OPTIMIZING CORPORATE DECISIONS FOR
DOMINANT HYDROCARBON PRODUCERS UNDER UNCERTAINTY

A Dissertation in
Energy and Mineral Engineering
by
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**ABSTRACT**

The production strategy of a dominant hydrocarbon producer can significantly affect the shape of the future of the hydrocarbon market (Nakov, A., and Nuno, G. 2011). This study focused on the role of a dominant producer in the hydrocarbon market; however, these findings could be applied to any industry extracting finite resources. The thesis was divided into four major chapters: 1) Capacity management, 2) Predicting decline parameters and development strategy for a capacity management model—an artificial expert system, 3) Optimal spare capacity, and 4) Integrated capacity management and spare capacity. Collectively, information offered in these four chapters can optimize the corporate decisions made by a dominant hydrocarbon producer that operates oil and/or gas fields. Each of these studies was discussed in each chapter.

The first study had to do with Capacity Management (CM) that is a complex dynamic optimization problem whose goal is to manage production capacity across a portfolio of producing assets to maximize the total portfolio plateau length and/or NPV. Field-level constraints included facility limitations, costs, and technical properties (i.e., reservoir characteristics, and crude or gas types). Moreover, there also were company-level constraints (e.g., supply and spare capacity commitments). Although the problem could have been solved deterministically, the presence of uncertainty, in reservoir performance and the hydrocarbon market, made the probabilistic approach more realistic. This problem was tackled in three sections: (1) an integrated stochastic optimization model was built to solve for the optimal production rate allocation for a portfolio of oil or gas fields under the uncertainties of the markets and reservoir performances, (2) A
sensitivity analysis was conducted for different market and reservoir models and parameters, and (3) A value of information (VOI) analysis was implemented to estimate the value of a more accurate expected demand. The various production allocation decisions, resulting from different economic and reservoir models, were compared with the goal of understanding the effect of these model parameters on decision-making. A Genetic Algorithm was implemented as the optimization algorithm. Results showed that the CM integrated model effectively maximized plateau length and mean NPV for the whole portfolio of fields. In addition, the optimal decisions in the CM problem were the function of the reservoir (i.e., reservoir quality, size, and maturity) and price (i.e., long-run equilibrium price) parameters. To maximize the total plateau length and/or the NPV, production from young fields with large decline exponents should be prioritized; then, mature fields with large decline exponents. In other words, decline exponent is the most impacting factor on the optimization problem. Capacity Management can add reserves with respect to time, delay development projects, increase profit, and reduce the uncertainty of the NPV. The relationship between the optimal production allocation decision and reservoir properties can be investigated for future studies; this may be achieved via regression analysis or machine learning techniques. This relationship can save significant amount of optimization time.

The second section looks at developing an artificial expert system for the Capacity Management Model. The real-world applicability of a research study can be a key element in its success and enhance its value to oil and gas companies. Boosting a research study with this applicability can increase the reliability of the results since actual
field data are being used rather than making an educated guess. The Capacity Management Model derived the proper production allocation for a portfolio of fields that maximized production plateau length while meeting the total target rate of output. This study was divided into two parts. In the first part, we predicted input parameters (decline curve parameters) for the CM model for given reservoir and development parameters. In the second part, we predicted a field development plan (drainage area) for a given set of reservoir properties, production rate and plateau length; production rate and plateau length were output from the CM model. Artificial Neural Network (ANN) and Genetic Programming (GP) methods were implemented to build the two prediction models. Predicting decline curve parameters and an optimal field development plan for any given set of reservoir properties constitutes a complex nonlinear optimization problem. Large variation in the magnitudes of various parameters (from 10e-04 for decline parameters to 10e07 for gas flow rates) further added to the computational complexity. These expert systems predicted decline parameters and a development plan for a specified system in a timely manner. In addition, no software can predict these parameters explicitly. In other words, the proposed expert system can predict endogenous parameters within seconds. Several existing studies addressed parameter estimation for the oil and gas industry (e.g., well testing results and multi-lateral well design) using artificial neural network methods. The prediction systems were tested against results from reservoir simulation; both systems showed excellent agreement with the simulation results. Moreover, the two implemented mechanisms (Artificial Neural Network and Genetic Programming) resulted in similarly accurate predictions that increased confidence in the constructed systems.
The proposed models eliminated the need for a reservoir simulator in describing an appropriate production profile for a specified set of reservoir properties and development plans, and describing a development plan that achieved a required rate and plateau length for a given reservoir. Results showed that ANN and GP expert systems predicted decline parameters and development plans with sufficient accuracy. For future studies, the expert systems built in this study can be enhanced for more complicated reservoirs like unconventional and heterogeneous reservoirs.

The third was spare capacity that can be a powerful tool for a major producer seeking to optimize its profit and increase its market power. Managing spare capacity under demand and price uncertainty is a complex optimization problem that requires sophisticated stochastic modeling and high computational capacity. This problem is best specified probabilistically, since it involves major investment in building and maintaining spare capacity volume, and may require a few years to develop the production facility. In other words, expected demand (at planning time) can be significantly different from actual realized demand. The problem was approached in three stages: 1) a stochastic optimization model was built to identify the optimal spare capacity under demand and crude price uncertainty, 2) sensitivity analysis was conducted for different demand and price forecasting models, and 3) a value of information analysis was conducted to quantify the impact of the accuracy of demand and price models. Acquiring spare capacity can increase profit and market power for a major crude oil producer. Spare capacity set the major producer as a price shock absorber (buffer mode), preventing prices from increasing (triggering alternative energy development) or from falling
(reducing profit). Moreover, increasing crude prices can reduce the market share of a major producer by motivating the development of non-conventional and alternative energy sources. This study focused specifically on optimizing economic profits. We analyzed this issue by specifying an integrated stochastic optimization model that simulated demand for oil, and mapped demand forecasts on production decisions. The optimum spare capacity, estimated from different price and demand model assumptions, was evaluated with the purpose of understanding the impact of these assumptions on spare capacity decisions. Results showed a reasonably narrow range of spare capacity levels that maximized the total profits of a major oil producer. We recommend, for future studies, analyzing the relationship between the optimal spare capacity to acquire and market parameters include crude prices, world reserves and global demand. This will speed up the process and enhance the understanding of the problem. Moreover, our method implemented can be used to analyze the problem of optimal gas storage capacity given the seasonality in demand for natural gas.

The last part of the study integrated the first two studies (capacity management and spare capacity). This was done by assuming that a major producer was producing a portfolio of existing oil fields at maximum production potential. The integrated spare capacity model recommended a level of spare capacity to build. After that, the capacity management model suggested the optimal production rate allocation. Results showed that the optimal production allocation was a function of reservoir properties and maturity.
TABLE OF CONTENTS

List of Figures .......................................................... xi
List of Tables .................................................................. xx
Acknowledgments............................................................ xxvii

Chapter 1 DYNAMIC OPTIMIZATION OF CAPACITY MANAGEMENT UNDER THE UNCERTAINTY OF RESERVOIR PROPERTIES AND MARKET VOLATILITY .................................................. 1

1.1. Introduction.................................................................................. 1
1.2. Literature Review ...................................................................... 4
  1.2.1. Optimization in the Oil and Gas Industry.............................. 4
  1.2.2. Price Forecasting ................................................................. 9
1.3. Problem Statement................................................................. 12
1.4. Methodology ........................................................................... 13
  1.4.1 Risk Analysis Workflow .................................................... 14
  1.4.2. Price Models ................................................................. 20
  1.4.3. Reservoir Models .......................................................... 33
  1.4.4. Cost Models ................................................................. 38
  1.4.5. Integrated Optimization Model ...................................... 44
1.5. Results and Discussion .......................................................... 67
  1.5.1. Deterministic Price and Production Forecast Models .......... 68
  1.5.2. Deterministic Production Forecast and Probabilistic Price Forecast . 74
  1.5.3. Probabilistic Price and Production Forecasts .................. 82
  1.5.4. Sensitivity Analysis ...................................................... 87
  1.5.5. Discussion .................................................................. 90
1.6. The Value of an Accurate Expected Demand (VOI Analysis) ......... 92
1.7. Conclusions and Recommendations for Future Work .................. 94
  1.7.1. Conclusions ................................................................. 94
  1.7.2. Recommendations for Future Research ............................ 98

Chapter 2 Predicting Decline Parameters and a Development Strategy for a Capacity Management Model: An Artificial Expert System ................................ 100

2.1. Introduction............................................................................. 100
2.2. Literature Review ................................................................. 103
  2.2.1. Machine Learning Overview ......................................... 103
2.3. Problem Statement............................................................... 124
2.4. Methodology ........................................................................ 126
  2.4.1. Reservoir Simulation Model ....................................... 126
2.4.2. Artificial Neural Network Expert Systems ........................................... 129
2.4.3. Genetic Programming Expert Systems ............................................... 136
2.5. Results and Discussion ............................................................................ 141
  2.5.1. Expert System-1 to Predict Decline Parameters and Plateau Length .. 142
  2.5.2. Expert System-2 to Predict Drainage Area ....................................... 162
2.6. Conclusions and Recommendations for Future Work ............................ 165
  2.6.1. Conclusions ....................................................................................... 165
  2.6.2. Recommendations for Future Research ............................................. 168

Chapter 3 Optimal Spare Capacity Level ......................................................... 169

  3.1. Introduction ............................................................................................ 169
  3.2. Literature Review .................................................................................. 170
    3.2.1. Genetic Algorithm .......................................................................... 170
    3.2.2. Capacity Planning in the Oil Industry .............................................. 176
  3.3. Problem Statement ................................................................................ 178
  3.4. Methodology ........................................................................................ 178
    3.4.1. Overview .......................................................................................... 179
    3.4.2. Price Model ...................................................................................... 182
    3.4.3. Demand Model ............................................................................... 196
    3.4.4. Cost Model ...................................................................................... 199
    3.4.5. Integrated Optimization Model ....................................................... 205
  3.5. Results and Discussion .......................................................................... 219
    3.5.1. Price = MRM and Demand = MRM-GBM .................................... 219
    3.5.2. Price and Demand Models: MRM-GBM ...................................... 233
    3.5.3. Summary of the Two Price Modeling Approach ............................ 248
    3.5.4. Sensitivity and Value of Information Analyses ............................... 251
  3.6. Conclusions and Recommendations for Future Work .......................... 261
    3.6.1. Conclusions ..................................................................................... 261
    3.6.2. Recommendations for Future Research ......................................... 262

Chapter 4 Integrating Spare Capacity and Capacity Management Studies ........ 262

  4.1. Introduction ............................................................................................ 262
  4.2. Problem Statement ................................................................................ 263
  4.3. Methodology ........................................................................................ 264
    4.3.1. Price Model ..................................................................................... 264
    4.3.2. Reservoir Model ............................................................................. 269
    4.3.3. Cost Models .................................................................................... 272
    4.3.4. Integrated Optimization Model ....................................................... 275
  4.4. Results and Discussion .......................................................................... 278
    4.4.1. Initial Non-Optimized Case ............................................................ 278
    4.4.2. Maximize Plateau Length ............................................................... 280
    4.4.3. Maximize Mean NPV ..................................................................... 282
    4.4.4. Maximize Plateau Length and Mean NPV .................................... 285
4.4.5. Maximize Plateau Length and Minimize Production Decline ........287
4.4.6. Summary ..............................................................................289
4.5. Conclusions and Recommendations for Future Work ..................292
  4.5.1. Conclusions ........................................................................292
  4.5.2. Recommendations for Future Research .................................293

Appendix A The Codes for the Expert Systems in Chapter 2 ..................294

  Generating Training Dataset ..........................................................294
  Preparing Simulation Files for Different Combination of Training data ....295
  Extracting Reservoir Simulation Results .........................................299
  Calculating Parameters Required for Training (i.e. Decline Parameters) ...300
  Code for Artificial Neural Network Training ....................................305
  Code for Genetic Programming Training .......................................309

Appendix B The Graphical User Interphase (GUI) for the Expert Systems in
  Chapter 2 ......................................................................................313

  The Code .......................................................................................315
    Code for the main window GUI ....................................................315
    Code for the First Expert System GUI .........................................317
    Code for the Second Expert System GUI .....................................349

Bibliography ..................................................................................378

  Chapter 1 .....................................................................................378
  Chapter 2 .....................................................................................382
  Chapter 3 .....................................................................................386
  Chapter 4 .....................................................................................387
LIST OF FIGURES

Figure 1-1. Risk Analysis Workflow ................................................................. 15

Figure 1-2. Historical Natural Gas Price ........................................................... 20

Figure 1-3. $p^*$ and $\eta$ Estimation for Standard Gas Price Using (AR(1))
  Regression ......................................................................................................... 25

Figure 1-4. Floating Price Model for Rich, Standard and Lean Gas Prices ........ 29

Figure 1-5. Mean Reversion Sample Path (Bukhari, 2011) ................................ 31

Figure 1-6. Mean Reversion Model Sample ...................................................... 33

Figure 1-7. Mean Reversion Model Sample ...................................................... 36

Figure 1-8. Mean Reversion Model Sample ...................................................... 36

Figure 1-9. Mean Reversion Model Sample ...................................................... 38

Figure 1-10. Drill Days for Onshore Drilling as Function of Reservoir Depth .... 40

Figure 1-11. Onshore Tangible Costs ............................................................... 42

Figure 1-12. Drill Days for Offshore Drilling as Function of Reservoir Depth .... 43

Figure 1-13. Offshore Tangible Costs ............................................................... 44

Figure 1-14. Production Rate Realized from a Newly Drilled Well as a Function
  of Depletion Stage .......................................................................................... 48

Figure 1-15. Integrated Model Processes .......................................................... 51

Figure 1-16. Initial Non-Optimized Production Profile and Cumulative
  Production .......................................................................................................... 71

Figure 1-17. Initial Non-Optimized Production Allocation and Plateau Length .... 71

Figure 1-18. Production Profile and Cumulative Production for Maximizing Total
  NPV and/or Total Plateau Length .................................................................... 72

Figure 1-19. Production Allocation and Plateau Length for Maximizing Total
  NPV and/or Total Plateau Length .................................................................... 72
Figure 1-20. Production Profile and Cumulative Production for Maximizing Total NPV without Supply Commitment Constraint ................................................................. 73

Figure 1-21. Production Profile and Cumulative Production for Maximizing Total Plateau Length without Supply Commitment Constraint ........................................... 74

Figure 1-22. Production Profile and Cumulative Production for Maximizing E[Total NPV] and/ or Total Plateau Length ................................................................. 78

Figure 1-23. Production Allocation and Plateau Length for Maximizing E[Total NPV] and/ or Total Plateau Length ................................................................. 78

Figure 1-24. Production Profile and Cumulative Production for Minimizing Average Annual Production Decline ................................................................. 79

Figure 1-25. Production Allocation and Plateau Length for Minimizing Average Annual Production Decline ................................................................. 80

Figure 1-26. Reserve Triangular Distribution for Field-1 ........................................ 84

Figure 1-27. Minimum Facility Operating Rate Triangular-Distribution for Field-1 ........................................................................................................ 84

Figure 1-28. Maximum Potential Rate Triangular-Distribution for Field-1 .......... 84

Figure 1-29. Reserve Triangular Distribution for Field-1 ........................................ 86

Figure 1-30. Tornado Chart for Total NPV by Varying Parameters by +10% and - 10% ........................................................................................................ 88

Figure 1-31. Tornado Chart for Total NPV by Varying Fields Parameters by +10% and -10% ........................................................................................................ 89

Figure 1-32. Tornado Chart for Total NPV by Varying Decline Exponent b by +10% and -10% ........................................................................................................ 89

Figure 1-33. Tornado Chart for Total NPV by Varying Decline Rate Di by +10% and -10% ........................................................................................................ 90

Figure 1-34. VOI Analysis for a More Accurate Demand Forecast ....................... 94

Figure 2-1. A Linear Problem for Perceptron (Kifer, 2014) ................................ 106

Figure 2-2. Two Connected Neurons (Hagan et al., 2002) .................................. 107

Figure 2-3. Artificial Neuron (Mohaghegh, 2000a) ............................................. 107
Figure 2-4. Transfer Functions (Priddy et al., 2005) ........................................... 109
Figure 2-5. Linear Transfer Functions (Hagan et al., 2002) .................................. 109
Figure 2-6. Single-layer Artificial Neural Network (Hagan et al., 2002) ............... 112
Figure 2-7. Multi-Layer Artificial Neural Network (Hagan et al., 2002) ............... 112
Figure 2-8. Recurrent Artificial Neural Network (Hagan et al., 2002) ................. 112
Figure 2-9. Biological Reproduction (Marsland, 2009) ........................................ 120
Figure 2-10. A chromosome with Five Genes ....................................................... 121
Figure 2-11. Single Point Crossover Operator (Mohaghegh, 2000b) .................... 123
Figure 2-12. Multi-Point Crossover Operator (Mohaghegh, 2000b) .................... 123
Figure 2-13. Mutation Operator (Mohaghegh, 2000b) ........................................ 123
Figure 2-14. No-Flow Boundaries ........................................................................ 126
Figure 2-15. Schematic of ANN-1 to Predict Plateau Length and Decline Parameter a ........................................................................................................ 135
Figure 2-16. Schematic of ANN-2 to Predict Decline Parameters b & c............. 135
Figure 2-17. Schematic of ANN-3 to Predict Drainage Area ............................... 136
Figure 2-18. Cross-plot for Predicting Plateau Length and Decline Parameter a .... 144
Figure 2-19. Cross-plot for Predicting Decline Parameters b & c ....................... 144
Figure 2-20. Comparison of Results from ANN and Simulator ............................ 145
Figure 2-21. Comparison of Results from ANN and Simulator ............................ 146
Figure 2-22. Comparison of Results from ANN and Simulator ............................ 146
Figure 2-23. Comparison of Results from ANN and Simulator ............................ 146
Figure 2-24. Comparison of Results from ANN and Simulator ............................ 147
Figure 2-25. Comparison of Results from ANN and Simulator ............................ 147
Figure 2-26. Comparison of Results from ANN and Simulator ............................ 147
Figure 2-27. Comparison of Results from ANN and Simulator. ................................. 148
Figure 2-28. Comparison of Results from ANN and Simulator. ................................. 148
Figure 2-29. Comparison of Results from ANN and Simulator. ................................. 148
Figure 2-30. Comparison of Results from ANN and Simulator. ................................. 149
Figure 2-31. Comparison of Results from ANN and Simulator. ................................. 149
Figure 2-32. Comparison of Results from ANN and Simulator. ................................. 149
Figure 2-33. Comparison of Results from ANN and Simulator. ................................. 150
Figure 2-34. Comparison of Results from ANN and Simulator. ................................. 150
Figure 2-35. Comparison of Results from ANN and Simulator. ................................. 150
Figure 2-36. Comparison of Results from ANN and Simulator. ................................. 151
Figure 2-37. Comparison of Results from ANN and Simulator. ................................. 151
Figure 2-38. Comparison of Results from ANN and Simulator. ................................. 151
Figure 2-39. Comparison of Results from ANN and Simulator. ................................. 152
Figure 2-40. Cross-plot for Predicting Plateau Length. ........................................... 154
Figure 2-41. Cross-plot for Predicting Decline Parameter a. ...................................... 154
Figure 2-42. Cross-plot for Predicting Decline Parameter b. ...................................... 155
Figure 2-43. Cross-plot for Predicting Decline Parameter c. ...................................... 155
Figure 2-44. Comparison of Results from GP and Simulator ..................................... 156
Figure 2-45. Comparison of Results from GP and Simulator ..................................... 156
Figure 2-46. Comparison of Results from GP and Simulator ..................................... 156
Figure 2-47. Comparison of Results from GP and Simulator ..................................... 157
Figure 2-48. Comparison of Results from GP and Simulator ..................................... 157
Figure 2-49. Comparison of Results from GP and Simulator ..................................... 157
Figure 2-50. Comparison of Results from GP and Simulator ..................................... 158
Figure 2-51. Comparison of Results from GP and Simulator........................................... 158
Figure 2-52. Comparison of Results from GP and Simulator........................................... 158
Figure 2-53. Comparison of Results from GP and Simulator........................................... 159
Figure 2-54. Comparison of Results from GP and Simulator........................................... 159
Figure 2-55. Comparison of Results from GP and Simulator........................................... 159
Figure 2-56. Comparison of Results from GP and Simulator........................................... 160
Figure 2-57. Comparison of Results from GP and Simulator........................................... 160
Figure 2-58. Comparison of Results from GP and Simulator........................................... 160
Figure 2-59. Comparison of Results from GP and Simulator........................................... 161
Figure 2-60. Comparison of Results from GP and Simulator........................................... 161
Figure 2-61. Comparison of Results from GP and Simulator........................................... 161
Figure 2-62. Comparison of Results from GP and Simulator........................................... 162
Figure 2-63. Comparison of Results from GP and Simulator........................................... 162
Figure 2-64. Cross-plot for Predicting Drainage Area....................................................... 163
Figure 2-65. Cross-plot for Predicting Drainage Area....................................................... 164
Figure 3-1. Biological Reproduction (Marsland, 2009)...................................................... 171
Figure 3-2. A Chromosome with Five Genes................................................................. 172
Figure 3-3. Single Point Crossover Operator (Mohaghegh, 2000b)..................................... 174
Figure 3-4. Multi-Point Crossover Operator (Mohaghegh, 2000b)..................................... 175
Figure 3-5. Mutation Operator (Mohaghegh, 2000b)......................................................... 175
Figure 3-6. Overview of the Spare Capacity Methodology.............................................. 181
Figure 3-7. Example of Demand Forecast.......................................................................... 182
Figure 3-8. West Texas Intermediate Crude Price Data..................................................... 183
Figure 3-9. GBM Lognormal Diffusion Process (Dias, 2010b)......................................... 186
Figure 3-10. P* and η Estimation for Crude Price Using (AR(1)) Regression. .......... 188
Figure 3-11. Mean Reversion Sample Path (Bukhari, 2011). ........................................... 190
Figure 3-12. Mean Reversion Model Sample of Crude Price........................................... 192
Figure 3-13. Arithmetic Brownian Motion Process (Dyer, 2011)................................. 194
Figure 3-14. Geometric Brownian Motion Process (Dyer, 2011). ................................. 194
Figure 3-15. Log-normal Diffusion Process of the GBM (Dias, 2010b)......................... 195
Figure 3-16. Weekly Crude Price and Supply between 1994 and 2012. ......................... 197
Figure 3-17. Monthly Crude Supply and Consumption between 1980 and 2012. ...... 197
Figure 3-18. Drill Days for Onshore Drilling as Function of Reservoir Depth........... 201
Figure 3-19. Onshore Tangible Costs. .................................................................................. 203
Figure 3-20. Onshore Oil Production Facility Base Costs............................................. 205
Figure 3-21. Onshore Oil Pipeline Costs............................................................................ 205
Figure 3-22. Expected NPV as a Function of Spare Capacity........................................ 221
Figure 3-23. Expected NPV as a Function of Spare Capacity........................................ 223
Figure 3-24. Expected NPV as a Function of Spare Capacity........................................ 224
Figure 3-25. Expected NPV as a Function of Spare Capacity........................................ 226
Figure 3-26. Expected NPV as a Function of Spare Capacity........................................ 227
Figure 3-27. Expected NPV as a Function of Spare Capacity........................................ 229
Figure 3-28. Expected NPV as a Function of Spare Capacity........................................ 230
Figure 3-29. Expected NPV as a Function of Spare Capacity........................................ 232
Figure 3-30. Expected NPV as a Function of Spare Capacity........................................ 232
Figure 3-31. Expected NPV as a Function of Spare Capacity........................................ 233
Figure 3-32. Expected NPV as a Function of Spare Capacity........................................ 234
Figure 3-33. Expected NPV as a Function of Spare Capacity........................................ 236
Figure 3-34. Expected NPV as a Function of Spare Capacity........................................237
Figure 3-35. Expected NPV as a Function of Spare Capacity........................................239
Figure 3-36. Expected NPV as a Function of Spare Capacity........................................240
Figure 3-37. Expected NPV as a Function of Spare Capacity........................................242
Figure 3-38. Expected NPV as a Function of Spare Capacity........................................244
Figure 3-39. Expected NPV as a Function of Spare Capacity........................................245
Figure 3-40. Expected NPV as a Function of Spare Capacity........................................247
Figure 3-41. Expected NPV as a Function of Spare Capacity........................................248
Figure 3-42. Optimum Spare Capacity as a Function of Production Duration..............250
Figure 3-43. Optimal Expected NPV as a Function of Production Duration..............251
Figure 3-44. Tornado Chart for Expected NPV..............................................................253
Figure 3-45. Optimization Sensitivity for Delta Demand.............................................255
Figure 3-46. Value of Perfect Information Analysis......................................................255
Figure 3-47. Value of Information Analysis for Delta Demand.....................................256
Figure 3-48. Optimization Sensitivity for Long-Run Equilibrium Price.....................257
Figure 3-49. Value of Information Analysis for Long-Run Equilibrium Price.............257
Figure 3-50. Optimization Sensitivity for Long-Run Equilibrium Demand..............258
Figure 3-51. Value of Information Analysis for Long-Run Equilibrium Demand........258
Figure 3-52. An optimization Sensitivity for Demand Volatility.................................259
Figure 3-53. Value of Information Analysis for Demand Volatility.............................260
Figure 4-1. Historical Data for Heavy Crude Price (1984–2013).................................265
Figure 4-2. Historical Data for the Three Crude Types (Bukhari, 2011)...................266
Figure 4-3. Medium and Heavy Crude Price Correlation Model................................268
Figure 4-4. Medium and Heavy Crude Price Correlation Model................................268
<table>
<thead>
<tr>
<th>Figure</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>4-5</td>
<td>Mean Reversion Model Sample.</td>
</tr>
<tr>
<td>4-6</td>
<td>Mean Reversion Model Sample.</td>
</tr>
<tr>
<td>4-7</td>
<td>Onshore Oil Production Facility Cost.</td>
</tr>
<tr>
<td>4-8</td>
<td>Offshore Oil Production Facility Cost.</td>
</tr>
<tr>
<td>4-9</td>
<td>Offshore Oil Production Facility Cost.</td>
</tr>
<tr>
<td>4-10</td>
<td>Offshore Oil Production Facility Cost.</td>
</tr>
<tr>
<td>4-11</td>
<td>Additional Rate from Newly Drilled Wells.</td>
</tr>
<tr>
<td>4-12</td>
<td>Non-Optimized Production Profile and Cumulative Production.</td>
</tr>
<tr>
<td>4-13</td>
<td>Non-Optimized Production Allocation and Plateau Length.</td>
</tr>
<tr>
<td>4-14</td>
<td>Production Profile and Cumulative Production for Maximizing Total Plateau Length.</td>
</tr>
<tr>
<td>4-15</td>
<td>Production Allocation and Plateau Length for Maximizing Total Plateau Length.</td>
</tr>
<tr>
<td>4-16</td>
<td>Production Profile and Cumulative Production for Maximizing Mean Total NPV.</td>
</tr>
<tr>
<td>4-17</td>
<td>Production Allocation and Plateau Length for Maximizing Mean Total NPV.</td>
</tr>
<tr>
<td>4-18</td>
<td>Production Profile and Cumulative Production for Maximizing Mean Total NPV and Total Plateau Length.</td>
</tr>
<tr>
<td>4-19</td>
<td>Production Allocation and Plateau Length for Maximizing Mean Total NPV and Total Plateau Length.</td>
</tr>
<tr>
<td>4-20</td>
<td>Production Profile and Cumulative Production for Maximizing Total Plateau Length and Minimizing Average Production Decline.</td>
</tr>
<tr>
<td>4-21</td>
<td>Production Allocation and Plateau Length for Maximizing Total Plateau Length and Minimizing Average Production Decline.</td>
</tr>
<tr>
<td>4-22</td>
<td>Impact of Discount Rate on Optimal Decisions.</td>
</tr>
<tr>
<td>4-23</td>
<td>Impact of Discount Rate on Mean NPV.</td>
</tr>
<tr>
<td>B-1</td>
<td>The Main Window for the GUI.</td>
</tr>
</tbody>
</table>
Figure B-2. The GUI for the Forward-Looking Expert System to Predict Decline Parameters and Plateau Length.................................................................314

Figure B-3. The GUI for the Inverse-Looking Expert System to Predict Drainage Area..............................................................315
LIST OF TABLES

Table 1-1. Natural Gas Types by Heating Content..........................................................13
Table 1-2. Historical Natural Gas Price...........................................................................21
Table 1-3. Volatility Calculation for Standard Gas Price................................................23
Table 1-4. P* and η Estimation for Standard Gas Price..................................................25
Table 1-5. Regression Parameters to Estimate P* and η...............................................26
Table 1-6. Estimated P* and η.......................................................................................26
Table 1-7. Estimation of Average Annual Growth Rate for Standard Gas Price.........27
Table 1-8. Parameters for Floating Price Models.........................................................28
Table 1-9. Floating Price Model for Rich, Standard and Lean Gas Prices.................29
Table 1-10. Parameters for the MRM Standard Gas Price Model..............................32
Table 1-11. Decline Curve Parameters for the 12 Fields.............................................37
Table 1-12. Rig Support and Supervision Rate in 1993 Dollars.................................41
Table 1-13. Rig Support and Supervision Rate in 2011 Dollars.................................41
Table 1-14. Definition of Field’s Remoteness (Kennedy, 1993).................................41
Table 1-15. Ranges of Field Parameters Classified by Gas Type..............................47
Table 1-16. Deduction Rates Sub-Module..................................................................53
Table 1-17. Floating Price Model Parameters.............................................................55
Table 1-18. Mean Reversion Model Parameters for Standard Gas..........................55
Table 1-19. Fields’ General Parameters for Deterministic Production Forecasting....60
Table 1-22. Production Forecast Parameters for Single-layer Homogenous Gas Reservoirs..........................................................61
Table 1-23. Well Cost Parameters...............................................................................61
Table 1-24. Production Sub-Module............................................................................63
Table 1-25. Deductions Sub-Module..................................................................................64

Table 1-26. Initial Non-Optimized Production Allocation..............................................71

Table 1-27. Initial Non-Optimized Production Allocation and Fields’ Properties......71

Table 1-28. Production Allocation for Maximizing Total NPV and/ or Total Plateau Length........................................................................................................72

Table 1-29. Production Allocation and Fields’ Properties for Maximizing Total NPV and/ or Total Plateau Length.................................................................73

Table 1-30. Production Allocation for Maximizing Total NPV without Supply Commitment Constraint.................................................................73

Table 1-31. Production Allocation for Maximizing Total Plateau Length without Supply Commitment Constraint .................................................................74

Table 1-32. Production Allocation for Maximizing E[Total NPV] and/ or Total Plateau Length........................................................................................................78

Table 1-33. Production Allocation by Gas Type for Maximizing E[Total NPV] and/ or Total Plateau Length.............................................................................78

Table 1-34. Production Allocation and Fields’ Properties for Maximizing E[Total NPV] and/ or Total Plateau Length.................................................................79

Table 1-35. Production Allocation for Minimizing Average Annual Production Decline........................................................................................................79

Table 1-36. Production Allocation by Gas Type for Minimizing Average Annual Production Decline.........................................................................................79

Table 1-37. Production Allocation and Fields’ Properties for Minimizing Average Annual Production Decline.............................................................................80

Table 1-38. Production Allocation for Maximizing E[NPV] under 0% Discount Rate........................................................................................................80

Table 1-39. Production Allocation by Gas Type for Maximizing E[NPV] under 0% Discount Rate..........................................................................................80

Table 1-40. Production Allocation and Fields’ Properties for Maximizing E[NPV] under 0% Discount Rate.............................................................................81

Table 1-41. Production Allocation for Maximizing E[NPV] under 50% Discount Rate........................................................................................................81
Table 1-42. Production Allocation by Gas Type for Maximizing E[NPV] under 50% Discount Rate. ........................................................................................................ 81

Table 1-43. Production Allocation and Fields’ Properties for Maximizing E[NPV] under 50% Discount Rate. ............................................................. 81

Table 1-44. Production Allocation for Maximizing E[NPV] Using Probabilistic Price and Production Forecast. ......................................................... 84

Table 1-45. Production Allocation by Gas Type for Maximizing E[NPV] Using Probabilistic Price and Production Forecast. ........................................ 85

Table 1-46. Production Allocation for Maximizing E[total Plateau Length] Using Probabilistic Price and Production Forecast. ........................................ 85

Table 1-47. Production Allocation by Gas Type for Maximizing E[total Plateau Length] Using Probabilistic Price and Production Forecast. .............. 85

Table 1-48. Production Allocation for Maximizing E[NPV] Using Probabilistic Price and Production Forecast. ......................................................... 86

Table 1-49. Production Allocation by Gas Type for Maximizing E[NPV] Using Probabilistic Price and Production Forecast. ........................................ 87

Table 1-50. Summary of Results. ............................................................................. 91

Table 2-1. Expert System 1.................................................................................... 125

Table 2-2. Expert System 2.................................................................................... 125

Table 2-3. Properties for Reservoir Simulation Model............................................. 129

Table 2-4. Properties for Designing Artificial Neural Network Models. .............. 133

Table 2-5. Properties for Designing Genetic Programming Models for Plateau Length, Decline Parameters a & c, and Drainage Area. ......................... 140

Table 2-6. Properties for Designing Genetic Programming Models for Decline Parameter b. ................................................................................. 141

Table 2-7. Reservoir Properties and Development Plans for 20 Randomly Generated Cases...................................................................................... 145

Table 3-1. Sample of Volatility Calculations for Crude Price............................... 184

Table 3-2. Sample of Drift Calculations for Crude Price. ....................................... 185
Table 3-3. \( P^* \) and \( \eta \) Estimation for Crude Price. .......................................................... 188
Table 3-4. Regression Parameters to Estimate \( P^* \) and \( \eta \). .......................................... 188
Table 3-5. Estimated \( P^* \) and \( \eta \) for Crude Price. ......................................................... 189
Table 3-6. Parameters for the MRM Crude Price Model.................................................... 192
Table 3-7. Rig Support and Supervision Rate in 1993 Dollars............................................ 202
Table 3-8. Rig Support and Supervision Rate in 2011 Dollars............................................ 202
Table 3-9. Definition of Field’s Remoteness (Kennedy, 1993)............................................ 202
Table 3-10. Base Costs for Camp Cost.............................................................................. 204
Table 3-11. Wellsite Costs................................................................................................. 204
Table 3-12. Production Facility Adjustment Factor. .......................................................... 204
Table 3-13. Field and Cost Parameters.............................................................................. 207
Table 3-14. Deduction Rates Sub-Module......................................................................... 209
Table 3-15. MRM-GBM Price Forecast Parameters.......................................................... 210
Table 3-16. MRM-GBM Demand Forecast Parameters..................................................... 211
Table 3-17. Field and Cost Parameters.............................................................................. 212
Table 3-18. Crude Price Sub-Module................................................................................. 213
Table 3-19. Production Sub-Module.................................................................................. 214
Table 3-20. Deductions Sub-Module................................................................................. 215
Table 3-21. Demand Forecast Model.................................................................................. 217
Table 3-22. Objective Function and Decision Variable Sub-Module................................ 218
Table 3-23. Optimal Spare Capacity................................................................................... 221
Table 3-24. Optimal Expected NPV................................................................................... 221
Table 3-25. Objective Function and Decision Variable Sub-Module................................ 222
Table 3-26. Optimal Spare Capacity................................................................................... 223
<table>
<thead>
<tr>
<th>Table</th>
<th>Description</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>3-51</td>
<td>Optimal Expected NPV.</td>
<td>238</td>
</tr>
<tr>
<td>3-52</td>
<td>Objective Function and Decision Variable Sub-Module</td>
<td>238</td>
</tr>
<tr>
<td>3-53</td>
<td>Optimal Spare Capacity.</td>
<td>239</td>
</tr>
<tr>
<td>3-54</td>
<td>Optimal Expected NPV.</td>
<td>239</td>
</tr>
<tr>
<td>3-55</td>
<td>Objective Function and Decision Variable Sub-Module</td>
<td>239</td>
</tr>
<tr>
<td>3-56</td>
<td>Optimal Spare Capacity.</td>
<td>241</td>
</tr>
<tr>
<td>3-57</td>
<td>Optimal Expected NPV.</td>
<td>241</td>
</tr>
<tr>
<td>3-58</td>
<td>Objective Function and Decision Variable Sub-Module</td>
<td>241</td>
</tr>
<tr>
<td>3-59</td>
<td>Optimal Spare Capacity.</td>
<td>242</td>
</tr>
<tr>
<td>3-60</td>
<td>Optimal Expected NPV.</td>
<td>243</td>
</tr>
<tr>
<td>3-61</td>
<td>Objective Function and Decision Variable Sub-Module</td>
<td>243</td>
</tr>
<tr>
<td>3-62</td>
<td>Optimal Spare Capacity.</td>
<td>244</td>
</tr>
<tr>
<td>3-63</td>
<td>Optimal Expected NPV.</td>
<td>244</td>
</tr>
<tr>
<td>3-64</td>
<td>Objective Function and Decision Variable Sub-Module</td>
<td>244</td>
</tr>
<tr>
<td>3-65</td>
<td>Optimal Spare Capacity.</td>
<td>246</td>
</tr>
<tr>
<td>3-66</td>
<td>Optimal Expected NPV.</td>
<td>246</td>
</tr>
<tr>
<td>3-67</td>
<td>Objective Function and Decision Variable Sub-Module</td>
<td>246</td>
</tr>
<tr>
<td>3-68</td>
<td>Optimal Spare Capacity as a Function of Production Duration</td>
<td>250</td>
</tr>
<tr>
<td>3-69</td>
<td>Optimal Expected NPV as a Function of Production Duration</td>
<td>250</td>
</tr>
<tr>
<td>4-1</td>
<td>Types of Crude.</td>
<td>264</td>
</tr>
<tr>
<td>4-2</td>
<td>Parameters for MRM Heavy Crude Price Model.</td>
<td>267</td>
</tr>
<tr>
<td>4-3</td>
<td>Price Correlation Coefficients.</td>
<td>267</td>
</tr>
<tr>
<td>4-4</td>
<td>Decline Curve Parameters for the 15 Fields.</td>
<td>271</td>
</tr>
<tr>
<td>4-5</td>
<td>Parameters for Drilling Costs.</td>
<td>274</td>
</tr>
</tbody>
</table>
Table 4-6. General Development Parameters .......................................................... 274
Table 4-7. Parameters for Production Facilities and Pipelines ............................... 275
Table 4-8. Field Parameter Assumptions .................................................................. 276
Table 4-9. Non-Optimized Production Allocation ..................................................... 279
Table 4-10. Production Allocation by Crude Type for Non-Optimized Case ............. 279
Table 4-11. Non-Optimized Production Allocation and Fields’ Properties .............. 280
Table 4-12. Production Allocation for Maximizing Total Plateau Length ................. 281
Table 4-13. Production Allocation by Crude Type for Maximizing Total Plateau Length ................................................................. 281
Table 4-14. Production Allocation and Fields’ Properties for Maximizing Total Plateau Length ......................................................................................... 282
Table 4-15. Production Allocation for Maximizing Mean Total NPV ....................... 283
Table 4-16. Production Allocation by Crude Type for Maximizing Mean Total NPV .............................................................................................................. 283
Table 4-17. Production Allocation and Fields’ Properties for Maximizing Mean Total NPV .............................................................................................................. 284
Table 4-18. Production Allocation for Maximizing Mean Total NPV and Total Plateau Length ................................................................. 285
Table 4-19. Production Allocation by Crude Type for Maximizing Mean Total NPV and Total Plateau Length ................................................................. 286
Table 4-20. Production Allocation and Fields’ Properties for Maximizing Mean Total NPV and Total Plateau Length ................................................................. 286
Table 4-21. Production Allocation for Maximizing Total Plateau Length and Minimizing Average Production Decline ................................................................. 288
Table 4-22. Production Allocation by Crude Type for Maximizing Total Plateau Length and Minimizing Average Production Decline ................................................................. 288
Table 4-23. Production Allocation and Fields’ Properties for Maximizing Total Plateau Length and Minimizing Average Production Decline ................................................................. 289
Table 4-24. Summary of Results ............................................................................. 290
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DEDICATION

To my kids, parents and wife
Chapter 1

DYNAMIC OPTIMIZATION OF CAPACITY MANAGEMENT UNDER THE UNCERTAINTY OF RESERVOIR PROPERTIES AND MARKET VOLATILITY

1.1. Introduction

Capacity Management, deterministically and probabilistically, demonstrates how managing a portfolio of natural gas fields can maximize total NPV and the plateau length for the whole portfolio under a demand constraint. Deterministically, the model identifies the production rate allocation among the fields that maximizes the portfolio plateau length. The optimization problem can then be expanded to include economic factors (i.e., cost and revenue) by specifying NPV as the objective function. Probabilistically, the optimization algorithm maximizes the expected value of the total plateau length and total NPV distributions. The uncertainties were incorporated in crude price and production forecasting models.

Capacity management is a portfolio optimization problem in that the production rate allocation that maximizes total plateau length is identified. (Deckers and Olsen, 1997) claimed that assigning production to fields with the least decline in capacity per unit produced should maximize the cumulative production vs. time for a portfolio of gas fields, i.e., maximize portfolio capacity (total capacity) as a function of time. Based on Deckers and Olsen, gas operators can extend the length of the portfolio plateau by judicious adjustment of the production rates from the fields. The computational
requirement for the optimization problem was increased by technical (i.e., reservoir characteristics, and crude or gas types) and corporate-level constraints (i.e., supply and spare capacity commitments). Uncertainties in reservoir performance were incorporated into and analyzed in the model. Dynamic (stochastic) optimization modeling was a more realistic approach than deterministic modeling for representing capacity management under uncertainties in reservoir performance and in the natural gas market. Unlike the deterministic approach, production profiles and gas prices were modeled as probability distributions in dynamic optimization. Simply put, capacity management is an optimization problem that balances the rate of extractions from the fields so that the stored reservoir energy is balanced and the total plateau length is extended. The balance of the stored reservoir energy was a function of field maturity, size, and quality. Our study differed from many optimization studies concerned with oil or gas field development, whether focusing on a single field or a portfolio of fields (Bukhari and Jablonowski, 2012, Bukhamseen et al., 2010, Bittencourt and Horne, 1997, Faya et al., 2007 a & b, Fichter, 2000, Tonnsen, 2008, Willigers et al., 2011, Willigers et al., 2011, Merritt and Miguel, 2000, and Yeten et al., 2002) in that we do not primarily focus on optimizing a well design, development strategy, reducing the number of wells required, or dramatically changing the state of a producer. Instead, the study followed an innovative approach in that the model rearranges the production rate from the existing fields. In other words, the implementation of our study is simple and practical. The optimization model extends the plateau of the portfolio of existing fields; this extended period can increase cumulative production with respect to time and increase the NPV. The decision on how to deplete nonrenewable producing assets is an important economic
and ethical decision, especially in the case of a major producer, because it can affect the availability of these assets to future generations and can affect the shape of the whole market. In other words, how a dominant producer depletes its resources can impact the future shape of the entire market (Nakov, A., and Nuno, G. 2011). Another advantage of capacity management is the delay of a development project and savings on significant time-value adjusted costs; the extension of total plateau length eliminates the need for the development field to overcome the decline in production. In other words, a dominant producer can, by implementing the proposed model, maintain its target rate for longer time without incurring any additional cost. Our model can increase confidence in supply commitments and improve supply management within the quota system (e.g., OPEC); this can involve political and strategic concepts beyond the scope of this study. A range of discount rate was analyzed to identify its impact on long-term value optimization and capacity management. The discount rate, used in NPV calculations, reflects the company’s objective and strategic planning. The applied discount rate can affect when and what types of constraints fields will encounter. An important aspect of the CM model can be realized when capacity becomes a constraint, i.e., once supply exceeds demand. Capacity is constrained by field maturity or by cost/profit analysis in the case of building new capacity. Low discount rates may be appropriate for capacity management studies in that decision makers seek to evaluate the portfolio of resources against long-term, low-risk alternatives, such as United States Treasury Bonds. This study analyzed the capacity management problem in three parts: (1) An integrated optimization model was built to solve for the optimal production allocation of a portfolio of fields under the uncertainty of commodity prices and reservoir performance, (2) Then, the impact of the discount rates
on optimal results was analyzed, and (3) A value of information (VOI) analysis was conducted to estimate the value of a more accurate demand forecast for the capacity management problem.

1.2. Literature Review

1.2.1. Optimization in the Oil and Gas Industry

Optimization and stochastic processes have many applications in the oil and gas industry. Most of the optimization problems in the oil and gas industry, concerned with optimizing a design of wells and production facilities, portfolio allocation, or well locations, are nonlinear problems that require a powerful optimization algorithm. The conventional process in portfolio optimization is to rank the projects based on their return. Other studies used the efficient frontier to identify a set of optimal solutions—in other words, it was a tool for analysis rather than optimization.

Our study employed an optimization algorithm to identify the optimal production allocation; our proposed model considered the interaction between the fields while solving for the optimal solution. Our study is unique because it maximizes profit without dramatic change in the development plan, in the design of a well or production facility. Simply, the production rates are rearranged between the oil or gas fields so that the plateau for the total portfolio is maximized while maintaining the total target daily rate. Moreover, there are no additional costs in implementing the recommended optimal solution by the CM model. Another advantage is that uncertainty is decreased by
accelerating production (extend the plateau) since most production is moved closer to the present time. The uncertainty of forecast prices increases over time. One of the biggest motivations for this study is that extending the length of the portfolio plateau could delay development projects required to overcome losses in production, saving billions of dollars in net present value (NPV).

(Downey, 1997) recommended ranking fields by their expected profitability index in portfolio optimization. His recommendation ignored the risk involved in each field and the interactions between fields. This recommendation does not diversify the portfolio as advised by (Markowitz, 1952). Markowitz is the founder of modern financial portfolio theory; this theory redefined portfolio selection to choose projects that maximize the expected return for a given risk, or minimize the risk for a given expected return for the portfolio. Markowitz defined the risk as variance in a portfolio’s return or expected return. Markowitz theory and conclusions were based on the stock market. According to Markowitz, the variance in a large portfolio depends on the covariance between assets, not on the variance within individual assets; that is why diversification reduces risk in the portfolio. (Sharpe, 1964) modified Markowitz’s concept and incorporated the efficient market in the analysis. Markowitz’s theory has many applications in different industries (Hertz, 1968). (Ball and Savage, 1999) modified Markowitz’s model so it could be applied to the oil and gas industry and pointed out that evaluation and selection of oil and gas projects based on expected return and required investment (i.e., expected NPV) were commonplace.

(Bukhari, 2011) established a workflow to optimize production allocation in the portfolio of producing oil fields under the uncertainty of prices. The optimization
problem handles 5 crude types based on API gravity. He claimed that the optimal allocation was a function of price differentials. Five different price forecast models were evaluated to analyze their impact on the optimal decision. The conclusion was that those fancy computational expensive price models did not impact the optimal decision.

(Aibassov, 2007) established a workflow to optimize share allocation of investment among 11 exploration fields; Markowitz’s Portfolio Theory was employed. Prices were forecast using Sequential Gaussian Simulation (SGS). Sanitized field data were generated, as well as efficient frontier graphs for three performance indicators: net present value NPV, profitability index PI, and growth rate of return GGR. The study did not employ an optimization algorithm (i.e., linear programming); rather, different sets of portfolio of fields were plotted as the function of risk and return and analyzed. Moreover, the study considered partial investment in field development. In the oil and gas industry, the decision is whether to develop a field or not rather than partial field development. The author characterized different sets of portfolios based on their risk, using the efficient frontier approach.

