was no additional improvement in Case 3b as shown in Figure 5.17 b.

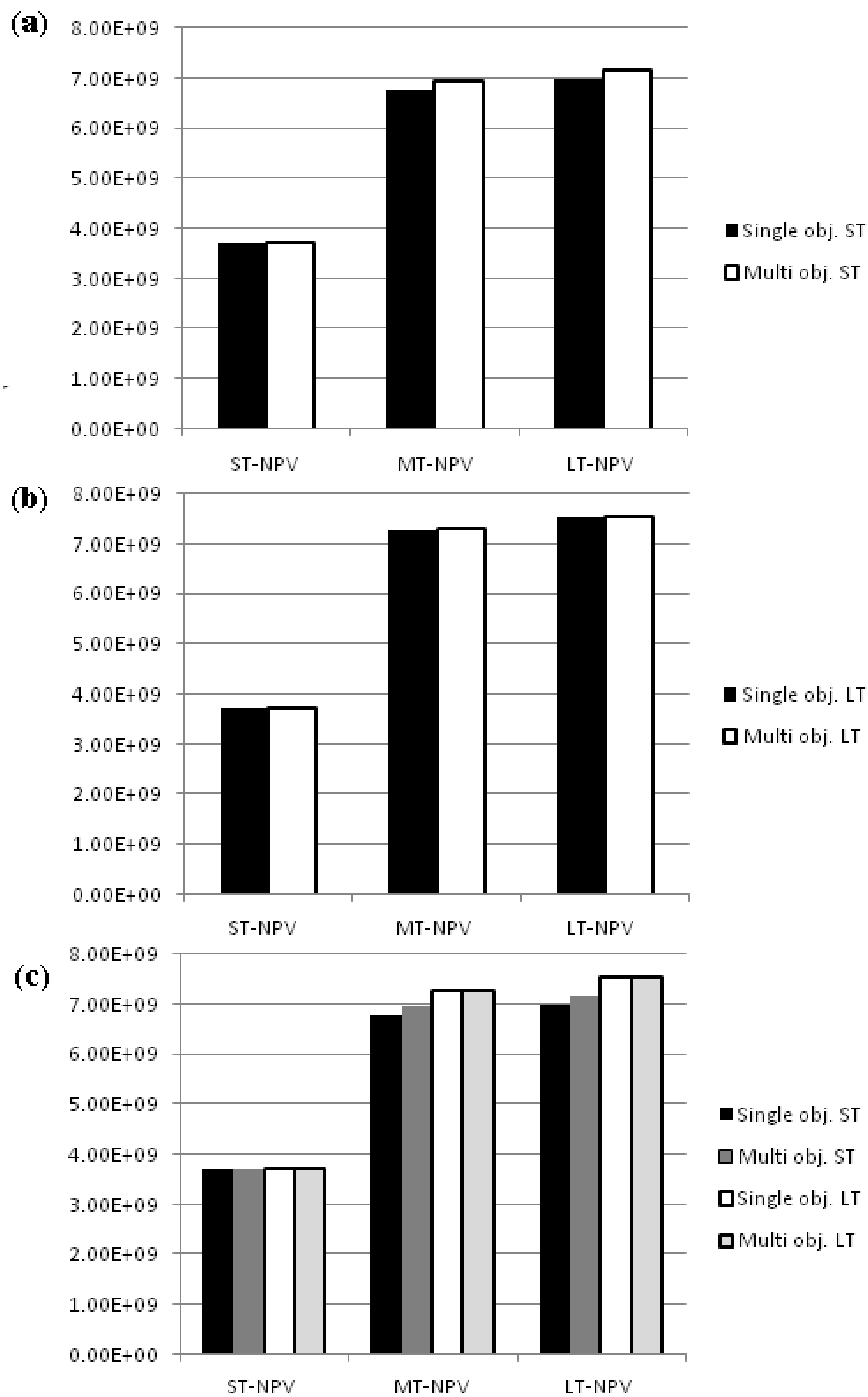

Figure 5.17: Comparison between the results of single and lexicographical multi objective optimization in Example 2

5.2.2 Reservoir Performance

In this section, the production profiles obtained from the lexicographic multiobjective optimization cases were compared to those obtained from single objective optimization cases. Figure 5.18 and Figure 5.19show this comparison in Example 1 and Example 2, respectively. Figure 5.18 a and Figure 5.19 a represents the comparison between Case 3a and Case 2a, while Figure 5.18 b and Figure 5.19 b are to compare Case 3b with Case 2c. Figure 5.18 c and Figure 5.19 c contain all of the above.