(Faya, 2006) developed a guideline—real asset risk management (RARM)—to manage and optimize the portfolio of fields. The proposed guideline improves communication within the company personnel, reduces the learning curve, and can optimize the entire process from exploration to field development, saving time and money. The study established a guideline for how people, tools, methods and organization should interact during portfolio management. Efficient frontier and portfolio optimization theory were implemented as an optimization tool.
(Lasdon et al., 2007) analyzed the problem of allocating available funds over a portfolio of 10 oil fields, 2 of that were exploration fields to achieve a tradeoff between return and risk. Mean Reversion price model was implemented in their study. The single-layer slightly compressible tank model was used to forecast production. The portfolio was ranked and optimized based on NPV and four risk measures: variance of NPV, NPV semi-variance, expected loss, and number of scenarios with negative NPV. The linear programming algorithm was used to solve the optimization problem. They concluded that using different performance measure (i.e., max NPV, or min expected loss) can result in significantly different funds allocation.

(Bittencourt and Horne, 1997) developed a genetic algorithm-based optimization model to optimize the location, type (i.e., vertical and horizontal), orientation of 33 wells for a given offshore field. Moreover, the location of the platform was optimized. Net present value was the objective function. Commercial reservoir simulator was implemented in the study to generate production profiles. They concluded that the developed algorithm was sufficient to solve the proposed problem in timely manner.

(Yeten et al., 2002) applied genetic algorithm GA and artificial neural network to optimize well type, location and trajectory in nonconventional reservoirs. Moreover, smart well control was optimized in the study using conjugate gradient algorithm.

(Abukhamsin, 2009) implemented continuous genetic algorithm to optimize well location and type, number of laterals, and trajectory design for an actual carbonate field in Saudi Arabia. The objective function was oil cumulative production over ten years. Sensitivity analysis was carried to identify the impact of algorithm parameters on the final solution. Different optimal results were obtained from coarse and fine reservoir
models. Helper tools such as Rejuvenation and Hill Climber were implemented to further optimize the solution.

(Tupac et al., 2008) developed an optimization model to determine that field(s) could be developed at present and that ones in the future. The model incorporated genetic algorithm and proxy for the reservoir simulator to optimize the development strategy for each field in the portfolio and maximize the NPV. After that, the algorithm considered the uncertainty in the market condition to ascertain that field should be developed now and that ones should be delayed. Crude prices were modeled as the Geometric Brownian Motion model.

(Al-Mudhafar et al., 2010) developed an optimization model to optimize the number and location of wells to develop a sector model of South Rumaila oil field. Genetic Algorithm was coupled with commercial reservoir simulator during to optimize the NPV. The result of the Genetic Algorithm GA was compared against the result of manually optimized strategy; the results were similar. However, the GA was faster and can save time.

(Emerick et al., 2009) proposed an optimization model based on Genetic Algorithm to optimize number, location and trajectory of producer and injector. Commercial reservoir simulator was coupled with the optimizer. The optimization model was applied to three actual fields and resulted in optimized NPV and oil recover from the strategy proposed the reservoir engineer.
1.2.2. Price Forecasting

Deterministic price models are commonly used in the oil and gas project evaluation for their simplicity. The price floating model assumes that price grows at a fixed annual rate. On the other hand, stochastic processes are commonly implemented to forecast prices for crude oil (Begg and Smit, 2007). (Bhar et al., 2008) stated that most non-stationary time series parameters (i.e., crude prices) consist of two processes: dynamic and cyclical deviation processes. The dynamic process is referred to as random walk or trend and is affected by supply and demand. The cyclical one is represented as an autoregressive model and is affected by information arrival (i.e., hurricanes). (Bukhari and Jablonowski, 2012, and Schwartz and Smith, 2000) reported that a stochastic price forecast has a significant impact on project evaluation. Our study investigated the impact of uncertainty in the price modeling parameters on optimal decisions. (Al-Harthy, 2007) claimed that previous studies had not investigated the impact of price modeling parameters on decision-making. Three common stochastic methods are used to forecast prices: Geometric Brownian Motion GBM, Mean Reversion Model MRM, and Mean Reversion Model with Jumps MRMJ.

The GBM is commonly used due to its simple implementation (Dias, 2010b). The GBM is a lognormal diffusion process that may be described by drift and volatility terms for the price (Dias, 2010b). The GBM underestimates the uncertainty of the downside of prices. A disadvantage of the GBM model is that it is a memoryless process (Dias, 2010b). The GBM predicts price based on the price of the previous time step; moreover, the GBM assumes that price changes are independent (Begg and Smit, 2007). Dias
reported that the statistical analysis of crude prices does not show memoryless behavior. The GBM can underestimate uncertainties in prices (Hahn and Dyer, 2007). However, GBM can be a proper forecast model if the prices are close to the long-run equilibrium price (Dias, 2004).

The MRM model incorporates the economical concept that price is correlated with the marginal cost of production (Dias, 2010c). Prices revert to a long-run equilibrium price with specific volatility and reversion rate. Moreover, MRM correlates prices to random information arrival; different types of information have different impacts on prices—up or down. When prices are relatively high, high-cost producers enter the market, increasing the supply and decreasing prices; however, when prices are relatively low, high-cost producers exit the market, reducing supply and increasing prices (Hosgor, 2009 and Dias, 2010c). (Schwartz, 1997 and Bessembinder et al., 1995) suggested that the MRM model accurately models commodity prices.

The MRMJ is an MRM model with jumps in prices. These jumps are modeled using a Poisson distribution with given jump size and frequency (Dias, 2010a and Dias and Rocha, 1998). The MRMJ incorporates abnormal information arrival (i.e., war, earthquake). In our study MRM was used to model prices because it is a preferred model from an economic perspective. Moreover, the MRMJ model requires the estimation of jump size and frequency that is impossible to accurately estimate from historical data.

(Hosgor, 2009) investigated the impact of different price forecast models on the optimal decision of production facility and on the value of the option to expand the facility in the future. GBM, MRM, and MRMJ were the models implemented in the
study. The study concerned with designing production facility for an offshore oil field with associated gas to maximize the NPV.

(Al-Harthy, 2007) reviewed the common stochastic price forecasting models: Geometric Brownian Motion, Mean Reversion and Mean Reversion with Jumps models. The impacts of the parameters for those models on the valuation of E&P projects were analyzed. It was concluded that MRM and MRM with jumps reflect the uncertainty in the NPV more than the GBM, and unlike MRM and MRM with jumps, the volatility of the GBM directly affect the volatility of the NPV. Moreover, he concluded that the current price and the long-run equilibrium price have significant impact on the NPV.

(Lima et al., 2005) presented a framework to estimate project volatility that is the standard deviation of the logarithm return. Project volatility is different than price volatility because most projects may not present linear relationship between average price and operating expenditures. Three stochastic price forecast models were incorporated in the study: Geometric Brownian Motion, Mean Reversion, and Independent Lognormal distribution models. Lima et al. concluded that the Geometric Brownian Motion and the independent lognormal distribution models resulted in higher project volatility than price volatility. However, the Mean Reversion model, in certain high-price cases, resulted in less project volatility than price volatility.

(Staber, 2006) presented an improved price forecast model. The model is a mean reversion model in that prices revert to actual future prices. The author claimed that the modified mean reversion model was better because the prices were updated continuously and the future prices were defined by experts around the world. Application of this model
accounted for the seasonality in prices. In other words, the prices reverted to the forecasted price rather than to the long-run equilibrium price.

1.3. Problem Statement

This section illustrates the problem solved by the proposed model. The purpose of managing a hypothetical major gas producer was to identify the production rate allocation that maximizes the length of the total plateau under the uncertainty of reservoir performance and market volatility. Moreover, analysis of the production rate allocation resulting from maximizing plateau length and NPV was of interest to management. The life of the project was 60 years of production for deterministic price and production forecasting and 40 for probabilistic price and production forecasting. The company was managing 12 existing fields that produced 3 types of natural gas (lean, standard, and rich gas) based on heating content in British Thermal Unit per standard cubic foot of gas (BTU/SCF) as shown in Table 1-1. Heating contents, in BTU/SCF, were 935, 1028, and 1236 for lean, standard, and rich gas, respectively. The company faced the following constraints in the optimization problem: 1) The production rate, for each field, was bounded by production potential and minimum facility operating rate, and 2) Total production from the fields must meet the total target rate. The production potential is the maximum allowable production rate needed to operate the reservoir efficiently and safely. The minimum facility operating rate is the minimum rate the facility must process to be an economical and safe operation. The total target rate represented the corporate supply commitment.
1.4. Methodology

The objectives of the study were to establish a workflow for optimizing production allocation for a portfolio of producing assets under the uncertainties of the market and reservoir performance, and examine the impact of these uncertainties on the allocation decision. This section contains a discussion of the methodology and models implemented to establish the workflow and conduct the required analyses.

The problem was a dynamic optimization in that the objective function (total plateau length of NPV) was maximized under the uncertainty of reservoir performance and/or natural gas price. The NPV is a function of the intrinsic commodity value (e.g., natural gas price), the realized production rate, and the costs of production. The intrinsic commodity value can differ from one field to the next. For the sake of simplicity, it was limited to three types of gas (lean, standard, and rich), based on the heating content in British Thermal Unit per standard cubic foot of gas (BTU/SCF). Table 1-1 shows these types of gas and associated heating contents that were 935, 1028, and 1236 BTU/scf for lean, standard, and rich gases, respectively. The U.S. wellhead historical price (Energy Information Administration, 2012) was used to model the standard gas price (National Petroleum Council, 2012; Matheson Gas, 2012). Then this wellhead price, in $/scf, was converted to $/BTU, from which the prices of the remaining gas types were calculated.

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<thead>
<tr>
<th>Gas Type</th>
<th>BTU/SCF</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lean Gas</td>
<td>935</td>
</tr>
<tr>
<td>Standard Gas</td>
<td>1028</td>
</tr>
<tr>
<td>Rich Gas</td>
<td>1236</td>
</tr>
</tbody>
</table>
Excel-addin, Risk Solver Platform (RSP), was used to build the integrated optimization model, which consists of reservoir performance models, price model, cost model, economic model, and optimization algorithms.

1.4.1 Risk Analysis Workflow

Risk analysis workflow was implemented to construct a workflow for CM under commodity price and reservoir performance uncertainties and to facilitate the analysis of the CM problem. This risk analysis workflow has been implemented in several optimization studies (Jablonowski et al., 2008; Purwar, 2008; Ettehad et al., 2009; Hosgor, 2009; Bukhari and Jablonowski, 2012). This section discusses the eight steps of the risk analysis workflow (Figure 1-1).
1.4.1.1. Define Optimization Approach

There are two conventional optimization approaches: asset-based and requirement-based (Mc Vay and Spivey, 2001, Ettehad, 2009, and Bukhari and Jablonowski, 2012). The asset-based approach is an unconstrained optimization approach; a performance attribute (e.g. NPV) is maximized by specifying the decision variables. On the other hand, the requirement-based approach is a constrained optimization approach; the performance attribute is maximized, while a functionality
requirement must be met, by specifying decision variables. The requirement-based approach was implemented in our study. Our model maximized the performance attribute (NPV and/or plateau length) by specifying the decision variables (fields’ production rates) and meeting functionality requirements (total daily target rate). Ettehad (2009) implemented the requirement-based approach to optimize the design of a gas storage facility. (The asset-based approach assumes that the price of oil is known, and then maximizes a performance attribute [for example, net present value] by modifying the fields’ production rates.) On the other hand, the requirement-based approach that was implemented in this study has a functionality requirement. We calculated the fields’ production rate allocation to maximize total NPV while meeting the functionality requirement, “total daily production rate”. Ettehad (2009) implemented the requirement-based approach to optimize gas storage facility design under uncertainty. Bukhari and Jablonowski (2012) implemented the approach to optimize the production allocation of crude oil fields under the uncertainty of crude prices. The functionality requirement, in this study, represented demand for natural gas and supply commitment contracts.

1.4.1.2. Identify Functionality Requirements

The functionality requirement is a constraint that must be met in an optimization problem for the model to be functional. It can be specified deterministically (Bukhari, and Jablonowski, 2012) or probabilistically (Ettehad, 2009). In this study, this requirement was defined as the total target daily rate as a deterministic value that represents the long-term contract commitment to supply natural gas.
1.4.1.3. Select Price and Production Forecasting Approach

After specifying the functionality requirement (total target daily rate), the forecasting approach for gas price and production rate should be specified. Price and production rate were forecasted deterministically and probabilistically as shown in the forecasting sections.

1.4.1.4. Initiate Production Rate Allocation

Decision variables (in this study, production rates for each field) must be initiated before solving the optimization problem. This was a critical step in our optimization model because the optimization problem was nonlinear in the decision variables. Initial values for decision variables can impact the global optimality condition; in other words, different initial values for decision variables can lead to different optimal solutions (e.g., local optima). Note, the total target daily rate and fields’ production rate were assigned in the optimization problem before the uncertain variable was revealed. This is because natural gas is sold in advance (supply contracts) and the production facilities are constructed year(s) before fields are placed in production. In other words, prices are revealed after those decisions are made.

1.4.1.5. Reveal Uncertain Variables

The uncertain variables (gas prices and reservoir performance) were sampled using the Latin Hypercube sampling method during the optimization process. In reality,
gas prices are realized after assigning fields’ production rates; this sequence of events results in risk and uncertainty. However, in the optimization process, the prices are revealed before the optimum production allocation is calculated. In other words, the optimizer knows in advance the realized price and optimizes accordingly. Stated another way, the optimizer tracks the gas prices over time and assigns high rates during a high price period and low rates during a low price period. This unrealistic sequence leads to anticipatory error (error of perfect information) as described by (Ettehad, 2009 and Bukhari and Jablonowki, 2012). The optimizer has perfect knowledge of future prices and optimizes accordingly. This anticipatory error was avoided in our model by restricting the algorithm to assign a single value to each field throughout the life of the project during the optimization process. As a result, the optimizer cannot respond to variation in price forecasts.

1.4.1.6. Maximize the Objective Function

Conventionally, an optimization problem consists of three parts: objective function, decision variables, and constraint(s). Some optimization problems do not require constraint. The objective function is yardstick for the optimization problem; the optimization algorithm calculates decision variables to maximize the objective function. In other words, the objective function is used to assess the performance of a process. In the deterministic approach, the objective function was a single value for a parameter (e.g., NPV). On the other hand, the objective function was a probability distribution for a parameter when applying the probabilistic approach. The optimizer cannot optimize a
probability distribution; instead, it can maximize the mean or minimize the variance in that distribution (Powell and Baker, 2010). This study maximized the mean of the objective function distribution, in the case of the probabilistic approach, as recommended by (Powell and Baker, 2010). The following objective functions were analyzed in the study: 1) NPV, 2) Plateau Length, 3) NPV and Plateau Length, 4) Mean of NPV, 5) Mean of Plateau Length, 6) Mean of NPV and Mean of Plateau Length.

1.4.1.7. Generate Probability Density Function for the Objective Function

This step was applicable only to the probabilistic forecasting approach. A probability distribution, in the form of probability density function PDF, was constructed for the objective function. The uncertain parameter(s) was sampled, from the stochastic forecast model, and an objective function was calculated. This process was repeated 1000 times to generate the PDF for the objective function.

1.4.1.8. Solve for the Optimum Production Allocation

This step involved with the optimization algorithms used to maximize the objective function. Genetic Programming (GP) and Nonlinear Programming techniques were implemented in the study.
1.4.2. Price Models

Two price forecast models were analyzed: the Floating Price Model (deterministic), and the Mean Reversion Model (Probabilistic). Our study followed the same procedures implemented in (Bukhari and Jablonowski, 2012) to calculate the required parameters and construct the models. Wellhead gas price historical data from 1990 to 2011 (Figure 1-2 and Table 1-2), were used to calculate the required parameters. Moreover, the long-run equilibrium price was estimated from the data.

Figure 1-2. Historical Natural Gas Price.
### 1.4.2.1. Gathering Historical Price Data

The study involved 12 existing fields that produced three different gas types based on the heating content in BTU/SCF as shown in (Table 1-1). The annual historical price data for standard gas were obtained from the U.S. Energy Information Administration (EIA, 2012) for the period 1990–2011.

<table>
<thead>
<tr>
<th>Date</th>
<th>U.S. Natural Gas Wellhead Price ($/Mscf)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1990</td>
<td>1.71</td>
</tr>
<tr>
<td>1991</td>
<td>1.64</td>
</tr>
<tr>
<td>1992</td>
<td>1.74</td>
</tr>
<tr>
<td>1993</td>
<td>2.04</td>
</tr>
<tr>
<td>1994</td>
<td>1.85</td>
</tr>
<tr>
<td>1995</td>
<td>1.55</td>
</tr>
<tr>
<td>1996</td>
<td>2.17</td>
</tr>
<tr>
<td>1997</td>
<td>2.32</td>
</tr>
<tr>
<td>1998</td>
<td>1.96</td>
</tr>
<tr>
<td>1999</td>
<td>2.19</td>
</tr>
<tr>
<td>2000</td>
<td>3.68</td>
</tr>
<tr>
<td>2001</td>
<td>4.00</td>
</tr>
<tr>
<td>2002</td>
<td>2.95</td>
</tr>
<tr>
<td>2003</td>
<td>4.88</td>
</tr>
<tr>
<td>2004</td>
<td>5.46</td>
</tr>
<tr>
<td>2005</td>
<td>7.33</td>
</tr>
<tr>
<td>2006</td>
<td>6.39</td>
</tr>
<tr>
<td>2007</td>
<td>6.25</td>
</tr>
<tr>
<td>2008</td>
<td>7.97</td>
</tr>
<tr>
<td>2009</td>
<td>3.67</td>
</tr>
<tr>
<td>2010</td>
<td>4.48</td>
</tr>
<tr>
<td>2011</td>
<td>3.95</td>
</tr>
</tbody>
</table>
1.4.2.2. Calculating Modeling Parameters for the Price Models

We analyzed deterministic and probabilistic price forecast approaches. This section discusses the calculation of the parameters required to construct the price forecast models. The following parameters were estimated from historical data (1990–2011): price volatility, long run equilibrium price, and price reversion rate. These parameters were estimated only for standard gas because the prices for rich and lean gas were calculated from the price for standard gas and the heating contents of the three types of gas.

1.4.2.2.1. Volatility of Gas Price (σ)

The price volatility was required for the Mean Reversion Model—a stochastic/probabilistic model. This term is the source of uncertainty in the forecasting process. Volatility is defined, in finance, as the standard deviation in logarithm returns (Bukhari and Jablonowski, 2012). (Table 1-3) shows the calculations for volatility from the standard gas price historical data. The first and second columns are date and prices, respectively. The third column represents the natural logarithm of the price of the current period while the fourth column contains the natural log of price of the previous period. The fifth column is the difference between the values in the third and fourth columns. The volatility is the standard deviation in entries in the fifth column. Annual crude oil prices are listed in the second column as shown in (Equation 1-1).

\[
\sigma = \text{Standard Deviation}[\ln P(t) - \ln P(t - 1)], \forall t
\]  

\[(1-1)\]
Table 1-3. Volatility Calculation for Standard Gas Price.

<table>
<thead>
<tr>
<th>Date</th>
<th>Standard Gas ($/Mscf)</th>
<th>Ln[P(t)]</th>
<th>Ln[P(t-1)]</th>
<th>Ln[P(t)]-Ln[P(t-1)]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Jun 30, 1990</td>
<td>1.71</td>
<td>0.49</td>
<td>0.54</td>
<td>-0.04</td>
</tr>
<tr>
<td>Jun 30, 1991</td>
<td>1.64</td>
<td>0.55</td>
<td>0.49</td>
<td>0.06</td>
</tr>
<tr>
<td>Jun 30, 1992</td>
<td>1.74</td>
<td>0.71</td>
<td>0.55</td>
<td>0.16</td>
</tr>
<tr>
<td>Jun 30, 1993</td>
<td>2.04</td>
<td>0.62</td>
<td>0.71</td>
<td>-0.10</td>
</tr>
<tr>
<td>Jun 30, 1994</td>
<td>1.85</td>
<td>0.44</td>
<td>0.62</td>
<td>-0.18</td>
</tr>
<tr>
<td>Jun 30, 1995</td>
<td>1.55</td>
<td>0.77</td>
<td>0.44</td>
<td>0.34</td>
</tr>
<tr>
<td>Jun 30, 1996</td>
<td>2.17</td>
<td>0.84</td>
<td>0.77</td>
<td>0.07</td>
</tr>
<tr>
<td>Jun 30, 1997</td>
<td>2.32</td>
<td>0.67</td>
<td>0.84</td>
<td>-0.17</td>
</tr>
<tr>
<td>Jun 30, 1998</td>
<td>2.19</td>
<td>0.78</td>
<td>0.67</td>
<td>0.11</td>
</tr>
<tr>
<td>Jun 30, 1999</td>
<td>3.68</td>
<td>1.30</td>
<td>0.78</td>
<td>0.52</td>
</tr>
<tr>
<td>Jun 30, 2000</td>
<td>4.00</td>
<td>1.39</td>
<td>1.30</td>
<td>0.08</td>
</tr>
<tr>
<td>Jun 30, 2001</td>
<td>4.95</td>
<td>1.08</td>
<td>1.39</td>
<td>-0.30</td>
</tr>
<tr>
<td>Jun 30, 2002</td>
<td>4.88</td>
<td>1.59</td>
<td>1.08</td>
<td>0.50</td>
</tr>
<tr>
<td>Jun 30, 2003</td>
<td>5.46</td>
<td>1.70</td>
<td>1.59</td>
<td>0.11</td>
</tr>
<tr>
<td>Jun 30, 2004</td>
<td>7.33</td>
<td>1.99</td>
<td>1.70</td>
<td>0.29</td>
</tr>
<tr>
<td>Jun 30, 2005</td>
<td>6.39</td>
<td>1.85</td>
<td>1.99</td>
<td>-0.14</td>
</tr>
<tr>
<td>Jun 30, 2006</td>
<td>6.25</td>
<td>1.83</td>
<td>1.85</td>
<td>-0.02</td>
</tr>
<tr>
<td>Jun 30, 2007</td>
<td>7.97</td>
<td>2.08</td>
<td>1.83</td>
<td>0.24</td>
</tr>
<tr>
<td>Jun 30, 2008</td>
<td>3.67</td>
<td>1.30</td>
<td>2.08</td>
<td>-0.78</td>
</tr>
<tr>
<td>Jun 30, 2009</td>
<td>4.48</td>
<td>1.50</td>
<td>1.30</td>
<td>0.20</td>
</tr>
<tr>
<td>Jun 30, 2010</td>
<td>3.95</td>
<td>1.37</td>
<td>1.50</td>
<td>-0.13</td>
</tr>
</tbody>
</table>

| σ          | 0.29               |

1.4.2.2. Long-run Equilibrium Price ($P^*$) and Reversion Rate ($\eta$)

The calculation of two parameters—long-run equilibrium price ($P^*$) and reversion rate ($\eta$)—required for the Mean Reversion Model (MRM) are discussed in this section. The two parameters were estimated via the same regression analysis. The MRM infers the economical concept that prices are correlated with the marginal cost of production. Prices revert to a long-run equilibrium price ($P^*$) with certain volatility ($\sigma$) and reversion
speed ($\eta$). Annual wellhead gas price data between 1990 and 2011 were used to estimate the two parameters.

The two parameters were calculated using the first-order autoregressive process AR(1) (Equation 1-2) in discrete time as recommended by (Dixit and Pindyck, 1994). (Equation 1-5) is a linear regression model of ($P_t$-$P_{t-1}$) as a function of $P_{t-1}$ with slope $b$, intercept $a$, and residual $\varepsilon_t$. (Equation 1-5) resulted from substituting (Equation 1-3 and 1-4) into (Equation 1-2). It is assumed that the residual term is normally distributed with mean zero and standard deviation equals to the standard error of the sample data ($\sigma_E$).

(Table 1-4) shows the data required to implement the AR(1) process and estimate $P^*$ and $\eta$. (Figure 1-3) shows the regression model as implemented, ($P_t$-$P_{t-1}$) as a function of $P_{t-1}$, to estimate the parameters. From the fitted regression model (Figure 1-3) and (Table 1-5), $\eta$ and $P^*$ were calculated from (Equation 1-9) and (Equation 1-8), respectively. (Table 1-6) shows the estimated values of 4.94 and 0.51 for $P^*$ and $\eta$, respectively.

\[
P_{(t)} - P_{(t-1)} = P^* \times (1 - e^{-\eta}) + (e^{-\eta} - 1) \times P_{(t-1)} + \varepsilon_t \tag{1-2}
\]

\[
P^*(1 - e^{-\eta}) = a \tag{1-3}
\]

\[
(e^{-\eta} - 1) = b \tag{1-4}
\]

\[
P_{(t)} - P_{(t-1)} = a + b \times P_{(t-1)} + \varepsilon_t \tag{1-5}
\]

\[
\varepsilon_t = N(0, \sigma_c) \tag{1-6}
\]

\[
\sigma_E = \text{Standard Error} \tag{1-7}
\]

\[
P^* = -\frac{a}{b} \tag{1-8}
\]

\[
\eta = -\ln(1 + b) \tag{1-9}
\]
Table 1-4. \( P^* \) and \( \eta \) Estimation for Standard Gas Price.

<table>
<thead>
<tr>
<th>Date</th>
<th>( P(t) )</th>
<th>( P(t-1) )</th>
<th>( P(t)-P(t-1) )</th>
<th>X-Variable</th>
<th>Y-Variable</th>
</tr>
</thead>
<tbody>
<tr>
<td>Jun 30, 1991</td>
<td>1.64</td>
<td>1.71</td>
<td>-0.07</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Jun 30, 1992</td>
<td>1.74</td>
<td>1.64</td>
<td>0.10</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Jun 30, 1993</td>
<td>2.04</td>
<td>1.74</td>
<td>0.30</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Jun 30, 1994</td>
<td>1.85</td>
<td>2.04</td>
<td>-0.19</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Jun 30, 1995</td>
<td>1.55</td>
<td>1.85</td>
<td>-0.30</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Jun 30, 1996</td>
<td>2.17</td>
<td>1.55</td>
<td>0.62</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Jun 30, 1997</td>
<td>2.32</td>
<td>2.17</td>
<td>0.15</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Jun 30, 1998</td>
<td>1.96</td>
<td>2.32</td>
<td>-0.36</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Jun 30, 1999</td>
<td>2.19</td>
<td>1.96</td>
<td>0.23</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Jun 30, 2000</td>
<td>3.68</td>
<td>2.19</td>
<td>1.49</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Jun 30, 2001</td>
<td>4.00</td>
<td>3.68</td>
<td>0.32</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Jun 30, 2002</td>
<td>2.95</td>
<td>4.00</td>
<td>-1.05</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Jun 30, 2003</td>
<td>4.88</td>
<td>2.95</td>
<td>1.93</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Jun 30, 2004</td>
<td>5.46</td>
<td>4.88</td>
<td>0.58</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Jun 30, 2005</td>
<td>7.33</td>
<td>5.46</td>
<td>1.87</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Jun 30, 2006</td>
<td>6.39</td>
<td>7.33</td>
<td>-0.94</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Jun 30, 2007</td>
<td>6.25</td>
<td>6.39</td>
<td>-0.14</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Jun 30, 2008</td>
<td>7.97</td>
<td>6.25</td>
<td>1.72</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Jun 30, 2009</td>
<td>3.67</td>
<td>7.97</td>
<td>-4.30</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Jun 30, 2010</td>
<td>4.48</td>
<td>3.67</td>
<td>0.81</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Jun 30, 2011</td>
<td>3.95</td>
<td>4.48</td>
<td>-0.53</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

\[ y = -0.2324x + 0.9504 \]
\[ R^2 = 0.129 \]

Figure 1-3. \( P^* \) and \( \eta \) Estimation for Standard Gas Price Using (AR(1)) Regression.
Table 1-5. Regression Parameters to Estimate P* and η.

<table>
<thead>
<tr>
<th>Regression Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>a</td>
</tr>
<tr>
<td>b</td>
</tr>
<tr>
<td>σε</td>
</tr>
</tbody>
</table>

Table 1-6. Estimated P* and η.

<table>
<thead>
<tr>
<th>MRM Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>P*</td>
</tr>
<tr>
<td>η</td>
</tr>
</tbody>
</table>

1.4.2.2.3. Annual Growth Rate for Prices

The annual price growth rate was required for the deterministic model implemented in the study, Price Floating Model. The model imposes a fixed annual growth rate to an initial price. The Floating Price model (Equation 1-10) was used to derive the equation for the growth rate r estimation (Equation 1-11). Annual wellhead price data (1990–2011) were used to estimate the average growth rate for standard gas prices as shown in (Table 1-7). The annual growth rate used in the study was 5% as shown in (Table 1-7).

\[ P_t = P_{t0} \times (1 + r)^t \]  \hspace{1cm} (1-10)

\[ r = \left( \frac{P_t}{P_{t0}} \right)^\frac{1}{t} - 1 \]  \hspace{1cm} (1-11)

Where

- \( P_t \): Gas price at current period
- \( P_{t0} \): Gas price at previous period
- \( r \): Annual price growth rate
t: Time in years

Table 1-7. Estimation of Average Annual Growth Rate for Standard Gas Price.

<table>
<thead>
<tr>
<th>Date</th>
<th>Time (Yrs)</th>
<th>U.S. Natural Gas Wellhead Price ($/Mscf)</th>
<th>Price Growth Rate (Fraction/Yr)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1990</td>
<td>0</td>
<td>1.71</td>
<td></td>
</tr>
<tr>
<td>1991</td>
<td>1</td>
<td>1.64</td>
<td>-0.041</td>
</tr>
<tr>
<td>1992</td>
<td>2</td>
<td>1.74</td>
<td>0.009</td>
</tr>
<tr>
<td>1993</td>
<td>3</td>
<td>2.04</td>
<td>0.061</td>
</tr>
<tr>
<td>1994</td>
<td>4</td>
<td>1.85</td>
<td>0.020</td>
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<td>5</td>
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<td>-0.019</td>
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<td>0.041</td>
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<tr>
<td>1997</td>
<td>7</td>
<td>2.32</td>
<td>0.045</td>
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<td>1998</td>
<td>8</td>
<td>1.96</td>
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<td>0.028</td>
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<td>2000</td>
<td>10</td>
<td>3.68</td>
<td>0.080</td>
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<tr>
<td>2001</td>
<td>11</td>
<td>4.00</td>
<td>0.080</td>
</tr>
<tr>
<td>2002</td>
<td>12</td>
<td>2.95</td>
<td>0.046</td>
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<tr>
<td>2003</td>
<td>13</td>
<td>4.88</td>
<td>0.084</td>
</tr>
<tr>
<td>2004</td>
<td>14</td>
<td>5.46</td>
<td>0.086</td>
</tr>
<tr>
<td>2005</td>
<td>15</td>
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<td>0.102</td>
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<tr>
<td>2006</td>
<td>16</td>
<td>6.39</td>
<td>0.086</td>
</tr>
<tr>
<td>2007</td>
<td>17</td>
<td>6.25</td>
<td>0.079</td>
</tr>
<tr>
<td>2008</td>
<td>18</td>
<td>7.97</td>
<td>0.089</td>
</tr>
<tr>
<td>2009</td>
<td>19</td>
<td>3.67</td>
<td>0.041</td>
</tr>
<tr>
<td>2010</td>
<td>20</td>
<td>4.48</td>
<td>0.049</td>
</tr>
<tr>
<td>2011</td>
<td>21</td>
<td>3.95</td>
<td>0.041</td>
</tr>
</tbody>
</table>

AVERAGE 3.645 0.049

1.4.2.3. **Natural Gas Price Modeling**

1.4.2.3.1. **Floating Price Model**

This model reflects a deterministic approach to price forecasting followed in this study. The floating price model imposes a fixed annual growth rate on price. The model assumes prices are inelastic to demand; this means a significant change in price has a
small impact on quantity demanded. In other words, demand increases over time as price increases. This model is widely used in the oil and gas industry (Bukhari and Jablonowski, 2012). Simply put, the model imposes an annual growth rate on an initial price (Equation 1-10). The initial price for standard gas was the long-run equilibrium price ($P^*$) calculated for MRM above. (Table 1-8) summarizes the parameters for the Floating Price model for the three types of natural gas.

The initial prices used in the study were the long-run mean prices ($P^*$), so that forecast models were mean equivalent. Table 4.10 shows the initial prices and growth rates for each crude grade used in this model. Table 4.11 and Figure 4.5 show the price forecasts of the Floating Price model. The table shows the heating contents gas price in $/Mscf and in $/MMBTU, and the annual growth rate. (Figure 1-4) shows the Floating Price model for the three types of gas over 40 years. (Table 1-9) shows a sample of the Floating Price Models for the three types of gas.

Table 1-8. Parameters for Floating Price Models.

<table>
<thead>
<tr>
<th>Gas Type</th>
<th>Heating Content (BTU/SCF)</th>
<th>Gas Prices ($/Mscf)</th>
<th>Gas Prices ($/MMBTU)</th>
<th>Gas Price Growth Rate (%/ Yr)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rich Gas</td>
<td>1236</td>
<td>$ 4.75</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Standard Gas</td>
<td>1028</td>
<td>$ 3.95</td>
<td>3.84</td>
<td>4.9%</td>
</tr>
<tr>
<td>Lean Gas</td>
<td>935</td>
<td>$ 3.59</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Figure 1-4. Floating Price Model for Rich, Standard and Lean Gas Prices.


<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Rich Gas Price ($/Mscf)</td>
<td>4.75</td>
<td>4.98</td>
<td>5.22</td>
<td>5.48</td>
<td>5.74</td>
<td>6.02</td>
<td>6.32</td>
<td>6.63</td>
<td>6.95</td>
<td>7.29</td>
<td>7.64</td>
</tr>
<tr>
<td>Standard Gas Price ($/Mscf)</td>
<td>3.95</td>
<td>4.14</td>
<td>4.34</td>
<td>4.56</td>
<td>4.78</td>
<td>5.01</td>
<td>5.25</td>
<td>5.51</td>
<td>5.78</td>
<td>6.06</td>
<td>6.36</td>
</tr>
<tr>
<td>Lean Gas Price ($/Mscf)</td>
<td>3.59</td>
<td>3.77</td>
<td>3.95</td>
<td>4.14</td>
<td>4.35</td>
<td>4.56</td>
<td>4.78</td>
<td>5.01</td>
<td>5.26</td>
<td>5.51</td>
<td>5.78</td>
</tr>
</tbody>
</table>

1.4.2.3.2. Mean Reversion Model (MRM)

1.4.2.3.2.1. Technical Background of Mean Reversion Model

The Mean Reversion Model is a more realistic approach to price forecasting, from an economic perspective, since it is believed that prices are correlated with marginal cost of production. The MRM reflects the decisions of suppliers as prices change. Suppliers increase quantity supplied in response to higher prices to maximize profit while they decrease production when prices are low to minimize losses. These types of reactions to
change in prices force prices to revert to a long-run equilibrium price (Bukhari, 2011). (Figure 1-5) illustrates how crude oil prices fluctuate and revert to a long-run equilibrium price over time; the blue line is crude prices and the red line is the long-run equilibrium price. Many different models have been developed to construct a Mean Reversion model. The Ornstein-Uhlenbeck model (Equation 1-12) used in this study has been commonly used due to its simplicity and practicality. In the formula, the term (P*-P) dictates the direction of the drift; the drift is positive if the current price is lower than the long-run mean price P*, and negative if the current price is greater than the long-run mean price P*. As a result, prices revert to the long-run equilibrium price P* by the drift term (Dias, 2010c). Moreover, the greater the difference between current price and long-run mean price, the greater the slope of reversion toward P*. The volatility grows initially and then stabilizes at a specific value over time (Dias, 2010c). (Equation 1-13) shows the logarithm for the price version of the MRM model, by substituting x=ln(P) in (Equation 1-12). Our preference was to work with the logarithm of price rather than price in constructing MRM because the logarithm of price is normally distributed that makes it easier to deal with than the lognormal distribution of price. Dealing with the logarithm of price facilitates Monte Carlo simulation and parameter estimation (Dias, 2010c). Parameter estimation becomes independent of price by working with the logarithm of price in the MRM model (Dias, 2010c).
Figure 1-5. Mean Reversion Sample Path (Bukhari, 2011).

\[ dP = \eta * P(P^* - P)dt + \sigma * P * dz \] (1-12)

Where

* \( P^* \) is the long-run equilibrium price
* \( \eta \) is the reversion rate
* \( dz \) (Wiener increment) = \( \varepsilon dt^{1/2} \)
* \( \varepsilon = \) standard normal distribution \( = N(0,1) \)
* \( \sigma = \) volatility of price

\[ dx = \eta(x^* - x)dt + \sigma dz \] (1-13)

Where

* \( x = \ln(P) \)

1.4.2.3.2.2. Formulation of Mean Reversion Model

(Equation 1-14) was the implemented Mean Reversion Model, that was a logarithm for the price version of the Ornstein-Uhlenbeck Mean Reversion Model.
(Equation 1-14) forecasts the price for a given time from the price for a previous time-step. The model requires the logarithm of price for the current time \( x(t) \), and the variance for the logarithm of price at the same period \( \text{Var}[x(t)] \); those two parameters can be calculated from (Equations 1-16 and 1-17), respectively. (Table 1-10) shows the parameters required to forecast prices, for standard gas, using MRM. The prices were forecasted using (Equation 1-14), by plugging the parameters from (Table 1-10) along with the calculated \( x(t) \) and \( \text{Var}[x(t)] \). (Figure 1-6) shows a sample price forecast using MRM for standard gas. A price floor of $0.90 was imposed on the MRM price model to avoid negative prices.

\[
P_t = e^{[x_t - \frac{1}{2} \text{Var}[x_t]]}
\]

\[
x^* = \ln(P^*)
\]

\[
x_t = x_{t-1} * e^{-\eta^* \Delta t} + x^* \ast (1 - e^{-\eta^* \Delta t}) + \sigma * \sqrt{(1 - e^{-2\eta^* \Delta t})/(2\eta^*)} * N(0,1)
\]

\[
\text{Var}[x_t] = (1 - e^{-2\eta^* t}) * \frac{\sigma^2}{2\eta}
\]

Table 1-10. Parameters for the MRM Standard Gas Price Model.

<table>
<thead>
<tr>
<th>Standard Gas Parameters</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>( \eta ) (Reversion Speed)</td>
<td>0.51</td>
</tr>
<tr>
<td>( P^* ) (Long-Run Mean Price)</td>
<td>4.94</td>
</tr>
<tr>
<td>( \ln(P^*) )</td>
<td>1.60</td>
</tr>
<tr>
<td>( \sigma ) (Volatility)</td>
<td>0.29</td>
</tr>
<tr>
<td>( P_{\text{min}} ) ($) / MMBTU</td>
<td>0.90</td>
</tr>
</tbody>
</table>
Figure 1-6. Mean Reversion Model Sample.

1.4.3. Reservoir Models

1.4.3.1. General Information

In our study, the production forecast model was based on Arps’ empirical model (Arps, 1945). Using a simplified production forecast model was sufficient for optimization, decision and risk analysis problems; moreover, it facilitated optimization and Monte Carlo simulation processes. The implementation of numerical reservoir simulation can limit optimization risk analysis (Monte Carlo simulation) study (Johnson et al., 2000; Lawal et al., 2008; Ettehadtavakkol et al., 2009). Decline curve analysis can substitute numerical reservoir simulators sufficiently, especially for gas reservoirs (Hook, 2010). Based on (Hook, 2010), decline curve analysis is more efficient when used to predict aggregate reservoir behavior (e.g., production profile for a portfolio of fields). (Odeh, 1969, 1982) suggested that the type of reservoir model should depend on the application and the objective of the study.
1.4.3.2. Modeling Assumptions

- It was assumed that the Arps empirical formula and material balance were sufficient to forecast production profile.
- Decline in a gas field follows hyperbolic decline.
- Each reservoir produces from a single-layer homogenous reservoir.
- Rich gas fields have been produced at higher rates due to their higher values. The cumulative productions for rich gas fields are higher than the fields for lean and standard gas.

1.4.3.3. Modeling Parameters

(Arps, 1945) developed the empirical relationship (Equations 1-18, 1-19, and 1-20) by examining production data from 149 oil fields during a pseudo-steady state period (Fetkovich et al., 1994, Li and Honre, 2003). The Arps formula is described by three parameters: initial flow rate ($q_i$), decline exponent or shape factor ($b$), and initial decline rate ($D_i$). $D_i$ is the rate at which the flow rate starts to decline; the decline exponent $b$ is the rate at which the initial decline rate $D_i$ changes with time. The decline curve from oil and gas fields can be classified into three categories based on the value of $b$: 1) Exponential decline (Equation 1-18), that tends to underestimate the reserves and is designated with a value of $b$ equal to 0 (in other words, the decline rate equals the initial decline rate $D_i$ throughout the declining part of the production profile); 2) Harmonic decline (Equation 1-19), that tends to overestimate the reserves and is designated by a value of $b$ equal to 1; and 3) Hyperbolic decline (Equation 1-20), that can be any curve between the harmonic
and exponential decline with a value of $b$ that varies between 0 and 1. (Figure 1-7) shows a sample of the three types of decline: exponential in green, harmonic in blue, and hyperbolic in red. Exponential decline is a straight line if plotted in a semi-log plot (Figure 1-8). Researchers attempted to interpret the Arps empirical formula physically (Li and Hore, 2003). An interpretation by (Fetkovich et al., 1994) proposed that the material balance and pseudo-steady state flow equations were the basis of the Arps model; moreover, they proposed a relationship between the parameters of the Arps equation and reservoir rock and fluid properties. The initial decline-rate $D_i$ and decline exponent $b$ are functions of the reservoir fluid and rock properties, and are calculated from production data. However, for simplicity they were calculated from (Equations 1-21, 1-22, 1-23, 1-24) as recommended by (Fetkovich et al., 1994), for single-layer homogenous reservoirs. The $n$ in those equations is the exponent of the back-pressure curve equations (Equations 1-25, 1-26). The value of $n$ varies between 0.5 and 1 for single-layer homogenous reservoirs where the $n$ of 1 represents low permeability reservoirs and the $n$ of 0.5 represents high permeability reservoirs (Fetkovich et al., 1994). (Table 1-11) summarizes the required parameter for decline curve analysis for the 12 natural gas fields. We intended to vary the values of $n$ over the 12 fields to analyze their impact on the optimization problem.

\[ q = q_i e^{-D_i t} \]  \hspace{1cm} (1-18)

\[ q = \frac{q_i}{(1+D_i t)} \]  \hspace{1cm} (1-19)

\[ q = \frac{q_i}{(1+bD_i t)^{1/b}} \]  \hspace{1cm} (1-20)

\[ D_i(Oil) = [(2n + 1)/2](q_i/EUR) \]  \hspace{1cm} (1-21)
\[ Di(Gas) = 2n(q_l/EUR) \] (1-22)

\[ b(Oil) = (2n - 1)/(2n + 1) \] (1-23)

\[ b(Gas) = (2n - 1)/2n \] (1-24)

\[ q_g = C_g \left( \bar{P}_r^2 - P_{wf}^2 \right)^n \] (1-25)

\[ q_o = J_o \left( \frac{P_r}{P_{r_i}} \right) \left( \bar{P}_r^2 - P_{wf}^2 \right)^n \] (1-26)

Figure 1-7. Mean Reversion Model Sample.

Figure 1-8. Mean Reversion Model Sample.
Table 1-11. Decline Curve Parameters for the 12 Fields.

<table>
<thead>
<tr>
<th>Field</th>
<th>Gas Type</th>
<th>Backpressure Exponents (n)</th>
<th>Decline Exponent (b)</th>
<th>Decline Rate (Di)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Rich Gas</td>
<td>0.65</td>
<td>0.23</td>
<td>0.16</td>
</tr>
<tr>
<td>2</td>
<td>Rich Gas</td>
<td>0.70</td>
<td>0.29</td>
<td>0.21</td>
</tr>
<tr>
<td>3</td>
<td>Rich Gas</td>
<td>0.68</td>
<td>0.26</td>
<td>0.14</td>
</tr>
<tr>
<td>4</td>
<td>Standard Gas</td>
<td>0.80</td>
<td>0.38</td>
<td>0.13</td>
</tr>
<tr>
<td>5</td>
<td>Standard Gas</td>
<td>0.78</td>
<td>0.36</td>
<td>0.17</td>
</tr>
<tr>
<td>6</td>
<td>Standard Gas</td>
<td>0.78</td>
<td>0.41</td>
<td>0.10</td>
</tr>
<tr>
<td>7</td>
<td>Standard Gas</td>
<td>0.85</td>
<td>0.44</td>
<td>0.08</td>
</tr>
<tr>
<td>8</td>
<td>Lean Gas</td>
<td>0.98</td>
<td>0.49</td>
<td>0.09</td>
</tr>
<tr>
<td>9</td>
<td>Lean Gas</td>
<td>1.00</td>
<td>0.50</td>
<td>0.11</td>
</tr>
<tr>
<td>10</td>
<td>Lean Gas</td>
<td>0.85</td>
<td>0.41</td>
<td>0.07</td>
</tr>
<tr>
<td>11</td>
<td>Lean Gas</td>
<td>0.81</td>
<td>0.38</td>
<td></td>
</tr>
<tr>
<td>12</td>
<td>Lean Gas</td>
<td>0.91</td>
<td>0.45</td>
<td></td>
</tr>
</tbody>
</table>

1.4.3.4. Production Profile Forecasting

The forecasting model requires the following parameters for each field: reserves, current cumulative production, production rate capacity, and end of plateau expressed as percentage of reserves. The model begins by forecasting production capacity, that was equal to the maximum production capacity specified for a field until the cumulative production equaled the end of the plateau value. At that point, the Arps hyperbolic equation was implemented to forecast capacity. Then, the production rate equals the value assigned by the optimization algorithm. If the production rate assigned was lower than the capacity of the field, the production rate continued at the same rate until it equaled the forecasted production capacity; then, the production rate followed the capacity profile. (Figure 1-9) shows a production profile forecast for Field 4. Initially, capacity equaled the maximum potential for the field; in other words, the field did not reach the end of the plateau stage. In year 6, the end of the plateau stage was reached and the capacity was forecasted using the Arps model. The production rate assigned by the optimizer continued until the rate equaled the forecasted capacity; at that point the rate followed the capacity profile.
1.4.4. Cost Models

(Kennedy, 1993) developed a cost model for oil and gas fields using actual data and commercial software. The cost model covers all aspects of field development; it incorporates oil and gas fields, onshore and offshore fields, drilling cost, pipeline costs, and facility costs. (Bittencourt, 1997) implemented this cost model for his field development optimization study. Our study incorporated only producing fields. As a result, pipeline and facility costs were not considered in our study.

We modified the actual cost model to account for horizontal drilling and inflation. The GDP deflator was used to move the cost model to 2011 dollars. Fifteen days were added to drill-days for drilling a 2000-ft. horizontal section. In other words, 133 ft./day rate of penetration was used to drill a horizontal section.
1.4.4.1. Modeling Assumptions

- The model was representative of actual costs.
- Rate of penetration was around 133 ft./day for drilling a horizontal section.
- The GDP price deflator was sufficient to account for the time value of money.

1.4.4.2. Modeling Parameters

The gas development cost aspect of the cost model was used since our study dealt with gas fields. This section details the two parts of the cost model implemented: onshore drilling costs and offshore drilling costs.