Example 1

In Case 3a we observed longer stabilized production period and faster decline afterward compared to the production rate in Case 2 (Figure 5.18 a). Also, longer stabilized production obtained from Case 3b than Case 2c, but the difference was not significant (Figure 5.18 b).

Example 2

In Case 3a,a longer production plateau was observed compared to Case 2a with almost the same decline rate afterward as in Figure 5.19 a. The plateau phase of Case 3b was slightly longer than in Case 2c but the decline afterward resulted in similar NPVs as shown earlier in Figure 5.17.

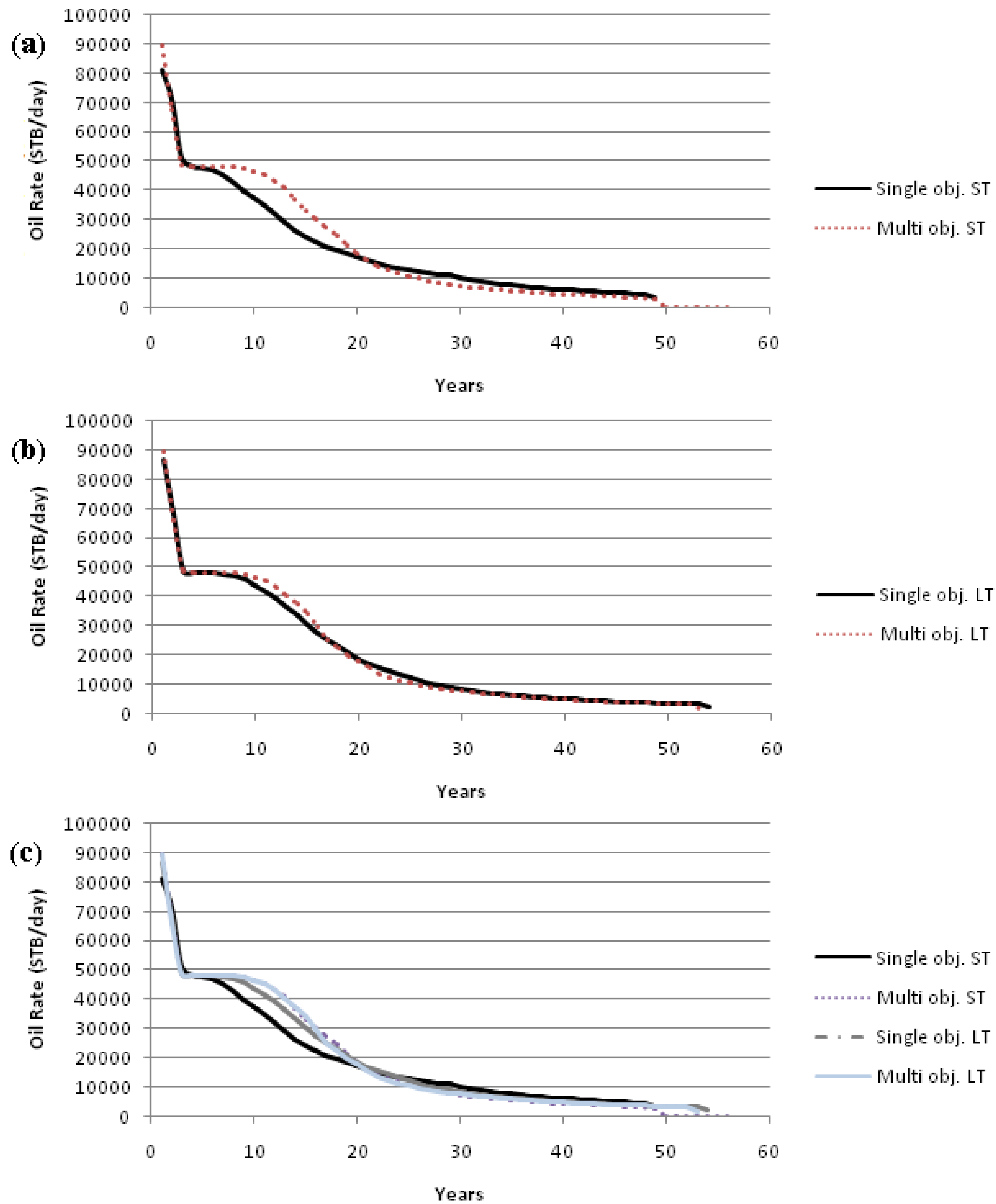

Figure 5.18: Production profile obtained from single and lexicographical multi objective optimization in Example 1

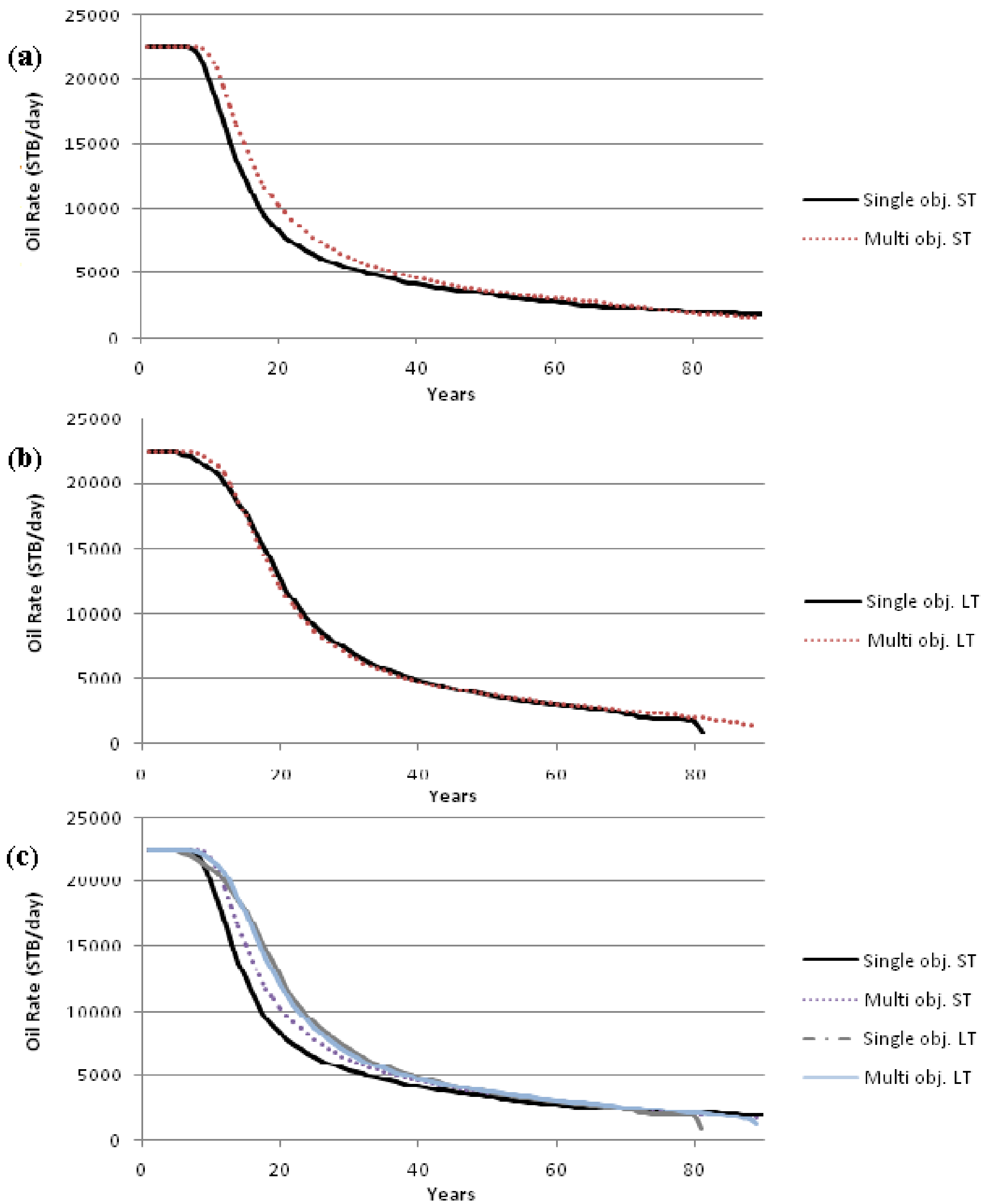

Figure 5.19: Production profile obtained from single and lexicographical multi objective optimization in Example 2

CHAPTER 6

CONCLUSIONS AND RECOMMENDATIONS

6.1 Conclusions

From the results and discussions, we can come up with the following conclusions:

1. The best well placement for a specified period is not necessarily the best for a different period. When the optimization is made on short project life period,there will be lower probability to achieve the optimum NPVsof medium and long term.
2. Although defining minimum spacing is necessary to come up with applicable results, it affects the results. We found that this effect varies from negligible to more noticeable depending on the density of wells to be completed in the reservoir.
3. We observed that the optimization of ST-NPV takes fewer function evaluations to find the optimum compared to the optimization of MT-NPV and LT-NPV.
4. Due to discounting of the NPV to the present time value of money, any production at the late life of the reservoir (e.g. after the 2^{5th} year) will not significantly affect the NPV. Therefore, there was no need to simulate the reservoir for very long period when NPV with constant oil price-index is used as objective function for the cases studied.
5. The lexicographic multiobjective approach compared to the regular single objective optimization yielded a well configuration that ensures better results in short, medium and long term investment scenarios.

6. A drawback of this approach is that it involves sequential optimization which requires more function evaluations and so more time and computational costs.

6.2 Recommendations

Since lexicographic approach sequentially optimizes the objectives, which requires higher number of function evaluations, studying other types of multiobjective optimization methods to optimize well placement for different investment term options is recommended.

NPV which has been used in this research as the objective function is a discounted value of money, this means earlier exploitation of the reservoir is the better in NPV term, but that may have an effect on the recovery factor. Therefore we recommend studying the effect of simulation time in well placement optimization with the use of recovery factor as objective function.

References

Andersson, J. (2000), A survey of multiobjective optimization in engineering design, *Department of Mechanical Engineering, Linköping University, Sweden*.

Awotunde, A. A., and N. Sibaweihi (2014), Consideration of Voidage Replacement Ratio in Well Placement Optimization, *SPE Economics & Management*, *6*(1), 40/54.

Awotunde, A., and Naranjo C. S.(2014), Well Placement Optimization Constrained to Minimum Well Spacing, SPE Latin American and Caribbean Petroleum Engineering Conference, Maracaibo, Venezuela.

Badru, O., and C. S. Kabir (2003), Well Placement Optimization in Field Development, in *2003 SPE Annual Technical Conference and Exhibition*, edited, SPE 84191 Denver, Colorado.

Bangerth, W., H. Klie, M. Wheeler, P. Stoffa, and M. Sen (2006), On optimization algorithm for the reservoir oil well placement problem, *Computational Geosciences*, *10*, 303/319.

BecknerB., and X. Song (1995), Field development planning using simulated annealing - optimal economic well scheduling and placement, paper presented at 1995 SPE Annual Technical Conference and Exhibition, Dallas, Texas.

Bellout, M. C., D. E. Ciaurri, L. J. Durlofsky, B. Foss, and J. Kleppe (2012), Joint optimization of oil well placement and controls, *ComputGeosci*, *16*, 1061/1079.

Bindemann, K. (1999), Production-Sharing Agreements: An Economic Analysis*Rep.*, Oxford Institute for Energy Studies.

Bittencourt, A. C., and R. N. Horne (1997), Reservoir Development and Design Optimization, in *1997 SPE Annual Technical Conference and Exhibition*, edited, SPE 38895 San Antonio, Texas, 05-08 October.

Bouzarkouna, Z., D. Ding, and A. Auger (2010), Using Evolution Strategy with Meta-models for Well Placement Optimization, paper presented at 12th European Conference on the Mathematics of Oil Recovery ECMOR XII, Oxford, United Kingdom.

Bouzarkouna, Z., D. Y. Ding, and A. Auger (2012), Well Placement Optimization under Uncertainty with CMA-ES Using the Neighborhood, in *ECMOR XIII – 13th European Conference on the Mathematics of Oil Recovery*, edited, Biarritz, France.

Bukhamsin, A., M. Farshi, and K. Aziz (2010), Optimization of multilateral well design and location in a real field using a continuous genetic algorithm, in *SPE/DS Saudi Arabia Section Technical Symposium and Exhibition*, edited, SPE 136944.

Castiñeira, D., F. O. Alpak, and D. Hohl (2009), Automatic Well Placement Optimization in a Channelized Turbidite Reservoir Using Adjoint Based Sensitivities, in *SPE Reservoir Simulation Symposium*, edited, SPE 119156, Texas, USA.