1.4.4.2.1. Onshore Drilling Costs

The drilling costs consist of tangible costs—the costs for tubular and casing—and the intangible costs—the costs for rig rental and support for the rig.

The intangible drilling costs include the cost of rig rental, and of rig support and supervision. The support and supervision costs cover the following items: contract labor, casing crew and equipment, cement services, bits, formation testing, equipment rental, fuel, water, power, logging, perforating, and miscellaneous wireline operations. The intangible drilling costs were calculated using (Equation 1-27), that was the product of the sum of rig rental and support rate, and rig time required to drill a well. The rig day-rate used in our study was $10,000/day that was the average for reported values for rig day-rate from different parts of the world by (Kennedy, 1993). The rig day-rate was then
escalated, using the GDP deflator, to $14,479/day in 2011 dollars. (Figure 1-10) was used to obtain drill days required to drill a well as a function of reservoir depth. Kennedy’s model had only the vertical-well curve; we added 15 days to drill a 2000-ft. horizontal section as shown in the figure. (Tables 1-12 and 1-13) show the support and supervision rates as a function of field’s remoteness, in 1993 and 2011 dollars, respectively. (Table 1-14) lists the definitions of the field’s remoteness (Kennedy, 1993).

Onshore tangible drilling costs include the costs of tubular and casings. The tangible costs can be obtained from (Figure 1-11), that expresses the costs in thousands of dollars as a function of well depth. The GDP deflator was implemented to bring the costs to 2011 dollars.

\[
\text{Intangible Drilling Costs} = \text{Rig Time} \times (\text{Rig Rental Rate} + \text{Support and Supervision Rate})
\]

(1-27)

Figure 1-10. Drill Days for Onshore Drilling as Function of Reservoir Depth.
Table 1-12. Rig Support and Supervision Rate in 1993 Dollars.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>7500</td>
<td>3750</td>
<td>10000</td>
<td>50000</td>
</tr>
<tr>
<td>2</td>
<td>10000</td>
<td>5000</td>
<td>15000</td>
<td>7500</td>
</tr>
<tr>
<td>3</td>
<td>12500</td>
<td>6250</td>
<td>20000</td>
<td>10000</td>
</tr>
<tr>
<td>4</td>
<td>15000</td>
<td>7500</td>
<td>30000</td>
<td>15000</td>
</tr>
<tr>
<td>5</td>
<td>20000</td>
<td>10000</td>
<td>50000</td>
<td>25000</td>
</tr>
</tbody>
</table>

Table 1-13. Rig Support and Supervision Rate in 2011 Dollars.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>10860</td>
<td>5430</td>
<td>14479</td>
<td>72397</td>
</tr>
<tr>
<td>2</td>
<td>14479</td>
<td>7240</td>
<td>21719</td>
<td>10860</td>
</tr>
<tr>
<td>3</td>
<td>18099</td>
<td>9050</td>
<td>28959</td>
<td>14479</td>
</tr>
<tr>
<td>4</td>
<td>21719</td>
<td>10860</td>
<td>43438</td>
<td>21719</td>
</tr>
<tr>
<td>5</td>
<td>28959</td>
<td>14479</td>
<td>72397</td>
<td>36198</td>
</tr>
</tbody>
</table>

Table 1-14. Definition of Field’s Remoteness (Kennedy, 1993).

<table>
<thead>
<tr>
<th>Remoteness</th>
<th>Characteristics</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>A mature area in terms of exploration and production in which rigs and oilfield services are readily available. This includes experienced personnel for supervision. In such places the annual well count is measured in 100's.</td>
</tr>
<tr>
<td>2</td>
<td>Similar to 1 but with a lower level of activity resulting in common costs being distributed over a smaller number of wells.</td>
</tr>
<tr>
<td>3</td>
<td>Typically this is an area with an active hydrocarbon industry which ensures the availability of goods and services.</td>
</tr>
<tr>
<td>4</td>
<td>Similar to 3 but with a relatively undeveloped supply industry. Some services may be available, but others may need to be established using foreign contractors.</td>
</tr>
<tr>
<td>5</td>
<td>Frontier areas in which exploration is taking place for the first time. In such areas, the service companies frequently work out of the oil company offices. Supervision of a well may be conducted both from the local and global headquarters of the companies participating.</td>
</tr>
</tbody>
</table>
1.4.4.2.2. Offshore Drilling Costs

The offshore drilling cost model was very similar to the onshore one; the differences were in the values of the model components since offshore drilling costs more than onshore drilling. Drilling costs consisted of tangible and intangible drilling costs.

The offshore intangible drilling costs include the cost of rig rental, and of rig support and supervision. The support and supervision costs cover the following items: contract labor, casing crew and equipment, cement services, bits, formation testing, equipment rental, fuel, water, power, logging, perforating, miscellaneous wireline operations, and offshore workboats and other marine support. The intangible drilling costs were calculated using (Equation 1-27), that was the product of the sum of rig rental and support rate, and rig time required to drill a well. The rig day-rate used in our study was $28,000/day, that was the average of reported values for the jack-up day-rate from
different parts of the world by (Kennedy, 1993). The rig day-rate was then escalated using the GDP deflator, to $41,000/day in 2011 dollars. (Figure 1-12) was used to obtain drill days required to drill a well as a function of reservoir depth. Kennedy’s model had only the vertical-well curve; we added 15 days to drill a 2000-ft. horizontal section as shown in the figure. (Tables 1-12 and 1-13) show the support and supervision rates, as a function of field’s remoteness, in 1993 and 2011 dollars, respectively. (Table 1-14) lists the definitions of the field’s remoteness (Kennedy, 1993).

Offshore tangible drilling costs include the costs of tubular and casings. The tangible costs can be obtained from (Figure 1-13), that expresses the costs in thousands of dollars as a function of well depth. The GDP deflator was implemented to bring the costs to 2011 dollars.

![Offshore Drill Days](image)

Figure 1-12. Drill Days for Offshore Drilling as Function of Reservoir Depth.
1.4.5. Integrated Optimization Model

The integration of all models in our study, including price models, cost models, reservoir simulation models, Monte Carlo simulation process, and optimization models, is discussed in this section. The integrated model turns raw numbers from the different models (i.e., price model) into a meaningful results and figures those can help in improving decision-making. This section details modeling assumptions and the formulation of the optimization problem, and offers a description of the integrated model.

This section describes how the different models in the study communicate and process the data. The integrated model receives meaningless numbers from the models (i.e., cost and reservoir simulation models), and returns meaningful results that can assist in decision-making. The topics discussed here are modeling assumptions, integrated
model flowchart, formulation of the optimization problem, and description of the integrated model.

1.4.5.1. Modeling Assumptions

1.4.5.1.1. Assumptions Related to Field Parameters Estimation

Actual field data for the portfolio of fields were difficult to acquire due to the political sensitivity of releasing such data. As a result, the parameters for the 12 fields were sanitized and generated hypothetically. (Table 1-15) shows the range of numbers, specified by industry experts, from that the parameters were selected. These ranges of numbers were classified by natural gas type and reflect actual field data. The heating content is the amount of energy stored in a specific volume of natural gas expressed in British Thermal Unit per standard cubic foot of gas (BTU/SCF). This heating content controls the price of a unit volume of natural gas. The portfolio of fields was assumed to produce three different types of natural gas, differentiated by heating content: Rich Gas (1236 BTU/SCF), Standard Gas (1025 BTU/SCF), and Lean Gas (935 BTU/SCF). The heating content for the U.S. standard natural gas is 1028 BTU/SCF (Matheson, 2012, National Petroleum Council, 2012). The reserve range, in trillion cubic feet, increases as the heating content decreases; this reflects the fact that gas fields rich in condensate (Rich Gas) have been produced at higher depletion rates due to their higher values. End of Plateau represents the point in time when a reservoir pressure cannot support the plateau rate, and the rate starts to decline. End of plateau was expressed in percentage of reserve range.
produced; for example, an end of plateau of 50% means that the production rate starts to decline once 50% of the reserves are produced. In other words, once the ratio of cumulative production to reserves equals to the end of plateau, the production rate starts to decline. The end of plateau ranges between 50 and 70% of reserves for all gas types. Current cumulative production represents the cumulative volume produced at the beginning of the study from each field, expressed in percentage of reserves. Similar to the ranges for the reserves, range of cumulative production was directly proportional to the value of heating content; in other words, the greater the heating content, the greater the cumulative volume produced due to the higher intrinsic value of the rich gas fields. The maximum annual depletion rate, expressed in percentage of reserves, reflects the physical constraints of the production facilities, that is based on reservoir engineering studies to ensure healthy and efficient production operations. This maximum depletion rate represents the upper bound of the decision variables in the optimization model. The minimum facility operating rate is the minimum production rate a facility must handle for economical and safe operations. The minimum facility operating rates represent the lower bound of the decision variables for the optimization problem. The next parameter is the annual decline rate at that the production capacity declines annually. This decline rate is not related to production forecasting; however, it is used to calculate the number of new wells required to offset the annual decline in production rate. In other words, the annual decline rate is a parameter for drilling cost calculations. Annual decline for rich gas fields is greater than for standard and lean gas fields because rich gas fields deplete at higher rates. Reservoir depth, expressed in feet, is a parameter required for the cost model implemented in the study. The production rate realized from a newly drilled well is a
function of cumulative production (reservoir maturity) and can be calculated from (Equation 1-28). This equation was developed by assuming new wells, in young fields (5% of reserve produced), can provide at a rate of 30,000 Mscfd while new wells, in mature fields (63% of reserve produced), can provide at a rate of 10,000 Mscfd. The relationship is developed by fitting a straight line between the two points as shown in (Figure 1-14). A floor value of 10,000 Mscfd was imposed on the formula to make it realistic (Equation 1-28). The range of fixed operational expenditure OPEX was expressed in $ per Mscf of original capacity required. The variable operating expenditure OPEX was expressed in $ per Mscf produced.

Table 1-15. Ranges of Field Parameters Classified by Gas Type.

<table>
<thead>
<tr>
<th>Crude Grade</th>
<th>Unit</th>
<th>Rich Gas</th>
<th>Standard Gas</th>
<th>Lean Gas</th>
</tr>
</thead>
<tbody>
<tr>
<td>Heating Content</td>
<td>BTU/SCF</td>
<td>1236</td>
<td>1028</td>
<td>935</td>
</tr>
<tr>
<td>Reserves Range</td>
<td>Trillion cf</td>
<td>1-27</td>
<td>3-55</td>
<td>5-80</td>
</tr>
<tr>
<td>End of Plateau</td>
<td>% of Depletion Stage</td>
<td>50-70</td>
<td>50-70</td>
<td>50-70</td>
</tr>
<tr>
<td>Current Cumulative Production</td>
<td>% of Reserves</td>
<td>25-63</td>
<td>15-58</td>
<td>5-54</td>
</tr>
<tr>
<td>Maximum Annual Depletion Rate Range</td>
<td>% of Reserves</td>
<td>2-8</td>
<td>2-6</td>
<td>2-4</td>
</tr>
<tr>
<td>Min Operating Rate</td>
<td>(% of Production Potential)</td>
<td>30</td>
<td>30</td>
<td>30</td>
</tr>
<tr>
<td>Annual Decline Rate of Production</td>
<td>(% of Original Capacity)</td>
<td>6</td>
<td>5</td>
<td>4</td>
</tr>
<tr>
<td>Depth of Reservoir</td>
<td>Ft</td>
<td>10,000-15,000</td>
<td>10,000-15,000</td>
<td>10,000-15,000</td>
</tr>
<tr>
<td>Well Costs</td>
<td>MS/MMscf Required</td>
<td>Kennedy’s Models</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Additional Rate from New Wells</td>
<td>Mscfd/ well</td>
<td>Max(10,000), (Add. Rate per Well = -34483 * Depletion Stage + 31724])</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fixed OPEX</td>
<td>($/Mscf)</td>
<td>45-100</td>
<td>55-115</td>
<td>65-130</td>
</tr>
<tr>
<td>Variable OPEX</td>
<td>($/Mscf)</td>
<td>0.30-1.0</td>
<td>0.50-1.20</td>
<td>0.70-1.40</td>
</tr>
</tbody>
</table>
Figure 1-14. Production Rate Realized from a Newly Drilled Well as a Function of Depletion Stage.

Additional Rate from New Well =

Max[(10,000) OR (−34483 * Depletion Stage + 31,724)] \hspace{1cm} (1-28)

1.4.5.1.2. General Modeling Assumptions

This section discusses important assumptions related to the integrated model.

1) Variable OPEX was assumed to be independent of natural hydrocarbon prices in the integrated model.

2) Fields can sustain a production rate for a whole year.

3) The annual depletion rate, for each field, was a percentage of the original reserve of that field.

4) The implemented Floating Price model and the Mean Reversion model were sufficient to forecast natural gas prices.

5) Each field produces from a single reservoir.

6) Reservoirs were modeled as single-layer homogenous in properties.
7) Fields were placed into production throughout the life of the study to ensure healthy pipelines and production facilities. This assumption relieves some computation load from the optimization algorithm and Monte Carlo simulation process.

8) All fields were existing and producing.

9) End of plateau represents a point in time, expressed in depletion stage or percentage of reserve, when capacity starts to decline.

10) Field production capacity was maintained by drilling new wells.

11) One thousand iterations were sufficient to minimize simulation error in the Monte Carlo simulation process.

1.4.5.2. Integrated Model Flowchart

(Figure 1-15) summarizes the processes of the integrated model, that follows similar approach implemented by (Bukhari and Jablonowski, 2011). The process starts by specifying the approach, deterministic or probabilistic, for forecasting prices and production profiles. Natural gas prices were forecasted deterministically using the Floating Price model, and probabilistically using the Mean Reversion Model. A production forecast was modeled using the Arps empirical model for both deterministic and probabilistic approaches; however, reserves were modeled probabilistically in the case of probabilistic production forecasting. The way the production forecast model was programmed makes the production profile a probability distribution when the reserves were modeled as probability distributions. Most of the uncertainty in reservoir
performance came from the uncertainty in reserves estimates. In the case of deterministic price and production rate forecasting, the outcomes were single price and production rate values for each time step, respectively. Those values were supplied to the economic evaluation model to calculate the net present value NPV for the entire company as a single value. On the other hand, in the case of probabilistic price and production profile forecasting, the outcomes were the probability distribution of price and production rate for each time step, respectively. Those probability distributions were supplied to the economic evaluation model to calculate the NPV as a probability distribution. Then, those production profiles and gas prices along with user input were supplied to the optimization algorithm, that iterates with price, production, cost, and economic models to calculate the production rate allocation and maximizes the specified objective function subject to the constraints of the problem. Three objective functions were analyzed in the study: total NPV, total plateau length, and both total NPV and total plateau length. In the case of the deterministic approach, those objective functions were single values. On the other hand, the objective functions were the mean of the probability distributions, in the case of the probabilistic approach, as recommended by (Powell and Baker, 2010). Genetic Algorithm GA (Evolutionary Algorithm) was the optimization algorithm implemented in our study due to its capability of searching many different areas, of feasible solutions, on parallel. In addition, the GA is capable of optimizing nonlinear and non-smooth optimization problems. Nonlinear optimization problems are those problems in that the objective function is a nonlinear function of the decision variables. The non-smooth problems involves discontinuity in the objective function; this discontinuity can stem from the use of the following functions: if, max, and min.
1.4.5.3. Optimization Problem Formulation

An optimization problem usually consists of three parts: objective function, decision variables, and constraints. Some optimization problems do not require constraint(s). The optimization algorithm searches for the proper value(s) for decision variable(s) in order to maximize the objective function while obeying the physical or financial constraint(s) (Bukhari, 2011). Three objective functions were evaluated. Deterministically, those functions were total NPV, total plateau length, and weighted sum of total NPV and total plateau length while probabilistically, those functions were E[total NPV], E[total plateau length], and E[weighted sum of total NPV and total plateau length]. The decision variables were the production rate for each field. Three constraints were imposed on the optimization model: 1) Minimum facility operating rate for each field (lower bound) to ensure safe and economical operation, 2) Production capacity for each field (upper bound), and 3) Total target daily rate, that represents supply contract commitment. Here is a summary of the optimization problem formulation.
Maximize:

Total NPV

Total Plateau Length

Total NPV + Total Plateau Length

By Calculating

\[
\text{Production Rate} \forall \text{ Fields}
\]

Subject to

\[
\text{Production Rate} \leq \text{Production Potential} \forall \text{ Fields}
\]

\[
\text{Production Rate} \geq \text{Minimum Facility Rate} \forall \text{ Fields}
\]

\[
\sum_{f=1}^{F} \text{Production Rate}(f) = \text{Total Target Rate}
\]

1.4.5.4. Integrated Model Description

The integrated model incorporates the various models within our study in order to turn raw numbers from the different models (i.e., price model) into meaningful results and figures that assist decision-making. The incorporated models were price models, production forecast models, cost models, economic models, Monte Carlo simulation processes, and an optimization algorithm. Risk Solver Platform (RSP), Excel Add-in, was the main tool used in our study to conduct various types of processes, including statistical processes, sampling and simulation, and optimization processes.

The integrated model was classified into three parts as recommended by (Powell and Baker, 2010): parameters module, calculations module, and input & output module.
This structure enhances the clarity of the model (Powell and Baker, 2010). This following section discusses these modules.

1.4.5.4.1. Parameter Module

The parameter module was divided into three sub-modules: Deduction Rates, Price Forecasting Parameters, and Fields’ Parameters.

1.4.5.4.1.1. Deduction Rates Sub-Module

This sub-module lists the deduction rates required in the economic model: tax rate, discount rate, and royalty rate. (Table 1-16) shows these deduction rates that were 35%, 10%, and 20% for tax rate, discount rate, and royalty rate, respectively. These values are reasonable for the oil and gas industry. The impact of the discount rate on the optimization problem was discussed in the sensitivity analysis section.

<table>
<thead>
<tr>
<th>Deduction Rates Sub-Module</th>
<th>35%</th>
<th>10%</th>
<th>20%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tax rate</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Discount Rate</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Royalty</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

1.4.5.4.1.2. Price Forecasting Parameter Sub-Module

The second sub-module lists the parameters required to forecast prices, deterministically and probabilistically. First, the deterministic price model (the Floating
Price model) assumes a known initial price and a fixed annual growth rate. Prices for the three different natural gas types (Rich, Standard, and Lean gas) were forecasted. From historical U.S. wellhead gas price (EIA 2012), expressed in $/Mscf, and the heating content of standard gas, the initial standard gas price was calculated in $/BTU using (Equation 1-29). Initial prices, in $/Mscf, for rich and lean gas were calculated from the standard gas price in $/BTU and the heating contents of the rich and lean gas using (Equation 1-30). (Table 1-17) shows the calculated initial prices in $/Mscf for the three gas types along with the annual growth rate of 5%, that was calculated from U.S. wellhead gas prices (1990-2011). Second, the probabilistic price forecast approach, that was the Mean Reversion model MRM, assumes that prices revert to a long-run equilibrium price (P*) with specific volatility (σ) and reversion rate (η). The MRM model assumes that prices are correlated with marginal cost of production, where suppliers react to changes in prices; these types of reactions force prices to revert to P*. A log of prices was used to build the MRM model because the distribution for the log of price is normal that was easier to deal with. The use of the log of price facilitates Monte Carlo simulation and parameter estimation. Parameter estimations are independent of log of price (Dias, 2010c). Prices for standard gas were forecasted using the MRM model. Then, the prices for the Rich and Lean gas were forecasted in a similar way for the deterministic approach using (Equations 1-29 and 1-30). (Table 1-18) shows the parameters required to forecast prices for standard gas using the MRM model.

\[
\text{Natural Gas Price} \left( \frac{\$}{BTU} \right) = \frac{\text{Gas Price} \left( \frac{\$}{SCF} \right)}{\text{Heating Content} \left( \frac{BTU}{SCF} \right)}
\] (1-29)
\[
\text{Natural Gas Price } \left( \frac{\$}{\text{MSCF}} \right) = \text{Gas Price} \left( \frac{\$}{\text{BTU}} \right) \ast \text{Heating Content} \left( \frac{\text{BTU}}{\text{SCF}} \right) \ast \]

1000

(1-30)

Table 1-17. Floating Price Model Parameters.

<table>
<thead>
<tr>
<th>Gas Type</th>
<th>Heating Content (BTU/SCF)</th>
<th>Gas Price ($/Mscf)</th>
<th>Gas Price ($/MMBTU)</th>
<th>Gas Price Growth Rate (%/Yr)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rich Gas</td>
<td>1236</td>
<td>$4.75</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Standard Gas</td>
<td>1028</td>
<td>$3.95</td>
<td>3.84</td>
<td>4.9%</td>
</tr>
<tr>
<td>Lean Gas</td>
<td>935</td>
<td>$3.59</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 1-18. Mean Reversion Model Parameters for Standard Gas.

<table>
<thead>
<tr>
<th>Standard Gas Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\eta) (Reversion Speed)</td>
</tr>
<tr>
<td>(P^*) (Long-Run Mean Price)</td>
</tr>
<tr>
<td>Ln(P^*)</td>
</tr>
<tr>
<td>(\sigma) (Volatility)</td>
</tr>
<tr>
<td>(P_{\min})($/MMBTU)</td>
</tr>
</tbody>
</table>

1.4.5.4.1.3. *Fields’ Parameters Sub-Module*

This sub-module presents the fields’ parameters needed for production forecasting and economic evaluation models. This sub-module consists of three sections: Fields’ General Parameters, Production Forecast Parameters, and Well Cost Parameters.

(Table 1-19) presents the fields’ general parameters for deterministic production forecasting; these parameters are gas type, heating content, reserves, end of plateau, current cumulative production, maximum annual depletion, production potential, facility minimum operating rate, and fixed and variable OPEX. The blue entries in the table are hard input while the black ones are functions of other parameters. The heating content was set by specifying the heating content for standard gas in the U.S. as 1028 BTU/SCF;
then the heating content was increased arbitrarily to 1236 BTU/SCF for rich gas and decreased to 935 BTU/SCF for lean gas. The reserves were specified from the range stated for each gas type in the general assumptions section. The end of plateau is the depletion stage for cumulative production when the production rate begins to decline; the values for the end of plateau were selected from ranges stated in the general assumptions section. Current cumulative production indicates the produced volume from each of the reservoirs at the beginning of the study. Moreover, it represents the maturity of the fields. The values of the current cumulative production are specified from the ranges stated in the general assumptions section. The maximum annual depletion rate, expressed in percentage of reserves, reflects the physical constraints of the production facilities, that were based on reservoir engineering studies to ensure healthy and efficient production and reservoir sweeping operations. The values for the maximum depletion rate were specified from the ranges stated in the general assumptions section. This maximum depletion rate represents the upper-bound of the decision variables in the optimization model. The original production potential, expressed in MMscfd, reflects the maximum depletion rate. The minimum facility operating rate is the minimum production rate a facility must handle for economical and safe operation. The minimum facility operating rates represent the lower-bound of the decision variables for the optimization problem. Fixed operating expenditures OPEX is the cost incurred once the field is in production. The variable OPEX is a function of the production rate.

In the probabilistic case, the fields’ general parameters differ only in the reserves. Our study evaluated, probabilistically, the reserves as triangular and lognormal distributions. Our model was designed such that the forecasted production profile was a
function of the reserve; in other words, the production profile was a probability distribution. (Table 1-20) shows the fields’ general parameters for triangular distribution for reserves. Triangular distribution requires three parameters: minimum value, most likely value, and maximum value. The base case reserves were the most likely value and were the reserves for the deterministic case (Table 1-19). The Uncertainty factor dictates how uncertain the reserve is; in other words, the factor affects distance between the minimum and maximum values of the reserves in the triangular distribution. Field size and maturity were incorporated in calculating the uncertainty factor as shown in (Equation 1-33). The uncertainty factor is the ratio of the field size ratio to the current cumulative production plus one-half; the one-half signifies the impact and increases the value of the uncertainty factor. The uncertainty factor increases as field size increases and decreases as current cumulative production increases; this reflects the fact that as field size increases, the uncertainty in reserves increases because more wells and production data are needed to cover a big reservoir than a smaller one. Moreover, the uncertainty in reserves decreases as current cumulative production increases (field matures); mature fields tend to reveal more information with production data. The field size ratio, for a specific field, was the ratio of its reserve to the total reserves as shown in (Equation 1-34). The minimum and maximum reserve values were calculated using (Equations 1-35 and 1-36), respectively. (Equation 1-35) states that if the uncertainty factor is less than 1, the minimum reserve value equals base case reserves minus the base case reserves times the uncertainty factor. However, if the uncertainty factor equals 1, a reserves floor value of 3 trillion SCF is imposed. This floor value prevents the reserves from having zero value. (Equation 1-36) states that the maximum reserve value equals the base case reserve
plus the base case reserve times the uncertainty factor. Note that plateau length is a probability distribution in the case of probabilistic reserves estimation.

The second method to model reserves is the lognormal distribution. (Table 1-21) shows the fields’ general parameters for lognormal distribution for reserves. The lognormal distribution requires two parameters: mean and standard deviation. The mean reserve is the value of the deterministic case for each field. The uncertainty factor dictates how large the standard deviation of the reserve distribution is; it represents how uncertain the reserve is. (Equation 1-37) states that the reserves’ standard deviation is the product of the reserve base case and the uncertainty factor. The uncertainty factor and field size ratio were calculated using the same equations in the triangular distribution reserve (Equation 1-33 and 1-34), respectively. The uncertainty factor is the ratio of the field size ratio to the current cumulative production plus one-half; the one-half signifies the impact and increases the value of the uncertainty factor. The uncertainty factor incorporates the impact of field size and maturity on the uncertainty of reserves. The uncertainty factor increases as field size increases and decreases as current cumulative production increases; this reflects the fact that as field size increases, uncertainty in reserves increases because more wells and production data are needed to cover a big reservoir. Moreover, the uncertainty in reserves decreases as current cumulative production increases (a field matures); mature fields tend to reveal more information with production data. Note that plateau length is a probability distribution in the case of probabilistic reserves estimation.

The second section has to do with the fields’ parameters sub-module and consists of the parameters required for a production forecast model. The decline curve analysis using the Arps empirical model was implemented to forecast production for each field.
There are different, numerical and analytical, reservoir models; for example, (Ettehadtavakko et al., 2009) built a mathematical reservoir tank model for optimization purposes. Our model implemented a simplified decline curve analysis model to analyze the problem of capacity management under uncertainties of reservoir performance and market behavior. The use of a numerical simulation model can limit the risk, uncertainty, and optimization analyses (Johnson et al., 2000; Lawal et al., 2008; Ettehadtavakkol et al., 2009). Moreover, the type and complication of the reservoir model implemented in a study depends on the application and objective of that study (Odeh, 1969, and Odeh, 1982). (Table 1-22) lists the parameters required for decline curve analysis for the 12 fields; these parameters assume that each field consists of a single-layer homogenous gas reservoir. The back pressure exponent n was selected randomly from the range 0.5 and 1, that represents a single-layer homogenous gas reservoir (Fetkovich et al., 1995). The decline exponent b and the initial decline rate Di were calculated from (Equations 1-31 and 1-32), respectively.

The last section of this sub-module lists the parameters required for the drilling cost model as shown in (Table 1-23). These parameters were estimated from (Kennedy, 1993; and Bittencourt and Horne, 1997). The reservoir depth was used to calculate the drill-day required to drill a well. The remoteness varies between 1 and 5 where 5 is the most remote. More details about these parameters can be found in the cost models section.
Table 1-19. Fields’ General Parameters for Deterministic Production Forecasting.

<table>
<thead>
<tr>
<th>Field</th>
<th>Gas Type</th>
<th>Heating Content (BTU/SCF)</th>
<th>Reserves (Trillion scf)</th>
<th>Base Case Reserves (Trillion scf)</th>
<th>Field Size Ratio</th>
<th>End of Plateau (% of Dep. Stage)</th>
<th>Maximum Annual Allowed Depletion Rate (%)</th>
<th>Original Production Potential (MMscf/d)</th>
<th>Facility Minimum Rate (MMscf/d)</th>
<th>OPEX, Fixed Cost ($/Mscf req.)</th>
<th>OPEX, Variable Cost ($/Mscf)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Rich Gas</td>
<td>1236</td>
<td>1236</td>
<td>1028</td>
<td>27.0</td>
<td>11.0</td>
<td>10.0</td>
<td>1028</td>
<td>65.0</td>
<td>0.95</td>
<td>0.4</td>
</tr>
<tr>
<td></td>
<td>Rich Gas</td>
<td>1236</td>
<td>1236</td>
<td>1028</td>
<td>27.0</td>
<td>11.0</td>
<td>10.0</td>
<td>1028</td>
<td>65.0</td>
<td>0.95</td>
<td>0.4</td>
</tr>
<tr>
<td></td>
<td>Lean Gas</td>
<td>1236</td>
<td>1236</td>
<td>1028</td>
<td>27.0</td>
<td>11.0</td>
<td>10.0</td>
<td>1028</td>
<td>65.0</td>
<td>0.95</td>
<td>0.4</td>
</tr>
<tr>
<td></td>
<td>Lean Gas</td>
<td>1236</td>
<td>1236</td>
<td>1028</td>
<td>27.0</td>
<td>11.0</td>
<td>10.0</td>
<td>1028</td>
<td>65.0</td>
<td>0.95</td>
<td>0.4</td>
</tr>
<tr>
<td></td>
<td>Lean Gas</td>
<td>Lean Gas</td>
<td>Lean Gas</td>
<td>Lean Gas</td>
<td>Lean Gas</td>
<td>Lean Gas</td>
<td>Lean Gas</td>
<td>Lean Gas</td>
<td>Lean Gas</td>
<td>Lean Gas</td>
<td>Lean Gas</td>
</tr>
</tbody>
</table>

Table 1-20. Fields’ General Parameters for Probabilistic Production Forecasting, Triangular Reserves.

<table>
<thead>
<tr>
<th>Field</th>
<th>Gas Type</th>
<th>Heating Content (BTU/SCF)</th>
<th>Reserves (Trillion scf)</th>
<th>Base Case Reserves (Trillion scf)</th>
<th>Field Size Ratio</th>
<th>End of Plateau (% of Dep. Stage)</th>
<th>Maximum Annual Allowed Depletion Rate (%)</th>
<th>Original Production Potential (MMscf/d)</th>
<th>Facility Minimum Rate (MMscf/d)</th>
<th>OPEX, Fixed Cost ($/Mscf req.)</th>
<th>OPEX, Variable Cost ($/Mscf)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Rich Gas</td>
<td>1236</td>
<td>1236</td>
<td>1028</td>
<td>27.0</td>
<td>11.0</td>
<td>10.0</td>
<td>1028</td>
<td>65.0</td>
<td>0.95</td>
<td>0.4</td>
</tr>
<tr>
<td></td>
<td>Rich Gas</td>
<td>1236</td>
<td>1236</td>
<td>1028</td>
<td>27.0</td>
<td>11.0</td>
<td>10.0</td>
<td>1028</td>
<td>65.0</td>
<td>0.95</td>
<td>0.4</td>
</tr>
<tr>
<td></td>
<td>Lean Gas</td>
<td>1236</td>
<td>1236</td>
<td>1028</td>
<td>27.0</td>
<td>11.0</td>
<td>10.0</td>
<td>1028</td>
<td>65.0</td>
<td>0.95</td>
<td>0.4</td>
</tr>
<tr>
<td></td>
<td>Lean Gas</td>
<td>1236</td>
<td>1236</td>
<td>1028</td>
<td>27.0</td>
<td>11.0</td>
<td>10.0</td>
<td>1028</td>
<td>65.0</td>
<td>0.95</td>
<td>0.4</td>
</tr>
<tr>
<td></td>
<td>Lean Gas</td>
<td>Lean Gas</td>
<td>Lean Gas</td>
<td>Lean Gas</td>
<td>Lean Gas</td>
<td>Lean Gas</td>
<td>Lean Gas</td>
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<td>Lean Gas</td>
<td>Lean Gas</td>
<td>Lean Gas</td>
</tr>
</tbody>
</table>

Table 1-21. Fields’ General Parameters for Probabilistic Production Forecasting, Lognormal Reserves.

<table>
<thead>
<tr>
<th>Field</th>
<th>Gas Type</th>
<th>Heating Content (BTU/SCF)</th>
<th>Reserves (Trillion scf)</th>
<th>Base Case Reserves (Trillion scf)</th>
<th>Field Size Ratio</th>
<th>End of Plateau (% of Dep. Stage)</th>
<th>Maximum Annual Allowed Depletion Rate (%)</th>
<th>Original Production Potential (MMscf/d)</th>
<th>Facility Minimum Rate (MMscf/d)</th>
<th>OPEX, Fixed Cost ($/Mscf req.)</th>
<th>OPEX, Variable Cost ($/Mscf)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Rich Gas</td>
<td>1236</td>
<td>1236</td>
<td>1028</td>
<td>27.0</td>
<td>11.0</td>
<td>10.0</td>
<td>1028</td>
<td>65.0</td>
<td>0.95</td>
<td>0.4</td>
</tr>
<tr>
<td></td>
<td>Rich Gas</td>
<td>1236</td>
<td>1236</td>
<td>1028</td>
<td>27.0</td>
<td>11.0</td>
<td>10.0</td>
<td>1028</td>
<td>65.0</td>
<td>0.95</td>
<td>0.4</td>
</tr>
<tr>
<td></td>
<td>Lean Gas</td>
<td>1236</td>
<td>1236</td>
<td>1028</td>
<td>27.0</td>
<td>11.0</td>
<td>10.0</td>
<td>1028</td>
<td>65.0</td>
<td>0.95</td>
<td>0.4</td>
</tr>
<tr>
<td></td>
<td>Lean Gas</td>
<td>1236</td>
<td>1236</td>
<td>1028</td>
<td>27.0</td>
<td>11.0</td>
<td>10.0</td>
<td>1028</td>
<td>65.0</td>
<td>0.95</td>
<td>0.4</td>
</tr>
<tr>
<td></td>
<td>Lean Gas</td>
<td>Lean Gas</td>
<td>Lean Gas</td>
<td>Lean Gas</td>
<td>Lean Gas</td>
<td>Lean Gas</td>
<td>Lean Gas</td>
<td>Lean Gas</td>
<td>Lean Gas</td>
<td>Lean Gas</td>
<td>Lean Gas</td>
</tr>
</tbody>
</table>
Table 1-22. Production Forecast Parameters for Single-layer Homogenous Gas Reservoirs.

<table>
<thead>
<tr>
<th>Field</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
<th>12</th>
</tr>
</thead>
<tbody>
<tr>
<td>Backpressure Exponents (n)</td>
<td>0.65</td>
<td>0.70</td>
<td>0.68</td>
<td>0.80</td>
<td>0.78</td>
<td>0.85</td>
<td>0.89</td>
<td>0.98</td>
<td>1.00</td>
<td>0.85</td>
<td>0.81</td>
<td>0.91</td>
</tr>
<tr>
<td>Decline Exponent (b)</td>
<td>0.23</td>
<td>0.29</td>
<td>0.26</td>
<td>0.38</td>
<td>0.36</td>
<td>0.41</td>
<td>0.44</td>
<td>0.49</td>
<td>0.50</td>
<td>0.41</td>
<td>0.38</td>
<td>0.45</td>
</tr>
<tr>
<td>Decline Rate (Di)</td>
<td>0.16</td>
<td>0.21</td>
<td>0.14</td>
<td>0.13</td>
<td>0.17</td>
<td>0.13</td>
<td>0.10</td>
<td>0.08</td>
<td>0.09</td>
<td>0.11</td>
<td>0.07</td>
<td>0.18</td>
</tr>
</tbody>
</table>

\[ b(gas) = \frac{2n-1}{2n} \]  
(1-31)

\[ Di(gas) = 2n \times \left( \frac{qi}{EUR} \right) \]  
(1-32)

\[ \text{Uncertainty Factor (UF)} = \frac{\text{Field Size Ratio}}{\text{Current Cumulative Production}} + 0.5 \]  
(1-33)

\[ \text{Field Size Ratio for a Field} = \frac{\text{Reserve for the Subject Field}}{\text{Sum of the reserves of All the Fields}} \]  
(1-34)

\[ \text{Min Reserve Value} = \text{if UF} > 1,3, \text{Base Case Reserve} - \text{Base Case Reserve} \times \text{UF} \]  
(1-35)

\[ \text{Max Reserve Value} = \text{Base Case Reserve} + \text{Base Case Reserve} \times \text{UF} \]  
(1-36)

\[ \text{Reserve Standard Deviation} = \text{Base Case Reserve} \times \text{UF} \]  
(1-37)

Table 1-23. Well Cost Parameters.

<table>
<thead>
<tr>
<th>Field</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
<th>12</th>
</tr>
</thead>
<tbody>
<tr>
<td>Depth of Reservoir (Ft)</td>
<td>11000</td>
<td>12500</td>
<td>14000</td>
<td>11750</td>
<td>15000</td>
<td>13000</td>
<td>10000</td>
<td>12500</td>
<td>15000</td>
<td>14000</td>
<td>13000</td>
<td></td>
</tr>
<tr>
<td>Environment</td>
<td>Onshore</td>
<td>Onshore</td>
<td>Offshore</td>
<td>Onshore</td>
<td>Onshore</td>
<td>Offshore</td>
<td>Offshore</td>
<td>Offshore</td>
<td>Offshore</td>
<td>Offshore</td>
<td>Onshore</td>
<td></td>
</tr>
<tr>
<td>Remoteness</td>
<td>1</td>
<td>1</td>
<td>2</td>
<td>1</td>
<td>3</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>Rig Day Well (Days)</td>
<td>72</td>
<td>96</td>
<td>96</td>
<td>83</td>
<td>163</td>
<td>83</td>
<td>53</td>
<td>96</td>
<td>86</td>
<td>112</td>
<td>96</td>
<td>106</td>
</tr>
<tr>
<td>Rig Dayrate ($/Day)</td>
<td>14480</td>
<td>14480</td>
<td>40542</td>
<td>14479</td>
<td>14479</td>
<td>40542</td>
<td>40542</td>
<td>14479</td>
<td>14479</td>
<td>40542</td>
<td>14479</td>
<td></td>
</tr>
<tr>
<td>Rig Support and Supervision Dayrate ($/Day)</td>
<td>5430</td>
<td>5430</td>
<td>10860</td>
<td>5430</td>
<td>9050</td>
<td>72397</td>
<td>72397</td>
<td>5430</td>
<td>5430</td>
<td>72397</td>
<td>14479</td>
<td>7240</td>
</tr>
<tr>
<td>Intangible Drilling Cost per Well (MM$)</td>
<td>1.43352</td>
<td>1.91136</td>
<td>4.935492</td>
<td>1.652447</td>
<td>3.835227</td>
<td>9.373937</td>
<td>5.985767</td>
<td>1.91126</td>
<td>1.71217</td>
<td>12.6492</td>
<td>5.28205</td>
<td>2.30221</td>
</tr>
<tr>
<td>Tangible Drilling Cost per Well (Tub. &amp; Csng.) (M$)</td>
<td>734</td>
<td>769</td>
<td>1824</td>
<td>787</td>
<td>1233</td>
<td>1713</td>
<td>7240</td>
<td>14479</td>
<td>1824</td>
<td>1077</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Annual Prod. Decline (MMscfd)</td>
<td>82</td>
<td>39</td>
<td>89</td>
<td>44</td>
<td>110</td>
<td>142</td>
<td>142</td>
<td>48</td>
<td>48</td>
<td>48</td>
<td>48</td>
<td>48</td>
</tr>
</tbody>
</table>
1.4.5.4.2. Cash Flow Calculations Module

This module is divided into six sub-modules for clarity, including gas prices, production, deductions, taxes, non-taxes items calculations, and net cash flow & NPV calculations. This section discusses these sub-modules. The final output of this module was the total NPV. The production sub-module calculated the daily and annual production and net revenue. Deductions sub-module incorporated OPEX and drilling costs into the NPV calculations. The taxes sub-module handled the tax. The non-tax items sub-module handled cash flow that does not impact tax payments. The net cash flow & NPV calculated the net cash flow NCF, discounted net cash flow DNCF and the net present value NPV. The calculations in this module were based on (Mian, 2011a, Mian, 2011b, and Hartman, 2006).

1.4.5.4.2.1. Gas Price Sub-Module

This section contains the price forecasting model. Gas prices were forecasted deterministically (Floating Price Model) and probabilistically (Mean Reversion Model) in our study. Both of these models are discussed in detail in the natural gas price modeling section.

1.4.5.4.2.2. Production Sub-Module

(Table 1-24) shows a sample of the production sub-module for five years of production. The table lists the parameters calculated in this sub-module, including daily
and annual gas production, annual revenues, cumulative gas production, and remaining reserves at the end of each year. Daily production, the decision variable, was supplied to the economic model from the optimization algorithm. Annual gas production was the product of daily production and 365 (Equation 1-38). Annual revenue was the product of the annual production and gas price. Annual cumulative production and remaining reserves were tracked for material balance purposes.

\[
\text{Annual Production} = \text{Daily Production} \times 365
\]  

(1-38)

<table>
<thead>
<tr>
<th>Production</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Time</td>
<td>Year</td>
</tr>
<tr>
<td>Average Production (MMscf/day)</td>
<td></td>
</tr>
<tr>
<td>Yearly Production (MMscf)</td>
<td></td>
</tr>
<tr>
<td>Royalty (MMscf)</td>
<td></td>
</tr>
<tr>
<td>Net Production (MMscf)</td>
<td></td>
</tr>
<tr>
<td>Net Revenues ($ million)</td>
<td></td>
</tr>
<tr>
<td>Cumulative Production (MMscf)</td>
<td></td>
</tr>
<tr>
<td>Remaining Reserves (Bscf)</td>
<td></td>
</tr>
</tbody>
</table>

1.4.5.4.2.3. Deductions Sub-Module

This sub-module handles the negative cash flow in the economic model. (Table 1-25) shows a sample of the deductions sub-module; the parameters in this sub-module include fixed and variable OPEX, depreciation, depletion, and drilling costs. Fixed operating expenditure OPEX was only incurred once the field was in production; this included the cost of overhead cost, insurance, etc. Variable OPEX was a function of production levels; it included the cost of chemicals, labor, etc. Variable OPEX is a function of reservoir properties and market conditions. All of the deduction items in this
sub-module are tax deductible. The tax-deductible items are subtracted before applying the tax. Depreciation and depletion, tax-deductible items, do not impact our economic model because these parameters are related to new development fields. Depreciation is a tax discount on the production facilities that a gas company receives because these facilities are wearing out and losing value; the tax discount is equivalent to the value lost each year from the production facilities’ values. Depletion is similar to depreciation; however the tax discount relates to the value of the reserves and how it is depleted with time.

Table 1-25. Deductions Sub-Module.

<table>
<thead>
<tr>
<th>Deductions</th>
<th>Year</th>
<th>0</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>OPEX</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fixed</td>
<td>$ million</td>
<td>119</td>
<td>119</td>
<td>119</td>
<td>119</td>
<td>119</td>
<td>119</td>
</tr>
<tr>
<td>Variable</td>
<td>$ million</td>
<td>149</td>
<td>149</td>
<td>149</td>
<td>149</td>
<td>149</td>
<td>149</td>
</tr>
<tr>
<td>Annual Decline Rate</td>
<td>(MMscfd)</td>
<td>123</td>
<td>123</td>
<td>123</td>
<td>123</td>
<td>123</td>
<td>123</td>
</tr>
<tr>
<td><strong>Drilling Costs</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Additional Rate per Well</td>
<td>(Mscfd)</td>
<td>12,758</td>
<td>11,900</td>
<td>11,041</td>
<td>10,182</td>
<td>10,000</td>
<td>10,000</td>
</tr>
<tr>
<td>No. of Wells Req.</td>
<td></td>
<td>10</td>
<td>11</td>
<td>12</td>
<td>13</td>
<td>13</td>
<td>13</td>
</tr>
<tr>
<td>Total Drilling Cost</td>
<td>$ million</td>
<td>21.67</td>
<td>23.84</td>
<td>26.01</td>
<td>28.18</td>
<td>28.18</td>
<td>28.18</td>
</tr>
</tbody>
</table>

1.4.5.4.2.4. Taxes Sub-Module

This sub-module subtracted the tax from the taxable income that was the revenue minus the tax deductible items (fixed and variable OPEX and drilling costs).

1.4.5.4.2.5. Non-Tax Items Sub-Module

Non-tax items are positive and negative cash flow that do not impact tax payments. In other words, they are tax deductible items, including capital expenditures,
salvage, net proceeds, and principal payments on a loan. Our model did not incorporate any of the non-tax items because all of the fields were existing and producing, eliminating the CAPAX; salvage value was negligible relative to the NPV; and financing was not considered, eliminating net proceeds and principal payments.

1.4.5.4.2.6. *Net Cash Flow and NPV Calculations Sub-Module*

This sub-module calculated the net cash flow NCF, discounted net cash flow DNCF, and the net present value NPV. The net cash flow was the sum of the positive and negative items each year. Then these values were discounted to adjust them for time using (Equation 1-39), resulting DNCF. Finally, the NPV was the sum of all the DNCF values. The NPV was one of the objective functions for our optimization problem.

\[
Present\ Value = \frac{Future\ Value}{(1+Discount\ Rate)^{Time}}
\]  

(1-39)

1.4.5.4.3. *Input and Output Module*

Most of the user interactions took place in this module. This module incorporated the formulation of the optimization problem and presented the final output from the model. It consisted of four sub-modules: inputs, objective function, decision variables, and constraints.
1.4.5.4.3.1. Users’ Input Sub-Module

In this sub-module, the total target daily rate was specified. This value represented the supply contract commitment to our company. The study considered a supply commitment of 22,000 MMscfd.

1.4.5.4.3.2. Objective Function Sub-Module

This sub-module is the first part of the optimization problem formulation in that the objective function was specified. The objective function is the yardstick used to measure the performance of an operation or process. Three objective functions were evaluated in the study total NPV, total plateau length, and a combination of both NPV and plateau length. A multiplier for the plateau length was incorporated so that the magnitude of the plateau length and the NPV was similar; the multiplier was the ratio of NPV to the plateau length. In the case of probabilistic price and/or production forecasting, the objective functions were the mean of the distributions of NPV and plateau length. The objective functions (NPV and PL), of the optimization problem, were not linear function of the decision variables (production rates); as a result, the optimization problem was a nonlinear problem and required nonlinear programming or genetic algorithms.
1.4.5.4.3.3. Decision Variables Sub-Module

This sub-module presents the set of decision variables that maximized the objective function. These decision variables, the fields’ production rates, were the variables over that management had control. Moreover, this set of decision variables formed the answer to the question presented in the introduction.

1.4.5.4.3.4. Constraints Sub-Module

Constraints define the feasible area of the solution for the optimization problem and present physical or financial restrictions to it. Our optimization problem faced three constraints: 1) The fields’ production rates had to be less than or equal to the production potential (physical constraint), 2) The fields’ production rates had to be greater than or equal to the facility minimum operating rates (physical and financial constraints), and 3) The total production rate had to meet the total daily target rate (financial constraints). Production potential is the maximum allowable rate to ensure safe and efficient operations. Facility minimum operating rate is the minimum rate at that a facility could operate safely and economically. The total target daily rate represented the supply contract commitment.