Cheng, G., YaoAn, Z. Wang, and K. Zhu (2012), Oil Well Placement Optimization using Niche Particle Swarm Optimization, in *Eighth International Conference on Computational Intelligence and Security*, edited, Guangzhou, GuangDong Province, China.

Cruz, P. S., R. N. Horne, and V. Deutsch (1999), The Quality Map: A Tool for Reservoir Uncertainty Quantification and Decision Making, in *1999 SPE Annual Technical Conference and Exhibition*, edited, SPE 56578 Houston, Texas.

Ding, D. (2008), Optimization of well placement using evolutionary algorithms, in *SPE EUROPEC/EAGE annual conference and exhibition*, edited, SPE 113525, Rome, Italy.

Emerick, A., E. Silva, B. Messer, L. Almeida, D. Szwarcman, M. Pacheco, and M. Vellasco (2009), Well placement optimization using a genetic algorithm with nonlinear constraints, in *SPE reservoir simulation symposium*, edited, SPE 118808, The Woodlands, Texas.

Forouzanfar, F., G. Li, and C. Reynolds (2010), A two-stage well placement optimization method based on adjoint gradient, in *2010 SPE annual technical conference and exhibition*, edited, SPE 135304, Florence, Italy.

Freund, R. M. (2004), Penalty and Barrier Methods for Constrained Optimization, *Massachusetts Institute of Technology*.

Guyaguler, B., and R. Horne (2000), Optimization of well placement, *Journal of Energy Resources Technology*, *122*(2), 64/70.

Güyagüler, B. (2002), optimization of well placement and assessment of uncertainty, PhD. thesis, stanford university.

Güyagüler, B., and R. N. Horne (2004), Uncertainty assessment of well placement optimization, *SPE Reservoir Evaluation& Engineering*, *7*(1), 24/32.

Gǚyagǚler, B., R. N. Horne, L. Rogers, and J. J. Rosenzweig (2000), Optimization of Well Placement in a Gulf of Mexico Waterflooding Project, in *SPE Annual Technical Conference and Exhibition*, edited, SPE 63221, Dallas, Texas.

Handels, M., M. J. Zandvlier, D. R. Brouwer, and J. D. Jansen (2007), Adjoint-Based Well-Placement Optimization Under Production Constraints, in *2007 SPE Reservoir Simulation Symposium*, edited, SPE 105797, Houston, Texas.

Hansen, N., and A. Ostermeier (2001), Completely Derandomized Self-Adaptation in Evolution Strategies, *Evol. Comput.* , *9*(2), 159/195.

Marler, R. T., and J. S. Arora (2004), Survey of multi-objective optimization methods for engineering, *Struct Multidisc Optim*, *26*, 369/395.

Montes, G., P. Bartolome, and A. L. Udias (2001), The Use of Genetic Algorithms in Well Placement Optimization, in *SPE Latin American and Caribbean Petroleum Engineering Conference,* edited, SPE 69439, Argentina.

Morales, A., H. Nasrabadi, and D. Zhu (2010), A modified genetic algorithm for horizontal well placement optimization in gas condensate reservoirs, in *SPE annual technical conference and exhibition*, edited, SPE 135182, Florence, Italy.

Morales, A., H. Nasrabadi, and D. Zhu (2011), A New Modified Genetic Algorithm for Well Placement Optimization under Geological Uncertainties, in *SPE EUROPEC/EAGE Annual Conference and Exhibition*, edited, SPE-143617-MS., Vienna, Austria.

Norrena, K. P., and C. V. Deutsch (2002), Automatic determination of well placement subject to geostatistical and economic constraints, paper presented at 2002 SPE International Thermal Operations and Heavy Oil Symposium and International Horizontal Well Technology Conference, Calgary, Alberta, Canada.

Onwunalu, J. E., and L. J. Durlofsky (2010), Application of a particle swarm optimization algorithm for determining optimum well location and type, *Computational Geosciences 14*, 183/198.

Ozdogan, U., and R. N. Horne (2006), Optimization of Well Placement Under Time-Dependent Uncertainty, *SPE Reservoir Evaluation & Engineering*, *9*(2), 135/145.

Ozdogan, U., A. Sahni, B. Yeten, B. Guyaguler, and W. H. Chen (2005), Efficient Assessment and Optimization of a Deepwater Asset Development Using Fixed Pattern Approach, in *2005 SPE Annual Technical Conference and Exhibition*, edited, SPE 95792, Dallas, Texas.