1.5. Results and Discussion

Allocating production rates across a portfolio of producing gas fields, with the goal of maximizing total plateau length and NPV, was a complex optimization problem.
There field-level constraints included facility limitations, costs, and technical properties (i.e., reservoir characteristics, and crude or gas types). Moreover, there were company-level constraints (e.g. supply and spare capacity commitments). Prices, and reservoir properties and performance, were among those uncertain parameters having an impact on decisions about the allocation problem; these uncertainties further complicated the modeling process. In order to implement the integrated stochastic optimization model, workflow and required models were defined: workflow, to define the scope of the uncertainty analysis; decline curve analysis, to forecast the production profile; stochastic processes, to forecast price; the drilling cost model; an economic evaluation model to calculate NPV; the Monte Carlo simulation process, uncertainties; and an optimization model, to identify the optimal production rate allocation. Implementing these components, the optimal production rate allocation was identified and the impact of price and reservoir performance uncertainties on the optimal allocation decisions was analyzed. Moreover, the impact of the discount rate on the optimal allocation decision was investigated.

This section discusses the optimum allocation decisions resulting from different price and production forecast modeling assumptions, and from different objective functions. Sensitivity analysis looked at the impact of modeling parameters on total NPV.

1.5.1. Deterministic Price and Production Forecast Models

Deterministic production and price forecasting (Floating Price Model) models were analyzed using a 10% discount rate and 22,000 MMscfd supply commitment.
(Table 1-26 and Figure 1-16) present a starting non-optimized point for comparison purposes. The initial case resulted in $140.06 billion in total NPV and one year of plateau. As expected, maximizing the total NPV or the total plateau length resulted in the same outcome as shown in (Tables 1-28 and 1-29 and Figures 1-18 and 1-19). (Table 1-28 and Figure 1-18) show the production profile, total NPV, total plateau length, and average annual production decline over the first 40 years. (Figure 1-19) shows the assigned production rate for each field and the resulting individual plateau length. (Table 1-29) shows the assigned production rates, upper and lower bounds, reserves, fields’ ages, decline rate Di, decline exponents b, and fixed and variable OPEX. According to (Table 1-28), the optimal NPV was $183.307 billion and total plateau length was seven years; in other words, maximizing the total NPV or plateau length added $43.25 billion in NPV and seven years in plateau length form the non-optimized scenario. Moreover, extending plateau length can delay development of new fields needed to make up for the loss in capacity. This delay can save millions of dollars in time-adjusted costs. From (Table 1-29), the production allocation, that maximized NPV and plateau length, was a function of reserve size, age of field, and decline exponent b. The decline exponent b is the rate of change in the decline rate and was a function of reservoir properties; the larger the b, the slower the decline. Field size and age related to the stored energy in the reservoir; this energy controls the sharpness or smoothness of the decline. The algorithm showed the allocation that maximizes the plateau length and reduces decline after the plateau ends; this strategy maximizes both total NPV and total plateau length. Maximizing total NPV results in maximizing total plateau length due to the discounting concept, that decreases the value of profits in later years. As a result, maximizing the
NPV accelerates production. In other words, extending the plateau accelerates the production for a company with a defined target daily rate.

To examine the impact of expected demand or the contract supply commitment, the optimization models were evaluated without the supply commitment constraint. The supply commitment constraint restricted the optimization algorithm to maximize the total NPV as shown in (Table 1-30 and Figure 1-20), that show the results of maximizing the total NPV without the supply commitment constraint. The optimizer places all fields at maximum potential, resulting in $200 billion and one year of plateau. On the other hand, maximizing plateau length without the supply commitment constraint placed all fields at the minimum facility operating rate with NPV of $82 billion and plateau length of seven years as shown in (Table 1-31 and Figure 1-21). This observation signifies the importance of identifying an accurate expected value of demand for gas; in other words, overestimating or under estimating the expected demand can be detrimental to total NPV. Value of information analysis (VOI) is presented in a later section to identify the magnitude of the impact of the expected demand. Specifically, the analysis identified the value of acquiring a more accurate expected demand.
Table 1-26. Initial Non-Optimized Production Allocation.

<table>
<thead>
<tr>
<th>Field</th>
<th>Optimum Production Rate (MMscfd)</th>
<th>Minimum Rate (MMscfd)</th>
<th>Production Status</th>
<th>Reserves Size (Trillion SCF)</th>
<th>Initial Depletion Stage (% of Reserves)</th>
<th>Decline Rate (Di)</th>
<th>Decline Exponent (b)</th>
<th>Flood OPEX $/Mscf</th>
<th>Variable OPEX $/Mscf</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1986</td>
<td>195</td>
<td>205</td>
<td>18</td>
<td>0.55</td>
<td>0.23</td>
<td>0.40</td>
<td>58.0</td>
<td>0.40</td>
</tr>
<tr>
<td>2</td>
<td>906</td>
<td>985</td>
<td>148</td>
<td>18</td>
<td>0.63</td>
<td>0.19</td>
<td>0.60</td>
<td>55.0</td>
<td>0.60</td>
</tr>
<tr>
<td>3</td>
<td>684</td>
<td>2219</td>
<td>273</td>
<td>10</td>
<td>0.25</td>
<td>0.17</td>
<td>0.75</td>
<td>90.0</td>
<td>0.80</td>
</tr>
<tr>
<td>4</td>
<td>855</td>
<td>198</td>
<td>236</td>
<td>20</td>
<td>0.35</td>
<td>0.12</td>
<td>0.95</td>
<td>80.0</td>
<td>0.95</td>
</tr>
<tr>
<td>5</td>
<td>2754</td>
<td>2740</td>
<td>93</td>
<td>20</td>
<td>0.58</td>
<td>0.17</td>
<td>0.75</td>
<td>90.0</td>
<td>0.80</td>
</tr>
<tr>
<td>6</td>
<td>1175</td>
<td>1699</td>
<td>247</td>
<td>45</td>
<td>0.16</td>
<td>0.12</td>
<td>0.95</td>
<td>80.0</td>
<td>0.95</td>
</tr>
<tr>
<td>7</td>
<td>3689</td>
<td>2740</td>
<td>256</td>
<td>56</td>
<td>0.15</td>
<td>0.09</td>
<td>0.95</td>
<td>80.0</td>
<td>0.95</td>
</tr>
<tr>
<td>8</td>
<td>3533</td>
<td>3562</td>
<td>296</td>
<td>65</td>
<td>0.10</td>
<td>0.078</td>
<td>0.95</td>
<td>100.0</td>
<td>1.10</td>
</tr>
<tr>
<td>9</td>
<td>4373</td>
<td>4134</td>
<td>296</td>
<td>80</td>
<td>0.35</td>
<td>0.081</td>
<td>0.50</td>
<td>90.0</td>
<td>0.75</td>
</tr>
<tr>
<td>10</td>
<td>3055</td>
<td>2905</td>
<td>256</td>
<td>25</td>
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<td>0.106</td>
<td>0.412</td>
<td>105.0</td>
<td>0.90</td>
</tr>
<tr>
<td>11</td>
<td>3545</td>
<td>3562</td>
<td>362</td>
<td>65</td>
<td>0.30</td>
<td>0.072</td>
<td>0.383</td>
<td>120.0</td>
<td>1.30</td>
</tr>
<tr>
<td>12</td>
<td>1205</td>
<td>1205</td>
<td>197</td>
<td>Upper Bound</td>
<td>11</td>
<td>0.54</td>
<td>0.182</td>
<td>0.451</td>
<td>1.20</td>
</tr>
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</table>

Figure 1-16. Initial Non-Optimized Production Profile and Cumulative Production.

Figure 1-17. Initial Non-Optimized Production Allocation and Plateau Length.

Table 1-27. Initial Non-Optimized Production Allocation and Fields’ Properties.
Table 1-28. Production Allocation for Maximizing Total NPV and/ or Total Plateau Length.

<table>
<thead>
<tr>
<th>Field</th>
<th>1</th>
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<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
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<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
<th>12</th>
</tr>
</thead>
<tbody>
<tr>
<td>Production Rate (MMscfd)</td>
<td>1026</td>
<td>336</td>
<td>2219</td>
<td>681</td>
<td>969</td>
<td>3012</td>
<td>2739</td>
<td>3234</td>
<td>3582</td>
<td>697</td>
<td>2966</td>
<td>539</td>
</tr>
<tr>
<td>Plateau Length (Years)</td>
<td>8</td>
<td>7</td>
<td>17</td>
<td>12</td>
<td>8</td>
<td>21</td>
<td>26</td>
<td>25</td>
<td>15</td>
<td>13</td>
<td>19</td>
<td>10</td>
</tr>
<tr>
<td>Total Plateau Length (Yrs)</td>
<td>7</td>
<td></td>
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<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>TOTAL NPV ($ Million)</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Discount Rate</td>
<td>10%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>Total Supply Commitment (MMscfd)</td>
<td>22000</td>
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<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average Annual Decline (MMscfd/Yr)</td>
<td>-417</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
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</tr>
</tbody>
</table>

Figure 1-18. Production Profile and Cumulative Production for Maximizing Total NPV and/ or Total Plateau Length.

Figure 1-19. Production Allocation and Plateau Length for Maximizing Total NPV and/ or Total Plateau Length.
Table 1-29. Production Allocation and Fields’ Properties for Maximizing Total NPV and/or Total Plateau Length.

<table>
<thead>
<tr>
<th>Field</th>
<th>Optimum Production Rate (MMscfd)</th>
<th>Potential Upper Bound (MMscfd)</th>
<th>Min. Rate Lower Bound (MMscfd)</th>
<th>Production Status</th>
<th>Reserves Size (Trillion SCF)</th>
<th>Initial Depletion Stage (% of Reserves)</th>
<th>Decline Rate (D)</th>
<th>Decline Exponent (b)</th>
<th>Fixed OPEX $/Mscf Req</th>
<th>Variable OPEX $/Mscf</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1026</td>
<td>2055</td>
<td>205</td>
<td>15</td>
<td>0.55</td>
<td>0.163</td>
<td>0.231</td>
<td>58.0</td>
<td>0.40</td>
<td>0.90</td>
</tr>
<tr>
<td>2</td>
<td>336</td>
<td>986</td>
<td>148</td>
<td>6</td>
<td>0.64</td>
<td>0.210</td>
<td>0.286</td>
<td>15.0</td>
<td>0.80</td>
<td>0.90</td>
</tr>
<tr>
<td>3</td>
<td>2219</td>
<td>2319</td>
<td>271</td>
<td>27</td>
<td>0.25</td>
<td>0.170</td>
<td>0.412</td>
<td>73.0</td>
<td>0.75</td>
<td>0.90</td>
</tr>
<tr>
<td>4</td>
<td>1096</td>
<td>230</td>
<td>99</td>
<td>10</td>
<td>0.35</td>
<td>0.128</td>
<td>0.375</td>
<td>80.0</td>
<td>0.80</td>
<td>0.90</td>
</tr>
<tr>
<td>5</td>
<td>2740</td>
<td>99</td>
<td>20</td>
<td>0.58</td>
<td>0.173</td>
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<td>0.95</td>
<td>0.95</td>
<td>0.90</td>
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<td>3012</td>
<td>247</td>
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<td>0.128</td>
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<td>0.90</td>
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<tr>
<td>7</td>
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<td>0.15</td>
<td>0.056</td>
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<td>0.65</td>
<td>100.0</td>
<td>1.10</td>
<td>1.10</td>
<td>1.10</td>
</tr>
<tr>
<td>8</td>
<td>3124</td>
<td>296</td>
<td>65</td>
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<td>0.078</td>
<td>0.490</td>
<td>120.0</td>
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<tr>
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<td>4384</td>
<td>80</td>
<td>0.35</td>
<td>0.085</td>
<td>0.500</td>
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<td>0.75</td>
<td>90.0</td>
<td>0.75</td>
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<tr>
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<td>1.30</td>
<td>120.0</td>
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</tr>
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<td>120.0</td>
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</table>

Table 1-30. Production Allocation for Maximizing Total NPV without Supply Commitment Constraint.

<table>
<thead>
<tr>
<th>Field</th>
<th>Production Rate (MMscfd)</th>
<th>Plateau Length (Years)</th>
<th>Total Plateau Length (Yrs)</th>
<th>TOTAL NPV ($ Million)</th>
<th>Discount Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2055</td>
<td>2</td>
<td>1</td>
<td>199,985</td>
<td>10%</td>
</tr>
<tr>
<td>2</td>
<td>986</td>
<td>1</td>
<td>1</td>
<td>199,985</td>
<td>10%</td>
</tr>
<tr>
<td>3</td>
<td>2219</td>
<td>16</td>
<td>16</td>
<td>199,985</td>
<td>10%</td>
</tr>
<tr>
<td>4</td>
<td>1096</td>
<td>5</td>
<td>25</td>
<td>199,985</td>
<td>10%</td>
</tr>
<tr>
<td>5</td>
<td>2740</td>
<td>1</td>
<td>25</td>
<td>199,985</td>
<td>10%</td>
</tr>
<tr>
<td>6</td>
<td>3012</td>
<td>1</td>
<td>25</td>
<td>199,985</td>
<td>10%</td>
</tr>
<tr>
<td>7</td>
<td>2740</td>
<td>1</td>
<td>25</td>
<td>199,985</td>
<td>10%</td>
</tr>
<tr>
<td>8</td>
<td>3124</td>
<td>1</td>
<td>25</td>
<td>199,985</td>
<td>10%</td>
</tr>
<tr>
<td>9</td>
<td>4384</td>
<td>1</td>
<td>25</td>
<td>199,985</td>
<td>10%</td>
</tr>
<tr>
<td>10</td>
<td>2555</td>
<td>1</td>
<td>25</td>
<td>199,985</td>
<td>10%</td>
</tr>
<tr>
<td>11</td>
<td>3562</td>
<td>1</td>
<td>25</td>
<td>199,985</td>
<td>10%</td>
</tr>
<tr>
<td>12</td>
<td>1205</td>
<td>1</td>
<td>25</td>
<td>199,985</td>
<td>10%</td>
</tr>
</tbody>
</table>

Figure 1-20. Production Profile and Cumulative Production for Maximizing Total NPV without Supply Commitment Constraint.
1.5.2. Deterministic Production Forecast and Probabilistic Price Forecast

Probabilistic price forecast (Mean Reversion Model MRM) and deterministic production forecast are evaluated here. The Mean Reversion price model accounts for the uncertainty in the market. The MRM is a stochastic process that assumes that prices are related to marginal cost of production; hence, it is one of the most economically-preferred price forecast models. This model requires a larger computational load than the deterministic approach due to the uncertainty (Monte Carlo) involved; as a result, the life of the project was reduced to 40 years. This section discusses the results from maximizing total plateau length and total NPV. Then the impact of the discount rate on the optimization problem was analyzed; three discount rate values were examined: 0%, 10%, and 50%. Extreme values were selected to facilitate the analysis and comparison.
Similar to the deterministic approach, the same set of decision variables resulted from maximizing the expected value of total NPV or the total plateau length, in the optimization problem as shown in (Tables 1-32, 1-33, and 1-34 and Figures 1-22 and 1-23). As mentioned above, the optimizer accelerated production by extending the plateau length since the problem was constrained by the total daily target rate; moreover, the optimizer finds the allocation that leads to the lowest production decline beyond the end of the plateau. This work flow for the optimizer is controlled by the discounting concept, that can decrease the value of the profit in later years. (Table 1-32 and Figure 1-22) show the production profile, $E[\text{total NPV}]$, total plateau length, and average annual production decline over the first 40 years. The optimal $E[\text{NPV}]$ was $125.252$ billion and total plateau length was seven years. In addition to the additional profit, extending plateau length can delay development of new fields needed to make up for the loss in capacity. This delay can save millions of dollars in time-adjusted costs. (Table 1-33) shows the production allocation by gas type; the algorithm allocates higher rates from lean gas fields because they were relatively larger and younger. (Figure 1-22) shows the assigned production rate for each field and the resulting individual plateau length. (Table 1-34) shows the assigned production rates, upper and lower bounds, reserves, fields’ ages, decline rate $D_i$, decline exponents $b$, and fixed and variable OPEX. The production allocation, that maximizes NPV and plateau length, is a function of reserve size, age of field, and decline exponent $b$. The decline exponent $b$ controls how the decline rate changes. The decline exponent $b$ is a function of reservoir properties; the larger the $b$, the slower the decline and the higher the field on the priority optimization list. Field size and age are related to the stored energy in the reservoir; this energy controls the sharpness or
smoothness of the decline. Since deterministic and probabilistic price models resulted in the same set of decision variables, there was no value added, by the type of price forecasting model, in the optimization problem. MRM can add significant value in the process of evaluating the value of the company or the risk involved; however, it does not add value in the decision about production allocation. The reason for this conclusion is that this was a comparative study and the prices for the different types of gas were correlated in a similar way for both price forecasting approaches. Then, minimizing the average annual production decline was evaluated for the whole portfolio, using the MRM price model as shown in (Tables 1-35, 1-36, and 1-37 and Figures 1-24 and 1-25). (Table 1-35 and Figure 1-24) show the production profile, $E[\text{total NPV}]$, total plateau length, and average annual production decline over the first 40 years. The $E[\text{NPV}]$ was $103.776$ billion with no plateau and average decline rate of $346$ MMscfd/Yr. The average annual production decline decreased from $417$ to $346$ MMscfd/Yr, in relation to maximizing $E[\text{NPV}]$ case. (Table 1-36) shows the production allocation by gas type; the algorithm allocated higher rates from lean gas fields, in comparison to maximizing the $E[\text{NPV}]$ case, because they are relatively larger and younger. (Figure 1-24) shows the assigned production rate for each field and the resulting individual plateau length. (Table 1-37) shows the assigned production rates, upper and lower bounds, reserves, fields’ ages, decline rate $D_i$, decline exponents $b$, and fixed and variable OPEX. The algorithm assigned more production rates from the lean gas fields to minimize average production decline. Interestingly, the algorithm allocated three out of five lean gas fields at maximum production potential. In other words, the algorithm placed a heavier load on the fields with the larger reserves and $b$ values. In general, the lean gas fields are larger
and younger. The reserve size had the greatest impact as a parameter on minimizing the average decline rate; decline exponent b came in second.

Three discount rate values were examined: 0%, 10%, and 50%. Extreme values were selected to facilitate analysis and comparison. The optimum results for the 10% discount rate were discussed earlier and shown in (Tables 1-32, 1-33, and 1-34 and Figures 1-22 and 1-23). The optimum allocation for the 0% discount rate was similar to the one for the 10% discount rate as shown in (Tables 1-38, 1-39, and 1-40). The only difference between 10% and 0% discounting was the E[total NPV], that were $347.187 billion and $125.252 billion for 0% and 10%, respectively. Although the discount rate did not have impact on the allocation decision, it had a significant impact on assessing the value of the company. On the other hand, maximizing the allocation decision using the 50% discount rate had an impact on the allocation decisions as shown in (Tables 1-41, 1-42, and 1-43). The E[total NPV] was $35.752 billion with three years of plateau. Using the 50% discount rate, the optimizer allocated more rates from rich and standard gas fields due to their higher intrinsic values. The rich gas fields represented 22.42%, with 50% discount rates in the total portfolio compared to 16.3% for the 0% & 10% discount rates. The standard gas fields represented 37.63%, with the 50% discount rate, of the total portfolio compared to 33.6% for the 0% discount rate. The lean gas rate dropped from 50.1% to 39.95% of the total portfolio when the discount rate was changed from 0% to 50%. In other words, the optimizer preferred high rates from the fields with higher intrinsic values in the case of large discount rates; a high discount rate can dramatically reduce the value of profits in later years. At the 10% and 0% discount rates the optimizer finds the allocation that maximizes plateau length and declines slowly after the plateau.
Table 1-32. Production Allocation for Maximizing E[Total NPV] and/or Total Plateau Length.

<table>
<thead>
<tr>
<th>Field</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
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<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
<th>12</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Production Rate (MMscfd)</td>
<td>1026</td>
<td>336</td>
<td>2219</td>
<td>681</td>
<td>969</td>
<td>3012</td>
<td>2739</td>
<td>3234</td>
<td>3582</td>
<td>697</td>
<td>2966</td>
</tr>
<tr>
<td></td>
<td>Percentage of Initial Potential Used (%)</td>
<td>28.51%</td>
<td>5.76%</td>
<td>99.98%</td>
<td>45.88%</td>
<td>7.68%</td>
<td>73.48%</td>
<td>99.98%</td>
<td>86.87%</td>
<td>73.87%</td>
<td>5.60%</td>
<td>76.09%</td>
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<tr>
<td></td>
<td>Plateau Length (Years)</td>
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<td>7</td>
<td>17</td>
<td>12</td>
<td>8</td>
<td>21</td>
<td>26</td>
<td>25</td>
<td>15</td>
<td>13</td>
<td>19</td>
</tr>
<tr>
<td></td>
<td>Total Plateau Length (Yrs)</td>
<td>7</td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td></td>
<td>E[Total NPV] ($ Million)</td>
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<td></td>
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</tr>
<tr>
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<td>Discount Rate</td>
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<td></td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
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<td>Total Supply Commitment (MMscfd)</td>
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<td></td>
<td></td>
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<td></td>
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<tr>
<td></td>
<td>Average Annual Decline (MMscfd/Yr)</td>
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<td></td>
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Table 1-33. Production Allocation by Gas Type for Maximizing E[Total NPV] and/or Total Plateau Length.

<table>
<thead>
<tr>
<th>Gas Type</th>
<th>Initial Production Rate (MMscfd)</th>
<th>Percentage of Total Supply Commitment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rich</td>
<td>3581</td>
<td>16.28%</td>
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<tr>
<td>Standard</td>
<td>7401</td>
<td>33.64%</td>
</tr>
<tr>
<td>Lean</td>
<td>11018</td>
<td>50.08%</td>
</tr>
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</table>

Figure 1-22. Production Profile and Cumulative Production for Maximizing E[Total NPV] and/or Total Plateau Length.

Figure 1-23. Production Allocation and Plateau Length for Maximizing E[Total NPV] and/or Total Plateau Length.
Table 1-34. Production Allocation and Fields’ Properties for Maximizing E[Total NPV] and/or Total Plateau Length.

<table>
<thead>
<tr>
<th>Field</th>
<th>Optimum Production Rate (MMscfd)</th>
<th>Potential Upper Bound (MMscfd)</th>
<th>Min. Rate Lower Bound (MMscfd)</th>
<th>Production Status</th>
<th>Reserves Size (Trillion SCF)</th>
<th>Initial Depletion Stage (% of Reserves)</th>
<th>Decline Rate (Di)</th>
<th>Decline Exponent (b)</th>
<th>Fixed OPEX $/Mscf Req</th>
<th>Variable OPEX $/Mscf</th>
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<tbody>
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<td>1026</td>
<td>2055</td>
<td>205</td>
<td>15</td>
<td>0.55</td>
<td>0.163</td>
<td>0.231</td>
<td>58.0</td>
<td>0.40</td>
<td>0.40</td>
</tr>
<tr>
<td>2</td>
<td>336</td>
<td>986</td>
<td>148</td>
<td>6</td>
<td>0.63</td>
<td>0.210</td>
<td>0.286</td>
<td>55.0</td>
<td>0.60</td>
<td>0.60</td>
</tr>
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<td>2219</td>
<td>2219</td>
<td>271</td>
<td>27</td>
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<td>0.170</td>
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<td>0.75</td>
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<td>681</td>
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<td>230</td>
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<td>0.375</td>
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<td>0.80</td>
<td>0.80</td>
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<tr>
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<td>969</td>
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<td>0.412</td>
<td>75.0</td>
<td>0.90</td>
<td>0.90</td>
</tr>
<tr>
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<tr>
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<td>3234</td>
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<td>90.0</td>
<td>0.75</td>
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<td>697</td>
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<td>296</td>
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<td>0.106</td>
<td>0.412</td>
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<td>0.90</td>
<td>0.90</td>
</tr>
<tr>
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<td>2966</td>
<td>3562</td>
<td>362</td>
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<td>0.072</td>
<td>0.383</td>
<td>120.0</td>
<td>1.30</td>
<td>1.30</td>
</tr>
<tr>
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<td>539</td>
<td>1205</td>
<td>197</td>
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<td>0.182</td>
<td>0.451</td>
<td>105.0</td>
<td>1.20</td>
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Table 1-35. Production Allocation for Minimizing Average Annual Production Decline.

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<tr>
<th>Field</th>
<th>Production Rate (MMscfd)</th>
<th>Percentage of Initial Potential Used (%)</th>
<th>Plateau Length (Years)</th>
<th>E[TOTAL NPV] ($ Million)</th>
<th>Discount Rate</th>
<th>Total Supply Commitment (MMscfd)</th>
<th>Average Annual Decline (MMscfd/Yr)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1270</td>
<td>45.44%</td>
<td>6</td>
<td>103,776</td>
<td>10%</td>
<td>22,000</td>
<td>-346</td>
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<tr>
<td>2</td>
<td>760</td>
<td>67.22%</td>
<td>2</td>
<td>733</td>
<td></td>
<td>1941</td>
<td></td>
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<tr>
<td>3</td>
<td>851</td>
<td>11.93%</td>
<td>4</td>
<td>1,914</td>
<td></td>
<td>1619</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>733</td>
<td>52.69%</td>
<td>5</td>
<td>16,194</td>
<td></td>
<td>15,444</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>1941</td>
<td>58.35%</td>
<td>6</td>
<td>161,944</td>
<td></td>
<td>15,444</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>1,914</td>
<td>19.68%</td>
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<td></td>
<td>1,544</td>
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<tr>
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<td>16,194</td>
<td>37.65%</td>
<td>10</td>
<td>161,944</td>
<td></td>
<td>161,944</td>
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</tr>
<tr>
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<td>100.00%</td>
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<td>15,444</td>
<td></td>
<td>15,444</td>
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</tr>
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<td>100.00%</td>
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<td>161,944</td>
<td></td>
<td>161,944</td>
<td></td>
</tr>
<tr>
<td>12</td>
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<td>99.94%</td>
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Table 1-36. Production Allocation by Gas Type for Minimizing Average Annual Production Decline.

<table>
<thead>
<tr>
<th>Gas Type</th>
<th>Initial Production Rate (MMscfd)</th>
<th>Percentage of Total Supply Commitment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rich</td>
<td>2881</td>
<td>13.10%</td>
</tr>
<tr>
<td>Standard</td>
<td>5837</td>
<td>26.53%</td>
</tr>
<tr>
<td>Lean</td>
<td>13282</td>
<td>60.37%</td>
</tr>
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</table>

Figure 1-24. Production Profile and Cumulative Production for Minimizing Average Annual Production Decline.
Figure 1-25. Production Allocation and Plateau Length for Minimizing Average Annual Production Decline.

Table 1-37. Production Allocation and Fields’ Properties for Minimizing Average Annual Production Decline.

<table>
<thead>
<tr>
<th>Field</th>
<th>Optimum Production Rate (MMscfd)</th>
<th>Potential Upper Bound (MMscfd)</th>
<th>Min. Rate Lower Bound (MMscfd)</th>
<th>Production Status</th>
<th>Reserves Size (Trillion SCF)</th>
<th>Initial Depletion Stage (% of Reserves)</th>
<th>Decline Rate (Di)</th>
<th>Decline Exponent (b)</th>
<th>Fixed OPEX $/Mscf Req</th>
<th>Variable OPEX $/Mscf</th>
<th>E[NPV] ($ Million)</th>
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</thead>
<tbody>
<tr>
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<td>205</td>
<td>205</td>
<td>15</td>
<td>0.55</td>
<td>0.183</td>
<td>0.231</td>
<td>18.0</td>
<td>0.40</td>
<td></td>
<td>347,187</td>
</tr>
<tr>
<td>2</td>
<td>760</td>
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<td>148</td>
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<td>0.63</td>
<td>0.210</td>
<td>0.286</td>
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<td>271</td>
<td>27</td>
<td>0.25</td>
<td>0.170</td>
<td>0.412</td>
<td>73.0</td>
<td>0.75</td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>733</td>
<td>1096</td>
<td>230</td>
<td>10</td>
<td>0.35</td>
<td>0.128</td>
<td>0.375</td>
<td>80.0</td>
<td>0.80</td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>1941</td>
<td>2740</td>
<td>99</td>
<td>20</td>
<td>0.58</td>
<td>0.173</td>
<td>0.359</td>
<td>90.0</td>
<td>0.95</td>
<td></td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>1819</td>
<td>3699</td>
<td>247</td>
<td>45</td>
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<td>0.128</td>
<td>0.412</td>
<td>75.0</td>
<td>0.90</td>
<td></td>
<td></td>
</tr>
<tr>
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<td>1544</td>
<td>2740</td>
<td>296</td>
<td>50</td>
<td>0.15</td>
<td>0.096</td>
<td>0.438</td>
<td>65.0</td>
<td>0.80</td>
<td></td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>2077</td>
<td>3562</td>
<td>296</td>
<td>65</td>
<td>0.10</td>
<td>0.078</td>
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<td>1.10</td>
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</tr>
<tr>
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<td>4384</td>
<td>296</td>
<td>80</td>
<td>0.35</td>
<td>0.085</td>
<td>0.500</td>
<td>90.0</td>
<td>0.75</td>
<td></td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>2055</td>
<td>2055</td>
<td>296</td>
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<td>0.412</td>
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<td>0.90</td>
<td></td>
<td></td>
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<td>3562</td>
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<td>1.30</td>
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<td></td>
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<tr>
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<td>1205</td>
<td>1205</td>
<td>197</td>
<td>11</td>
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<td>0.182</td>
<td>0.451</td>
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Table 1-38. Production Allocation for Maximizing E[NPV] under 0% Discount Rate.

<table>
<thead>
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<th>Field</th>
<th>Production Rate (MMscfd)</th>
<th>Percentage of Initial Potential Used (%)</th>
<th>Total Plateau Length (Yrs)</th>
<th>paginator</th>
<th>E[TOTAL NPV] ($ Million)</th>
<th>Discount Rate</th>
<th>Total Supply Comittment (MMscfd)</th>
<th>Average Annual Decline (MMscfd/Yr)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
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<td>28.51%</td>
<td>8</td>
<td>0%</td>
<td>347,187</td>
<td>539</td>
<td>22000</td>
<td>-417</td>
</tr>
<tr>
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<td>336</td>
<td>5.76%</td>
<td>7</td>
<td>0%</td>
<td>2966</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>2199</td>
<td>99.98%</td>
<td>17</td>
<td>0%</td>
<td>11018</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>681</td>
<td>99.98%</td>
<td>12</td>
<td>0%</td>
<td>7401</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>969</td>
<td>45.88%</td>
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<td>0%</td>
<td>3582</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>3012</td>
<td>73.48%</td>
<td>7</td>
<td>0%</td>
<td>3582</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>2739</td>
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<td>21</td>
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<td>3582</td>
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</tr>
<tr>
<td>8</td>
<td>3234</td>
<td>73.48%</td>
<td>26</td>
<td>0%</td>
<td>3582</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
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<td>3582</td>
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<td>25</td>
<td>0%</td>
<td>3582</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>697</td>
<td>5.60%</td>
<td>15</td>
<td>0%</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>11</td>
<td>2966</td>
<td>76.09%</td>
<td>19</td>
<td>0%</td>
<td>11018</td>
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</tr>
<tr>
<td>12</td>
<td>11018</td>
<td>21.02%</td>
<td>10</td>
<td>0%</td>
<td>7401</td>
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Table 1-39. Production Allocation by Gas Type for Maximizing E[NPV] under 0% Discount Rate.

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<thead>
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<th>Gas Type</th>
<th>Initial Production Rate (MMscfd)</th>
<th>Percentage of Total Supply Commitment</th>
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<tr>
<td>Rich</td>
<td>3581</td>
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</tr>
<tr>
<td>Standard</td>
<td>7401</td>
<td>33.64%</td>
</tr>
<tr>
<td>Lean</td>
<td>11018</td>
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</table>
Table 1-40. Production Allocation and Fields’ Properties for Maximizing E[NPV] under 0% Discount Rate.

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<th>Field</th>
<th>Optimum Production Rate (MMscfd)</th>
<th>Potential Upper Bound (MMscfd)</th>
<th>Min. Rate Lower Bound (MMscfd)</th>
<th>Production Status</th>
<th>Reserves Size (Trillion SCF)</th>
<th>Initial Depletion Stage (% of reserves)</th>
<th>Decline Rate (D)</th>
<th>Decline Exponent (b)</th>
<th>Fixed OPEX $/Mscf Req</th>
<th>Variable OPEX $/Mscf</th>
</tr>
</thead>
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<td>0.210</td>
<td>0.286</td>
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<td>0.60</td>
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<td>2219</td>
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<td>0.170</td>
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<td>0.75</td>
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<td>0.173</td>
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<td>0.95</td>
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<td>0.490</td>
<td>100.0</td>
<td>1.10</td>
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</tr>
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<td>3582</td>
<td>4384</td>
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<td>0.085</td>
<td>0.500</td>
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<td>0.072</td>
<td>0.383</td>
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<td>1.30</td>
<td></td>
</tr>
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<td>197</td>
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<td>0.182</td>
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Table 1-41. Production Allocation for Maximizing E[NPV] under 50% Discount Rate.

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<th>Field</th>
<th>Production Rate (MMscfd)</th>
<th>Percentage of Initial Potential Used (%)</th>
<th>Plateau Length (Yrs)</th>
<th>Total Plateau Length (Yrs)</th>
<th>E[TOTAL NPV] ($ Million)</th>
<th>Discount Rate</th>
<th>Total Supply Commitment (MMscfd)</th>
<th>Average Annual Decline (MMscfd/Yr)</th>
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<td>1470</td>
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<td>50%</td>
<td>-424</td>
</tr>
<tr>
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<td>2219</td>
<td>99.99%</td>
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<td>14</td>
<td>3699</td>
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<td>50%</td>
<td>-424</td>
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<td>1470</td>
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<td>-424</td>
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<tr>
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<td>1470</td>
<td>100.00%</td>
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<td></td>
<td>50%</td>
<td>-424</td>
</tr>
<tr>
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<td>3699</td>
<td>100.00%</td>
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<td>5</td>
<td>3699</td>
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<td>50%</td>
<td>-424</td>
</tr>
<tr>
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<td></td>
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<td>50%</td>
<td>-424</td>
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<tr>
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<td>3562</td>
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<td></td>
<td>3562</td>
<td></td>
<td>50%</td>
<td>-424</td>
</tr>
<tr>
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<td></td>
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<td>50%</td>
<td>-424</td>
</tr>
<tr>
<td>10</td>
<td>2055</td>
<td>50%</td>
<td></td>
<td></td>
<td>2055</td>
<td></td>
<td>50%</td>
<td>-424</td>
</tr>
<tr>
<td>11</td>
<td>3562</td>
<td>50%</td>
<td></td>
<td></td>
<td>3562</td>
<td></td>
<td>50%</td>
<td>-424</td>
</tr>
<tr>
<td>12</td>
<td>1205</td>
<td>50%</td>
<td></td>
<td></td>
<td>1205</td>
<td></td>
<td>50%</td>
<td>-424</td>
</tr>
</tbody>
</table>

Table 1-42. Production Allocation by Gas Type for Maximizing E[NPV] under 50% Discount Rate.

<table>
<thead>
<tr>
<th>Gas Type</th>
<th>Initial Production Rate (MMscfd)</th>
<th>Percentage of Total Supply Commitment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rich</td>
<td>4932</td>
<td>22.42%</td>
</tr>
<tr>
<td>Standard</td>
<td>8279</td>
<td>37.63%</td>
</tr>
<tr>
<td>Lean</td>
<td>8789</td>
<td>39.95%</td>
</tr>
</tbody>
</table>

Table 1-43. Production Allocation and Fields’ Properties for Maximizing E[NPV] under 50% Discount Rate.

<table>
<thead>
<tr>
<th>Field</th>
<th>Optimum Production Rate (MMscfd)</th>
<th>Potential Upper Bound (MMscfd)</th>
<th>Min. Rate Lower Bound (MMscfd)</th>
<th>Production Status</th>
<th>Reserves Size (Trillion SCF)</th>
<th>Initial Depletion Stage (% of reserves)</th>
<th>Decline Rate (D)</th>
<th>Decline Exponent (b)</th>
<th>Fixed OPEX $/Mscf Req</th>
<th>Variable OPEX $/Mscf</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2047</td>
<td>2055</td>
<td>205</td>
<td>15</td>
<td>0.55</td>
<td>0.163</td>
<td>0.213</td>
<td>58.0</td>
<td>0.40</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>659</td>
<td>986</td>
<td>148</td>
<td>6</td>
<td>0.63</td>
<td>0.210</td>
<td>0.286</td>
<td>55.0</td>
<td>0.60</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>2219</td>
<td>2219</td>
<td>271</td>
<td>27</td>
<td>0.25</td>
<td>0.170</td>
<td>0.412</td>
<td>73.0</td>
<td>0.75</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>1014</td>
<td>1096</td>
<td>230</td>
<td>10</td>
<td>0.35</td>
<td>0.128</td>
<td>0.375</td>
<td>80.0</td>
<td>0.80</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>1470</td>
<td>2740</td>
<td>99</td>
<td>20</td>
<td>0.58</td>
<td>0.173</td>
<td>0.359</td>
<td>90.0</td>
<td>0.95</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>3699</td>
<td>3699</td>
<td>247</td>
<td>45</td>
<td>0.16</td>
<td>0.128</td>
<td>0.412</td>
<td>75.0</td>
<td>0.90</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>2740</td>
<td>2740</td>
<td>296</td>
<td>50</td>
<td>0.15</td>
<td>0.096</td>
<td>0.438</td>
<td>65.0</td>
<td>0.80</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>3562</td>
<td>3562</td>
<td>296</td>
<td>65</td>
<td>0.10</td>
<td>0.078</td>
<td>0.490</td>
<td>100.0</td>
<td>1.10</td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>4384</td>
<td>4384</td>
<td>296</td>
<td>80</td>
<td>0.35</td>
<td>0.085</td>
<td>0.500</td>
<td>90.0</td>
<td>0.75</td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>2055</td>
<td>2055</td>
<td>296</td>
<td>25</td>
<td>0.54</td>
<td>0.106</td>
<td>0.412</td>
<td>105.0</td>
<td>0.90</td>
<td></td>
</tr>
<tr>
<td>11</td>
<td>3562</td>
<td>362</td>
<td>362</td>
<td>65</td>
<td>0.30</td>
<td>0.072</td>
<td>0.383</td>
<td>120.0</td>
<td>1.30</td>
<td></td>
</tr>
<tr>
<td>12</td>
<td>1205</td>
<td>1205</td>
<td>197</td>
<td>11</td>
<td>0.54</td>
<td>0.182</td>
<td>0.451</td>
<td>105.0</td>
<td>1.20</td>
<td></td>
</tr>
</tbody>
</table>
1.5.3. Probabilistic Price and Production Forecasts

The analysis of optimizing the allocation decision under the uncertainty of market prices and reservoir performance is discussed here. The uncertainty of market prices was modeled using the Mean Reversion Model while the uncertainty in reservoir performance and properties was modeled by specifying the fields’ reserves as probability distributions. The reserves were designed as triangular and lognormal distributions as discussed below.

The uncertainty in reserves is one of the main uncertainties to deal with in field development decisions. This reserve uncertainty comes from the fact that reservoirs exist thousands of feet below the ground and the mechanisms under that those reservoirs form. Uncertainties in many reservoir properties can impact the reserves estimates; those parameters include permeability, porosity, reservoir thickness, PVT properties, reservoir extension, etc. The uncertainty in reserves can impact the length of the plateau. In our model, this uncertainty was correlated with reservoir size and age as shown in the Reservoir Models section.

1.5.3.1. Reserves as Triangular Distribution

In this section, reserves were modeled as triangular distribution; (Figures 1-26, 1-27, and 1-28) show the distributions of reserve, maximum potential, and minimum operating rate for Field-1. The triangular distribution was specified by three parameters minimum, maximum, and most likely values. The assignment of these parameters for all the fields was discussed in the Reservoir Models section. All scenarios evaluated here assumed a 10% discount rate and 22,000 MMscfd supply commitment. (Tables 1-44 and
show the results for maximizing the $E[\text{total NPV}]$ under the uncertainties of market price and reservoir properties. The optimal $E[\text{total NPV}]$ was $111.368$ billion and $E[\text{plateau length}]$ was 4 years. (Tables 1-46 and 1-47) show the results for maximizing the $E[\text{total plateau length}]$ under the uncertainties of market price and reservoir properties. The optimal $E[\text{total NPV}]$ was $100.947$ billion and $E[\text{total plateau length}]$ was five years. Comparing (Tables 1-45 and 1-47), the optimizer allocated more rates from the rich gas field when optimizing $E[\text{NPV}]$ and allocated more rates from the lean gas fields when optimizing $E[\text{PL}]$. The higher intrinsic value for rich gas increased the $E[\text{NPV}]$ while the size (large reserve) and age (young fields) for lean gas fields increased the $E[\text{PL}]$. This comparison was a relative one; when maximizing the $E[\text{NPV}]$, the optimizer was still allocating a large portion of the target daily rate from lean gas fields due to their properties.

By managing the quantity of reserves available and energy stored in the portfolio of fields, the plateau length can be extended. This analysis supports (Deckers/Olsen 1997) claim that states to maximize the cumulative production (i.e., portfolio capacity) with respect to time for a portfolio of gas fields, production should be preferentially allocated to fields with the least decline in capacity per unit produced.
Figure 1-26. Reserve Triangular Distribution for Field-1.

Figure 1-27. Minimum Facility Operating Rate Triangular-Distribution for Field-1.

Figure 1-28. Maximum Potential Rate Triangular-Distribution for Field-1.

Table 1-44. Production Allocation for Maximizing E[NPV] Using Probabilistic Price and Production Forecast.

<table>
<thead>
<tr>
<th>Field</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
<th>12</th>
</tr>
</thead>
<tbody>
<tr>
<td>Production Rate (MMscfd)</td>
<td>1183</td>
<td>402</td>
<td>2080</td>
<td>690</td>
<td>903</td>
<td>3251</td>
<td>2845</td>
<td>3630</td>
<td>3333</td>
<td>879</td>
<td>2393</td>
<td>411</td>
</tr>
<tr>
<td>Percentage of Initial Potential Used (%)</td>
<td>43.44%</td>
<td>8.91%</td>
<td>113.43%</td>
<td>29.90%</td>
<td>-0.72%</td>
<td>33.28%</td>
<td>70.09%</td>
<td>50.53%</td>
<td>35.58%</td>
<td>9.92%</td>
<td>65.07%</td>
<td>18.31%</td>
</tr>
<tr>
<td>Plateau Length (Years)</td>
<td>6</td>
<td>6</td>
<td>16</td>
<td>14</td>
<td>9</td>
<td>34</td>
<td>34</td>
<td>38</td>
<td>26</td>
<td>12</td>
<td>22</td>
<td>10</td>
</tr>
<tr>
<td>E[Total Plateau Length] (Yrs)</td>
<td>4</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>E[TOTAL NPV] ($ Million)</td>
<td>111,368</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Discount Rate</td>
<td>10%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total Supply Commitment (MMscfd)</td>
<td>22000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Table 1-45. Production Allocation by Gas Type for Maximizing E[NPV] Using Probabilistic Price and Production Forecast.

<table>
<thead>
<tr>
<th>Gas Type</th>
<th>Initial Production Rate (MMscfd)</th>
<th>Percentage of Total Supply Commitment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rich</td>
<td>3665</td>
<td>16.66%</td>
</tr>
<tr>
<td>Standard</td>
<td>7689</td>
<td>34.95%</td>
</tr>
<tr>
<td>Lean</td>
<td>10646</td>
<td>48.39%</td>
</tr>
</tbody>
</table>

Table 1-46. Production Allocation for Maximizing E[total Plateau Length] Using Probabilistic Price and Production Forecast.

<table>
<thead>
<tr>
<th>Field</th>
<th>Production Rate (MMscfd)</th>
<th>Percentage of Initial Potential Used (%)</th>
<th>Plateau Length (Years)</th>
<th>Total Plateau Length (Yrs)</th>
<th>E[Plateau Length] (Years)</th>
<th>Discount Rate</th>
<th>Total Supply Commitment (MMscfd)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>616</td>
<td>40.66%</td>
<td>5</td>
<td>5</td>
<td>5</td>
<td>10%</td>
<td>22000</td>
</tr>
<tr>
<td>2</td>
<td>296</td>
<td>14.42%</td>
<td>25</td>
<td>25</td>
<td>25</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>666</td>
<td>54.77%</td>
<td>24</td>
<td>24</td>
<td>24</td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>333</td>
<td>2.71%</td>
<td>9</td>
<td>9</td>
<td>9</td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>822</td>
<td>3.48%</td>
<td>28</td>
<td>28</td>
<td>28</td>
<td></td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>2504</td>
<td>47.41%</td>
<td>41</td>
<td>41</td>
<td>41</td>
<td></td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>2389</td>
<td>48.96%</td>
<td>22</td>
<td>22</td>
<td>22</td>
<td></td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>4865</td>
<td>93.85%</td>
<td>10</td>
<td>10</td>
<td>10</td>
<td></td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>4505</td>
<td>23.41%</td>
<td>9</td>
<td>9</td>
<td>9</td>
<td></td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>616</td>
<td>62.54%</td>
<td>22</td>
<td>22</td>
<td>22</td>
<td></td>
<td></td>
</tr>
<tr>
<td>11</td>
<td>3637</td>
<td>65.57%</td>
<td>4</td>
<td>4</td>
<td>4</td>
<td></td>
<td></td>
</tr>
<tr>
<td>12</td>
<td>751</td>
<td>58.29%</td>
<td>4</td>
<td>4</td>
<td>4</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 1-47. Production Allocation by Gas Type for Maximizing E[total Plateau Length] Using Probabilistic Price and Production Forecast.

<table>
<thead>
<tr>
<th>Gas Type</th>
<th>Initial Production Rate (MMscfd)</th>
<th>Percentage of Total Supply Commitment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rich</td>
<td>1578</td>
<td>7.17%</td>
</tr>
<tr>
<td>Standard</td>
<td>6048</td>
<td>27.49%</td>
</tr>
<tr>
<td>Lean</td>
<td>14374</td>
<td>65.34%</td>
</tr>
</tbody>
</table>

1.5.3.2. Reserves as Lognormal Distribution

In this section, reserves were modeled as lognormal distribution; (Figure 1-29) shows the distributions for the reserve in Field-1. The lognormal distribution was specified by two parameters: mean value and standard deviation. The assignment of these parameters for all fields was discussed in the Reservoir Models section. This section discusses the case of the 10% discount rate and 22,000 MMscfd supply commitment.
(Tables 1-48 and 1-49) show the results from maximizing the $E[\text{total NPV}]$ under the uncertainties of market price and reservoir properties. The optimal $E[\text{total NPV}]$ was $83.473$ billion and $E[\text{plateau length}]$ was two years. According to (Table 1-49), the percentages were close to those from maximizing $E[\text{total NPV}]$ using triangular reserve distribution. This confirms our conclusion that the optimal decision was a function of reserve size, age and decline exponent $b$. The different values for $E[\text{total NPV}]$ and $E[\text{total PL}]$ were due to the different assumption of lognormal distribution rather than triangular distribution.

![Reserve Triangular Distribution for Field-1.](image)

**Table 1-48. Production Allocation for Maximizing $E[\text{NPV}]$ Using Probabilistic Price and Production Forecast.**

<table>
<thead>
<tr>
<th>Field</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
<th>12</th>
</tr>
</thead>
<tbody>
<tr>
<td>Production Rate (MMscfd)</td>
<td>1052</td>
<td>536</td>
<td>2221</td>
<td>757</td>
<td>1266</td>
<td>3036</td>
<td>2517</td>
<td>2388</td>
<td>3281</td>
<td>1097</td>
<td>2891</td>
<td>959</td>
</tr>
<tr>
<td>Percentage of Initial Potential Used (%)</td>
<td>28.02%</td>
<td>83.13%</td>
<td>36.00%</td>
<td>70.66%</td>
<td>97.48%</td>
<td>1299.78%</td>
<td>334.42%</td>
<td>11.44%</td>
<td>0.90%</td>
<td>106.93%</td>
<td>81.33%</td>
<td>67.49%</td>
</tr>
<tr>
<td>Plateau Length (Years)</td>
<td>8</td>
<td>1</td>
<td>32</td>
<td>7</td>
<td>1</td>
<td>15</td>
<td>25</td>
<td>41</td>
<td>41</td>
<td>1</td>
<td>17</td>
<td>4</td>
</tr>
</tbody>
</table>

$E[\text{Total Plateau Length}]$ (Yrs) | 2
$E[\text{TOTAL NPV}]$ ($\text{Million}$) | 83,473
Discount Rate | 10%
Total Supply Commitment (MMscfd) | 22000
Table 1-49. Production Allocation by Gas Type for Maximizing $E[\text{NPV}]$ Using Probabilistic Price and Production Forecast.

<table>
<thead>
<tr>
<th>Gas Type</th>
<th>Initial Production Rate (MMscfd)</th>
<th>Percentage of Total Supply Commitment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rich</td>
<td>3809</td>
<td>17.31%</td>
</tr>
<tr>
<td>Standard</td>
<td>7576</td>
<td>34.43%</td>
</tr>
<tr>
<td>Lean</td>
<td>10615</td>
<td>48.25%</td>
</tr>
</tbody>
</table>

1.5.4. Sensitivity Analysis

Deterministic price and production forecast models were used in the sensitivity analysis. (Figure 1-30) contains a tornado chart for the total NPV as a function of model parameters. The tornado chart shows how the total NPV is sensitive to changing parameters by +10% and -10% of their base case values. Discount rate, tax rate, and price growth rate were the parameters with the greatest impact on the total NPV value as shown in the figure. Varying the discount rate by +10% and -10% can change the value of the company from $11 billion to -$10 billion; in other words a very profitable company can become bankrupt by changing the discount rate. Moreover, tax rate and price growth rate can change the value of a company from a positive few billion dollars to a negative few billion dollars as shown in the figure. It was essential to evaluate these parameters with proper accuracy in the process of valuing a company. In the second tornado chart (Figure 1-31), the analysis focused on the reserves and end of plateau. Although the impact of these two parameters was smaller than that from the discount rate, it was still significant and could be $1-2$ billion. (Figures 1-32 and 1-33) show the tornado charts for the decline exponent $b$ and decline rate $D_i$, respectively. The two production forecast parameters have an impact on total NPV with a magnitude of tens to
hundreds of millions of dollars. The analyses in this section show that in addition to the impact on the optimal allocation decision, reserves, decline exponent b, and decline rate Di can impact the value of a company.

Figure 1-30. Tornado Chart for Total NPV by Varying Parameters by +10% and -10%.
Figure 1-31. Tornado Chart for Total NPV by Varying Fields Parameters by +10% and -10%.

Figure 1-32. Tornado Chart for Total NPV by Varying Decline Exponent b by +10% and -10%. 
Figure 1-33. Tornado Chart for Total NPV by Varying Decline Rate $D_i$ by $+10\%$ and $-10\%$.

1.5.5. Discussion

This section presents the findings, challenges, and limitations of the study. From the results reported earlier, the type price forecasting model (MRM and Floating Price Models) did not impact the decision regarding optimal allocation. In other words, there was no value added from implementing one price model over the other, and no incentive to take on extra costs to investigate which model is being followed by the market. However, the type of price model had a significant impact on company value, as shown in (Table 1-50). (Table 1-50) summarizes the NPV, plateau length, and average production decline for the different evaluated models. The NPV values for the Floating Price model and the MRM (deterministic production) were $183,307$ million and $125,252$ million, respectively. It was essential to investigate the behavior of prices when evaluating the NPV for a company.
On the other hand, the type of reservoir production model has a significant impact on both the optimal allocation decision and on assessing the NPV of a company. Specifically, the following parameters have a significant impact on the allocation decision: reserve size and age, and decline exponent b. Mitigating the risk in those parameters was recommended. Another parameter that can impact both the allocation decision and the assessing of the NPV was the discount rate. The optimizer prioritizes the allocation list of fields based on the reserve size and age, and decline exponent, to maximize NPV, for low discount rate values. However, above a certain value of discount rate, the optimizer starts to allocate more rates for the fields with high intrinsic value to boost the NPV since revenue in later years is severely penalized.

Table 1-50. Summary of Results.

<table>
<thead>
<tr>
<th>Price Model</th>
<th>Floating Price</th>
<th>MRM</th>
<th>MRM</th>
<th>MRM</th>
<th>MRM</th>
<th>MRM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Production Model</td>
<td>Deterministic</td>
<td>Deterministic</td>
<td>Deterministic</td>
<td>Prob. Triangular</td>
<td>Prob. Triangular</td>
<td>Prob. Lognormal</td>
</tr>
<tr>
<td>Maximizing?</td>
<td>NPV or PL</td>
<td>NPV or PL</td>
<td>Average Decline</td>
<td>E[Total NPV]</td>
<td>E[Total PL]</td>
<td>E[Total NPV]</td>
</tr>
<tr>
<td>Total NPV (MM$)</td>
<td>183,307</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Plateau Length (Years)</td>
<td>7</td>
<td>7</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>E[Total NPV] (MM$)</td>
<td>125,252</td>
<td>103,776</td>
<td>111,368</td>
<td>100,947</td>
<td>83,473</td>
<td></td>
</tr>
<tr>
<td>E[Plateau Length] (Years)</td>
<td>4</td>
<td>5</td>
<td>2</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average Annual Decline (MMscfd/Yr)</td>
<td>417</td>
<td>417</td>
<td>346</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Trying to find a global optimum was a challenge because the optimization problem was nonlinear in decision variables. As a result, the optimization algorithm (nonlinear programming or Genetic Programming) did not guarantee global optimality. Many optimization runs were performed with different starting points and different optimization parameters (i.e., mutation and crossover rate). Another challenge was cost estimation; an extensive search for a reliable cost model was conducted. A reliable model was implemented that was first used by (Kennedy, 1993 and Bittencourt, 1997).
Moreover, field parameters estimation was a challenge due to the sensitivity of releasing such information. Field parameters in the study were estimated by industry experts to ensure the reliability of the study.

One study limitation involved the optimizer, that did not guarantee global optima because the optimization problem was nonlinear in decision variables. To increase the probability of reaching global optima, many optimization runs, with different initial values for the decision variables were required. Moreover, the optimizer had to be allowed to search for a long time, with no improvement, before terminating the process. Another trick for Genetic Programming GP was to manipulate the process with the mutation and crossover rates. Mutation and crossover were used as searching methods for the GP algorithm. Another study limitation was the use of decline curve analysis to forecast production. Decline curve analysis was sufficient for the purpose of our study; however, the accuracy of the results can be increased by using numerical simulator.

1.6. The Value of an Accurate Expected Demand (VOI Analysis)

The supply commitment contract has a significant impact on the optimal allocation decision as shown in the earlier results where optimizing NPV or PL can significantly differ when removing the supply commitment constraint. The VOI analysis evaluated the maximum monetary value the gas company was willing to pay to reduce the risk in the supply commitment. Since the optimal allocation decision reacts to the change in the value of the supply commitment, there can be a maximum value that the company should pay to reduce the risk in the supply commitment; this maximum
monetary value is the value of perfect information (VOI). This section discusses the process of calculating the value of acquiring perfect information on the expected demand for gas (supply commitment). The analyses in this section were implemented in the deterministic production and price forecasting models for simplicity and clarity.

The VOI analysis requires two cases involving the uncertain variable. Supply commitment was assigned 22,000 MMscfd and 29,000 MMscfd for the base case and alternate case, respectively. (Figure 1-34) summarizes the process of calculating the value of perfect information. The first step involved deciding about acquiring perfect information on which case of the supply commitment to be realized. If perfect information is acquired, the optimizer calculates the optimal allocation for each case; total NPV for the base and alternate cases were $179.25 billion and $200.848 billion, respectively. These two NPV values were optimal. On the other hand, if perfect information is not acquired, the optimizer solves for the base case; then either one of the two cases is realized. If the base case is realized, the allocation decision is optimal at a total NPV of $179.25 billion; however, if the alternate case is realized, the allocation decision is suboptimal at a total NPV of $179.25 billion. The value of perfect information is the NPV lost if the alternate case is realized and the information is not acquired. The VOI was $21.598 billion, that is the difference between NPV B and NPV C in (Figure 1-34). In other words, the impact of supply commitment can be in the tens of billions of dollars.
1.7. Conclusions and Recommendations for Future Work

1.7.1. Conclusions

Allocating production rates across a portfolio of producing gas fields, with the goal of maximizing NPV and plateau length, was a computationally challenging problem. Uncertainties in prices and reservoir performance add to the complexity of the problem. In this study, risk analysis workflow and an integrated optimization model were implemented to solve this dynamic optimization problem. The integrated model accounts for field level and corporate level constraints. Field level constraints include technical attributes (i.e., reservoir properties), facility constraint, and costs while corporate level
constraint was represented by supply contract commitment. Using the proposed model, the impact of the following items was evaluated: 1) Uncertainty in gas price, 2) Uncertainty in reservoir performance, 3) Discount rate, 4) Average production decline rate, and 5) Total daily target rate. Then, a value of perfect information (VOI) analysis was conducted to identify the maximum monetary value the gas company was willing to pay to mitigate the risk in the expected demand for gas. The optimal allocation decision is a function of reservoir age and size, reservoir quality and commodity prices. To maximize total portfolio NPV and plateau length, production rate from young fields with large decline exponents should be prioritized; then, the production from mature fields with large decline exponents. In general, the decline exponent has the greatest impact while the reservoir size has a relatively small impact. Below are concluding remarks:

1. Total NPV and total plateau length, for a portfolio of producing fields, can be maximized by managing the production rates across fields while maintaining a total daily target rate. Moreover, extending total plateau length can delay development projects needed to overcome losses in production. This delay of development projects can save millions of dollars in time-adjusted costs.

2. Price forecasting models do not impact the optimal allocation decision. Evaluated price models (Floating Price and MRM) resulted in the same optimal allocation decision.

3. Reservoir properties, especially reservoir size and age, and decline exponent b, can significantly impact the optimal production allocation decisions. Moreover, uncertainty in reservoir performance can impact the optimal allocation decision. Field maturity was the parameter that had the greatest
impact when NPV was maximized for deterministic production cases. For probabilistic cases, field size was the parameter with the greatest impact when $\text{E}[\text{plateau length}]$ was maximized. However, the intrinsic value for crude and size of reservoir significantly impacted the allocation decision when $\text{E}[\text{NPV}]$ was maximized.

4. To maximize total portfolio NPV and plateau length, production from young fields with large decline exponents should be prioritized; then, the production from mature fields with large decline exponents. Here the impact of reservoir size is relatively small.

5. Uncertainties in gas price and reservoir properties had a significant impact on company valuation. These uncertainties can turn a profitable company into a losing one. It was important to incorporate uncertainty in prices and reservoir properties when evaluating the NPV for a company.

6. The estimation of the expected demand (supply contract commitment) can significantly impact the optimal allocation decision. The value of perfect information was carried out to assess the maximum monetary value of paying to mitigate risk in expected demand. The impact of expected demand on total NPV can be in the tens of billions of dollars.

7. The set of optimal allocation decisions, provided by the integrated model, was reliable one. Although the optimization problem was nonlinear in decision variables, multiple runs with different properties were conducted until no further improvements could be achieved.
8. The simplified reservoir model facilitates the optimization and Monte Carlo simulation processes.

9. The error of perfect information (Anticipatory error) was avoided in the study by restricting the ability of the optimization algorithm to track the path of uncertain variable (e.g., gas prices) and suggest an optimal solution, that follows the uncertain variable to optimize the objective function. This was done by giving the optimizer the role to provide single rate value for each field. This production rate represents the rate for the production plateau for that field. The Anticipatory error is a common error in dynamic optimization studies.

10. The option of shutting down fields during dynamic optimization was initially incorporated in our model. However, this option was not considered during the analyses because it reduced the reliability of the study. Allowing the optimizer to shutdown fields (depending on prices and profits) reveals unknown parameters to the optimizer; hence, it is anticipatory error. All values, negative and positive, of NPV should be analyzed.

11. Risk Solver Platform (RSP) provides fast-solving algorithms and Monte Carlo simulation sampling. This allows for robust sensitivity analysis and optimization processes. The speed of the RSP allowed for the evaluation of different scenarios and optimization parameters.
1.7.2. Recommendations for Future Research

1. In our study, a simplified decline curve analysis and material balance model were implemented. The implementation of numerical simulation in the capacity management can be investigated.

2. An integrated model was built to optimize the allocation decision. One may try to find relationships between the reservoir properties and the optimal assigned rates. Furthermore, the possibility of building a regression model to predict the optimal allocation from the reservoir properties can be considered.

3. The decision variables for our problem were the fields’ production rates. Other fields’ parameters can be investigated as decision variables. One important parameter to consider is the depletion rate for each field. Rather than assigning a production rate, a depletion rate is assigned to maximize total NPV. The depletion rate is related to time value of money and discounting concepts. It is the percentage of original reserves a resource is depleted annually. One may think that optimizer will deplete fields with higher intrinsic values at higher depletion rates. However, the problem is not a simple due to the presence of parameters that constrain the depletion rate, including safety of reservoir, recoverable volume of gas, economy of operation, demand, etc.

4. The total NPV, PL, E[total NPV], and E[PL] were the objective functions used in the study. Another possible objective function to evaluate are the standard deviation of the NPV or PL distributions, or the cost of operation.
The standard deviation can be minimized to minimize project risk and increase confidence in achieving a specific NPV.
Chapter 2

Predicting Decline Parameters and a Development Strategy for a Capacity Management Model: An Artificial Expert System

2.1. Introduction

Real-world applicability of a research study can be a key element in its success and its value to oil and gas companies. Enhancing a research study with applicability can increase the reliability of the results. The capacity management model, in the previous chapter, allocated production rates to a portfolio of fields in order to maximize total NPV or total plateau length while meeting a total daily target rate. Decline curve analysis and a material balance model were implemented to forecast production for each field to facilitate optimization and Monte Carlo simulation processes. Moreover, decline curve parameters were estimated from (Fetkovich, 1994) due to the sensitivity of releasing actual field data. The Capacity Management model requires reservoir properties (i.e., decline curve parameters), price model, cost model, reservoir model and delivers a set of production rates that maximizes the objective function, NPV or plateau length for the portfolio. This study proposes two artificial expert systems; the first one predicts decline curve parameters and plateau length for a given reservoir properties, development plan, and production rate. The second expert system predicts a development plan for a given reservoir properties, production rate and plateau length. The first system provides the decline parameters, that represent actual reservoir properties, as input to the Capacity Management model. This makes the Capacity Management model practical and more reliable. The second system recommends a development plan (drainage area) for a given
Capacity Management output (plateau length and production rate) along with actual reservoir properties (porosity, permeability, reservoir thickness, etc.). The first system can be used to identify decline curve parameters for actual fields, and feed those parameters to the Capacity Management model. Then, after the Capacity Management model optimizes the NPV or the plateau length, the optimal plateau length and production rates can be provided to the second expert system, that recommends a development plan for the field. These two expert systems increase the applicability of the Capacity Management model for actual field data.

Predicting production profile characteristics (i.e., plateau length and decline parameters), for a given reservoir and development plan, is a nonlinear and computationally expensive problem. The fact that these parameters are indirect product or numerical reservoir simulators adds to the complexity of the problem. Conventionally, the decline parameters are estimated by fitting a curve through the production profile, that can be obtained via the reservoir simulator. Determining a development plan for a specified production rate and plateau length can be achieved using a trial and error approach that involves a numerical reservoir simulator. The proposed expert systems can deliver essential parameters that are not a direct output of a reservoir simulation. Each expert system can replace hundreds of simulation runs and hundreds of hours of engineering analysis to identify the development plan and the decline rate properties.

Building the expert systems was achieved in five parts: 1) Generating input and output data to cover all feasible ranges of the parameters, using a numerical reservoir simulator, 2) Preparing and cleaning the data—this step can affect the accuracy of predictability of an expert system (Marsland, 2009), 3) Designing the expert system, 4) Modifying the
design of the expert system until acceptable accuracy has been achieved, and 5) Testing the predictability or generalization of the expert system using randomly generated data and comparing the expert system’s output against the numerical simulator’s results.


Results showed excellent predictability for the two systems. Moreover, the two implemented mechanisms (Artificial Neural Network and Genetic Programming) resulted in similarly accurate predictions that increased confidence in the constructed systems. The proposed models are complimentary to numerical simulators. However, as tools these models can provide reservoir engineers with essential parameters in a timely manner.
2.2. Literature Review

2.2.1. Machine Learning Overview

“Machine learning, then, is about making computers modify or adapt their actions (whether these actions are making predictions, or controlling a robot) so that these actions get more accurate, where accuracy is measured by how well the chosen actions reflect the correct ones” (Marsland, 2009, p. 5). In other words, machine learning involves teaching a computer or a robot to perform tasks that we cannot do or cannot explain how to do, including playing a game (e.g., chess) or predicting an output of a complex system (Kifer, 2014). Based on (Marsland, 2009), there are four types of Machine Learning: 1) Supervised learning, 2) Unsupervised learning, 3) Reinforcement learning, 4) Evolutionary learning. First, supervised learning is a training process in that actual input and output data are provided to the training algorithm with the goal of generalization that is to predict an output with good accuracy from an input value. Supervised learning is used to predict and classify the data set. A supervised learning technique was implemented to train our two expert systems with both ANN and GP (Marsland, 2009 and Kifer, 2014). Second, unsupervised learning is a training process in that only input data is provided to the algorithm with the goal of clustering the data into groups. The algorithm tries to identify inputs with similar characteristics (Marsland, 2009). Third, Reinforcement learning is used to explore or navigate a maze; between supervised and unsupervised learning, the algorithm is identified when the answer is wrong but does not correct it (Marsland, 2009). This type of machine learning can be used in artificial intelligence to navigate a maze-like chess (Kifer, 2014). Fourth, Evolutionary learning is
a learning process in that biological evolution is mimicked to identify the fittest (best) prediction model. Biological organisms adapt and genetically change to survive in an environment (Marsland, 2009). This evolutionary learning was the basis for the GP algorithm implemented in the study. This section discusses the basis for the Artificial Neural Network ANN and the Genetic Programming GP.

2.2.1.1. Artificial Neural Networks

Artificial Neural Network (ANN) is a mathematical formulation that mimics the ability of the human brain to learn by experience and generalize (Marsland, 2009 and Priddy et al., 2005). Moreover, ANN can be viewed as a multi-layer perceptron MLP. A perceptron is a linear classifier as shown in (Figure 2-1) where w is a vector of weights for the circles. The perceptron is an algorithm that classifies the red and blue circles with solid line. A simple linear problem can be solved with a simple algorithm. However, practical data involve a nonlinear relationship and require a more complicated model to be solved (Marsland, 2009). The problem of nonlinearity can be addressed by adding a feature parameter to the problem; for example, a variable $x^2$ can be added to take care of the nonlinearity if a relationship between $y$ and $x$ is being evaluated (Kifer, 2014). The second approach to solving a nonlinear model involves implementing a more complicated algorithm (i.e., ANN)—this was the approach implemented in this study. In other words, ANN is a multi-layer perceptron or a combination of many linear models. Simply put, ANN searches for a nonlinear relationship between provided input and output so that the relationship can be used to predict the output for a new value of input (generalization).
Neurons are the processing units of a brain, which contains around 100 billion neurons (Marsland, 2009). (Figure 2-2) shows two connected neurons; each neuron consists of cell body, axon, and dendrites. Neurons receive signals from other neurons through dendrites; then, those signals are processed in the cell body and can cause the neuron to fire or not. If the neuron fires a signal, the signal travels through the axon to another neuron. The point at which an axon meets a dendrite is called a synapse. Synapses are classified as excitatory and inhibitory; excitatory synapses motivate the neurons to fire while inhibitory makes the neurons less likely to fire (Marsland, 2009). Neurons transmit chemicals to raise or lower the electrical potential of the neuron body; this potential dictates the firing process of a neuron. Each neuron is connected to thousands of other neurons, resulting in around 100 trillion synapses in a brain (Marsland, 2009). Learning in the brain happens through a process called plasticity, which modifies the strength of synaptic connections and creates new connections. Many early studies analyzed real neurons; Hodgkin and Huxley (1952) studied the actual neurons of a giant squid and came up with differential equations to compute the membrane potential of a neuron based on chemical concentrations (Marsland, 2009). (McCulloch and Pitts, 1943) presented the earliest simple mathematical model for a neuron. McCulloch and Pitts presented the neuron as (Marsland, 2009):

1. A set of weight $w_i$, that represents the synapses.
2. An adder to sum the input signals. This represents the collection of electrical charges in the membrane.
3. An activation function that controls whether a neuron fires or not for a given set of input.
The input represents signals coming from other neurons through the synapses. Those synapses have strength (weight) that impacts the strength of the signals. These weights are multiplied with the input. Then the weighted signals are summed up (Equations 2-1 and 2-2) to evaluate whether the weighted sum is greater than a preset threshold (neuron fires), or less than the threshold (neuron does not fire). (Figure 2-3) shows an artificial neuron. (Equation 2-1) shows the dot product of the input vector I and weight vector W. In (Equation 2-2), w₀ is the neuron’s threshold or the bias, and i₀ is a dummy input with value of 1. The sign of the weight represents the type of synapses—positive for excitatory and negative for inhibitory (Marsland, 2009).

\[ Y = I \cdot W \]  \hspace{1cm} (2-1)

\[ Y = i_0 w_0 + i_1 w_1 + i_2 w_2 + \cdots + i_n w_n \]  \hspace{1cm} (2-2)

Figure 2-1. A Linear Problem for Perceptron (Kifer, 2014).
2.2.1.1.1. Artificial Neuron Model

The neuron is the building element for an ANN; (Figure 2-2) and (Figure 2-3) show a sample of an actual neuron and an artificial neuron, respectively. In (Figure 2-3), the I’s are the inputs while the w’s are the neuron weights. The following assumptions are made during the modeling of the artificial neural network (Fausett, 1994):

1. Information comes about through processes in the neurons (unit element of the ANN).
2. Processed information (signals) transfer between neurons through links.

3. Each link possesses a weight that multiplies the processed signal to adjust the strength of the signal.

4. An activation function and a threshold function are applied to the neuron’s input to determine whether it should fire or not.

The weighted sum of the input and weights are presented in (Equation 2-2) where I’s are the input and w’s are the weights. I₀ is a dummy input with value of 1, and w₀ is the bias or threshold value for a neuron. During the training of a network, the weights are the only variable over which we have control; in other words, ANN training occurs by modifying the weights (Marsland, 2009). The processed signals are transferred to another neuron or to the output node via a transfer function (activation function).

2.2.1.12. Transfer Functions

Transfer functions (activation functions), and a threshold function control whether a neuron fires or not. The threshold function usually takes the form of a step function (Figure 2-4) to simulate the neutrons’ action of firing or not firing. The step function has a sudden jump in the middle; this jump creates discontinuity. During the training process of an ANN, this threshold function (step function) is differentiated to minimize the error. Differentiating the threshold function at the jump is not possible. However, this problem can be solved by implementing a transfer function that looks like the threshold function. The step function is similar to the mathematical S-shaped function; (Figure 2-4) shows popular transfer functions including the sigmoid function, linear threshold function,
bipolar step function, hyperbolic tangent function, and bipolar linear function. Sigmoid functions are the commonly used ones. (Figure 2-5) shows the linear transfer function, commonly used at the output nodes. ANN can produce output without de-normalizing (Minakowski, 2008). Below are some of the activation functions:

- The linear function: \( f(x) = x \)  
- The sigmoid function: \( f(x) = \frac{1}{1+e^{-x}} \) 
- The hyperbolic tangent function: \( f(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \) 
- The step function: \( f(x) = \begin{cases} a & \text{if } x < c \\ b & \text{if } x > c \end{cases} \) 
- The linear threshold function: \( f(x) = \begin{cases} x & \text{if } x < b \\ a & \text{if } x > b \end{cases} \) 

![Figure 2-4. Transfer Functions (Priddy et al., 2005).](image1)

![Figure 2-5. Linear Transfer Functions (Hagan et al., 2002).](image2)
Sigmoid transfer functions are commonly used in multi-layer back-propagation feed-forward ANN; the terms multi-layer, back-propagation, and feed-forward are discussed below. The log-sigmoid and hyperbolic tangent sigmoid functions continuous nonlinear function that scale input values to values between 0 and 1, for log-sigmoid, and \(-1\) and 1 for hyperbolic tangent. Those sigmoid functions are recommended for training ANN, which tackles reservoir engineering problems (Ramgulam et al., 2007).

2.2.1.1.3. Types of Artificial Neural Network

The simplest form of ANN a perceptron that can solve simple linear problems. However, more complicated models might be needed to solve complicated nonlinear problems. Artificial neural network can be classified into three types: 1) Single-layer feed-forward networks, 2) Multi-layer feed-forward networks, and 3) Recurrent networks. In training an ANN, we can change the number of hidden layers, change the number of neurons in a layer, or add backward connections from output back to the input (Marsland, 2009). The first two approaches represent the feed-forward ANN while the last approach represents the recurrent ANN.

The simplest form of ANN is the perceptron, which is a single-layer ANN (Figure 2-6). A layer or collection of neurons works together to calculate the relationship between input and output; those neurons are connected to the input and output; however, they are not connected. Basically, the single-layer ANN consists of an input layer, a hidden layer, and an output layer. The input layer is a vector of the input values. The hidden layer that is the layer of neurons between input and output layers consists of the neurons and
contains the weight and bias matrix, and activation and threshold functions. Each element in the input vector is connected to a neuron in the hidden layer via a weight matrix. The hidden layer results in the output layer that contains the output values of the problem.

The second is the multilayer feed-forward ANN. This type of ANN can handle very complicated nonlinear prediction and classification problems. The architectures of single-layer and multi-layer ANN are similar; the only difference is that the multi-layer ANN has more than one hidden layer of neurons. (Figure 2-7) shows a sample of a 3-hidden layer ANN; the output of each hidden layer of neurons forms the inputs for the next layer of neurons. This kind of ANN, multi-layer feed-forward back-propagation, was implemented in this study.

The last type of ANN is the recurrent networks, which connects the output layer back to the input layer (Figure 2-8). First, input values are supplied to the ANN, which performs an iteration to the output layer; then, the resulting outputs are sent back to the input to update the weights and biases. In other words, outputs are used to update the output value of the next time-step (Bukhamseen, 2014).
Figure 2-6. Single-layer Artificial Neural Network (Hagan et al., 2002).

Figure 2-7. Multi-Layer Artificial Neural Network (Hagan et al., 2002).

Figure 2-8. Recurrent Artificial Neural Network (Hagan et al., 2002).
2.2.1.1.4. Feed-forward Back-propagation Artificial Neural Network

Training an ANN occurs in two parts: 1) Going forward through the input values and weight and biases to calculate the output value, and 2) Going backward from the output layer through the hidden layer to update the weight and biases all the way back to the input layer.

In the feed-forward part, the inputs are fed through the network to decide which neurons are firing; the outputs are calculated. The errors are sent backward through the network to minimize the error using a learning algorithm like gradient descent; first the error is calculated at the output (i.e., sum of squared error). Then the gradient of those errors are calculated to update the weights in the network; the update process starts from the layer connected to the output layer. After that, the weights in the previous layer are updated; this process continues all the way back to the input layer (Marsland, 2009).

Back-propagation is the most frequently used ANN (Maren et al., 1990). The differentiability of sigmoid activation functions is very important to the success of back-propagation ANN. In order to update those weights to minimize the error, the activation function must be differentiable.

2.2.1.1.5. Training Algorithms

Training algorithms are responsible for updating the weights and biases of the network. A commonly used training algorithm is gradient descent, which calculates the gradient of error with respect to the weights. The gradient of a function is the direction in which the function increases or decreases the most. In other words, gradient descent
updates the weights in a steepest direction the error function decreases. Other training algorithms included the conjugate gradient, the Levenberg-Marquardt (LM) algorithm, and the resilient back-propagation algorithm (Bukhamseen, 2014). Scaled conjugate gradient algorithm performed the best for our models.

Scaled conjugate gradient SCG algorithm eliminates the need for a line search at each iteration, which is required by the standard conjugate gradient algorithm, saving significant computation time (Bukhamseen, 2014). SCG incorporates the model-trust region approach from the Levenberg-Marquardt algorithm in order to scale the step size of the conjugate gradient (Møller, 1993). Although SCG may require more iterations to converge than some algorithms, each iteration converges faster than those algorithms (Beale et al., 2013).

2.2.1.1.6 Generalization and Over-fitting

One of the uses of ANN is generalization, or the ability of a model to predict set outputs for new set inputs. During the training process, allowing the ANN to train for very long time can cause over-fitting, which means that the ANN fitted the model and the noise in the model. In other words, the ANN memorized the data and cannot predict correct output if a new set of input that is not part of the training data set. When to stop training is a critical decision as discussed below. This introduces the concept of convergence criteria for the ANN.

The convergence criterion for ANN is the improvement of the error from the previous iteration. Local minima can cause early convergence; this problem can be
tackled by increasing the number of iterations with the hope of getting out of the local minima, and by introducing a momentum term in the learning algorithm as shown in (Equation 2-8). The momentum term gives the gradient of the error a strong push if a minimum is found; if the error function increases after the push, the training algorithm will go back to the minima found (Kifer, 2014, Fausett, 1994, and Bukhamseen, 2014). In the equation, \( \gamma \) is the momentum coefficient \((0 \geq \gamma > 1)\), \( w \) is the weight, \( \alpha \) is the learning rate, and \( \epsilon \) is the error function. The selection of the number of hidden layers and number of neurons in each hidden layer can affect the convergence speed. Few neurons can cause poor predictability of the ANN while too many neurons can cause over-fitting. Moreover, functional links such as the mathematical relation between input and output can increase the convergence speed. Functional links strengthen the relationship between input and output parameters.

Over-fitting or memorization can be detected by splitting the data set into three parts: training, validation, and testing. The training data set is used to train the ANN; however, during the training process the validation data set is used to calculate the error. If the training error is decreasing while the validation error is increasing or constant, this is a strong indication that the ANN is over-fitting (fitting the model and the noise). This problem of over-fitting is tackled by two techniques: regularization and early stopping. Early stopping can be employed by splitting the data set into three parts: training, validation, and testing. The training data set is used to train the ANN while the validation set is used during the training and evaluate the error on the validation data set. The training process is terminated after a preset number of iterations from the point where the error on the validation data set stops decreasing. The testing data set is used to evaluate
the ability of the ANN to predict and generalize; this data set is new to the ANN and is not involved in the training (Beale et al., 2013). The second technique for avoiding overfitting is regularization, which reduces the values of the weights by penalizing the large weights in the error function as shown in (Equation 2-10) (Kife, 2014). (Equation 2-9) shows the mean squared error where N is number of input, t is the target, and y is the output. (Equation 2-10) shows the mean squared error with regularization where μ is the performance ratio and can be any value between 0 and 1, k is the number of weights in the model, and W is the weights and bias vector. The regularization process forces the training algorithm to reduce the values of weights and biases (Kifer, 2014, and Beale et al., 2013). Early stopping and regularization techniques were implemented in our models.

\[
\Delta w_k(i) = -\alpha \frac{\delta e}{\delta w_k} + \gamma \Delta w_k(i - 1)
\]  
(2-8)

\[
MSE = \frac{1}{N} \sum_{i=1}^{N} (t_i - y_i)^2
\]  
(2-9)

\[
MSE_{reg} = \mu * \left[ \frac{1}{N} \sum_{i=1}^{N} (t_i - y_i)^2 \right] + (1 - \mu) * \left[ \frac{1}{k} \sum_{j=1}^{k} W_j^2 \right]
\]  
(2-10)

2.2.1.1.7. Uses of Artificial Neural Network in the Oil and Gas Industry

ANN has been very successful in the oil and gas industry due to its real-time capability, robustness against noise and generalization (Ali, 1994). It has been successfully implemented in pressure transient analysis (AlAbbad, 2012), forecasting reservoir performance and estimating reservoir properties (Almousa, 2013), assist history matching (Bukhamseen, 2014), optimization of non-conventional well type, location and
trajectory (Yeten et al., 2002), reservoir characterization (Mohaghegh, 2000a), surface facility modeling (Mohaghegh, 2005), reservoir performance of hydraulically fractured horizontal wells (Kulga, 2010).

(BuKhamseen, 2014) proposed a set of expert systems to address the spatial and temporal changes in production. Six Artificial Neural Network-based expert systems were developed for the following issues: history matching, formation damage, hydraulic fracture, reservoir compaction, tarmat breakdown, and natural fractures. In the history matching study, an expert system used the production profile to identify or reduce uncertainties in the reservoir parameters that can improve history matching. In the formation damage part, plugged perforations and skin build up were identified from production profile. For hydraulic fracturing, the expert system identified the characteristics (width, half length, and permeability) of the fracture from the production profiles. In the reservoir compaction study, the expert system identified the impact of porosity and permeability reduction on production behavior. In the tarmat section, the expert system identified the time and location of the breakdown in the tar-mat from the production behavior. In the last section, expert system identified the location of fractures, fracture spacing, and fracture permeability.

(Bansal, 2011) developed expert systems based on an artificial neural network. The systems could characterize tight oil reservoirs, recommend development parameter and location, and predict cumulative production over two years. The results of the system were checked against data on actual fields.

(Bansal, 2009) developed an artificial-based expert system to model the behavior of heavy oil during in-situ combustion, which is an enhanced oil recovery technique for
heavy oil. The system predicted cumulative production (oil, water, and gas), peak temperatures of combustion zone, its location and velocity.

(AlAbbad, 2012) developed an artificial neural network expert system to predict virtual well test data at infill locations to be drilled. The results of the expert systems were confirmed against reservoir simulation data.

(Alrumah, 2011) developed an artificial neural network system to predict water saturation around vertical and horizontal wellbores. The system effectively predicted changes in water saturation over time.

(Almousa, 2013) developed an expert system to predict multilateral well design for a specific production profile and to evaluate reservoir properties. The systems were developed for single-phase gas and for gas fields with water drive. In addition to well design, the expert system predicted reservoir properties for a given production profile and well design.

(Ayala and Ertekin, 2007) developed a neuro-simulation tool to analyze the performance of gas cycling operations in gas condensate reservoirs. The results of the neuro-simulation system agreed with the output from a compositional simulator. Case studies showed a significant improvement in the capabilities of designing optimal production schemes for exploitation in gas condensate fields.

(Kulga, 2010) developed an expert system to predict the performance of hydraulically fractured horizontal wells in tight gas sands. The system can predict production decline parameters and handle several production regimes.

These studies were concerned with characterizing reservoirs and evaluating the performance of a specific reservoir system. However, they did not complement the expert
system with a decision support model similar to that in our proposal. Our expert system complemented the capacity management model. In other words, our expert system made the capacity management optimization model applicable to actual fields.

2.2.1.2. Genetic Programming (GP)

Genetic programming uses Genetic Algorithm GA to identify a symbolic regression relationship between inputs and an output that minimizes the error between the output and the target. This section discusses the Genetic Algorithm optimization algorithm.

2.2.1.2.1. Overview of Genetic Algorithm GA

The GA is a searching optimization algorithm that employs biological evolution and sexual reproduction mechanisms into mathematical searching formulation (Marsland, 2009). The algorithm employs concepts similar to those in biological evolution and the survival of the fittest introduced by (Darwin, 1859). In biological reproduction, each parent passes one of their two chromosomes (Figure 2-9). As a result, the child has similarities from both parents; however, random mutations occur when copying the chromosomes, resulting in changes over time. These changes can be attributed to the surviving processes and adapting to a specific environment. The “Genetic Algorithm is a computational approximation to how evolution performs search, which is by altering the genome and thus changing the fitness of individuals” (Marsland, 2009, p. 270). To model
the Genetic Algorithm, the following items are needed (Marsland, 2009): 1) Identify a fitness function similar to the objective function (measurement of performance) of a process, 2) Select a method to select proper parents from an entire population, and 3) Select a breeding method to generate offsprings. This process allowed the commingling of parents’ chromosomes.

Figure 2-9. Biological Reproduction (Marsland, 2009).

2.2.1.2.2. The Process of the GA

A set of solutions (single chromosome) is represented as a string of unit elements (genes) as shown in (Figure 2-10). The figure shows a set of solutions with five parameters. Genes can be represented as binary or real numbers; binary representation has a computation advantage. An entire population of individuals (solutions) is initialized at the beginning of the GA process. After the initialization, fitness evaluation, parent selection, and new solution reproduction are performed in sequence. In our problem the
set of individuals were the functions and weights that form the relationship between inputs and output.

![Figure 2-10. A chromosome with Five Genes.](image)

The evaluation of fitness function is problem-specific. Each problem has different fitness functions. Our model used the sum of square errors as the fitness function. The GA evaluates the fitness function for all individuals in the first population and ranks them. Then, the selected individuals are bred together to produce the second generation. This process continues until a convergence criterion is reached (i.e., improvement of error).

2.2.1.2.3. Parent Selection

Selected parents needed to be relatively fit, compared to other members, so that the fitness function is improved for the next generation. This selection method exploits and improves the current solution. However, exploration of new solutions can be performed by allowing some of the weak strings to breed as well. There are two common methods for parent selection: truncation selection and fitness proportional selection.

Truncation selection selects a specified percentage of the best strings to mate and ignores the rest. The GA algorithm selects strings to mate, with equal probability, from
the best strings selected based on a specified percentage (Marsland, 2009). This method restricts the exploration for new solutions.

Fitness proportional selection involves selecting a string probabilistically. Each individual can be selected with a probability proportional to its fitness (Marsland, 2009). This is a better method because it allows for exploitation and exploration.

### 2.2.1.2.4 Producing New Individual

After selecting the parents, genetic operators decide how to combine those two strings. Two common genetic operators are discussed here: crossover and mutation.

The crossover operator selects a point at random in the strings of the two parents. Then, two new strings are formed by combining the first part of the first parent and the second part of the second parent and vise-versa as shown in (Figure 2-11). This process is known as single point crossover. Single point crossover can be expanded by selecting multi random points in each parents and swab the genes; this operator is called multi-point crossover and shown in (Figure 2-12). Crossover incorporates global exploration for the optimal solution; the parents produce totally different children (Marsland, 2009 and Mohaghegh, 2000b).

The mutation operator randomly alters one unit element of a string as shown in (Figure 2-13). The operator changes the value of each element of a string with low probability. Mutation operator exploits the current solution and performs local search.

A problem with the GA is that fitness function can decrease or increase. The fitness function can decrease because the parents are not copied into the new generation
and their offspring are not as good (Marsland, 2009). This problem can be tackled by elitism and tournament. Elitism is to copy the best strings in the current population without any changes; however, it can limit the exploration of a better solution since some of the best strings are not mated. In the tournament method, parents compete against their two children, and the fittest two is moved to the next generation (Marsland, 2009). All of these operators, crossover, mutation, elitism, and tournament, were implemented in our study.

Figure 2-11. Single Point Crossover Operator (Mohaghegh, 2000b).

Figure 2-12. Multi-Point Crossover Operator (Mohaghegh, 2000b).

Figure 2-13. Mutation Operator (Mohaghegh, 2000b).
2.2.1.2.4. Advantages of Genetic Algorithm

Here are some advantages of the GA:

1. Its powerful capability of parallel searching different areas with the feasible solution.
2. Can solve complicated nonlinear, non-smooth, noisy optimization problems.
3. The GA is designed to search for global optima rather than local one. The algorithm perform exploitation for improving current solution (local search), and exploration to search for new solution (global search). Exploitation and exploration are incorporated by mutation and crossover, respectively (Marsland, 2009).
4. Gradient calculation is not required, speeding the process significantly (Abukhamsin, 2009).
5. Unlike ANN, functional links do not improve the convergence and the results. Functional links are mathematical relationship between input and output parameters.

2.3. Problem Statement

In this study, two expert systems were developed to facilitate the capacity management integrated model and make it more practical. The first expert system predicts plateau length and decline parameters required to forecast production profile as a function of reservoir initial pressure, thickness, porosity, permeability, and drainage area of the well (Table 2-1). The second expert system predicts well drainage area as a
function of reservoir initial pressure, thickness, porosity, and permeability, and plateau length (Figure 2-2). The predicted decline parameters assumes hyperbolic decline (Equation 2-11); for simplicity the form of (Equation 2-12) was used in the study. Both equations are the same. The parameters a, b, and c in (Equation 2-12) were predicted by expert system 1. Our models assume homogenous and isotropic reservoir and all wells produces at the same rate; these assumptions reduce the reservoir model into one-well-model. No-flow boundaries were created around each of the wells, resulting in similar models for all the wells (Ertekin, 2013). In other words, all the wells have the same drainage area. (Figure 2-14) shows a schematic for the no-flow Boundaries.

Table 2-1. Expert System 1.

<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>Independent Variable</th>
</tr>
</thead>
<tbody>
<tr>
<td>Plateau Length</td>
<td>Reservoir Initial Pressure</td>
</tr>
<tr>
<td>Decline Parameter a</td>
<td>Reservoir Thickness</td>
</tr>
<tr>
<td>Decline Parameter b</td>
<td>Reservoir Porosity</td>
</tr>
<tr>
<td>Decline Parameter c</td>
<td>Reservoir Permeability</td>
</tr>
<tr>
<td></td>
<td>Well Drainage Area</td>
</tr>
</tbody>
</table>

Table 2-2. Expert System 2.

<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>Independent Variable</th>
</tr>
</thead>
<tbody>
<tr>
<td>Well Drainage Area</td>
<td>Reservoir Initial Pressure</td>
</tr>
<tr>
<td></td>
<td>Reservoir Thickness</td>
</tr>
<tr>
<td></td>
<td>Reservoir Porosity</td>
</tr>
<tr>
<td></td>
<td>Reservoir Permeability</td>
</tr>
<tr>
<td></td>
<td>Plateau Length</td>
</tr>
</tbody>
</table>

\[ q_t = \frac{q_i}{(1+D_i+b*t)^R} \]  \hspace{1cm} (2-11)

\[ q_t = \frac{a}{(1+b*t)^c} \]  \hspace{1cm} (2-12)
Two experts systems with predictability were developed to facilitate the capacity management integrated model. The first expert system predicted the decline parameters and plateau length as function of reservoir initial pressure, thickness, porosity, permeability, well drainage area, and flow rate. The second expert system predicted well drainage area as function of initial reservoir pressure, porosity, permeability, thickness, plateau length, and flow rate. This section discusses data preparation, systems development using ANN, and systems development using GP.

2.4.1. Reservoir Simulation Model

Commercial numerical reservoir simulator, Computer Modeling Group CMG, was used to produce the production profile for all the required cases to train the ANN and
the GP models. Black oil simulator was used for the study since we were not concerned with the compositional changes of the gas in the reservoir.

To train the ANN and the GP model, large data set (inputs and outputs) was required. The input variables were varied and the resulted outputs were recorded. The larger the data set, the better the predictability of the expert systems; however, there has to be a limit to the size. We started with a relatively small data set of 100 pairs, and we kept increasing as needed if the training was not sufficient; the data set used for the training the expert systems consisted of 3000 pairs of input and output. (Table 2-3) shows the properties required to build the reservoir simulation and the range of input parameters from that those parameters were sampled. Matlab was used to sample the input parameters, and pass the data to the reservoir simulation. Latin Hypercube sampling technique was implemented to sample the input variables. From (Table 2-3), reservoir thickness ranged between 50 and 800 ft, porosity ranged between 8% and 20%, permeability ranged between 8 and 100 millidarcy, drainage area ranged between 50 and 250 acres, flow rates ranged between 10 and 36 MMscfd, and reservoir pressure ranged between 2000 and 5000 psi. Those ranges were estimated to represents actual field data. The other parameters required by the simulators were obtained from literatures or from correlation (e.g. Corey’s correlation for relative permeability). The reservoir simulation models were run for 40 years of production with 10 days increment to capture the early decline for some cases. Fitting the hyperbolic decline curve, through the results of the simulator, was performed using Ezfit function in matlab. The function requires the form of the equation of the fitted curve through the data. (Equation 2-13) is the hyperbolic decline used in the study. For simplicity, the equation provided to Ezfit function was in
the form of (Equation 2-14) where \( a \) is the initial production rate, \( b \) is the product of \( D_i \) and \( b \), and \( c \) is the reciprocal of \( b \). In (Equation 2-13), \( D_i \) is the initial decline rate, and \( b \) is the rate of change of \( D_i \).

\[
q = \frac{q_i}{(1 + b D_i t)^{1/b}} \quad \text{(2-13)}
\]

\[
q = \frac{a}{(1 + bt)^c} \quad \text{(2-14)}
\]
Table 2-3. Properties for Reservoir Simulation Model.

<table>
<thead>
<tr>
<th>Field Parameters</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Reservoir Thickness (ft)</td>
<td>50 to 800</td>
</tr>
<tr>
<td>Top of Reservoir Depth (ft)</td>
<td>10,000</td>
</tr>
<tr>
<td>PHI</td>
<td>8% to 20%</td>
</tr>
<tr>
<td>Kx=Ky=Kz (md)</td>
<td>8 to 100</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Development Parameters</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Time Step (days)</td>
<td>50</td>
</tr>
<tr>
<td># of Well(s)</td>
<td>1</td>
</tr>
<tr>
<td>Drainage Area (Acre)</td>
<td>39 to 250</td>
</tr>
<tr>
<td>Drainage Area (ft2)</td>
<td>1690000 to 10890000</td>
</tr>
<tr>
<td>Flow Rate (SCFD)</td>
<td>9,000,000 to 36,000,000</td>
</tr>
<tr>
<td>Dx=Dy (ft)</td>
<td>1300 to 3300</td>
</tr>
<tr>
<td># of Layers</td>
<td>2</td>
</tr>
<tr>
<td>Layer Thickness (ft)</td>
<td>25 to 400</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Simulation Parameters</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Reference Depth (ft)</td>
<td>10,500</td>
</tr>
<tr>
<td>Pressure at Reference (psi)</td>
<td>2000 to 5000</td>
</tr>
<tr>
<td>Datum Depth (ft)</td>
<td>10,500</td>
</tr>
<tr>
<td>Aquifer?</td>
<td>NO</td>
</tr>
<tr>
<td>Depth of WGC (ft)</td>
<td>1900</td>
</tr>
<tr>
<td>T (F)</td>
<td>150</td>
</tr>
<tr>
<td>Gas Density</td>
<td>5.80E-02</td>
</tr>
<tr>
<td>Reference Pressure (psi)</td>
<td>14.696</td>
</tr>
<tr>
<td>Water Density</td>
<td>61.6381</td>
</tr>
<tr>
<td>Starting Date</td>
<td>1/1/2013</td>
</tr>
<tr>
<td>Life of the Project (Yrs)</td>
<td>40</td>
</tr>
<tr>
<td>P Max (psi)</td>
<td>5000</td>
</tr>
<tr>
<td>Rock Compressibility (psi-1)</td>
<td>0.000001</td>
</tr>
<tr>
<td>Swc</td>
<td>0.15</td>
</tr>
<tr>
<td>Swcrit</td>
<td>0.15</td>
</tr>
<tr>
<td>Sgc</td>
<td>0.05</td>
</tr>
<tr>
<td>Sgcri</td>
<td>0.1</td>
</tr>
<tr>
<td>Krw@100Sw</td>
<td>1</td>
</tr>
<tr>
<td>Krg@Swc</td>
<td>0.85</td>
</tr>
<tr>
<td>Exponent (Cemented Sand Stone)</td>
<td>4</td>
</tr>
</tbody>
</table>

2.4.2. Artificial Neural Network Expert Systems

This section discusses the data preparation and the ANN design for the two expert systems. Training the first expert system was challenging for the following reasons: 1)
production decline was represented by decline parameters that were obtained by curve fitting, 2) The huge difference in magnitude between the parameters (decline parameters $\approx 10^{-4}$ and flow rate $\approx 10^7$). Fitting a curve was not perfect, that can be represented by the coefficient of determination $R^2$. Initially, cases with $R^2$ greater than 90% were used and resulted in poor expert system. However, the predictability of the system was improved when the cases with $R^2$ greater than 98% were used. It was hard to fit a curve with $R^2$ of 100%. The issue of magnitude variation was tackled by using the logarithm and inverse of hyperbolic-sin of inputs and outputs. The logarithm and the inverse of hyperbolic-sin compacted the range of the numbers. Another and the most impacting trick in training the first expert system with ANN was to split the expert system into two ANN models. The first ANN model predicted the plateau length and decline parameter “a” from the reservoir properties and the rate. Then, the reservoir properties and the output of the first ANN (plateau length and decline parameter “a”) were used as input for the second ANN to predict decline parameters b & c. Here is how this process helped training the ANN. First, an ANN model was built to predict the parameters that were predicted with good accuracy from the previous trials of ANN models. Plateau length and decline parameter a were predicted with 8% error when predicted all the parameters from one ANN model while the other two decline parameters have error percentage more than 90%. When splitting the ANN into two models, the error of predicting plateau length and decline parameter a dropped down to 2% and of predicting b & c to 33%; the combined error for all the parameters was around 17%. Although the error for predicting the decline parameters b & c was relatively large, the predicted production profiles were very close to the CMG results. By implementing this
process, information from the output of the first ANN was used as input to predict the last two decline parameters. Matlab was used to build and train all the ANN models in this study.