Pan, Y., and R. N. Horne (1998), Improved Methods for Multivariate Optimization of Field Development Scheduling and Well Placement Design, in *SPE Annual Technical Conference and Exhibition*, edited, SPE 49055 Louisiana.

Sarma, P., and W. H. Chen (2008), Efficient Well Placement Optimization with Gradient-Based Algorithms and Adjoint Models, in *2008 SPE Intelligent Energy Conference and Exhibition*, edited, SPE 112257, Amsterdam, The Netherlands.

V., A., D. L.J., O. J.E., and A. K. (2006), Optimization of nonconventional wells under uncertainty using statistical proxies, *Computational Geosciences*, *10*, 389/404.

Vlemmix, S., G. Joosten, D. Brouwer, and J. Jansen (2009), Adjoint-based well trajectory optimization in a thin oil rim, in *SPE EUROPEC/EAGE annual conference and exhibition*, edited, SPE 121891, Amsterdam, The Netherlands.

Waltz, F. M. (1967), An engineering approach: hierarchical optimization criteria, *IEEE Trans. Autom. Control AC*, *12*, 179/180.

Wang, C., G. Li, and A. C. Reynolds (2007), Optimum Well Placement for Production Optimization, in *2007 SPE Eastern Regional Meeting*, edited, SPE 111154 Lexington, Kentucky, U.S.A.

Wang, H., D. E. Ciaurri, L. J. Durlofsky, and A. Cominelli (2011), Optimal Well Placement under Uncertainty using a Retrospective Optimization Framework, in *Reservoir Simulation Symposium*, edited, SPE 141950, Texas, USA.

Yeten, B., L. Durlofsky, and K. Aziz (2003), Optimization of nonconventional well type, location and trajectory, *SPE Journal 8*, 200/210.

Zandvliet, M., M. Handels, G. van Essen, D. Brouwer, and J. Jansen (2008), Adjoint-based well-placement optimization under production constraints, *SPE Journal*, *13*(4), 392/399.

Zhang, K., G. Li, A. C. Reynolds, J. Yao, and L. Zhang (2010), Optimal well placement using an adjoint gradient, *Journal of Petroleum Science and Engineering*, *73*(3), 220/226.

ECLIPSE technical description.

APPENDEX A

RESERVOIR SIMULATION MODEL

Table B.1 displays the properties for each reservoir example used to build the reservoir simulation model. Figure B.1 shows the dead oil PVT data and Figure B.2 illustrates the relative permeability data for the reservoir fluids.Figure B.3shows the range of permeability values for reservoir Example 2.

Table B.1: Properties for reservoir simulation model

Property	**Example 1**	**Example 2**
Reservoir size	13,125*13,125*200 ft (75*75*4 cells)	12,800*12,800*225 ft (64*64*3 cells)
Grid size	175*175*50 ft	200*200*75 ft
Control rate	Oil rate 3000 STB/D Water injection rate 3000 STB/D	Oil rate 1500 STB/D Water injection rate 3000 STB/D
Well economic limit	Minimum oil rate 100 obpd Maximum water cut 97%	Minimum oil rate 100 obpd Maximum water cut 97%
Field economic limit	Minimum oil rate 3000 obpd Maximum water cut 97%	Minimum oil rate 3000 obpd Maximum water cut 97%
Horizontal permeability	Figure 3.3	Figure 3.5
Porosity	Figure 3.4	0.27 for the top, 0.17 for the middle and 0.11 for the bottom layer
k_v/ k_h	0.2	0.2
Relative permeability	Figure B.2	Figure B.2
PVDO	Figure B.1	Figure B.1
Solubility	0.4 MSCF/STB @ Pb =1900 psia	0.4 MSCF/STB @ Pb =1900 psia
Rock compressibility	3.0E-6 psi^{-1}@ 4014.7 psia	3.0E-6 psi^{-1}@ 4014.7 psia
Oil density	52.1 lb/cuft	52.1 lb/cuft
Gas density	0.06054 lb/cuft	0.06054 lb/cuft
Water density	62.238 lb/cuft	62.238 lb/cuft
Water compressibility	3.13E-6 psi^{-1}@ 4014.7 psia	3.13E-6 psi^{-1}@ 4014.7 psia
Water viscosity	0.31 cp	0.31 cp
Water FVF	1.029	1.029
Minimum BHP for producers	2000 psia	2000 psia
Maximum BHP for injectors	6500 psia	6500 psia