### 2.4.2.1. Data Preparation

After generating the 3000 cases, cases without production decline were removed from the data set because they did not have decline parameters; surprisingly that the proposed ANN predicted those cases without decline successfully, which increased the confidence in the predictability of the model.

The data set was filtered again with R$^2$ of fitted curve for decline parameters. Cases with R$^2$ less than 98% were removed from the data set to increase the predictability of the ANN models.

Before feeding the data into the training process, they were normalized between -1 and 1 as recommended by (Kifer, 2014 and Marsland, 2009). This normalization stabilizes the training process and improves predictability of the ANN model.

Functional links were incorporated in the data set; those links can be inserted in the input or output. Those functional links are mathematical expressions formed by applying mathematical operations between inputs and outputs And can strengthen the relationship between the input and the output during the training process. Functional links used in the study are presented in the results section.
2.4.2.2. Designing the Artificial Neural Network

This section discusses the design process for ANN models in our study. Designing an ANN involves deciding on the type of ANN (i.e., back-propagation, recurrent, etc.), transfer function, training function, learning function, performance function, number of hidden layer, number of neuron in each hidden layer, number of iteration, how to split the data set (training, validation, and testing), how to set early stopping criteria, and how to measure the predictability of each ANN model.

Matlab (a programming language) was used to design and train the ANN models. (Table 2-4) shows the designing properties implemented in training the ANN models. All the ANN models built in this study were Feed-forward back-propagation Artificial Neural Network since it showed best performance. The data set was randomly sorted into training, testing, and validation sets. The largest portion of the data set (93%) was assigned to training; each of the testing and validation data sets represents 3% of the whole data set. Transfer functions or activation functions, that control whether a neuron fires or not, were sigmoid functions including log-sigmoid (logsig) and hyperbolic tangent sigmoid (tansig). Many training functions were used; however, the scaled conjugate gradient training function (trainscg) resulted in the best ANN models. Learning function, resulted in best ANN models, was gradient descent with momentum weight and bias (learngdm). The performance function was a function for evaluating the training process during the training; mean sum of square error with regularization was used as performance function. The number of hidden layer(s) varied depending on the problem tackled, between 2 and 6 hidden layers. Number of neurons in each hidden layer varied
between 20 and 160. The number of iterations used in the training process varied between 1500 and 8000. The early stopping was set by specifying the maximum number of iteration passed without improvement in validation error; this was set to be 10 of the total number of iterations. During the training process, hundreds of trained ANN models were developed, each with different numbers of neurons. To decide which model was best, mean absolute error (Equation 2-15) was used.

Table 2-4. Properties for Designing Artificial Neural Network Models.

<table>
<thead>
<tr>
<th>Property</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>ANN Type</td>
<td>Feed-Forward Back-Propagation</td>
</tr>
<tr>
<td>Split of Dataset</td>
<td>Training: 93%   Testing: 3%   Validation: 3%</td>
</tr>
<tr>
<td>Transfer Function</td>
<td>Sigmoid Functions: log-sigmoid &amp; hyperbolic tangent sigmoid</td>
</tr>
<tr>
<td>Training Function</td>
<td>Scaled Conjugate Gradient</td>
</tr>
<tr>
<td>Learning Function</td>
<td>Gradient descent with momentum weight and bias</td>
</tr>
<tr>
<td>Performance Function</td>
<td>Mean Sum of Square Error with Regularization</td>
</tr>
<tr>
<td>Number of Hidden Layer</td>
<td>1 to 6</td>
</tr>
<tr>
<td>Number of Neuron in Each Layer</td>
<td>20 to 160</td>
</tr>
<tr>
<td>Number of Iteration</td>
<td>1500 to 8000</td>
</tr>
<tr>
<td>Max. No. of Iteration without Improvement</td>
<td>10% of Total Number of Iteration</td>
</tr>
<tr>
<td>Prediction Error</td>
<td>Mean Absolute Error</td>
</tr>
</tbody>
</table>

\[
\text{Mean Absolute Error} = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{|\text{ANN}_i - \text{Target}_i|}{\text{Target}_i} \right|
\]  

(Figure 2-15) shows the structure of the first ANN, which predicts plateau length and decline parameter \( a \). The ANN consisted of 1 input layer, 6 hidden layers, and 1 output layer. The input layer consisted of 5 neurons (inputs)—drainage area, flow rate, thickness, porosity, permeability, initial pressure, and the Eigen value of the matrix \( M \) in the figure. \( M \) is a matrix of permeability, thickness, drainage area, and flow rate. The output layer consisted of 12 neurons (outputs); 2 out of those 12 are outputs and the remaining are functional links. The functional links used were combinations of flow rate, drainage area, porosity, permeability, initial reservoir pressure, and the decline.
parameters b and c. The transfer, training, learning functions used were logsig, trainscg, and learngdm, respectively.

(Figure 2-16) shows the structure of the second ANN that predicts the decline parameters b and c. The ANN consisted of 1 input layer, 5 hidden layers, and 1 output layer. The input layer consisted of 9 neurons (inputs)—drainage area, flow rate, thickness, porosity, permeability, initial pressure, the Eigen value of the matrix M in the figure, plateau length, and decline parameter a. Note, plateau length and decline parameter ‘a’ were obtained from the first ANN. The output layer consisted of 6 neurons (outputs); 2 out of those 6 were outputs and the remaining were functional links. The functional links used were combinations of flow rate, drainage area, porosity, permeability, and the decline parameter c. The transfer, training, learning functions used were tansig, trainscg, and learngdm, respectively.

(Figure 2-17) shows the structure of the third ANN, that predicts the drainage area. The ANN consisted of 1 input layer, 6 hidden layers, and 1 output layer. The input layer consisted of 6 neurons (inputs)—flow rate, plateau length, thickness, porosity, permeability, and initial pressure. The output layer consisted of one neuron (output). The transfer, training, learning functions used were tansig, trainscg, and learngdm, respectively.
Figure 2-15. Schematic of ANN-1 to Predict Plateau Length and Decline Parameter “a”.

Figure 2-16. Schematic of ANN-2 to Predict Decline Parameters “b” & “c”.
2.4.3. Genetic Programming Expert Systems

This section discusses the data preparation and the GP design for the two expert systems. Each Genetic Programming GP model can predict only one output. As a result, 5 GP models were built here to predict the three decline parameters, plateau length, and the drainage area. Although one GP training run can take longer than ANN, the number of training runs in GP was much less than ANN. GP training takes longer because of the involved huge number of solution sets (population) to be evaluated at each iteration. On the other hand, ANN requires much more of trial and error process in the design. GP strength is in the process of finding an optimal solution (predictive model); there are relatively few parameters to be modified during the training for the GP compared to the
ANN including mutation and crossover rates, generation and population size, tournament size, elite fraction, maximum number of gene and tree depth, and fitness function. The variations of these parameters were small. An advantage of the GP is that it does not require functional links to strengthen the relationship between inputs and outputs.

2.4.3.1. Data Preparation

Similar to ANN data preparation, cases without production decline were removed from the data set because they did not have decline parameters. The GP model predicted the cases where production profile does not decline properly as shown in the result section. This agreement between the GP and the simulation increased our confidence in the expert system.

The data set was filtered again with $R^2$ or fitted curve for decline parameters. Cases with $R^2$ less than 98% were removed from the data set to increase the predictability of the GP models.

Before supplying the data set to the GP algorithm, a transformation and scaling of the data set were performed. The data set was transformed using the logarithm function to compress the range of numbers of the different parameters. This transformation enhances the performance of the training process. Then, the data set was scaled to zero mean and unit variance.
2.4.3.2. Designing the Genetic Programming Algorithm

This section discusses the designing process for the GP models in our study. Designing an GP model consists of selecting fitness function; mutation, crossover, and direct copy rates; generation and population size; tournament size; elite fraction; maximum number of gene and tree depth; how to split the data set into training, testing, and validation; and how to classify the goodness of the GP model.

Matlab, programming language, was used in the designing and training processes for the GP model. The GP algorithm implemented in this study was developed by (Searson et al., 2010). (Table 2-5) shows the design parameters for the GP models that predict plateau length, decline parameters a and c, and drainage area. (Table 2-6) shows the design parameters for the GP model, which predicts decline parameter b. Developing the predictive model for decline parameter b was challenging; as a result, the number of population, generation, maximum allowed gene and tree depth were increased as shown in (Table 2-6). Modifying those four parameters significantly improved the predictability of the GP model as shown in the results section. The first parameter in the designing process is the fitness function. The fitness function is problem specific and can take any form. For our problem, the mean sum of squared error was used to evaluate the training process (Equation 2-16). Mutation, crossover, and direct copy are methods to produce new solution from the previous generation (iteration). Mutation rate is the rate, of the population, at that random element unit of a gene is randomly modified; 10% mutation rate was used for all the models in the study. Crossover rate is the percentage of a population enters the crossover pool where gene exchange takes place; 85% was used as
a crossover rate for all models in the study. Direct copy involved copying the best solutions from the previous generation to the next one; 5% direct copy rate was used for all models in the study. Generation size represents the number of iterations to be performed during the training process; 1000 generations were used for all parameters except for the decline parameter b where 1900 generations were used. Although early stopping criterion can be specified, that criterion was disabled for our study to minimize the possibility of local minima. The problem of over-fitting or memorization was not encountered. Population size is the number of individuals or solutions in each generation (iteration) of training. Population size of 500 was used for all the parameters except for the decline parameter b where 1000 generations were used. Tournament size and elite fraction are used to select parents (solutions from previous generation) to be mated together. Tournament selection is to select few individuals form the population to compete, based on fitness function, to be selected for mutation, crossover, or direct copy. Tournament selection is adjusted by the tournament size; if the tournament size is large, weak individuals have less chance to be selected. The tournament size for the b decline parameter was 5 and for the remaining models were 7. Elitism involves copying individuals without alteration to the next population, and it is controlled by the elite fraction, which is the percentage of the best individuals in the population to be directly copied to the next generation. To clarify the concept of maximum number of genes and tree depth, the regression model (Equation 2-17) should be explained. This equation, is the general form used to build the GP predictive model where y-hat is the parameter to be predicted, w0 is the bias, w1 to wN are the weights of the model, and the trees are randomly generated functions. The trees are functions of the dependent variables, inputs,
and can take any form (e.g., sin, tan, exp, etc.) specified by the user. The number of genes, \( N \), is the number of weights or elements in each individual. The depth of the tree controls how many inputs are presented in each tree. (Equation 2-18) shows an example of a single individual that consists of 4 genes and a maximum tree depth of 5. For our models the maximum number of genes were 12 for the b model and 11 for the other parameters, and the maximum tree depth was 11 for the b model and 10 for the others. The data set was divided into 75%, 10%, and 15% for training, testing, and validation, respectively. To evaluate the accuracy of the GP predictive model, Root Mean Square error RMS was used (Equation 2-19).

Table 2-5. Properties for Designing Genetic Programming Models for Plateau Length, Decline Parameters \( a \) & \( c \), and Drainage Area.

<table>
<thead>
<tr>
<th>Fitness Function</th>
<th>Sum of Square Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mutation rate</td>
<td>0.1</td>
</tr>
<tr>
<td>Crossover Rate</td>
<td>0.85</td>
</tr>
<tr>
<td>Direct Copy</td>
<td>0.05</td>
</tr>
<tr>
<td>Generation Size</td>
<td>1000</td>
</tr>
<tr>
<td>Population Size</td>
<td>500</td>
</tr>
<tr>
<td>Tournament Size</td>
<td>7</td>
</tr>
<tr>
<td>Elite Fraction</td>
<td>0.05</td>
</tr>
<tr>
<td>Maximum No. of Gene</td>
<td>11</td>
</tr>
<tr>
<td>Maximum Tree Depth</td>
<td>10</td>
</tr>
<tr>
<td>Split of Dataset</td>
<td>Training: 75% Testing: 10% Validation: 15% Root Mean Square RMS</td>
</tr>
<tr>
<td>Prediction Error</td>
<td></td>
</tr>
</tbody>
</table>
Table 2-6. Properties for Designing Genetic Programming Models for Decline Parameter

<table>
<thead>
<tr>
<th>Fitness Function</th>
<th>Sum of Square Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mutation rate</td>
<td>0.1</td>
</tr>
<tr>
<td>Crossover Rate</td>
<td>0.85</td>
</tr>
<tr>
<td>Direct Copy</td>
<td>0.05</td>
</tr>
<tr>
<td>Generation Size</td>
<td>1900</td>
</tr>
<tr>
<td>Population Size</td>
<td>1000</td>
</tr>
<tr>
<td>Tournament Size</td>
<td>5</td>
</tr>
<tr>
<td>Elite Fraction</td>
<td>0.05</td>
</tr>
<tr>
<td>Maximum No. of Gene</td>
<td>12</td>
</tr>
<tr>
<td>Maximum Tree Depth</td>
<td>11</td>
</tr>
<tr>
<td>Split of Dataset</td>
<td>Training: 75% Testing: 10% Validation: 15%</td>
</tr>
<tr>
<td>Prediction Error</td>
<td>Root Mean Square RMS</td>
</tr>
</tbody>
</table>

\[
Mean \ Sum \ of \ Squared \ Error = \frac{1}{n} \sum_{i=1}^{n} (GP_i - Target_i)^2 \quad (2-16)
\]

\[
\hat{y} = w_0 + w_1Tree_1 + \cdots + w_NTree_N \quad (2-17)
\]

\[
y = 9.45 + 0.259x^2 - 0.00212 * tanh(x_1 - x_3) * (x_3x_1 + 7.663473x_4) - 28.31x_3 + 1079 * tanh(tanh(0.02395x_3)) \quad (2-18)
\]

\[
RMS = \sqrt{\frac{\sum_{i=1}^{n} (GP_i - Target_i)^2}{n}} \quad (2-19)
\]

2.5. Results and Discussion

Development a predictive model for decline parameters, assuming hyperbolic decline, for given reservoir properties and development plan was complex nonlinear and computationally expensive problem. Another complex nonlinear problem tackled here was predicting a development plan for given reservoir properties, plateau length and flow rate. These parameters require analysis and curve fitting for the results of the numerical simulator. Workflow and required models, to build the two expert systems, were
established: workflow to define the designing process for the ANN and GP experts systems, the Latin Hypercube model to sample reservoir properties, reservoir simulation models to generate production profile for the different cases, curve-fitting model to fit the hyperbolic decline curve through the production profile, Artificial Neural Network model to develop the ANN expert systems, and Genetic Programming model to develop the GP expert systems. This section discusses and compares the results of the expert systems against the results of the numerical simulator; moreover, the accuracies of the expert systems are presented.

2.5.1. Expert System-1 to Predict Decline Parameters and Plateau Length

The results shown in this section represent the expert system-1, that predicts decline parameters and plateau length for a given set of drainage area, reservoir thickness, reservoir porosity, reservoir permeability, and reservoir initial pressure.

2.5.1.1. Artificial Neural Network Results

(Figure 2-18) shows the cross-plots for predicting the plateau length and decline parameter “a” using the testing data set. The cross-plot shows the prediction of the expert system against the actual values of the numerical simulator. In other words, the closer the data to the 45 degrees line, the more accurate the prediction of the expert system. From the figure, the prediction accuracy was acceptable with a combined error of 2.2% (mean absolute error). (Figure 2-19) shows the cross-plots for predicting the decline parameters
b and c using the testing data set. Although the data were scattered, it followed a trend along the 45 degrees line; the error of predicting these two decline parameters was 33%. The combined error for the expert system was around 17%. To test the predictability of the expert system, results of reservoir simulation model of 20 randomly generated cases were compared against the predicted values of the expert system. (Table 2-7) shows the reservoir properties and development plans for those 20 cases. (Figures 2-20 to 2-39) show the resulting production profiles of the reservoir simulator (CMG) and the expert system for the 20 cases. The red-dashed line represents the simulator data, and the blue solid line represents the expert system data. The predicted profiles were in good agreement with the simulator data. (Figures 2-29 and 2-35) show some stability issues in the simulator output. The profiles seemed to fluctuate but actually they were not. A close look at the scale of the production profile axis reveals that the fluctuations were very small; this fluctuation can be a result of the very long production time, 40 years, and very small time steps, 10 days.
Figure 2-18. Cross-plot for Predicting Plateau Length and Decline Parameter a.

Figure 2-19. Cross-plot for Predicting Decline Parameters b & c.
Table 2-7. Reservoir Properties and Development Plans for 20 Randomly Generated Cases.

<table>
<thead>
<tr>
<th>Area (ft²)</th>
<th>Flow Rate (SCFD)</th>
<th>Thickness (ft)</th>
<th>Porosity</th>
<th>Permeability (md)</th>
<th>Initial Pressure (psi)</th>
</tr>
</thead>
<tbody>
<tr>
<td>9,151,084</td>
<td>15,179,104</td>
<td>69</td>
<td>0.1607</td>
<td>97</td>
<td>3075</td>
</tr>
<tr>
<td>8,870,720</td>
<td>19,672,790</td>
<td>331</td>
<td>0.1302</td>
<td>25</td>
<td>2852</td>
</tr>
<tr>
<td>5,718,822</td>
<td>27,091,993</td>
<td>219</td>
<td>0.1098</td>
<td>30</td>
<td>4917</td>
</tr>
<tr>
<td>8,404,200</td>
<td>17,814,252</td>
<td>45</td>
<td>0.1483</td>
<td>47</td>
<td>3953</td>
</tr>
<tr>
<td>6,705,631</td>
<td>31,010,468</td>
<td>190</td>
<td>0.0898</td>
<td>11</td>
<td>2968</td>
</tr>
<tr>
<td>2,549,292</td>
<td>35,055,151</td>
<td>274</td>
<td>0.1397</td>
<td>71</td>
<td>4350</td>
</tr>
<tr>
<td>4,016,657</td>
<td>28,387,983</td>
<td>114</td>
<td>0.1431</td>
<td>56</td>
<td>2207</td>
</tr>
<tr>
<td>3,090,178</td>
<td>22,454,635</td>
<td>360</td>
<td>0.1568</td>
<td>92</td>
<td>2546</td>
</tr>
<tr>
<td>3,725,404</td>
<td>25,107,112</td>
<td>126</td>
<td>0.1873</td>
<td>52</td>
<td>4587</td>
</tr>
<tr>
<td>4,882,501</td>
<td>11,268,540</td>
<td>392</td>
<td>0.1988</td>
<td>66</td>
<td>4488</td>
</tr>
<tr>
<td>7,102,001</td>
<td>33,933,333</td>
<td>148</td>
<td>0.1691</td>
<td>17</td>
<td>3576</td>
</tr>
<tr>
<td>1,987,547</td>
<td>32,416,498</td>
<td>369</td>
<td>0.1269</td>
<td>45</td>
<td>3246</td>
</tr>
<tr>
<td>10,052,251</td>
<td>30,049,714</td>
<td>86</td>
<td>0.1937</td>
<td>20</td>
<td>2304</td>
</tr>
<tr>
<td>10,882,914</td>
<td>15,993,025</td>
<td>168</td>
<td>0.1182</td>
<td>80</td>
<td>4801</td>
</tr>
<tr>
<td>8,110,209</td>
<td>25,580,215</td>
<td>31</td>
<td>0.0843</td>
<td>88</td>
<td>2024</td>
</tr>
<tr>
<td>7,592,265</td>
<td>9,042,323</td>
<td>261</td>
<td>0.0948</td>
<td>36</td>
<td>3689</td>
</tr>
<tr>
<td>5,071,407</td>
<td>23,132,699</td>
<td>309</td>
<td>0.1778</td>
<td>73</td>
<td>3357</td>
</tr>
<tr>
<td>9,633,408</td>
<td>20,711,053</td>
<td>234</td>
<td>0.1130</td>
<td>33</td>
<td>4245</td>
</tr>
<tr>
<td>5,992,037</td>
<td>12,907,401</td>
<td>208</td>
<td>0.1728</td>
<td>62</td>
<td>2696</td>
</tr>
<tr>
<td>2,862,575</td>
<td>13,575,206</td>
<td>295</td>
<td>0.1013</td>
<td>83</td>
<td>3851</td>
</tr>
</tbody>
</table>

Figure 2-20. Comparison of Results from ANN and Simulator.
Figure 2-21. Comparison of Results from ANN and Simulator.

Figure 2-22. Comparison of Results from ANN and Simulator.

Figure 2-23. Comparison of Results from ANN and Simulator.
Figure 2-24. Comparison of Results from ANN and Simulator.

Figure 2-25. Comparison of Results from ANN and Simulator.

Figure 2-26. Comparison of Results from ANN and Simulator.
Figure 2-27. Comparison of Results from ANN and Simulator.

Figure 2-28. Comparison of Results from ANN and Simulator.

Figure 2-29. Comparison of Results from ANN and Simulator.
Figure 2-30. Comparison of Results from ANN and Simulator.

Figure 2-31. Comparison of Results from ANN and Simulator.

Figure 2-32. Comparison of Results from ANN and Simulator.
Figure 2-33. Comparison of Results from ANN and Simulator.

Figure 2-34. Comparison of Results from ANN and Simulator.

Figure 2-35. Comparison of Results from ANN and Simulator.
Figure 2-36. Comparison of Results from ANN and Simulator.

Figure 2-37. Comparison of Results from ANN and Simulator.

Figure 2-38. Comparison of Results from ANN and Simulator.
2.5.1.2. Genetic Programming Results

Four GP models were developed to predict each parameter since GP was designed to predict one parameter at a time. First, the performance of each GP model was evaluated via the cross-plot of predicted data vs. actual data, and the prediction error (RMS) of each model. Then, the performance of the overall expert system, the four models combined, was evaluated by evaluating the production profiles of 20 randomly generated cases, resulting from the numerical simulator and from the expert system. (Figure 2-40) shows the training, testing, and validation-cross-plots of actual data vs. predicted data, for predicting plateau length. The cross-plot shows that almost all data points fall on the 45 degrees line with testing error of 0.024 and $R^2$ was 99.92%. (Figure 2-41) shows the training, testing, and validation cross-plots, of actual data vs. predicted data, for predicting decline parameter a. All cross-plots show that almost all data points fall on the 45 degrees line with testing error of 0.024 and $R^2$ of 99.55%. (Figure 2-42) shows the training, testing, and validation cross-plots of actual data vs. predicted data, for

Figure 2-39. Comparison of Results from ANN and Simulator.
predicting decline parameter b. Although the data were scattered, it followed the 45 degrees line with testing error of 0.94 and $R^2$ was 65.19%. The 0.94 is not a percentage since the error was an RMS, equivalent to mean absolute difference. On the other hand, $R^2$ of 65% can be acceptable depending on the overall performance of the expert system. (Figure 2-43) shows the training, testing, and validation cross-plots, of actual data vs. predicted data, for predicting decline parameter c. The cross-plots show that data points were clustered around the 45 degrees line with testing error of 0.17 and $R^2$ was 98.57%. To test the predictability of the expert system, results of reservoir simulation model of 20 randomly generated cases were compared against the predicted values of the expert system. (Table 2-7) shows the reservoir properties and development plans for those 20 cases. (Figures 2-44 to 2-63) compare the results of the reservoir simulator (CMG) and the expert system for the 20 cases. The red-dashed line represents the simulator data, and the blue solid line represents the expert system data. The predicted profiles were in good agreement with the simulator data. (Figures 2-53 and 2-59) shows the same stability issue as in (Figures 2-29 and 2-35).
Figure 2-40. Cross-plot for Predicting Plateau Length.

Figure 2-41. Cross-plot for Predicting Decline Parameter a.
Figure 2-42. Cross-plot for Predicting Decline Parameter b.

Figure 2-43. Cross-plot for Predicting Decline Parameter c.
Figure 2-44. Comparison of Results from GP and Simulator.

Figure 2-45. Comparison of Results from GP and Simulator.

Figure 2-46. Comparison of Results from GP and Simulator.
Figure 2-47. Comparison of Results from GP and Simulator.

Figure 2-48. Comparison of Results from GP and Simulator.

Figure 2-49. Comparison of Results from GP and Simulator.
Figure 2-50. Comparison of Results from GP and Simulator.

Figure 2-51. Comparison of Results from GP and Simulator.

Figure 2-52. Comparison of Results from GP and Simulator.
Figure 2-53. Comparison of Results from GP and Simulator.

Figure 2-54. Comparison of Results from GP and Simulator.

Figure 2-55. Comparison of Results from GP and Simulator.
Figure 2-56. Comparison of Results from GP and Simulator.

Figure 2-57. Comparison of Results from GP and Simulator.

Figure 2-58. Comparison of Results from GP and Simulator.
Figure 2-59. Comparison of Results from GP and Simulator.

Figure 2-60. Comparison of Results from GP and Simulator.

Figure 2-61. Comparison of Results from GP and Simulator.
2.5.2. Expert System-2 to Predict Drainage Area

This section discusses the results and accuracy of the second expert system, which predicts the drainage area required for given flow rate, plateau length, reservoir porosity, reservoir permeability, reservoir thickness, and reservoir initial pressure.
2.5.2.1. Artificial Neural Network Results

Here, the results and accuracy of the ANN expert system were evaluated. The performance of the expert system was evaluated via cross-plot of the predicted data vs. the actual data and via the prediction error of the system. (Figure 2-64) shows the cross-plot for predicting the drainage area using the testing data set. Predicted data was plotted against the actual simulator data. Most of the data fall on the 45-degree line with testing error of 1.5%.

![Cross-plot for Predicting Drainage Area](image)

Figure 2-64. Cross-plot for Predicting Drainage Area.

2.5.2.2. Genetic Programming Results

Here, the results and accuracy of the GP expert system were evaluated. The performance of the expert system was evaluated via cross-plot of the predicted data vs.
the actual data and via the prediction error of the system. (Figure 2-65) shows the training, testing, and validation cross-plots, of actual data vs. predicted data, for predicting drainage area. All cross-plot show that most of the data points fall on the 45-degree line with testing error of 0.024 (RMS) and $R^2$ was 99.92%.

![Cross-plots for Predicting Drainage Area](image)

Figure 2-65. Cross-plot for Predicting Drainage Area.

Fitting curve through production profile was challenging because the fitted curve has to take hyperbolic decline formula. Another challenge was preparing 3000 cases of data sets and using them for training. The major challenge in the study was designing an expert system to predict the decline parameters, especially the decline exponent $b$. Although the predicted decline exponent resulted in acceptable production profile, the error of 33% was significant. The reason for the difficulty in predicting the decline parameters was the following:

1. The fitted curve was not perfect as can be represented with the coefficient of determination $R^2$. As mentioned above, as the $R^2$ was restricted to larger
values (98%) for the curves to be considered in the training, the more accurate was the prediction. In other words, curve fitted with $R^2$ equal to 100% should be considered for training to obtain better results.

2. Huge variations in the magnitude of the training data set were clear in the differences in magnitude between decline parameters, with magnitude $\sim 10^{-4}$, and production rate, with magnitude $\sim 10^7$.

A limitation of the study was the assumption of homogenous and isotropic reservoir properties. This assumption was sufficient for the capacity management model because it implemented a tank-like model. However, actual fields are heterogeneous and anisotropic.

2.6. Conclusions and Recommendations for Future Work

2.6.1. Conclusions

Developing a proxy for numerical reservoir simulator to predict production performance was a complex, nonlinear, and computationally expensive process. This process was further complicated by developing a proxy for non-direct results from the numerical reservoir simulation model. Two expert systems, using Artificial Neural Network and Genetic Programming techniques, were developed to predict the plateau length and decline parameters or predict drainage area for given reservoir properties and development plans. In total, four expert systems were developed. Those expert systems were used to evaluate their accuracies against the reservoir simulator. The ANN and GP
expert systems sufficiently predicted plateau length, decline parameters and development
plan for each field. Moreover, the agreement between the results of the ANN and GP
expert systems increased our confidence in using the systems for predictions. Below are
concluding remarks:

1. An artificial Neural Network can be implemented to develop a sufficient
predictive model that can predict plateau length and decline parameters for
given reservoir properties and development plans with a combined error of
17%.

2. An Artificial Neural Network can be implemented to develop a sufficient
predictive model that can predict drainage areas for given reservoir properties
and development plans with a prediction error of 1.5%.

3. Genetic Programming can be implemented to develop a sufficient predictive
model that can predict plateau length and decline parameters for given
reservoir properties and development plans.

4. Genetic Programming can be implemented to develop a sufficient predictive
model that can predict drainage areas for given reservoir properties and
development plans.

5. Genetic Programming requires less effort to implement than the Artificial
Neural Network because GP does not require functional links and can find a
sufficient model from a few training runs. However, each run for GP takes
significantly longer time than a run for ANN.

6. ANN can solve more complicated problems than GP because ANN is faster in
executing the training algorithm and very powerful in dealing with nonlinear
problems. This is due to the capability of increasing the number of hidden layers and neurons.

7. Both ANN and GP resulted in sufficient expert systems. However, we are more confident with the ANN results from the 20 testing cases shown in the results section.

8. ANN has many more parameters than GP, so it is harder to implement, but it gives the training process a wide range of options for training, learning, transfer, and performance functions. The abundance of these functions gives the advantage to ANN over the GP in solving very complicated problems.

9. ANN is very sensitive to functional links. This can be advantageous to ANN from the perspective that very hard problem can be solve by the addition of functional links.

10. The first expert system (predicts decline parameter) is very sensitive to the goodness of fit of the curve fitted through the reservoir simulation data.

11. Big variations in the magnitude of the data set can be detrimental to developing an ANN or GP predictive models. Transforming the data set, using the logarithm of hyperbolic sin functions, can help compress the magnitude and enhance the training process.

12. Calculating the decline parameters by fitting curve thought production profile should be very accurate for enhancing the training process. Fitting some cases with excellent accuracy and other with relatively low accuracy can mislead the training algorithm. The training algorithm tries to find a relationship
between inputs and outputs; the cases with low accuracy can have slightly different relations than the cases with high accuracy.

### 2.6.2. Recommendations for Future Research

1. This study assumed homogenous and isotropic reservoirs. The development of an expert system for heterogeneous anisotropic reservoirs can be investigated.

2. The expert systems developed in the study predicted parameters for the capacity management integrated model. An expert system that can predict the final outcome of the capacity management model can be considered. The final outcome of the capacity management model was the optimal production allocation of a portfolio of fields that maximized the total NPV or plateau length while maintaining a total target daily rate.

3. Artificial Neural Network and Genetic Programming are the machine learning algorithms implemented to develop the expert systems. Other possible machine learning techniques for developing expert systems are support vector machines and decision trees.
Chapter 3

Optimal Spare Capacity Level

3.1. Introduction

A production strategy for a dominant oil producer can affect prices, supply and demand for oil, as well as the entire oil market (Nakov, A., and Nuno, G., 2011). Acquiring spare capacity is essential for an oil producer who seeks to optimize his/her company’s economic and market power. In other words, acquiring spare capacity increases expected profit and market power for the dominant producer. Spare capacity sets the major producer as a price shock absorber (buffer mode), preventing prices from hitting the roof (motivating the development in alternative energy industry) or from dropping (reducing profit). In addition, major oil producers can lose market share, in the case of price increases, by commercializing the development of non-conventional and alternative energy sources. In other words, major oil producer can alter prices by acquiring spare capacity, making doing so important. Optimizing spare capacity under demand and price uncertainties is a complex optimization problem that requires sophisticated stochastic and computationally expensive processes. This problem has been specified probabilistically because it involves major investment in building and maintaining spare capacity volume, which may require years before actual production is online. In other words, expected demand during planning can differ from actual demand at the time of production. The problem in acquiring optimal spare capacity volume is
applicable to oil markets; however, the same process can be implemented in the gas market to tackle the issue of optimal gas storage capacity. The gas market, unlike the oil market, involves long-term contracts. The spare capacity study, if implemented for the gas market, would tackle the issue of demand seasonality.

In this study, prices were forecasted using the Mean Reversion Model (MRM) and a combination of the Mean Reversion Model and the Geometric Brownian Motion (GBM). The combination of the MRM and the GBM was modeled as the MRM model where the logn-run price ($P^*$) was modeled as the GBM as recommended by (Dias, 2010a). The demand was forecasted as a combination of the MRM and the GBM models. The problem of optimal spare capacity was tackled in three parts: 1) An integrated optimization model developed to solve for optimal spare capacity volume under the uncertainty of price and demand, 2) The impact of uncertainty in the demand model on optimal results was analyzed, and 3) Sensitivity and value of information (VOI) analyses were performed to analyze the impact of demand and price forecast parameters on optimal results.

3.2. Literature Review

3.2.1. Genetic Algorithm

The GA is an optimization algorithm that employs biological evolution and sexual reproduction mechanisms in mathematical searching formulations (Marsland, 2009). The algorithm employs similar concepts to those found in biological evolution and the
survival of the fittest as introduced by (Darwin, 1859). In biological reproduction, each parent passes one of their two chromosomes (Figure 3-1). As a result, the child has characteristic from both parents; however, random mutations occur when copying the chromosomes, resulting in changes over time. These changes can be attributed to the surviving processes and adapting to a specific environment. “Genetic Algorithm is a computational approximation to how evolution performs search, which is by altering the genome and thus changing the fitness of individuals” (Marsland, 2009, p.270). To model a Genetic Algorithm, the following items are needed (Marsland, 2009): 1) Identify a fitness function similar to the objective function (measurement of performance) of a process, 2) Identify a selection method for selecting proper parents from an entire population, and 3) Select a breeding method to generate offspring; this is how to combine the chromosomes of the parents.

Figure 3-1. Biological Reproduction (Marsland, 2009).
3.2.1.1. The Process of the GA

A set of solutions (single chromosome) is represented as a string of unit elements (genes) as shown in (Figure 3-2). The figure shows a set of solutions with five parameters. Genes can be represented as binary or real numbers; binary representation has a computation advantage. Consequently, an entire population of individuals is initialized in the GA; initial solutions are initiated at the beginning of the GA process. After that fitness evaluation, parent selection, and new solution reproduction are performed in sequence. In our problem the set of parameters are the functions and weights that form the relationship between inputs and output.

Figure 3-2. A Chromosome with Five Genes.

Evaluation of the fitness function is problem-specific. Each problem has a different fitness function. Our model used the sum of square errors as the fitness function. The GA evaluates the fitness function for all individuals in the first population and ranks them. Then, the selected individuals are bred together to produce the second generation. This process continues until a convergence criterion is reached (i.e., improvement of error).
3.2.1.2. Parent Selection

Selected parents need to be relatively fit, compared to other members, so that the fitness function is improved in the next generation. This selection method exploits and improves the current solution. However, exploration of new solutions can be performed by allowing some of the weak strings to breed as well. There are two common methods for parent selection: truncation selection and fitness proportional selection.

Truncation selection selects a specified percentage of the best strings for mating and ignores the rest. Strings are selected, with equal probability, from the best strings selected based on a specified percentage (Marsland, 2009). This method restricts the exploration of new solutions.

Fitness proportional selection is used to select a string probabilistically. Each individual can be selected with a probability proportional to fitness (Marsland, 2009). This is a better method because it allows for exploitation and exploration.

3.2.1.3. Producing New Individual

After selecting the parents, genetic operators decide how to combine those two strings. Two common genetic operators are discussed here: crossover and mutation.

The crossover operator selects a point at random in the strings of the two parents. Then, two new strings are formed by combining the first part of the first parent and the second part of the second parent and vice-versa as shown in (Figure 3-3). This process is known as single-point crossover. Single-point crossover can be expanded by selecting multi random points in each parents and swabbing the genes; this operator is called multi-
point crossover and shown in (Figure 3-4). Crossover incorporates global exploration for the optimal solution; the parents produce totally different children (Marsland, 2009 and Mohaghegh, 2000b).

The mutation operator randomly alters one unit element of a string as shown in (Figure 3-5). The operator changes the value of each element of a string with low probability. Mutation operator exploits the current solution and performs a local search.

A problem with the GA is that fitness function can decrease or increase. The fitness function can decrease because the parents are not being copied into the new generation and their offspring are not as good (Marsland, 2009). This problem can be tackled via elitism and tournament. Elitism involves copying the the best strings in the current population without any changes; however, doing so can limit the exploration of a better solution since some of the best strings are not mated. In the tournament method, parents compete against their two children, and the fittest two move to the next generation (Marsland, 2009).

Figure 3-3. Single Point Crossover Operator (Mohaghegh, 2000b).
Figure 3-4. Multi-Point Crossover Operator (Mohaghegh, 2000b).

Figure 3-5. Mutation Operator (Mohaghegh, 2000b).

### 3.2.1.4. Advantages of Genetic Algorithm

Advantages of the GA include the following:

1. Its powerful capability for parallel searching different areas with the feasible solution.

2. Its ability to solve complicated nonlinear, non-smooth, noisy optimization problems.

3. Its ability to search for global optima rather than local ones. The algorithm perform exploitation for improving current solutions (local search), and exploration to search for new solutions (global search). Exploitation and exploration are incorporated via mutation and crossover, respectively (Marsland, 2009).
4. Gradient calculation is not required, speeding the process significantly (Abukhamsin, 2009).

5. Functional links are not required. Unlike ANN, functional links do not improve the convergence and results. Functional links are mathematical relationships between input and output parameters.

3.2.2. Capacity Planning in the Oil Industry

(Hoogwerf, 2005) developed an optimization model to optimize the capacity planning of transfer stations for natural gas. The study identified optimal gas transfer station design for a given forecasted demand. The forecasted demand considered the possibility of new delivery contract and was done by planning experts. The optimization process was done in two steps: 1) Develop design scenarios, and 2) Match the forecasted demand with the resulted capacity for the designed scenarios. The feasibility of designed station was based on the inlet pressure and heat capacity. Mismatch of forecasted demand was analyzed to determine the deficiency in the station. The designed scenarios covered the worst cases like equipment overloading and failure. The optimization problem was linearized and solved linearly. The developed model improved the process in the planning department at Gasunie.

(Dougherty and Chang, 1993) developed an optimization model to optimize development and production from gas field(s) to deliver the requested rate vs. time for each transfer stations. More than one field can be connected to a station depending on the capacity of the field. The optimization model determined schedule for drilling wells and
production rate for each field. Reservoir simulator, nodal analysis deliverability
equations, and economic models were incorporated in the generalized model.

(Omar, 1984) developed a model for world oil demand based econometrics. The
purpose of the study was to analyze the impact of changes in the economic activity in the
oil consuming regions on the world demand for oil.

(Nakov and Nuno, 2011) developed an equilibrium model for global oil market,
that resulted in crude prices, consumption, and production as results of profit maximizing
decisions of exporters and importers. Dominant firm with competitive fringe model was
implemented. They provided a price markup term to determine the optimal spare capacity
of the dominant firm. The price markup determined the optimal production quantity for
dominant firm in the residual demand curve; the optimal condition was where marginal
revenue equals marginal cost. Their model was successful in regenerating the jump in oil
production of the dominant firm during Iraq and Kuwait Gulf War. They concluded that
it was optimal for a dominant oil producer to acquire spare capacity.

Most of the capacity studies handle the demand for oil deterministically as a
single number (Bukhari, 2011, Dougherty and Chang, 1993, and Omar, 1984). Our study
was the first of its kind in term of calculating a probability of using a specified spare
capacity. Our proposed methodology enabled us to calculate an economically optimal
spare capacity volume to acquire based on historical behavior of demand for crude. This
methodology recommends an optimal spare capacity for a dominant producer to acquire.
This can adds billions of dollars in the expected NPV for the dominant firm. No work has
been done in this area of research.
3.3. Problem Statement

The management of a major oil producer includes identifying the economically optimal level of spare capacity for the company to acquire under the uncertainties in world demand and crude price, given the historical data on global demand for oil. The company assumes the production of any amount of spare capacity throughout the life of the study. In other words, reserves limitation was not considered in the study; however, development and production costs increases with higher level of spare capacity. Moreover, the company possesses only onshore oil fields.

The company produces West Texas Intermediate (WTI) crude type from all fields; hence, WTI price was used in the study. All fields have the same cost functions and models. In other words, all fields and reservoirs are identical and located at the same depth and have the same distance to processing facilities.

3.4. Methodology

This study establishes a workflow that identifies the optimal volume of spare capacity for a major oil producer to acquire under the uncertainties of price and demand for oil. The problem was a dynamic optimization where the objective function was the expected NPV resulted from acquiring the spare capacity. This section discusses the established workflow and models developed to achieve the goals of this study and analyze the impact of demand and price model on optimal spare capacity volume.
3.4.1. Overview

The basic concept behind this study was that developing and maintaining spare capacity requires significant investment; however, this spare capacity can bring profit when it is used. The economics of spare capacity can be divided into costs and expected revenue; expected revenue was used rather than revenue because using the spare capacity volume was uncertain. Computing the development and maintenance costs of the spare capacity was done by implementing the cost model developed by (Kennedy, 1993) and implemented by (Bittencourt, 1997). Calculating the probability of using a specified volume of spare capacity was a challenging process. (Figure 3-6) summarizes the process of the spare capacity study. The green squares represent developed models and the blue squares were user-defined parameters of output from a model. The process starts with the demand forecast model, modeled as a combination of two stochastic processes— the Mean Reversion and Geometric Brownian Motion models. In this combined demand model, the demand was forecasted as the Mean Reversion Model (MRM); however, long-run equilibrium demand (Dem*) was modeled as the Geometric Brownian Motion (GBM) model. The long-run equilibrium demand was modeled independently using the GBM before it was incorporated in the MRM model. From the probabilistic demand model, average demand was calculated over a specified period of time. The demand was forecasted as probability distribution each year with mean and standard deviation as shown in (Figure 3-7). The figure is a made-up example to show the method of calculating the average demand. The average demand, over the specified period of time, is the average of the mean of the demand distribution each year. The blue line represents
the mean of the demand distribution each year and the orange line is the average demand, which is the average of the values on the blue line. The same approach was implemented to calculate the average demand of the study and referred as base demand. It was assumed that on average the calculated average demand was consumed, and any volume above this average was spare capacity. For example, if the average demand for the first five years of forecasted demand is 80 MMBD, any volume above the 80 MMBD is spare capacity at any point in time. The period over that the average demand was calculated can impact the probability of using a spare capacity and the optimal decision as discussed in the results section. The cumulative density function CDF of the demand was used to calculate the probability of using a specific value of spare capacity. This probability, the specified capacity volume, and the forecasted price result in the expected revenue. The expected revenue and the cost models were incorporated in the economic evaluation model to calculate the NPV of acquiring and maintaining the spare capacity volume.

Achieving economic optimality, from acquiring spare capacity, is the goal of this study. This study does not tackle the topic of market power, price formation and game theory. We are not concerned with modeling the price setting ability of a dominant firm. Our goal is to examine the potential economic profit that a hypothetical dominant producer can realize by acquiring spare capacity, given that the price setting power of any dominant producer will be imperfect in practice, and therefore uncertainties in demand for and price of crude will remain. These uncertainties can be described by means, drifts and volatilities of crude prices and demand using stochastic models and historical data. Stochastic price and demand models could in turn serve as reasonable representations of future market circumstances and a dominant producer’s potential imperfect responses to
them. To model the value to a dominant producer of spare production capacity, we developed such a stochastic demand model and use it to calculate the probability that a producer will utilize a specific level of spare capacity. To capture uncertainty, we generated 120,000 iterations of stochastic demand under various price paths, and used the resulting cumulative density function to gauge the probability that demand will exceed existing capacity by a sufficient (specified) volume.

Figure 3-6. Overview of the Spare Capacity Methodology.
3.4.2. Price Model

Two probabilistic price forecast models were analyzed: the Mean Reversion Model MRM and the Mean Reversion Model with the Geometric Brownian Motion Model. The second model was a combination of two stochastic processes; an MRM Model, in which the long-run equilibrium price $P^*$ was modeled as Geometric Brownian Motion model (GBM) as recommended by (Dias, 2010a). (Figure 3-8) shows the historical data used to calculate the parameters required for the two price forecast models. The figure shows weekly prices between 1986 and 2014 for West Texas Intermediate crude (WTI).
Historical data on price (Figure 3-8) were obtained from the Energy Information Administration (EIA, 2014). The data between 1986 and 2014 were used to calculate the volatility and drift of prices because it had been recommended to use as much data as possible to calculate the volatility (Dias, 2010c). However, data between 2008 and 2014 were used to calculate the long-run equilibrium price and reversion rate because it was believed that crude prices established a new long-run equilibrium price starting in 2008 (Xu, 2010 and Bukhari, 2011).

3.4.2.2. Calculating Modeling Parameters for the Price Models

This section discusses the calculations of the parameters required to build the price forecast models, including volatility and drift of crude price, long-run equilibrium price, and reversion rate.
3.4.2.2.1. Volatility of Crude Price (σ)

Volatility, parameter for MRM model, is the standard deviation of the logarithm returns (Bukhari and Jablonowski, 2012) as shown in (Equation 3-1). Price volatility introduces uncertainty in the Mean Reversion Model. Weekly crude price, for West Texas Intermediate, was used to calculate the volatility of crude price. (Table 3-1) shows a sample of the calculations of the volatility in historical data. The first two columns are the date and price of crude. The third and fourth columns are the natural logarithm of price for the current period and previous period, respectively. The last column is the difference between the values in the third and fourth columns. The volatility is the standard deviation in entries in the fifth column. The calculated volatility must be converted to annual volatility by multiplying the weekly volatility by the square root of 52. The table shows the weekly and annual volatilities. The annual volatility used in the study was 0.3149.

\[
\sigma = \text{Standard Deviation} [\ln P(t) - \ln P(t - 1)], \ \forall \ t \tag{3-1}
\]

Table 3-1. Sample of Volatility Calculations for Crude Price.

<table>
<thead>
<tr>
<th>Time (Yrs)</th>
<th>Crude Oil Price ($/bbl)</th>
<th>Ln[P(t)]</th>
<th>Ln[P(t-1)]</th>
<th>Ln[P(t)]-Ln[P(t-1)]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Jan 31, 2014</td>
<td>97.29</td>
<td>4.58</td>
<td>4.57</td>
<td>0.01</td>
</tr>
<tr>
<td>Feb 07, 2014</td>
<td>97.78</td>
<td>4.58</td>
<td>4.58</td>
<td>0.01</td>
</tr>
<tr>
<td>Feb 14, 2014</td>
<td>100.21</td>
<td>4.61</td>
<td>4.58</td>
<td>0.02</td>
</tr>
<tr>
<td>Feb 21, 2014</td>
<td>102.93</td>
<td>4.63</td>
<td>4.61</td>
<td>0.03</td>
</tr>
<tr>
<td>Feb 28, 2014</td>
<td>102.77</td>
<td>4.63</td>
<td>4.63</td>
<td>0.00</td>
</tr>
<tr>
<td>Mar 07, 2014</td>
<td>103.07</td>
<td>4.64</td>
<td>4.63</td>
<td>0.00</td>
</tr>
<tr>
<td>Mar 14, 2014</td>
<td>99.55</td>
<td>4.60</td>
<td>4.64</td>
<td>-0.03</td>
</tr>
<tr>
<td>Mar 21, 2014</td>
<td>99.77</td>
<td>4.60</td>
<td>4.60</td>
<td>0.00</td>
</tr>
</tbody>
</table>

\[
\sigma \ (\text{Weekly}) = 0.044
\]

\[
\sigma \ (\text{Anually}) = 0.3149
\]
3.4.2.2. Drift of Crude Price (α)

The drift is a parameter of the Geometric Brownian Motion Model, which is a lognormal diffusion process. The drift controls the path or growth rate of the GBM diffusion process as shown in (Figure 3-9). (Table 3-2) shows a sample of the calculations for drift. The first two columns are the date and price of crude. The third and fourth columns are the natural logarithms of price for the current period and previous period, respectively. The last column is the difference between the values in the third and fourth columns. The average of logarithm returns is calculated by averaging the entries in the last column. Using (Equation 3-2), the average of logarithm returns, and the calculated volatility in the previous section, the drift is calculated. (Equation 3-3) shows the calculation of the drift; the first term is the average of logarithm returns. The calculated weekly drift was multiplied by the square-root of 52 to convert it to an annual basis. The annual drift used in the study was 0.0225, as shown in (Table 3-2).

Table 3-2. Sample of Drift Calculations for Crude Price.

<table>
<thead>
<tr>
<th>Date</th>
<th>Crude Oil Price ($/bbl)</th>
<th>Ln[P(t)]</th>
<th>Ln[P(t-1)]</th>
<th>Ln[P(t)]-Ln[P(t-1)]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Jan 31, 2014</td>
<td>97.29</td>
<td>4.58</td>
<td>4.57</td>
<td>0.01</td>
</tr>
<tr>
<td>Feb 07, 2014</td>
<td>97.78</td>
<td>4.58</td>
<td>4.58</td>
<td>0.01</td>
</tr>
<tr>
<td>Feb 14, 2014</td>
<td>100.21</td>
<td>4.61</td>
<td>4.58</td>
<td>0.02</td>
</tr>
<tr>
<td>Feb 21, 2014</td>
<td>102.93</td>
<td>4.63</td>
<td>4.61</td>
<td>0.03</td>
</tr>
<tr>
<td>Feb 28, 2014</td>
<td>102.77</td>
<td>4.63</td>
<td>4.63</td>
<td>0.00</td>
</tr>
<tr>
<td>Mar 07, 2014</td>
<td>103.07</td>
<td>4.64</td>
<td>4.63</td>
<td>0.00</td>
</tr>
<tr>
<td>Mar 14, 2014</td>
<td>99.55</td>
<td>4.60</td>
<td>4.64</td>
<td>-0.03</td>
</tr>
<tr>
<td>Mar 21, 2014</td>
<td>99.77</td>
<td>4.60</td>
<td>4.60</td>
<td>0.00</td>
</tr>
</tbody>
</table>

(α-(1/2) σ²) 0.001
α Annual 0.0225
Figure 3-9. GBM Lognormal Diffusion Process (Dias, 2010b).

\[(\alpha - \frac{1}{2} \sigma^2) = \text{Average}[\ln P(t) - \ln P(t - 1)], \forall t \] 
\[\alpha = (\alpha - \frac{1}{2} \sigma^2) + \left(\frac{1}{2} \sigma^2\right) \] 

3.4.2.2.3. Long-run Equilibrium Price \((P^*)\) and Reversion Rate \((\eta)\)

This section details the calculations of the long-run equilibrium price \((P^*)\) and reversion rate \((\eta)\), required for the Mean Reversion Model (MRM). The basis of the MRM is that prices correlate with the marginal cost of production. During the MRM process, prices revert to a long-run equilibrium price \(P^*\) with a volatility \(\sigma\) and reversion speed \(\eta\). Weekly WTI crude price data between 2008 and 2014 were used to calculate the long-run equilibrium price and reversion rate. The two parameters were calculated using the first-order autoregressive process AR(1) (Equation 3-4) in discrete time (Dixit and Pindyck, 1994). Substituting (Equations 3-5 and 3-6) into (Equation 3-2) results in (Equation 3-7), which is a linear regression model of \((P_t - P_{t-1})\) as a function of \(P_{t-1}\) with slope \(b\), intercept \(a\), and residual \(\epsilon_t\). Regression models assume that the residual term is...
normally distributed with zero mean and standard deviation equal to the standard error for the sample data. (Table 3-3) and (Figure 3-10) show the data required for the AR(1) process to estimate $P^*$ and $\eta$. The figure shows $(P_t - P_{t-1})$ as a function of $P_{t-1}$. The regression model is fitted through the data using a least squares approach with ‘a’ as the intercept and ‘b’ as the slope. The long-run equilibrium price $P^*$ and the reversion rate were calculated using (Equation 3-11) and (Equation 3-10), respectively. The long-run equilibrium price $P^*$ and the reversion rate used in the study were 88.90 and 0.83, as shown in (Table 3-5). The calculated weekly reversion rate was multiplied by 52 to convert it to an annual rate.

\[ P_{(t)} - P_{(t-1)} = P^* (1 - e^{-\eta}) + (e^{-\eta} - 1) * P_{(t-1)} + \varepsilon_t \]  
(3-4)

\[ P^*(1 - e^{-\eta}) = a \]  
(3-5)

\[ (e^{-\eta} - 1) = b \]  
(3-6)

\[ P_{(t)} - P_{(t-1)} = a + b * P_{(t-1)} + \varepsilon_t \]  
(3-7)

\[ \varepsilon_t = N(0, \sigma_c) \]  
(3-8)

\[ \sigma_R = \text{Standard Error} \]  
(3-9)

\[ P^* = \frac{-a}{b} \]  
(3-10)

\[ \eta = -\ln(1 + b) \]  
(3-11)
Table 3-3. P* and η Estimation for Crude Price.

<table>
<thead>
<tr>
<th>Date</th>
<th>P(t)</th>
<th>P(t-1)</th>
<th>P(t)-P(t-1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Jan 04, 2008</td>
<td>94.76</td>
<td>98.17</td>
<td>-3.41</td>
</tr>
<tr>
<td>Jan 11, 2008</td>
<td>91.51</td>
<td>94.76</td>
<td>-3.25</td>
</tr>
<tr>
<td>Jan 18, 2008</td>
<td>89.41</td>
<td>91.51</td>
<td>-2.10</td>
</tr>
<tr>
<td>Feb 01, 2008</td>
<td>91.14</td>
<td>89.41</td>
<td>1.73</td>
</tr>
<tr>
<td>Feb 08, 2008</td>
<td>89.08</td>
<td>91.14</td>
<td>-2.06</td>
</tr>
<tr>
<td>Feb 15, 2008</td>
<td>94.13</td>
<td>89.08</td>
<td>5.05</td>
</tr>
<tr>
<td>Feb 22, 2008</td>
<td>99.61</td>
<td>94.13</td>
<td>5.48</td>
</tr>
<tr>
<td>Feb 29, 2008</td>
<td>100.84</td>
<td>99.61</td>
<td>1.23</td>
</tr>
<tr>
<td>Mar 07, 2008</td>
<td>103.44</td>
<td>100.84</td>
<td>2.60</td>
</tr>
<tr>
<td>Mar 14, 2008</td>
<td>109.35</td>
<td>103.44</td>
<td>5.91</td>
</tr>
<tr>
<td>Mar 21, 2008</td>
<td>105.28</td>
<td>109.35</td>
<td>-4.07</td>
</tr>
<tr>
<td>Mar 28, 2008</td>
<td>104.49</td>
<td>105.28</td>
<td>-0.79</td>
</tr>
<tr>
<td>Apr 04, 2008</td>
<td>103.46</td>
<td>104.49</td>
<td>-1.03</td>
</tr>
</tbody>
</table>

Figure 3-10. P* and η Estimation for Crude Price Using (AR(1)) Regression.

Table 3-4. Regression Parameters to Estimate P* and η.

<table>
<thead>
<tr>
<th>Regression Parameters</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>a</td>
<td>1.41</td>
</tr>
<tr>
<td>b</td>
<td>-0.02</td>
</tr>
<tr>
<td>σe</td>
<td>5.51</td>
</tr>
</tbody>
</table>
3.4.2.3. Price Modeling

This section discusses the formulation of the Mean Reversion and the Geometric Brownian Motion processes.

3.4.2.3.1. Mean Reversion Model MRM

3.4.2.3.1.1. Technical Background of the MRM

The Mean Reversion Model is a more realistic approach for price forecasting, from the economic perspective, since it is believed that prices are correlated with marginal cost of production. The MRM reflects the decisions of suppliers as prices change. Suppliers increase quantity supplied as response to higher prices to maximize profit while they decrease the production when prices are low to minimize losses. These types of reactions force prices to revert to a long-run equilibrium price (Bukhari, 2011). (Figure 3-11) shows a sample path for a Mean Reversion Model on crude price; the blue line is crude prices and the red line is the long-run equilibrium price. Many different models have been developed to construct a Mean Reversion model. The Ornstein-Uhlenbeck model (Equation 3-12) used in this study is commonly selected due to its simplicity and practicality (Dias, 2010c). In the formula, the term \((P^*-P)\) dictates the

<table>
<thead>
<tr>
<th>MRM Parameters</th>
<th>(P^*)</th>
<th>88.90</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\eta) (Annually)</td>
<td>0.83</td>
<td></td>
</tr>
</tbody>
</table>

Table 3-5. Estimated \(P^*\) and \(\eta\) for Crude Price.
direction of the drift; the drift is positive when the current price is lower than the long-run mean price \( P^* \), and it is negative when the current price is greater than the long-run mean price \( P^* \). As a result, prices revert to the long-run equilibrium price \( P^* \) proportionally to the drift term (Dias, 2010c). Moreover, the greater the difference between current price and long-run mean price, the greater the tendency to revert toward \( P^* \). The volatility grows initially and then stabilizes at a specific value over time (Dias, 2010c). (Equation 3-13) shows the logarithm of the price version of the MRM model, by substituting \( x = \ln(P) \) in (Equation 3-12). Working with the logarithm of price rather than price in constructing MRM is preferred because the logarithm of price is normally distributed, which made it easier to work with than the lognormal distribution of price. Dealing with the logarithm of price facilitates the Monte Carlo simulation and parameter estimation (Dias, 2010c). Parameter estimation becomes independent of price by working with the logarithm of price in the MRM model (Dias, 2010c).

Figure 3-11. Mean Reversion Sample Path (Bukhari, 2011).

\[
dP = \eta * P^*(P^* - P)dt + \sigma * P * dz
\]  

(3-12)
Where

P* the long-run equilibrium price

η reversion rate

dz (Wiener increment)= ε dt^{1/2}

ε = Standard Normal Distribution = N(0,1)

σ = Volatility of Price

\[ dx = \eta(x^* - x)dt + \sigma dz \]  

(3-13)

Where

x = ln(P)

3.4.2.3.1.2. Formulation of the MRM

The logarithm for the price version of the Ornstein-Uhlenbeck Mean Reversion model (Equation 3-14) was implemented. During the MRM process, the logarithm of price of the current time x(t), and the variance of the logarithm of price at the same period Var[x(t)] were calculated from (Equations 3-16 and 3-17), respectively. (Table 3-6) shows the parameters implemented in the MRM forecast model for crude price. The MRM crude price model was developed by plugging the calculated x(t), Var[x(t)], and the parameters from (Table 3-6) in (Equation 3-14). (Figure 3-12) shows a sample of the MRM crude price model used in the study. A price floor of $40 was imposed on the MRM model to avoid negative values.

\[ P_t = e^{(x_t - \frac{1}{2}Var[x_t])} \]  

(3-14)

\[ x^* = \ln(P^*) \]  

(3-15)
\[ x_t = x_{t-1} \ast e^{[-\eta \Delta t]} + x^* \ast (1 - e^{[-\eta \Delta t]}) + \sigma \ast \sqrt{(1 - e^{[-2\eta \Delta t]})/(2\eta)} \ast N(0,1) \quad (3-16) \]

\[ Var[x_t] = (1 - e^{[-2\eta t]}) \ast \frac{\sigma^2}{2\eta} \quad (3-17) \]

Table 3-6. Parameters for the MRM Crude Price Model.

<table>
<thead>
<tr>
<th>MRM Parameters for Crude Price</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \eta ) (Reversion Speed)</td>
</tr>
<tr>
<td>( P^* ) (Long-Run Mean Price)</td>
</tr>
<tr>
<td>Ln( (P^*) )</td>
</tr>
<tr>
<td>( \sigma ) (Volatility)</td>
</tr>
<tr>
<td>( P_{min} )</td>
</tr>
</tbody>
</table>

![MRM Crude Price](image)

Figure 3-12. Mean Reversion Model Sample of Crude Price.

3.4.2.3.2. Geometric Brownian Motion Model GBM

The Geometric Brownian Motion model (GBM) was used in the second price forecast model—a combination of the MRM and the GBM models. The MRM-GBM model is a Mean Reversion Model in which the long-run equilibrium price \( P^* \) was modeled as a Geometric Brownian Motion model. In other words, the GBM process was
conducted independently from the MRM process. This section presents background on the GBM model and discusses its formulation process.

3.4.2.3.2.1. Technical Background of the GBM

The Brownian motion was first introduced in 1827 by Robert Brown to describe the movement of small particles subjected to large numbers of random collisions (Dyer, 2011 and Bukhari, 2011). The Brownian motion is a stochastic process with zero mean and variance of one at each time step and is a special case of the Markov process (Dyer, 2011). The Brownian motion, known as the Wiener process, does not incorporate time. Incorporating Brownian motion with growth rate (drift) led to Arithmetic Brownian Motion (ABM), which is a combination of linear growth rate and random growth for a normal distribution (Dyer, 2011 and Bukhari, 2011). The ABM process can be presented as shown in (Equation 3-18); (Figure 3-13) shows an example of the ABM process. A more representative model for price forecasting is the Geometric Brownian Motion model (GBM). The GBM is a combination of proportional and random proportional (normally distributed) growth (Dyer, 2011). The GBM can be formulated using (Equation 3-19); (Figure 3-14) shows an example of the GBM process. Simply put, the GBM is a lognormal diffusion process as shown in (Figure 3-15) (Dias, 2010b).

\[ P(t + 1) = P(t) + \alpha * dt + \sigma * dz \]  
(3-18)

\[ dP = \alpha * P * dt + \sigma * P * dz \]  
(3-19)

Where

\[ dz \text{ (Wiener increment)} = \varepsilon dt^{1/2} \]
ε = Standard Normal = N(0,1)

α = Drift or trend

σ = Volatility of P

Figure 3-13. Arithmetic Brownian Motion Process (Dyer, 2011).

Figure 3-14. Geometric Brownian Motion Process (Dyer, 2011).
Economists argue about the applicability of the GBM model to forecast prices; however, it has been widely used due to its simplicity and practicality (Bukhari, 2011). (Equation 3-19) is the general form of the GBM; the first term on the right side of the equation controls the growth rate and the second term controls the uncertainty or volatility of the process (Dias, 2010b and Bukhari 2011). (Equation 3-20) is the result of substituting $p=\ln(P)$ in (Equation 3-19) and applying Ito’s Lemma (Dixit, 1993). (Equation 3-20) is the logarithm of the price version of the GBM model. (Equation 3-21) is the discrete form of (Equation 3-20). Working with the logarithm of price has the following advantages (Dias, 2010b):

1. It facilitates the implementation of the Monte Carlo simulation process.
2. It is easier to work with the normal distribution of logarithm of price than the log-normal distribution of the price.
3. It facilitates the estimation of the modeling parameters since the parameters are independent of the logarithm of price.

\[ dp = d(lnP) = \left( \alpha - \frac{1}{2} \sigma^2 \right) dt + \sigma dz \] (3-20)
\[ P(t) = P(t - 1) \times e^{\left(\alpha - \frac{1}{2} \sigma^2\right) \Delta t + \sigma N(0,1) \sqrt{\Delta t}} \]  

(3-21)

3.4.2.3.2.2. Parameters for the GBM

The GBM model was used to model the long-run equilibrium price \( P^* \) in the MRM forecast model. The required parameters for the GBM model are the drift and the volatility of prices. The volatility and drift used in the study were 0.31 and 0.0225, respectively.

3.4.3. Demand Model

The demand was modeled as a combination of the Mean Reversion model and the Geometric Brownian Motion model. The basis of the demand forecast model was the MRM model; however, the long-run equilibrium demand \( \text{Dem}^* \) was modeled as GBM. Demand can be modeled as GBM for capacity planning studies (Liang, 2003). Since demand is correlated with prices (Figure 3-16), the MRM-GBM combined mode was believed to be a more realistic model. Weekly world crude production and consumption data between 1994 and 2012 were used to calculate the parameters required for the demand forecast model. The crude oil world production and consumption data were obtained from Energy Information Administration (EIA).
Figure 3-16. Weekly Crude Price and Supply between 1994 and 2012.

3.4.3.1. Historical Data

World crude production data between 1994 and 2012 were used to develop the demand forecast model in this study (Figure 3-16). Crude production was used instead of consumption because the available production data set was significantly larger than the one for the consumption; moreover, the historical production and consumption data is almost identical as shown in (Figure 3-17).

Figure 3-17. Monthly Crude Supply and Consumption between 1980 and 2012.
3.4.3.2. Calculating Modeling Parameters for the Demand Models

This section discusses the calculations of the parameters required to build the demand forecast model, including volatility and drift of crude demand, long-run equilibrium demand, and reversion rate.

3.4.3.2.1. Volatility of Crude Demand (σ)

Volatility is the standard deviation in logarithm returns. The same procedure implemented in calculating price volatility earlier was used in demand volatility calculations. Weekly world crude production data between 1994 and 2012 were used for the volatility calculation. The annual demand volatility used in the study was 0.0278.

3.4.3.2.2. Drift of Crude Demand (α)

The drift is a parameter for the Geometric Brownian Motion model, which is a lognormal diffusion process. The drift controls the path or the growth rate of the GBM diffusion process. The same procedure implemented in calculating price drift earlier was used in demand drift calculations. Weekly world crude production data between 1994 and 2012 were used for the drift calculation. The annual demand drift used in the study was 0.0146.
3.4.3.2.3. Long-run Equilibrium Demand ($Dem^*$) and Reversion Rate ($\eta$)

During the MRM process, demand reverts to a long-run equilibrium demand $Dem^*$ with a volatility $\sigma$ and reversion speed $\eta$. Weekly world crude production data between 2008 and 2012 was used to calculate the long-run equilibrium demand and reversion rate. The long-run equilibrium demand and demand reversion rate were estimated in the same procedure as the long-run equilibrium price and reversion rate for price. The long-run equilibrium demand and demand reversion rate used in the study were 88,428 MBD and 0.52, respectively.

3.4.3.3. Demand Modeling

The demand was modeled as a Mean Reversion Model in which the long-run equilibrium demand $Dem^*$ was modeled as Geometric Brownian Motion. Using the calculated demand parameters, the MRM-GBM combined model was implemented in a similar way as implemented in the price MRM-GBM model. The MRM and the GBM processes are discussed in the price modeling section.

3.4.4. Cost Model

The cost model used in this study was developed by (Kennedy, 1993) and (Bittencourt, 1997). Kennedy’s model incorporates oil, gas, onshore, and offshore fields; moreover, it handles the costs of drilling, pipeline, and production facility. Our study handled only onshore oil fields. Kennedy used actual field data and commercial software
to develop the model. The cost model was modified to account for horizontal drilling and for inflation. Fifteen days were added to the drill-days model to drill 2000 ft. horizontal lateral; it was assumed that the rate of penetration was 133 ft./day for horizontal drilling. GDP deflator was used to express the cost model in 2011 dollars (GDP Price Deflator, 2012).

3.4.4.1. Modeling Assumptions

1. The cost model was reliable and representative of actual costs.
2. Rate of Penetration for horizontal drilling was 133 ft./day.
3. GDP price deflator was proper for expressing the cost model in 2011 dollars.

3.4.4.2. Modeling Parameters for Onshore Fields

The study handled onshore oil fields; cost models for onshore oil fields were implemented in the study. This section discusses the cost models for onshore drilling, pipeline, and production facility.

3.4.4.2.1. Onshore Drilling Costs

The drilling costs are divided into tangible and intangible drilling costs. The tangible drilling costs cover the cost of tubular and casing, and the intangible costs cover the cost for rig rental and support for the rig.
The intangible drilling costs cover the costs of rig rental and rig support and supervision. Rig support and supervision include contract labor, casing crew and equipment, cement services, bits, formation testing, equipment rental, fuel, water, power, logging, perforating, and miscellaneous wireline operations. The intangible drilling cost was the product of rig rental & support, and rig time required to drill a well as shown in (Equation 3-22). The rig day-rate used in the study was $14,479/day in 2011 dollars. Drill days required to drill a well as a function of reservoir depth can be obtained from (Figure 3-18). Fifteen days were added to drill 2,000 ft. of horizontal lateral. (Tables 3-7 and 3-8) show the support and supervision rates as a function of fields’ remoteness in 1993 and 2011 dollars, respectively. (Table 3-9) lists the definitions of the field’s remoteness (Kennedy, 1993).

Onshore drilling costs were estimated from (Figure 3-19), which expresses the costs of tubular and casings in the thousands of dollars as a function of well depth. The GDP price deflator was used to express the costs in 2011 dollars.

\[ \text{Intangible Drilling Costs} = \text{Rig Time} \times (\text{Rig Rental Rate} + \text{Support and Supervision Rate}) \]  

(3-22)

Figure 3-18. Drill Days for Onshore Drilling as Function of Reservoir Depth.
Table 3-7. Rig Support and Supervision Rate in 1993 Dollars.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>7500</td>
<td>3750</td>
<td>10000</td>
<td>50000</td>
</tr>
<tr>
<td>2</td>
<td>10000</td>
<td>5000</td>
<td>15000</td>
<td>7500</td>
</tr>
<tr>
<td>3</td>
<td>12500</td>
<td>6250</td>
<td>20000</td>
<td>10000</td>
</tr>
<tr>
<td>4</td>
<td>15000</td>
<td>7500</td>
<td>30000</td>
<td>15000</td>
</tr>
<tr>
<td>5</td>
<td>20000</td>
<td>10000</td>
<td>50000</td>
<td>25000</td>
</tr>
</tbody>
</table>

Table 3-8. Rig Support and Supervision Rate in 2011 Dollars.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>10860</td>
<td>5430</td>
<td>14479</td>
<td>72397</td>
</tr>
<tr>
<td>2</td>
<td>14479</td>
<td>7240</td>
<td>21719</td>
<td>10860</td>
</tr>
<tr>
<td>3</td>
<td>18099</td>
<td>9050</td>
<td>28959</td>
<td>14479</td>
</tr>
<tr>
<td>4</td>
<td>21719</td>
<td>10860</td>
<td>43438</td>
<td>21719</td>
</tr>
<tr>
<td>5</td>
<td>28959</td>
<td>14479</td>
<td>72397</td>
<td>36198</td>
</tr>
</tbody>
</table>

Table 3-9. Definition of Field’s Remoteness (Kennedy, 1993).

<table>
<thead>
<tr>
<th>Remoteness</th>
<th>Characteristics</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>A mature area in terms of exploration and production in which rigs and oilfield services are readily available. This includes experienced personnel for supervision. In such places the annual well count is measured in 100’s.</td>
</tr>
<tr>
<td>2</td>
<td>Similar to 1 but with a lower level of activity resulting in common costs being distributed over a smaller number of wells.</td>
</tr>
<tr>
<td>3</td>
<td>Typically this is an area with an active hydrocarbon industry which ensures the availability of goods and services.</td>
</tr>
<tr>
<td>4</td>
<td>Similar to 3 but with a relatively undeveloped supply industry. Some services may be available, but others may need to be established using foreign contractors.</td>
</tr>
<tr>
<td>5</td>
<td>Frontier areas in which exploration is taking place for the first time. In such areas, the service companies frequently work out of the oil company offices. Supervision of a well may be conducted both from the local and global headquarters of the companies participating.</td>
</tr>
</tbody>
</table>
3.4.4.2. Development Costs

Development cost handles the cost related to the development of new fields, including camp cost, well-site costs, production facility costs, and pipeline costs. The camp cost is function of field remoteness and can be calculated using (Equation 3-23), which is a function production rate. (Table 3-10) shows the base cost for camp costs calculations. The camp base cost used in the study was $1.448 million; the well-site cost used in the study was $0.1014 million. (Table 3-11) shows the well-site costs as a function of terrain and reservoir depth. The onshore oil production facility was estimated from (Figure 3-20), which expresses the facility costs as a function of flow rate. (Table 3-12) lists cost adjustment factors for production facility costs recommended by (Kennedy, 1993). The costs for the oil pipeline were estimated from (Figure 3-21), which expresses the costs as dollar per distance between field and production facility as a function flow.

Figure 3-19. Onshore Tangible Costs.
rate. The figure shows the pipeline costs for the following environments: rain forest, mountains, agricultural, and savannah. Our study used agricultural environment.

\[
Camp\ Cost = Base\ Cost \times \left( \frac{Production\ Rate(MBD)}{10} \right)^{0.6}
\]  

(3-23)

Table 3-10. Base Costs for Camp Cost.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.5</td>
<td>0.724</td>
</tr>
<tr>
<td>2</td>
<td>1</td>
<td>1.448</td>
</tr>
<tr>
<td>3</td>
<td>2.5</td>
<td>3.620</td>
</tr>
<tr>
<td>4</td>
<td>5</td>
<td>7.240</td>
</tr>
<tr>
<td>5</td>
<td>10</td>
<td>14.479</td>
</tr>
</tbody>
</table>

Table 3-11. Wellsite Costs.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>&lt;7500 ft</td>
<td>&gt;7500 ft</td>
</tr>
<tr>
<td>Arctic</td>
<td>1.5</td>
<td>2</td>
</tr>
<tr>
<td>Temerate Forest</td>
<td>0.3</td>
<td>0.8</td>
</tr>
<tr>
<td>Desert</td>
<td>0.06</td>
<td>0.15</td>
</tr>
<tr>
<td>Agricultural</td>
<td>0.03</td>
<td>0.07</td>
</tr>
<tr>
<td>Savannah</td>
<td>0.05</td>
<td>0.12</td>
</tr>
<tr>
<td>Rain Forest</td>
<td>1</td>
<td>2.5</td>
</tr>
<tr>
<td>Swamp/Marsh</td>
<td>1.5</td>
<td>3.5</td>
</tr>
</tbody>
</table>

Table 3-12. Production Facility Adjustment Factor.

<table>
<thead>
<tr>
<th></th>
<th>1-2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Remoteness/Logistics Factor:</td>
<td>1-2</td>
</tr>
<tr>
<td>Construction Difficulty Factor</td>
<td>1-2</td>
</tr>
<tr>
<td>Equipment Complexity Factor:</td>
<td>1-1.75</td>
</tr>
<tr>
<td>Enclosing Equipment Factor</td>
<td>1.5-2</td>
</tr>
</tbody>
</table>
3.4.5. Integrated Optimization Model

This section discusses the integration of all models in our study, including price models, demand models, cost models, Monte Carlo simulation process, and optimization models. The integrated converts the inputs from each model into meaningful results and charts; those results and charts can help improve decision-making and identify the optimality of an objective function. This section details fields parameters, modeling
assumptions, formulation of the optimization problem, and description of the integrated model.

3.4.5.1. Field Parameters

(Figure 3-13) lists the field parameters required for cost calculations. It was assumed that all fields possess similar properties. From the table, reservoir depth was 10,000 ft., the field environment was onshore agricultural, additional rate from new wells was 6 MBD, the distance between field and production facility was 150 km, the camp base cost was $1.448 million, well-site cost was $0.1014 million, rig day rate per well was 61 days, rig day-rate $14,479 per day, rig support day-rate was $7,240 per day, intangible drilling cost per well was $1.325 million, tangible drilling cost per well was $7240 million, annual production decline was 5%, fixed operating expenditure was 5% of the capital expenditure, variable operating expenditure was $1.5 per barrel, contingency drilling cost was 15% or drilling costs, production facility base cost was $63 million per 1000 MBD, and the pipeline cost was 491,000 $/km per 100 MBD.
### 3.4.5.2. Modeling Assumptions

This section lists important assumptions incorporated in the modeling processes.

1. Fields can sustain the production rate throughout the life of the study by drilling.

2. All fields in the study possess the same properties.

3. Combined MRM-GBM model was sufficient to model demand for oil.

<table>
<thead>
<tr>
<th>General Cost Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>Environment</td>
</tr>
<tr>
<td>Remoteness</td>
</tr>
<tr>
<td>Terrain</td>
</tr>
<tr>
<td>Additional Rate per Well (MBD)</td>
</tr>
<tr>
<td>Pipeline Length (km)</td>
</tr>
<tr>
<td>Life of the Facilities (Years)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Camp Costs Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>Base Cost (million $)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Development Well Costs Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wellsite Cost (million $)</td>
</tr>
<tr>
<td>Rig Day Well (Days)</td>
</tr>
<tr>
<td>Rig Dayrate ($/Day)</td>
</tr>
<tr>
<td>Rig Support and Supervision Dayrate ($/Day)</td>
</tr>
<tr>
<td>Intangible Drilling Cost per Well (MM$/S)</td>
</tr>
<tr>
<td>Tangible Drilling Cost per Well (Tub. &amp; Cong.) (MM$)</td>
</tr>
<tr>
<td>Total Annual Drilling Costs per Well (MM$)</td>
</tr>
<tr>
<td>Annual Prod. Decline (% of Spare Capacity)</td>
</tr>
<tr>
<td>OPEX, Fixed Cost (% CAPAX)</td>
</tr>
<tr>
<td>OPEX, Variable Cost ($/bbl)</td>
</tr>
<tr>
<td>Contingency Cost (% Total Drilling Cost)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Production Facilities Costs Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>Production Facility Base Cost for 100 MBD (MM$)</td>
</tr>
<tr>
<td>Remoteness/ Logistics Factor</td>
</tr>
<tr>
<td>Construction Difficulty Factor</td>
</tr>
<tr>
<td>Equipment Complexity Factor</td>
</tr>
<tr>
<td>Enclosing Equipment Factor</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Pipeline Costs Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pipeline Cost for 100 MBD (SM/km)</td>
</tr>
</tbody>
</table>

Table 3-13. Field and Cost Parameters.
3.4.5.3. Optimization Problem Formulation

The optimization problem consists of Objective function, decision variable(s), and constraint(s). The objective function is performance measurement for a process. The constraints are physical or financial restrictions imposed on the optimization problem. The objective function, for our study, was the expected value of the NPV. The decision variable was the spare capacity volume. The spare capacity has to be greater than or equal to zero; this physical constraint was imposed on the optimization problem. The optimization problem can be summarized as follows:

Maximize

\[ E[\text{Total NPV}] \]

By Calculating

\[ \text{Spare Capacity Volume} \]

Subject to

\[ \text{Spare Capacity} \geq 0 \]

3.4.5.4. Integrated Model Description

The integrated model integrates all developed models in the study to output results and charts that can help in improving decision-making. The models developed in the study include price models, demand models, cost models, economic models, Monte Carlo simulation processes, and optimization model. Risk Solver Platform (RSP) was used to develop and run those models. The integrated model was divided into three parts: parameters module, calculations module, and input and output module. This structure is
recommended by (Powell and Baker, 2010) to increase the simplicity and clarity of the model. The three modules are discussed in this section.

### 3.4.5.4.1 Parameter Module

This module was divided into four sub-modules: deduction rates, price forecast parameters, demand forecast parameters, and cost calculation parameters.

#### 3.4.5.4.1.1 Deduction Rates Sub-Module

(Table 3-14) shows the deduction rates sub-module, which lists the tax rate, discount rate, and the royalty used in the economic evaluation model. The tax rate, discount rate, and royalty were 15%, 10%, and 20%, respectively. These values are reasonable and commonly used in the oil and gas industry.

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Tax rate</td>
<td>15%</td>
</tr>
<tr>
<td>Discount Rate</td>
<td>10%</td>
</tr>
<tr>
<td>Royalty</td>
<td>20%</td>
</tr>
</tbody>
</table>

#### 3.4.5.4.1.2 Price Forecast Parameters Sub-Module

This sub-module contains the parameters required to model the crude price as Mean Reversion Model where the long-run equilibrium price $P^*$ was modeled as Geometric Brownian Motion GBM. (Table 3-15) shows the parameters required for the price forecast model; these parameters are reversion rate, long-run equilibrium price,
price volatility, and price drift. The values of these parameters were calculated as shown in the price model section. Reversion rate, long-run equilibrium price and price volatility are required for the MRM model. On the other hand, price volatility and drift are required for the GBM model.

Table 3-15. MRM-GBM Price Forecast Parameters.

<table>
<thead>
<tr>
<th>Crude Price Forecast Parameters</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>η (Reversion Speed)</td>
<td>0.83</td>
</tr>
<tr>
<td>P* (Long-Run Mean Price)</td>
<td>88.90</td>
</tr>
<tr>
<td>Ln(P*)</td>
<td>4.49</td>
</tr>
<tr>
<td>σ (Volatility)</td>
<td>0.31</td>
</tr>
<tr>
<td>α (Drift)</td>
<td>0.02</td>
</tr>
<tr>
<td>P_{min}</td>
<td>40.00</td>
</tr>
</tbody>
</table>

3.4.5.4.1.3. Demand Forecast Parameters Sub-Module

This sub-module contains the parameters required to model the crude demand as The Mean Reversion Model where the long-run equilibrium demand Dem* was modeled as Geometric Brownian Motion GBM. (Table 3-16) shows the parameters required for the demand forecast model; these parameters are reversion rate, long-run equilibrium price, demand volatility, and demand drift. The values of these parameters were calculated as shown in the demand model section. Reversion rate, long-run equilibrium demand and demand volatility are required for the MRM model. On the other hand, demand volatility and drift are required for the GBM model.
Table 3-16. MRM-GBM Demand Forecast Parameters.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\text{Dem}_0) (Initial Demand)</td>
<td>88000.00</td>
</tr>
<tr>
<td>(\text{Dem}_{\text{min}}) (Minimum Demand)</td>
<td>58000.00</td>
</tr>
<tr>
<td>(\eta) (Demand Reversion Speed)</td>
<td>0.52</td>
</tr>
<tr>
<td>(\text{Dem}^*) (Long-run Equilibrium Demand)</td>
<td>88428.24</td>
</tr>
<tr>
<td>(\ln(\text{Dem}^*))</td>
<td>11.39</td>
</tr>
<tr>
<td>(\sigma) (Volatility)</td>
<td>0.03</td>
</tr>
<tr>
<td>(\alpha) (Drift)</td>
<td>0.01</td>
</tr>
</tbody>
</table>

3.4.5.4.1.4. Field Cost Parameters Sub-Module

This sub-module presents the fields’ parameters required for the cost model. (Figure 3-17) shows the field parameters required for cost calculations. From the table, reservoir depth was 10,000 ft., the field environment was onshore agricultural, additional rate from newly drilled wells was 6 MBD, the distance between field and production facility was 150 km, the camp base cost was $1.448 million, the well-site cost was $0.1014 million, rig day rate per well was 61 days, rig day-rate $14,479 per day, rig support day-rate was $7,240 per day, intangible drilling cost per well was $1.325 million, tangible drilling cost per well was $7240 million, annual production decline was 5%, fixed operating expenditure was 5% of the capital expenditures, variable operating expenditures were $1.5 per barrel, contingency drilling cost was 15% or drilling costs, production facility base cost was $63 million per 1000 MBD, and the pipeline cost was 491,000 $/km per 100 MBD.
Table 3-17. Field and Cost Parameters.

<table>
<thead>
<tr>
<th>General Cost Parameters</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Depth of Reservoir (ft)</td>
<td>10000</td>
</tr>
<tr>
<td>Environment</td>
<td>Onshore</td>
</tr>
<tr>
<td>Remoteness</td>
<td>2</td>
</tr>
<tr>
<td>Terrain</td>
<td>Agricultural</td>
</tr>
<tr>
<td>Additional Rate per Well (MBD)</td>
<td>6</td>
</tr>
<tr>
<td>Pipeline Length (km)</td>
<td>150</td>
</tr>
<tr>
<td>Life of the Facilities (Years)</td>
<td>25</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Field Costs Parameters</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Base Cost (million $)</td>
<td>1.448</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Development Well Costs Parameters</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Wellsite Cost (million $)</td>
<td>0.1014</td>
</tr>
<tr>
<td>Rig Day Well (Days)</td>
<td>61</td>
</tr>
<tr>
<td>Rig Dayrate ($/Day)</td>
<td>14479</td>
</tr>
<tr>
<td>Rig Support and Supervision Dayrate ($/Day)</td>
<td>7240</td>
</tr>
<tr>
<td>Intangible Drilling Cost per Well (MM$)</td>
<td>1.324859</td>
</tr>
<tr>
<td>Tangible Drilling Cost per Well (Tub. &amp; Cong.) (M$)</td>
<td>674</td>
</tr>
<tr>
<td>Total Annual Drilling Costs per Well (MM$)</td>
<td>1.999</td>
</tr>
<tr>
<td>Annual Prod. Decline (% of Spare Capacity)</td>
<td>5%</td>
</tr>
<tr>
<td>OPEX, Fixed Cost (% CAPAX)</td>
<td>5%</td>
</tr>
<tr>
<td>OPEX, Variable Cost ($/bbl)</td>
<td>1.5</td>
</tr>
<tr>
<td>Contingency Cost (% Total Drilling Cost)</td>
<td>15%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Production Facilities Costs Parameters</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Production Facility Base Cost for 100 MBD (MM$)</td>
<td>63.0</td>
</tr>
<tr>
<td>Remoteness/Logistics Factor</td>
<td>1.05</td>
</tr>
<tr>
<td>Construction Difficulty Factor</td>
<td>1.30</td>
</tr>
<tr>
<td>Equipment Complexity Factor</td>
<td>1.25</td>
</tr>
<tr>
<td>Enclosing Equipment Factor</td>
<td>1.60</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Pipeline Costs Parameters</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Pipeline Cost for 100 MBD ($/km)</td>
<td>491.0</td>
</tr>
</tbody>
</table>

### 3.4.5.4.2. Cash Flow Calculations Module

This module was divided into six sub-modules, including crude price, production, deductions, taxes, non-tax items, and net cash flow and NPV calculations sub-modules. The production sub-module calculates annual production and net revenue. The deductions sub-module handles the capital and operating expenditures. Taxes sub-module incorporates the tax payments. The non-tax items include cash flow that does not impact tax payment. The net cash flow and NPV calculations sub-module results in the net cash flow (NCF) and in the net present value (NPV), which were the final outputs of the
economic model. The calculations in this module are based on (Mian, 2011a, Mian, 2011b, and Hartman, 2006).

3.4.5.4.2.1. Crude Price Sub-Module

This sub-module contains the forecasted crude prices using either the MRM model or the MRM-GBM combined model. Both processes were discussed in detail in the price model section. (Table 3-18) shows a sample of the crude price sub-module.

Table 3-18. Crude Price Sub-Module.

<table>
<thead>
<tr>
<th>Time</th>
<th>Crude Oil Price</th>
<th>Var[X(t)]</th>
<th>X(t)= &quot;LN(P)&quot;</th>
<th>LN[P*]</th>
<th>P*</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>88.90</td>
<td>4.49</td>
<td>88.90</td>
<td>4.49</td>
<td>88.90</td>
</tr>
<tr>
<td>1</td>
<td>91.18</td>
<td>4.54</td>
<td>107.56</td>
<td>4.68</td>
<td>107.56</td>
</tr>
<tr>
<td>2</td>
<td>93.90</td>
<td>4.57</td>
<td>88.77</td>
<td>4.49</td>
<td>88.77</td>
</tr>
<tr>
<td>3</td>
<td>113.68</td>
<td>4.76</td>
<td>114.67</td>
<td>4.74</td>
<td>114.67</td>
</tr>
<tr>
<td>4</td>
<td>110.39</td>
<td>4.73</td>
<td>128.38</td>
<td>4.86</td>
<td>128.38</td>
</tr>
<tr>
<td>5</td>
<td>89.76</td>
<td>4.53</td>
<td>105.62</td>
<td>4.66</td>
<td>105.62</td>
</tr>
<tr>
<td>6</td>
<td>60.73</td>
<td>4.14</td>
<td>106.19</td>
<td>4.67</td>
<td>106.19</td>
</tr>
<tr>
<td>7</td>
<td>85.09</td>
<td>4.47</td>
<td>93.76</td>
<td>4.54</td>
<td>93.76</td>
</tr>
</tbody>
</table>

3.4.5.4.2.2. Production Sub-Module

This sub-module handles the following items: daily and annual oil production, annual revenues, expected revenues, and cumulative production of the company. (Table 3-19) shows a sample of this sub-module. Average daily production was the volume of spare capacity, the decision variable in the optimization model. Annual revenue was the product of annual production and crude price. The expected revenue was the product of annual revenue and the probability of using the specified spare capacity volume.
3.4.5.4.2.3. Deductions Sub-Module

This sub-module incorporates the cost of developing and maintaining the spare capacity volume. (Table 3-20) shows a sample of the deductions sub-module. Green highlighted parameters are operating expenditures and the orange ones are capital expenditures. Fixed OPEX was incurred only if the field was on production and it covers the cost of the items that are paid the same amount regardless of the production rate (e.g. insurance). Variable OPEX was a function of production rate and covers items related to it (e.g., chemicals and labors). Camp cost, well-site cost, tangible & intangible drilling costs, and production facility and pipeline costs were discussed in the cost model section.

The green highlighted items are tax-deductible and received a tax discount. In other words, these items were subtracted from income before applying the tax rate. Depreciation is a tax discount on the production facilities; the company receives it because these facilities are wearing out and losing value. The tax discount is equivalent to the value lost each year in the production facilities’ values. The depreciation annual discount was calculated from (Equation 3-24), the capital expenditure divided by the life of the facility. This discount value was subtracted from income before applying the tax rate. This discount item continued until the value of CAPEX was exhausted. There were

Table 3-19. Production Sub-Module.

<table>
<thead>
<tr>
<th></th>
<th>mbbl/day</th>
<th>0</th>
<th>0</th>
<th>2,678</th>
<th>2,678</th>
<th>2,678</th>
<th>2,678</th>
<th>2,678</th>
<th>2,678</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average Production</td>
<td></td>
<td>0</td>
<td>0</td>
<td>2,678</td>
<td>2,678</td>
<td>2,678</td>
<td>2,678</td>
<td>2,678</td>
<td>2,678</td>
</tr>
<tr>
<td>Yearly Production</td>
<td>mbbl</td>
<td>0</td>
<td>0</td>
<td>977,602</td>
<td>977,602</td>
<td>977,602</td>
<td>977,602</td>
<td>977,602</td>
<td>977,602</td>
</tr>
<tr>
<td>Royalty</td>
<td>mbbl</td>
<td>0</td>
<td>0</td>
<td>195,520</td>
<td>195,520</td>
<td>195,520</td>
<td>195,520</td>
<td>195,520</td>
<td>195,520</td>
</tr>
<tr>
<td>Net Production</td>
<td>mbbl</td>
<td>0</td>
<td>0</td>
<td>782,082</td>
<td>782,082</td>
<td>782,082</td>
<td>782,082</td>
<td>782,082</td>
<td>782,082</td>
</tr>
<tr>
<td>Net Revenues</td>
<td>$ million</td>
<td>0</td>
<td>0</td>
<td>94,619</td>
<td>120,542</td>
<td>90,672</td>
<td>51,861</td>
<td>53,517</td>
<td>87,353</td>
</tr>
<tr>
<td>Expected Revenues</td>
<td>$ million</td>
<td>0</td>
<td>0</td>
<td>4,952</td>
<td>8,209</td>
<td>6,377</td>
<td>3,294</td>
<td>3,046</td>
<td>4,121</td>
</tr>
<tr>
<td>Cumulative Production</td>
<td>mbbl</td>
<td>0</td>
<td>0</td>
<td>977,602</td>
<td>1,955,205</td>
<td>2,932,807</td>
<td>3,910,410</td>
<td>4,888,012</td>
<td>5,865,614</td>
</tr>
</tbody>
</table>
two Dt (annual discount) in the table because there were two capital expenditures in two separate years. Each Dt handled one of the CAPEX items.

\[
D_t = \frac{\text{CAPEX}}{\text{Life of Facility}} \quad \text{(3-24)}
\]

Table 3-20. Deductions Sub-Module.

<table>
<thead>
<tr>
<th>Time</th>
<th>Fixed $ million</th>
<th>Variable $ million</th>
<th>Capex Cost $ million</th>
<th>Drilling Costs</th>
<th>Production Facility Costs $ million</th>
<th>Pipeline Costs $ million</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
</tr>
<tr>
<td></td>
<td>6</td>
<td>7</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0</td>
<td>0</td>
<td>0</td>
<td>200.17</td>
<td>200.17</td>
<td>200.17</td>
<td>200.17</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>0</td>
<td>1,466</td>
<td>1,466</td>
<td>1,466</td>
<td>1,466</td>
</tr>
<tr>
<td>2</td>
<td>80.07</td>
<td>80.07</td>
<td>134</td>
<td>134</td>
<td>134</td>
<td>134</td>
</tr>
<tr>
<td>3</td>
<td>80.07</td>
<td>80.07</td>
<td>134</td>
<td>134</td>
<td>134</td>
<td>134</td>
</tr>
<tr>
<td>4</td>
<td>80.07</td>
<td>80.07</td>
<td>134</td>
<td>134</td>
<td>134</td>
<td>134</td>
</tr>
<tr>
<td>5</td>
<td>80.07</td>
<td>80.07</td>
<td>134</td>
<td>134</td>
<td>134</td>
<td>134</td>
</tr>
<tr>
<td>6</td>
<td>80.07</td>
<td>80.07</td>
<td>134</td>
<td>134</td>
<td>134</td>
<td>134</td>
</tr>
<tr>
<td>7</td>
<td>80.07</td>
<td>80.07</td>
<td>134</td>
<td>134</td>
<td>134</td>
<td>134</td>
</tr>
</tbody>
</table>

3.4.5.4.2.4. Taxes Sub-Module

This sub-module subtracted the tax-deductible items from the income and applied the tax rate.