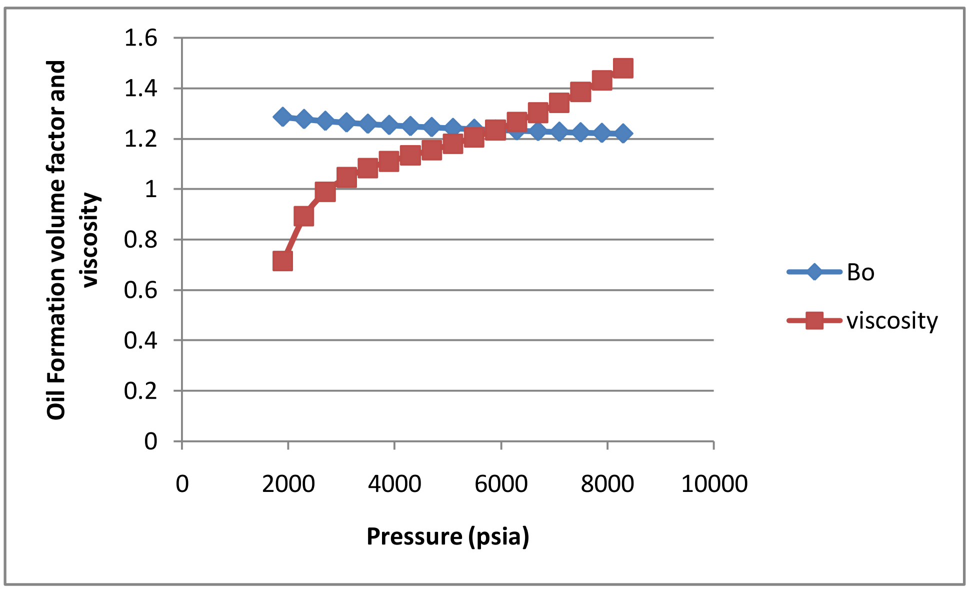

Figure B.1: Dead oil PVT data

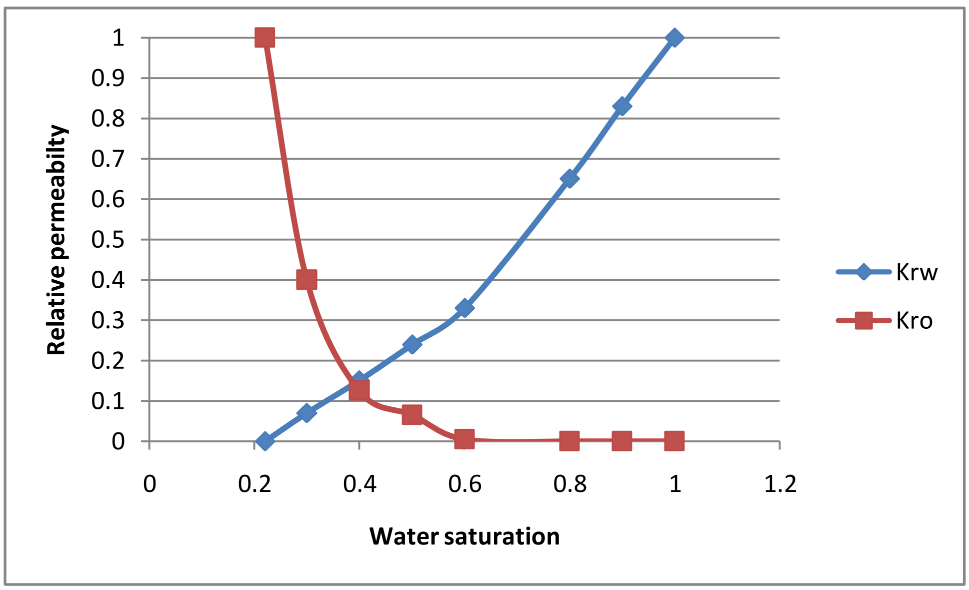

Figure B.2: Relative permeability curve

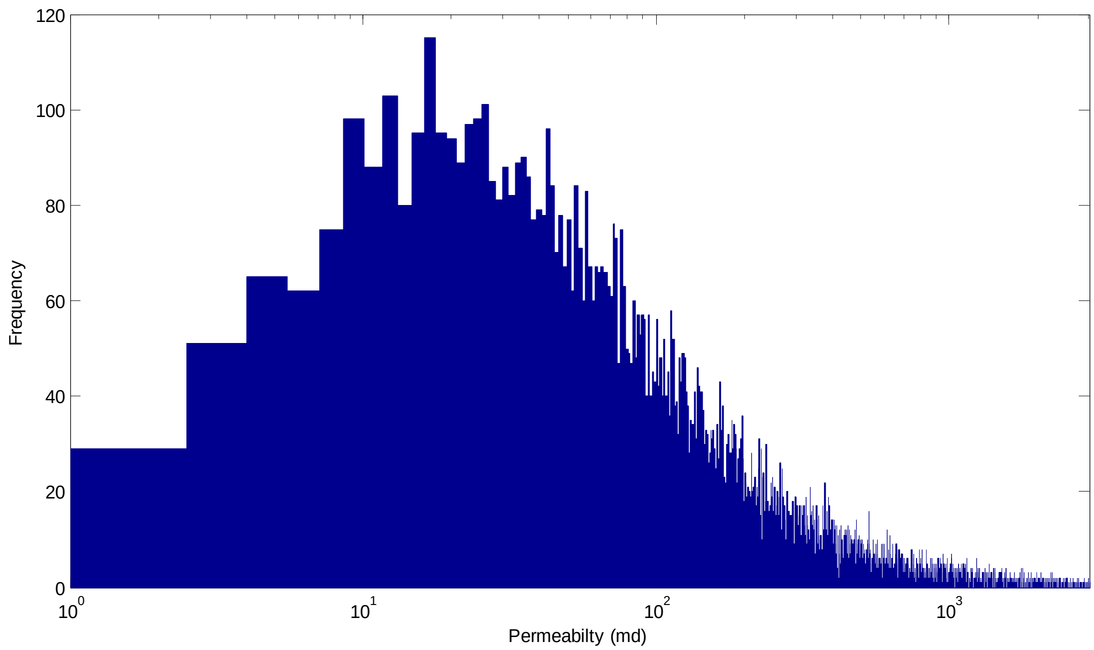

Figure B.3: Permeability values range for Example 2

APPENDEX B

CMA-ES OPTIMIZATION PARAMETERS

Table C.1Displays part of the optimization parameters used in this work.

Table C.1: CMA-ES parameters

Parameter	**value**
Problem size (N)	$2*N_{well}$
Tolerance	-1E19
Initial point variables (Xstart)	random
Upper limit (ux)	The highest cell index: 75 in example 1 64 in example 2
Lower limit (lx)	1 is the lowest cell index
Standard deviation (σ)	0.3*(ux-lx)
Number of function evaluations (Feval)	6000
Population size (Np)	4 + 3 * log(N)
Number of iterations (Montes, et al.)	Feval/Np
Parent number (μ)	Np /2
Number of re-evaluated for uncertainty	0.05* Np
Uncertainty treatment threshold	0.5
Cumulation constant for uncertainty	0.3
Rank change cutoff	2* Np /3
factor for increasing sigma (α)	1+2/(N+10)
Epsilon	1E-7
Cumulation constant for step-size (cs)	(μ +2)/(N+ μ +3)
Damping for step-size	1 + 2*max(0,sqrt((μ-1)/(N+1))-1) + cs
Cumulation constant for covariance matrix	4/(N+4)
Learning rate for rank-one update	2 / ((N+1.3)^2+ μ)
Learning rate for rank-mu update	2 * (μ -2+1/ μ) / ((N+2)^2+ μ)

Vitae

Name	:Osama Mutrif Siddig
Nationality	:Sudanese
Date of Birth	:3/18/1988
Email	:osamam90@gmail.com
Address	:Khartoum North, Khartoum, Sudan
Academic Background	:MSc. In Petroleum Engineering (2014) from King Fahd University of Petroleum and Minerals
	BSc. In Petroleum Engineering (2009) from University of Khartoum
Publications	:Effect of Project Life Time on Well Placement Optimization, O. Mutrif Siddig, A. Awotunde, A. Hashim Ahmed and M.S. Jamal, 76th EAGE Conference & Exhibition, June 2014, Amsterdam, Netherlands.
	A Pareto-based Well Placement Optimization, A. Hashim Ahmed, A. Awotunde, O. Mutrif Siddig and M.S. Jamal, 76th EAGE Conference & Exhibition, June 2014, Amsterdam, Netherlands.