3.4.5.4.2.5. Non-Tax Items Sub-Module

Non-tax items are positive and negative cash flow, which do not impact tax payments. In other words, they are tax-deductible items, including capital expenditures, salvage, net proceeds, and principal payments on a loan. Our model incorporated only CAPEX for non-tax items. Our model did not incorporate salvage value because it was
negligible relative to the NPV; and financing was not considered, eliminating net proceeds and principal payments.

3.4.5.4.2.6. Net Cash Flow and NPV Calculations Sub-Module

This sub-module calculates the net cash flow NCF, discounted net cash flow DNCF, and the net present value NPV. The NCF was the annual sum of the positive and negative cash flow. Then, NCF was discounted, using (Equation 3-25), to express the cash flow in present dollars and result in the DNCF. Finally, the NPV was the sum of all the DNCF values. The NPV the objective function for our optimization problem.

\[
Present\ Value = \frac{Future\ Value}{(1+Discount\ Rate)^{Time}} \tag{3-25}
\]

3.4.5.4.3. Input and Output Module

This module consists of the demand model, optimization model, user input, and final output of the study. The module was divided into two sub-modules: demand model sub-module, and objective function and decision variable sub-module.

3.4.5.4.3.1. Demand Model Sub-Module

The demand model was formulated using the combined MRM-GBM model as discussed in the price model section. The combined MRM-GBM model involved huge
amounts of uncertainties and required significant sampling to minimize the simulation error in the Monte Carlo simulation process. The size of the sample used in the study was 150,000 to stabilize the expected value of the NPV. This sub-module was placed in the input and output module instead of the calculation module because the user interacts with the demand model in calculating the probability of using a specified spare capacity.

First, the user specifies the duration of the demand forecast. Then, the demand is forecasted stochastically throughout the specified duration as shown in (Table 3-21). The average demand in each year is calculated. The probability of using spare capacity requires inputs from the second sub-module. Consequently, it is discussed in the objective function and decision variable sub-module.

Table 3-21. Demand Forecast Model.

<table>
<thead>
<tr>
<th>Year</th>
<th>0</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dem*</td>
<td>88428.24</td>
<td>88307.12</td>
<td>90692.34</td>
<td>91354.70</td>
<td>94336.34</td>
<td>93384.04</td>
<td>96502.96</td>
<td>99532.32</td>
</tr>
<tr>
<td>Ln(Dem*)</td>
<td>11.39</td>
<td>11.39</td>
<td>11.42</td>
<td>11.42</td>
<td>11.45</td>
<td>11.44</td>
<td>11.48</td>
<td>11.51</td>
</tr>
<tr>
<td>X(t) = &quot;ln(Dem)&quot;</td>
<td>11.39</td>
<td>11.37</td>
<td>11.39</td>
<td>11.39</td>
<td>11.42</td>
<td>11.42</td>
<td>11.46</td>
<td>11.43</td>
</tr>
<tr>
<td>Var[X(t)]</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.0007</td>
<td>0.0007</td>
</tr>
<tr>
<td>Dem(t)</td>
<td>88000.00</td>
<td>87005.59</td>
<td>88101.87</td>
<td>88447.30</td>
<td>91354.73</td>
<td>95185.78</td>
<td>92409.16</td>
<td>94545.30</td>
</tr>
<tr>
<td>Average Demand, MBD</td>
<td>88691</td>
<td>89631</td>
<td>90731</td>
<td>91933</td>
<td>93207</td>
<td>94531</td>
<td>95895</td>
<td></td>
</tr>
<tr>
<td>Probability of Using Spare Capacity</td>
<td>1</td>
<td>0.020</td>
<td>0.052</td>
<td>0.068</td>
<td>0.070</td>
<td>0.064</td>
<td>0.057</td>
<td>0.047</td>
</tr>
</tbody>
</table>

3.4.5.4.3.2. **Objective Function and Decision Variable Sub-Module**

This sub-module contains the objective function, decision variable and user input. (Table 3-22) shows the objective function and decision variable sub-module. The first step was to average the average demand from (Table 3-21); the result was the base demand used in the model as shown in (Table 3-22). It was assumed that, on average, the base demand was consumed throughout the life of the study, and any volume consumed
above this base demand was considered as spare capacity. This average can be calculated over the life of the project or over a specified period of time (e.g. first five year). The Impact of the duration, over which the average demand was calculated, was analyzed. Then a spare capacity was calculated by the optimization algorithm to maximize the expected NPV of the company. The delta demand was an epsilon, which was required to calculate the probability of the specified spare capacity. The cumulative density function CDF of the forecasted demand each year was used to calculate the probability of using the spare capacity. The calculated probability from a CDF of a specific event happening was zero (Ross, 2009). Ross recommended using a small difference from that specific event and calculating the area under the CDF between the two points; this should be representative of the probability of the specific event happening. The delta demand used in the study was 800 MBD; this was reasonable given that the spare capacity volume was in thousands of MBD. The expected NPV was the objective function of the study.

Table 3-22. Objective Function and Decision Variable Sub-Module.

<table>
<thead>
<tr>
<th>Average of Average Demand, MBD</th>
<th>90839</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spare Capacity, MBD</td>
<td>2678.36</td>
</tr>
<tr>
<td>New Capacity, MBD</td>
<td>93517</td>
</tr>
<tr>
<td>Delta Demand, MBD</td>
<td>800</td>
</tr>
<tr>
<td>Number of Wells Required Initially</td>
<td>224</td>
</tr>
<tr>
<td>Spare Capacity (MBD)</td>
<td>2678</td>
</tr>
<tr>
<td>Production Duration (Yrs)</td>
<td>5</td>
</tr>
<tr>
<td>NPV ($ million)</td>
<td>7204</td>
</tr>
<tr>
<td>Mean of NPV ($ million)</td>
<td>4838</td>
</tr>
<tr>
<td>Variance of NPV</td>
<td>66335283</td>
</tr>
</tbody>
</table>
3.5. Results and Discussion

Identifying the optimal spare capacity volume for a major oil producer to acquire was a complex and computationally expensive dynamic optimization problem. The problem involved uncertainties in price and in demand. The study identified a methodology for identifying the probability of using a specified spare capacity for a given year, and identifying the economically optimal spare capacity level for a major oil producer given the historical behavior of prices and demand. The workflow and required models to develop the integrated optimization model were defined: workflow to identify the scope of the study, stochastic processes to forecast crude price and demand, cost model to estimate development and maintenance costs, economic evaluation model to calculate the NPV, Monte Carlo simulation process to sample uncertain variables, and an optimization model to calculate the optimal spare capacity volume to acquire. These models and workflow resulted in the optimal spare capacity volume for a major oil producer to acquire. The impact of price model and demand model parameters on the optimal decision was analyzed. This section discusses the optimal decisions resulted from different demand model assumptions; sensitivity analysis and value of information is presented to discuss the impact of price and demand model assumptions on the optimal decision and on the expected NPV.

3.5.1. Price = MRM and Demand = MRM-GBM

This section discusses the optimization resulted from forecasting price as Mean Reversion Model and the demand as the combined Mean Reversion Model where the
long-run equilibrium demand was modeled as the Geometric Brownian Motion model. Two approaches for calculating the base demand were analyzed here. The first approach averaged the mean of the forecasted demand over the first five years; the second approach averaged the mean of the forecasted demand over the life of the project. In the second approach, uncertainty was high since it handled further data into the future; as a result, the probability of using the specified spare capacity was significantly lower than from implementing the first approach.

3.5.1.1. Mean Demand Based on First Five Years

Calculating the base demand can significantly impact the optimal spare capacity to acquire and the expected NPV resulted from that spare capacity. This section presents the results for cases when the base demand was calculated as the average of the mean demand for the first five years. Using the first five years rather than the life of the project increases the probability of using spare capacity because base demand is closer to the mode of the demand distribution in each year.

3.5.1.1.1. Five Years of Production

(Figure 3-22) shows the expected NPV as a function of spare capacity volume when the study handles only five years of production. Interestingly, the function was concave, indicating that there was an optimal solution for the problem. The optimal spare capacity was around 2,500 MBD, resulting in expected NPV of around $3900 million.
(Tables 3-23 and 3-24) show the results of the optimization algorithm. These results show that the optimal spare capacity and expected NPV were 2,514 MBD and $3,860 million, respectively. (Table 3-25) shows the demand model and the probability of using the spare capacity for each year in the last row.

Figure 3-22. Expected NPV as a Function of Spare Capacity.

Table 3-23. Optimal Spare Capacity.

<table>
<thead>
<tr>
<th>Average of Average Demand, MBD</th>
<th>90839</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spare Capacity, MBD</td>
<td>2513.94</td>
</tr>
<tr>
<td>New Capacity, MBD</td>
<td>93353</td>
</tr>
<tr>
<td>Delta Demand, MBD</td>
<td>800</td>
</tr>
<tr>
<td>Number of Wells Required Initially</td>
<td>210</td>
</tr>
</tbody>
</table>

Table 3-24. Optimal Expected NPV.

<table>
<thead>
<tr>
<th>Spare Capacity (MBD)</th>
<th>2514</th>
</tr>
</thead>
<tbody>
<tr>
<td>Production Duration (Yrs)</td>
<td>5</td>
</tr>
<tr>
<td>NPV ($ million)</td>
<td>2387</td>
</tr>
<tr>
<td>Mean of NPV ($ million)</td>
<td>3860</td>
</tr>
<tr>
<td>Variance of NPV</td>
<td>3991568</td>
</tr>
</tbody>
</table>
3.5.1.1.2. Ten Years of Production

(Figure 3-23) shows the expected NPV as a function of spare capacity volume when the study handles 10 years of production. From the figure, the optimal spare capacity was around 3,000 MBD, resulting in expected NPV of around $3,500 million. (Tables 3-26 and 3-27) show the results of the optimization algorithm. These results indicated that the optimal spare capacity and expected NPV were 3,000 MBD and $4,577 million, respectively. Although (Figure 3-23) and (Table 3-26) show the same optimal level of spare capacity, they resulted in different expected NPV. This discrepancy stemmed from the simulation error in the Monte Carlo simulation process. In other words, different realizations resulted in different expected NPV; however, the trend for expected NPV was the same and resulted in the same optimal spare capacity. The simulation error can be resolved by increasing the number of iterations in the Monte Carlo simulation process; up to 150,000 iterations were used in the study. (Table 3-28) shows the demand model and the probability of using the spare capacity for each year in the last row. The probability values dropped from those which resulted from five years of production.
Figure 3-23. Expected NPV as a Function of Spare Capacity.

Table 3-26. Optimal Spare Capacity.

<table>
<thead>
<tr>
<th>Spare Capacity (MBD)</th>
<th>2999.75</th>
</tr>
</thead>
<tbody>
<tr>
<td>New Capacity (MBD)</td>
<td>93838</td>
</tr>
<tr>
<td>Delta Demand, MBD</td>
<td>800</td>
</tr>
<tr>
<td>Number of Wells Required Initially</td>
<td>250</td>
</tr>
</tbody>
</table>

Table 3-27. Optimal Expected NPV.

<table>
<thead>
<tr>
<th>Spare Capacity (MBD)</th>
<th>3000</th>
</tr>
</thead>
<tbody>
<tr>
<td>Production Duration (Yrs)</td>
<td>10</td>
</tr>
<tr>
<td>NPV ($ million)</td>
<td>4262</td>
</tr>
<tr>
<td>Mean of NPV ($ million)</td>
<td>4577</td>
</tr>
<tr>
<td>Variance of NPV</td>
<td>5803819</td>
</tr>
</tbody>
</table>

Table 3-28. Objective Function and Decision Variable Sub-Module.

<table>
<thead>
<tr>
<th>Year</th>
<th>0</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
<th>12</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dem*</td>
<td>88428.24</td>
<td>86415.06</td>
<td>89494.77</td>
<td>90777.67</td>
<td>90474.66</td>
<td>93973.79</td>
<td>95775.30</td>
<td>96587.33</td>
<td>97493.09</td>
<td>100134.55</td>
<td>108845.59</td>
<td>103751.47</td>
<td>109327.73</td>
</tr>
<tr>
<td>Var[X(t)]</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Dem(t)</td>
<td>88800.10</td>
<td>87779.99</td>
<td>89853.91</td>
<td>91739.46</td>
<td>94038.59</td>
<td>97044.10</td>
<td>99756.70</td>
<td>100962.96</td>
<td>101410.63</td>
<td>104844.41</td>
<td>102942.39</td>
<td>100554.06</td>
<td>105994.38</td>
</tr>
<tr>
<td>Average Demand, MBD</td>
<td>88691</td>
<td>89531</td>
<td>90731</td>
<td>91694</td>
<td>93008</td>
<td>94552</td>
<td>95886</td>
<td>97291</td>
<td>98714</td>
<td>100161</td>
<td>101633</td>
<td>101218</td>
<td></td>
</tr>
<tr>
<td>Probability of Using Spare Capacity</td>
<td>1</td>
<td>0.014</td>
<td>0.046</td>
<td>0.063</td>
<td>0.067</td>
<td>0.064</td>
<td>0.056</td>
<td>0.049</td>
<td>0.041</td>
<td>0.035</td>
<td>0.031</td>
<td>0.026</td>
<td>0.022</td>
</tr>
</tbody>
</table>
3.5.1.1.3. Fifteen Years of Production

(Figure 3-24) shows the expected NPV as a function of spare capacity volume when the study handles fifteen years of production. The optimal spare capacity was around 2,800 MBD, resulting in expected NPV of around $3,600 million. (Tables 3-29 and 3-30) show the result of the optimization algorithm. These results show that the optimal spare capacity and expected NPV were 2,973 MBD and $3,594 million, respectively. (Table 3-31) shows the demand model and the probability of using the spare capacity for each year in the last row. The probability of using a spare capacity approaches zero for the later years.

![Mean NPV Vs. Spare Capacity (15Yrs)](image)

Figure 3-24. Expected NPV as a Function of Spare Capacity.

Table 3-29. Optimal Spare Capacity.

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Average of Average Demand, MBD</td>
<td>90839</td>
</tr>
<tr>
<td>Spare Capacity, MBD</td>
<td>2972.62</td>
</tr>
<tr>
<td>New Capacity, MBD</td>
<td>93811</td>
</tr>
<tr>
<td>Delta Demand, MBD</td>
<td>800</td>
</tr>
<tr>
<td>Number of Wells Required Initially</td>
<td>248</td>
</tr>
</tbody>
</table>
3.5.1.4. Twenty Years of Production

(Figure 3-25) shows the expected NPV as a function of spare capacity volume when the study handles 20 years of production. The optimal spare capacity was around 2,500 MBD, resulting in expected NPV around $3,600 million. (Tables 3-32 and 3-31) show the result of the optimization algorithm. These results indicated that the optimal spare capacity and expected NPV were 2,508 MBD and $3,659 million, respectively. (Table 3-33) shows the demand model and the probability of using the spare capacity for each year in the last row. The probability values of using a spare capacity were very small.
Figure 3.25. Expected NPV as a Function of Spare Capacity.

Table 3.32. Optimal Spare Capacity.

<table>
<thead>
<tr>
<th>Average of Average Demand, MBD</th>
<th>90839</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spare Capacity, MBD</td>
<td>2507.68</td>
</tr>
<tr>
<td>New Capacity, MBD</td>
<td>93347</td>
</tr>
<tr>
<td>Delta Demand, MBD</td>
<td>800</td>
</tr>
<tr>
<td>Number of Wells Required Initially</td>
<td>209</td>
</tr>
</tbody>
</table>

Table 3.33. Optimal Expected NPV.

<table>
<thead>
<tr>
<th>Spare Capacity (MBD)</th>
<th>2508</th>
</tr>
</thead>
<tbody>
<tr>
<td>Production Duration (Yrs)</td>
<td>20</td>
</tr>
<tr>
<td>NPV ($ million)</td>
<td>3217</td>
</tr>
<tr>
<td>Mean of NPV ($ million)</td>
<td>2659</td>
</tr>
<tr>
<td>Variance of NPV</td>
<td>4534330</td>
</tr>
</tbody>
</table>

Table 3.34. Objective Function and Decision Variable Sub-Module.

| Year | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 |
|------|---|---|---|---|---|---|---|---|---|---|----|----|----|----|----|----|----|----|----|----|----|----|    |
| Dem* | 88428.24 | 89802.76 | 90106.53 | 92274.57 | 94649.83 | 97325.41 | 98460.17 | 99952.25 | 102685.73 | 99626.49 | 100668.69 | 98995.89 | 93472.70 | 91571.51 | 91634.68 | 89575.62 | 94571.99 | 95675.62 | 98646.17 | 100563.36 | 109514.93 | 114628.84 | 116683.75 |
| Ln(Dem*) | 11.39 | 11.41 | 11.41 | 11.43 | 11.46 | 11.50 | 11.51 | 11.54 | 11.57 | 11.59 | 11.61 | 11.63 | 11.67 | 11.71 | 11.75 | 11.80 | 11.85 | 11.90 | 11.95 | 12.00 | 12.05 | 12.10 | 12.15 | 12.20 |
| Var[X(t)] | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Dem(t) | 88000.00 | 85600.98 | 88891.04 | 87823.46 | 92504.08 | 95294.18 | 92198.79 | 96985.61 | 97900.05 | 97479.49 | 98677.97 | 100399.05 | 98000.04 | 97792.88 | 92775.14 | 90021.59 | 92067.90 | 91705.51 | 94042.23 | 98263.81 | 99818.34 | 104169.73 | 108562.36 | 110948.19 | 112581.73 | 114238.29 | 115920.16 | 117628.08 | 119359.00 |
| Probability of Using Spare Capacity | 1.00 | 0.95 | 0.93 | 0.90 | 0.87 | 0.84 | 0.81 | 0.77 | 0.74 | 0.70 | 0.66 | 0.62 | 0.58 | 0.54 | 0.50 | 0.46 | 0.42 | 0.39 | 0.36 | 0.33 | 0.30 | 0.27 | 0.24 | 0.21 | 0.18 | 0.15 | 0.13 | 0.10 | 0.08 | 0.06 |
3.5.1.1.5. Twenty-Five Years of Production

(Figure 3-26) shows the expected NPV as a function of spare capacity volume when the study handled 25 years of production. The optimal spare capacity was around 2,300 MBD, resulting in expected NPV around $2,000 million. (Tables 3-35 and 3-36) show the result of the optimization algorithm. These indicate that the optimal spare capacity and expected NPV were 2,349 MBD and $1,950 million, respectively. (Table 3-37) shows the demand model and the probability of using the spare capacity for each year in the last row. The probability values of using a spare capacity were very small. The expected value of NPV dropped significantly due to the drop in the probability values.

![Mean NPV Vs. Spare Capacity (25Yrs)](image)

Figure 3-26. Expected NPV as a Function of Spare Capacity.

<table>
<thead>
<tr>
<th>Table 3-35. Optimal Spare Capacity.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average of Average Demand, MBD</td>
</tr>
<tr>
<td>Spare Capacity, MBD</td>
</tr>
<tr>
<td>New Capacity, MBD</td>
</tr>
<tr>
<td>Delta Demand, MBD</td>
</tr>
<tr>
<td>Number of Wells Required Initially</td>
</tr>
</tbody>
</table>
This section presents the results for cases in which base demand was calculated as the average of the mean demand over the life of the project. Using life of the project to calculate the base demand increases the uncertainty of our model since data further in the future were used to calculate average demand. The case of averaging over the life of the project was presented to show the uncertainty involved in the study and its impact on the decisions. In other words, the probability values in this section were expected to be very small in comparison to those in the previous section (base demand was based on the first five years).

3.5.1.2.1. Five Years of Production

The results for this case were the same for five years of production in the previous case since the life of the project here was five years. (Figure 3-27) shows the expected
NPV as a function spare capacity volume when the study handles five years of production. The optimal spare capacity was around 2,500 MBD, resulting in expected NPV around $3,900 million. (Tables 3-38 and 3-39) show the result of the optimization algorithm. These show that the optimal spare capacity and expected NPV were 2,514 MBD and $3,860 million, respectively. (Table 3-40) shows the demand model and the probability of using the spare capacity for each year in the last row.

Figure 3-27. Expected NPV as a Function of Spare Capacity.

Table 3-38. Optimal Spare Capacity.

<table>
<thead>
<tr>
<th>Average of Average Demand, MBD</th>
<th>90839</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spare Capacity, MBD</td>
<td>2513.94</td>
</tr>
<tr>
<td>New Capacity, MBD</td>
<td>93353</td>
</tr>
<tr>
<td>Delta Demand, MBD</td>
<td>800</td>
</tr>
<tr>
<td>Number of Wells Required Initially</td>
<td>210</td>
</tr>
</tbody>
</table>

Table 3-39. Optimal Expected NPV.

<table>
<thead>
<tr>
<th>Spare Capacity (MBD)</th>
<th>2514</th>
</tr>
</thead>
<tbody>
<tr>
<td>Production Duration (Yrs)</td>
<td>5</td>
</tr>
<tr>
<td>NPV ($ million)</td>
<td>2387</td>
</tr>
<tr>
<td>Mean of NPV ($ million)</td>
<td>3860</td>
</tr>
<tr>
<td>Variance of NPV</td>
<td>3991568</td>
</tr>
</tbody>
</table>

Figure 3-27. Expected NPV as a Function of Spare Capacity.
3.5.1.2.2. Ten Years of Production

(Figure 3-28) shows the expected NPV as a function of spare capacity volume when the study handles 10 years of production. From the figure, the optimal spare capacity was around 1,300 MBD, resulting in expected NPV around $800 million. (Tables 3-41 and 3-42) show the results of the optimization algorithm. They show that the optimal spare capacity and expected NPV were 1,307 MBD and $842 million, respectively. The drop in the spare capacity and in the expected NPV stemmed from the drop in the probability values of using the spare capacity. (Table 3-43) shows the demand model and the probability of using the spare capacity for each year in the last row. The probability values have dropped from the one resulted from five years of production.

![Figure 3-28. Expected NPV as a Function of Spare Capacity.](image-url)
3.5.1.2.3. Fifteen Years of Production

(Figure 3-29) shows the expected NPV as a function of spare capacity volume when the study handles 15 years of production. From the figure, all spare capacity values resulted in negative expected NPV, indicating that there was no spare capacity to acquire.
Figure 3-29. Expected NPV as a Function of Spare Capacity.

3.5.1.2.4. Twenty Years of Production

(Figure 3-30) shows the expected NPV as a function of spare capacity volume when the study handles 20 years of production. From the figure, all spare capacity values resulted in negative expected NPV, indicating that there was no spare capacity to acquire.

Figure 3-30. Expected NPV as a Function of Spare Capacity.
3.5.1.2.5. Twenty Five Years of Production

(Figure 3-31) shows the expected NPV as a function of spare capacity volume when the study handles 2five years of production. From the figure, all spare capacity values resulted in negative expected NPV, indicating that there was no spare capacity to acquire.

![Mean NPV Vs. Spare Capacity (25Yrs)](image)

Figure 3-31. Expected NPV as a Function of Spare Capacity.

3.5.2. Price and Demand Models: MRM-GBM

This section presents the output resulting from implementing the combined MRM-GBM model for price and demand forecasting. The two approaches for calculating the base demand were evaluated.

3.5.2.1. Mean Demand was Based on First Five Years

Calculating the base demand can significantly impact optimal spare capacity to acquire and the expected NPV resulting from that spare capacity. This section presents the results for the cases in which the base demand was calculated as the average of the
mean demand for the first five years. Using the first five years rather than the life of the project increases the probability of using the spare capacity because the base demand was close to the mode of the demand distribution in each year.

3.5.2.1.1. Five Years of Production

(Figure 3-32) shows the expected NPV as a function spare capacity volume when the study handles only five years of production. From the figure, the optimal spare capacity was around 2,600 MBD, resulting in expected NPV around 4,900 million dollars. (Table 3-44 and 3-45) show the result of the optimization algorithm. From the optimization results, the optimal spare capacity and expected NPV were 2,678 MBD and $4,838 million, respectively. (Table 3-46) shows the demand model and the probability of using the spare capacity for each year in the last row. The impact of incorporating the GBM modeling process in the price forecast model was clear. The GBM was a log-normal diffusion process; in other words, the GBM increases the values of the forecasted prices and increases the optimal spare capacity and expected NPV.

![Mean NPV Vs. Spare Capacity (5Yrs)](image)

Figure 3-32. Expected NPV as a Function of Spare Capacity.
Table 3-44. Optimal Spare Capacity.

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Average of Average Demand, MBD</td>
<td>90839</td>
</tr>
<tr>
<td>Spare Capacity, MBD</td>
<td>2678.36</td>
</tr>
<tr>
<td>New Capacity, MBD</td>
<td>93517</td>
</tr>
<tr>
<td>Delta Demand, MBD</td>
<td>800</td>
</tr>
<tr>
<td>Number of Wells Required Initially</td>
<td>224</td>
</tr>
</tbody>
</table>

Table 3-45. Optimal Expected NPV.

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Spare Capacity (MBD)</td>
<td>2678</td>
</tr>
<tr>
<td>Production Duration (Yrs)</td>
<td>5</td>
</tr>
<tr>
<td>NPV ($ million)</td>
<td>7204</td>
</tr>
<tr>
<td>Mean of NPV ($ million)</td>
<td>4838</td>
</tr>
<tr>
<td>Variance of NPV</td>
<td>66335283</td>
</tr>
</tbody>
</table>

Table 3-46. Objective Function and Decision Variable Sub-Module.

<table>
<thead>
<tr>
<th>Year</th>
<th>0</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dem*</td>
<td>88428.24</td>
<td>88307.12</td>
<td>90692.34</td>
<td>91354.70</td>
<td>94336.34</td>
<td>93384.04</td>
<td>96502.96</td>
<td>99532.32</td>
</tr>
<tr>
<td>Ln(Dem*)</td>
<td>11.39</td>
<td>11.39</td>
<td>11.42</td>
<td>11.42</td>
<td>11.45</td>
<td>11.44</td>
<td>11.48</td>
<td>11.51</td>
</tr>
<tr>
<td>X(t) = &quot;ln(Dem)&quot;</td>
<td>11.39</td>
<td>11.37</td>
<td>11.39</td>
<td>11.39</td>
<td>11.42</td>
<td>11.42</td>
<td>11.46</td>
<td>11.46</td>
</tr>
<tr>
<td>Var[X(t)]</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.0007</td>
<td>0.0007</td>
</tr>
<tr>
<td>Dem(t)</td>
<td>88000.00</td>
<td>87005.59</td>
<td>88101.87</td>
<td>88447.30</td>
<td>91354.73</td>
<td>95185.78</td>
<td>92409.16</td>
<td>94545.30</td>
</tr>
<tr>
<td>Average Demand, MBD</td>
<td>88691</td>
<td>89631</td>
<td>90731</td>
<td>91933</td>
<td>93207</td>
<td>94531</td>
<td>95895</td>
<td></td>
</tr>
<tr>
<td>Probability of Using Spare Capacity</td>
<td>1</td>
<td>0.020</td>
<td>0.052</td>
<td>0.068</td>
<td>0.070</td>
<td>0.064</td>
<td>0.057</td>
<td>0.047</td>
</tr>
</tbody>
</table>

3.5.2.1.2. Ten Years of Production

(Figure 3-33) shows the expected NPV as a function of spare capacity volume when the study handles only ten years of production. From the figure, the optimal spare capacity is around 2,600 MBD, which results in expected NPV around $6,600 million. (Tables 3-47 and 3-48) show the results of the optimization algorithm. These show that the optimal spare capacity and expected NPV are 3,563 MBD and $6,739 million, respectively. (Table 3-49) shows the demand model and the probability of using the spare capacity for each year in the last row. The impact of incorporating the GBM modeling process in the price forecast model is clear. The GBM is a log-normal diffusion process;
in other words, the GBM increases the values of the forecasted prices and increases the optimal spare capacity and expected NPV.

Figure 3-33. Expected NPV as a Function of Spare Capacity.

Table 3-47. Optimal Spare Capacity.

<table>
<thead>
<tr>
<th>Spare Capacity (MBD)</th>
<th>3562.53</th>
</tr>
</thead>
<tbody>
<tr>
<td>New Capacity, MBD</td>
<td>94402</td>
</tr>
<tr>
<td>Delta Demand, MBD</td>
<td>800</td>
</tr>
<tr>
<td>Number of Wells Required Initially</td>
<td>297</td>
</tr>
</tbody>
</table>

Table 3-48. Optimal Expected NPV.

<table>
<thead>
<tr>
<th>Spare Capacity (MBD)</th>
<th>3563</th>
</tr>
</thead>
<tbody>
<tr>
<td>Production Duration (Yrs)</td>
<td>10</td>
</tr>
<tr>
<td>NPV ($ million)</td>
<td>36</td>
</tr>
<tr>
<td>Mean of NPV ($ million)</td>
<td>6739</td>
</tr>
<tr>
<td>Variance of NPV</td>
<td>231,310,363</td>
</tr>
</tbody>
</table>

Table 3-49. Objective Function and Decision Variable Sub-Module.

<table>
<thead>
<tr>
<th>Year</th>
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<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
<th>12</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dem*</td>
<td>88428.24</td>
<td>88635.25</td>
<td>90755.22</td>
<td>97329.42</td>
<td>99933.35</td>
<td>97774.24</td>
<td>94750.35</td>
<td>93110.25</td>
<td>93105.66</td>
<td>96184.41</td>
<td>94331.62</td>
<td>92444.31</td>
<td>94799.60</td>
</tr>
<tr>
<td>Var[ln(Dem)]</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
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<td>0.007</td>
<td>0.007</td>
<td>0.007</td>
<td>0.007</td>
<td>0.007</td>
</tr>
<tr>
<td>Dem(t)</td>
<td>88000.00</td>
<td>90177.58</td>
<td>90596.98</td>
<td>90520.78</td>
<td>96089.25</td>
<td>97686.86</td>
<td>98248.45</td>
<td>97416.76</td>
<td>97796.10</td>
<td>97196.52</td>
<td>97212.68</td>
<td>94083.26</td>
<td>94653.82</td>
</tr>
<tr>
<td>Average Demand, MBD</td>
<td>88691</td>
<td>89631</td>
<td>90731</td>
<td>91035</td>
<td>91208</td>
<td>94333</td>
<td>95896</td>
<td>97290</td>
<td>98713</td>
<td>101660</td>
<td>101632</td>
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</tr>
<tr>
<td>Probability of Using Spare Capacity</td>
<td>1</td>
<td>0.008</td>
<td>0.036</td>
<td>0.056</td>
<td>0.063</td>
<td>0.064</td>
<td>0.057</td>
<td>0.059</td>
<td>0.043</td>
<td>0.037</td>
<td>0.031</td>
<td>0.027</td>
<td>0.023</td>
</tr>
</tbody>
</table>
3.5.2.1.3. Fifteen Years of Production

(Figure 3-34) shows the expected NPV as a function of spare capacity volume when the study handles only fifteen years of production. From the figure, the optimal spare capacity was around 3,500 MBD, resulting in expected NPV around 6,100 million dollars. (Table 3-50 and 3-51) show the result of the optimization algorithm. From the optimization results, the optimal spare capacity and expected NPV were 3,594 MBD 6,144 million dollar, respectively. (Table 3-52) shows the demand model and the probability of using the spare capacity for each year in the last row. The impact of incorporating the GBM modeling process in the price forecast model was clear. The GBM was a log-normal diffusion process; in other words, the GBM increases the values of the forecasted prices and increases the optimal spare capacity and expected NPV.

![Mean NPV Vs. Spare Capacity (15Yrs)](image)

Figure 3-34. Expected NPV as a Function of Spare Capacity.
238

Table 3-50. Optimal Spare Capacity.

<table>
<thead>
<tr>
<th>Spare Capacity (MBD)</th>
<th>3594.46</th>
</tr>
</thead>
<tbody>
<tr>
<td>New Capacity, MBD</td>
<td>94434</td>
</tr>
<tr>
<td>Delta Demand, MBD</td>
<td>800</td>
</tr>
<tr>
<td>Number of Wells Required Initially</td>
<td>300</td>
</tr>
</tbody>
</table>

Table 3-51. Optimal Expected NPV.

<table>
<thead>
<tr>
<th>Spare Capacity (MBD)</th>
<th>3594</th>
</tr>
</thead>
<tbody>
<tr>
<td>Production Duration (Yrs)</td>
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</tr>
<tr>
<td>NPV ($ million)</td>
<td>5023</td>
</tr>
<tr>
<td>Mean of NPV ($ million)</td>
<td>6144</td>
</tr>
<tr>
<td>Variance of NPV</td>
<td>288508354</td>
</tr>
</tbody>
</table>

Table 3-52. Objective Function and Decision Variable Sub-Module.

<table>
<thead>
<tr>
<th>Year</th>
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<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
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<th>11</th>
<th>12</th>
<th>13</th>
<th>14</th>
<th>15</th>
<th>16</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dem*</td>
<td>88684.04</td>
<td>88772.68</td>
<td>8775.45</td>
<td>8856.98</td>
<td>9021.87</td>
<td>9087.62</td>
<td>9056.27</td>
<td>9031.23</td>
<td>8862.71</td>
<td>8616.86</td>
<td>8618.76</td>
<td>8590.76</td>
<td>8579.73</td>
<td>8583.40</td>
<td>8656.89</td>
<td>8797.98</td>
<td>8963.57</td>
</tr>
<tr>
<td>[ln(Dem*)]</td>
<td>0.00</td>
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<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
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<tr>
<td>Dem(t)</td>
<td>88000.00</td>
<td>89195.80</td>
<td>89805.63</td>
<td>87216.66</td>
<td>88223.22</td>
<td>88483.82</td>
<td>91798.94</td>
<td>94267.62</td>
<td>95998.18</td>
<td>96213.38</td>
<td>98213.07</td>
<td>100055.97</td>
<td>98496.98</td>
<td>942152.51</td>
<td>946458.53</td>
<td>995229.28</td>
<td>110000.20</td>
</tr>
<tr>
<td>Average Demand, MBD</td>
<td>88691</td>
<td>89632</td>
<td>90731</td>
<td>91934</td>
<td>93209</td>
<td>94533</td>
<td>95897</td>
<td>97292</td>
<td>98714</td>
<td>100161</td>
<td>101633</td>
<td>103128</td>
<td>104614</td>
<td>106127</td>
<td>107661</td>
<td>109213</td>
<td>110784</td>
</tr>
<tr>
<td>Probability of Using Spare Capacity</td>
<td>1</td>
<td>0.008</td>
<td>0.011</td>
<td>0.015</td>
<td>0.025</td>
<td>0.036</td>
<td>0.056</td>
<td>0.082</td>
<td>0.094</td>
<td>0.103</td>
<td>0.110</td>
<td>0.116</td>
<td>0.121</td>
<td>0.125</td>
<td>0.129</td>
<td>0.132</td>
<td>0.134</td>
</tr>
</tbody>
</table>

3.5.2.1.4. Twenty Years of Production

(Figure 3-35) shows the expected NPV as a function of spare capacity volume when the study handles only 20 years of production. From the figure, the optimal spare capacity was around 3,100 MBD, resulting in expected NPV of approximately $5,100 million. (Tables 3-53 and 3-54) show the result of the optimization algorithm. These results showed that the optimal spare capacity and expected NPV were 3,107 MBD and $5,123 million, respectively. (Table 3-55) shows the demand model and the probability of using the spare capacity for each year in the last row. The impact of incorporating the GBM modeling process in the price forecast model was clear. The GBM was a log-
normal diffusion process; in other words, the GBM increases the values of the forecasted prices and increases the optimal spare capacity and expected NPV.

![Mean NPV Vs. Spare Capacity (20Yrs)](image)

Figure 3.35. Expected NPV as a Function of Spare Capacity.

### Table 3.53. Optimal Spare Capacity.

<table>
<thead>
<tr>
<th>Spare Capacity, MBD</th>
<th>New Capacity, MBD</th>
<th>Average of Average Demand, MBD</th>
</tr>
</thead>
<tbody>
<tr>
<td>3107</td>
<td>93946</td>
<td>90839</td>
</tr>
</tbody>
</table>

### Table 3.54. Optimal Expected NPV.

<table>
<thead>
<tr>
<th>Spare Capacity (MBD)</th>
<th>Production Duration (Yrs)</th>
<th>NPV ($ million)</th>
<th>Mean of NPV ($ million)</th>
<th>Variance of NPV</th>
</tr>
</thead>
<tbody>
<tr>
<td>3107</td>
<td>20</td>
<td>-1970</td>
<td>5123</td>
<td>228227748</td>
</tr>
</tbody>
</table>

### Table 3.55. Objective Function and Decision Variable Sub-Module.

<table>
<thead>
<tr>
<th>Probability of Using Spare Capacity</th>
<th>Mean of Avg Demand, MBD</th>
<th>Variance of Avg Demand, MBD</th>
<th>AVG Dem*</th>
<th>Dem* (mill)</th>
<th>Var[X(t)]</th>
<th>Dem(t)</th>
<th>Mean of NPV ($)</th>
<th>Variance of NPV ($)</th>
<th>Year</th>
<th>Prob of Using Spare Capacity</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.000</td>
<td>88428.24</td>
<td>11.39</td>
<td>88691</td>
<td>89631</td>
<td>0.000</td>
<td>88000</td>
<td>12,977</td>
<td>11,785</td>
<td>239</td>
<td>0.000</td>
</tr>
<tr>
<td>0.013</td>
<td>88469.83</td>
<td>11.40</td>
<td>89662</td>
<td>89643</td>
<td>0.000</td>
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<tr>
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<td>11.41</td>
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<td>88000</td>
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<tr>
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<td>89653</td>
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<td>89655</td>
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<tr>
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<td>11,785</td>
<td>239</td>
<td>0.002</td>
</tr>
</tbody>
</table>
3.5.2.1.5. Twenty Five Years of Production

(Figure 3-36) shows the expected NPV as a function spare capacity volume when the study handles only 25 years of production. From the figure, the optimal spare capacity was around 3,000 MBD, resulting in expected NPV around $4,500 million. (Tables 3-56 and 3-57) show the result of the optimization algorithm. These results show that the optimal spare capacity and expected NPV were 2,998 MBD and $4,467 million, respectively. (Table 3-58) shows the demand model and the probability of using the spare capacity for each year in the last row. The impact of incorporating the GBM modeling process in the price forecast model was clear. The GBM was a log-normal diffusion process; in other words, the GBM increases the values of the forecasted prices and increases the optimal spare capacity and expected NPV.

![Mean NPV Vs. Spare Capacity (25Yrs)](image-url)

Figure 3-36. Expected NPV as a Function of Spare Capacity.
Table 3-56. Optimal Spare Capacity.

<table>
<thead>
<tr>
<th>Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average of Average Demand, MBD</td>
<td>90839</td>
</tr>
<tr>
<td>Spare Capacity, MBD</td>
<td>2998.11</td>
</tr>
<tr>
<td>New Capacity, MBD</td>
<td>93837</td>
</tr>
<tr>
<td>Delta Demand, MBD</td>
<td>800</td>
</tr>
<tr>
<td>Number of Wells Required Initially</td>
<td>250</td>
</tr>
</tbody>
</table>

Table 3-57. Optimal Expected NPV.

<table>
<thead>
<tr>
<th>Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spare Capacity (MBD)</td>
<td>2998</td>
</tr>
<tr>
<td>Production Duration (Yrs)</td>
<td>25</td>
</tr>
<tr>
<td>NPV ($ million)</td>
<td>20272</td>
</tr>
<tr>
<td>Mean of NPV ($ million)</td>
<td>4467</td>
</tr>
<tr>
<td>Variance of NPV</td>
<td>210653891</td>
</tr>
</tbody>
</table>

Table 3-58. Objective Function and Decision Variable Sub-Module.

<table>
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<tr>
<th>Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
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</tr>
<tr>
<td>Ln(Dem*)</td>
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</tr>
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</tr>
<tr>
<td>Var[X(t)]</td>
<td>0.00</td>
</tr>
<tr>
<td>Average Demand, MBD</td>
<td>88691</td>
</tr>
<tr>
<td>Probability of Using Spare Capacity</td>
<td>0.00</td>
</tr>
</tbody>
</table>

3.5.2.2. Mean Demand Based on Life of Project

This section presents the results for cases when the base demand was calculated as the average of the mean demand over the life of the project. Using life of the project to calculate the base demand increases the uncertainty of our model since data further in the future were used to calculate average demand. The case of averaging over the life of the project was presented to show the uncertainty involved in the study and its impact on decisions.
3.5.2.1.1. Five Years of Production

(Figure 3-37) shows the expected NPV as a function of spare capacity volume when the study handled only five years of production. From the figure, the optimal spare capacity was around 2,600 MBD, resulting in expected NPV around $4,900 million. (Tables 3-59 and 3-60) show the results of the optimization algorithm. These results show that the optimal spare capacity and expected NPV were 2,678 MBD and $4,838 million, respectively. (Table 3-61) shows the demand model and the probability of using the spare capacity for each year in the last row. The impact of incorporating the GBM modeling process in the price forecast model was clear. The GBM was a log-normal diffusion process; in other words, the GBM increased the values of the forecasted prices and increased the optimal spare capacity and expected NPV.

![Mean NPV Vs. Spare Capacity (5Yrs)](image)

Figure 3-37. Expected NPV as a Function of Spare Capacity.

Table 3-59. Optimal Spare Capacity.

<table>
<thead>
<tr>
<th>Average of Average Demand, MBD</th>
<th>90839</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spare Capacity, MBD</td>
<td>2678.36</td>
</tr>
<tr>
<td>New Capacity, MBD</td>
<td>93517</td>
</tr>
<tr>
<td>Delta Demand, MBD</td>
<td>800</td>
</tr>
<tr>
<td>Number of Wells Required Initially</td>
<td>224</td>
</tr>
</tbody>
</table>
3.5.2.1.2. Ten Years of Production

(Figure 3-38) shows the expected NPV as a function spare capacity volume when the study handles only ten years of production. From the figure, the optimal spare capacity was around 1,600 MBD, resulting in expected NPV around $1,850 million. (Tables 3-62 and 3-63) show the results of the optimization algorithm. These results show that the optimal spare capacity and expected NPV were 1,679 MBD and $1,868 million, respectively. (Table 3-64) shows the demand model and probability of using the spare capacity for each year in the last row.
Figure 3-38. Expected NPV as a Function of Spare Capacity.

Table 3-62. Optimal Spare Capacity.

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Average of Average Demand, MBD</td>
<td>94079</td>
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<tr>
<td>Spare Capacity, MBD</td>
<td>1678.91</td>
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<tr>
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</tr>
<tr>
<td>Delta Demand, MBD</td>
<td>800</td>
</tr>
<tr>
<td>Number of Wells Required Initially</td>
<td>140</td>
</tr>
</tbody>
</table>

Table 3-63. Optimal Expected NPV.

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Spare Capacity (MBD)</td>
<td>1679</td>
</tr>
<tr>
<td>Production Duration (Yrs)</td>
<td>10</td>
</tr>
<tr>
<td>NPV ($ million)</td>
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<tr>
<td>Mean of NPV ($ million)</td>
<td>1868</td>
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<td>Variance of NPV</td>
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</table>

Table 3-64. Objective Function and Decision Variable Sub-Module.

<table>
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<th>Year</th>
<th>Dem*</th>
<th>Ln(Dem*)</th>
<th>X(t) = ln(Dem)</th>
<th>Var[X(t)]</th>
<th>Dem(t)</th>
<th>Average Demand, MBD</th>
<th>Probability of Using Spare Capacity</th>
</tr>
</thead>
<tbody>
<tr>
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<td>11.39</td>
<td>11.39</td>
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<td>95332.25</td>
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3.5.2.1.3. Fifteen Years of Production

(Figure 3-39) shows the expected NPV as a function spare capacity volume when the study handles only fifteen years of production. The curve in the figure was not very stable due to the high uncertainty involved in the model; price and demand forecast combined models, and the length of the project resulted in this huge uncertainty in the model. From the figure, The optimal spare capacity was around 200 MBD, that results in expected NPV around 90 million dollars. (Tables 3-65 and 3-66) show the result of the optimization algorithm. From the optimization results, the optimal spare capacity and expected NPV were 240 MBD and $12 million, respectively. (Table 3-67) shows the demand model and the probability of using the spare capacity for each year in the last row. Incorporating the GBM modeling process in the price forecast model made building spare capacity for fifteen years of production feasible and resulted in positive expected NPV.

![Mean NPV Vs. Spare Capacity (15Yrs)](image)

Figure 3-39. Expected NPV as a Function of Spare Capacity.
Table 3-65. Optimal Spare Capacity.

| Average of Average Demand, MBD | 97596 |
| Spare Capacity, MBD | 239.98 |
| New Capacity, MBD | 97836 |
| Delta Demand, MBD | 800 |
| Number of Wells Required Initially | 20 |

Table 3-66. Optimal Expected NPV.

| Spare Capacity (MBD) | 240 |
| Production Duration (Yrs) | 15 |
| NPV ($ million) | 407 |
| Mean of NPV ($ million) | 12 |
| Variance of NPV | 1169333 |

Table 3-67. Objective Function and Decision Variable Sub-Module.

<table>
<thead>
<tr>
<th>Year</th>
<th>0</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
<th>12</th>
<th>13</th>
<th>14</th>
<th>15</th>
<th>16</th>
<th>17</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dem*</td>
<td>88428.24</td>
<td>90782.44</td>
<td>94526.68</td>
<td>101324.29</td>
<td>103199.28</td>
<td>105595.58</td>
<td>107904.83</td>
<td>109321.95</td>
<td>110830.59</td>
<td>112441.69</td>
<td>113917.18</td>
<td>115316.14</td>
<td>116622.68</td>
<td>117835.95</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ln(Dem*)</td>
<td>11.39</td>
<td>11.41</td>
<td>11.46</td>
<td>11.51</td>
<td>11.53</td>
<td>11.57</td>
<td>11.61</td>
<td>11.64</td>
<td>11.68</td>
<td>11.74</td>
<td>11.78</td>
<td>11.79</td>
<td>11.79</td>
<td>11.79</td>
<td>11.79</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Var[X(t)]</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dem(t)</td>
<td>88000.00</td>
<td>88761.50</td>
<td>90102.85</td>
<td>96456.44</td>
<td>98106.65</td>
<td>102065.87</td>
<td>104492.94</td>
<td>105036.91</td>
<td>110638.93</td>
<td>118259.52</td>
<td>123085.16</td>
<td>124577.75</td>
<td>126632.39</td>
<td>127975.20</td>
<td>129526.15</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average Demand, MBD</td>
<td>88691</td>
<td>89631</td>
<td>90731</td>
<td>91934</td>
<td>93208</td>
<td>94532</td>
<td>95896</td>
<td>97291</td>
<td>98713</td>
<td>100161</td>
<td>101632</td>
<td>103127</td>
<td>104613</td>
<td>106127</td>
<td>107660</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Probability of Using Spare Capacity</td>
<td>1</td>
<td>0.000</td>
<td>0.004</td>
<td>0.017</td>
<td>0.032</td>
<td>0.042</td>
<td>0.047</td>
<td>0.049</td>
<td>0.045</td>
<td>0.042</td>
<td>0.039</td>
<td>0.035</td>
<td>0.030</td>
<td>0.027</td>
<td>0.024</td>
<td>0.022</td>
<td>0.018</td>
<td>0.014</td>
</tr>
</tbody>
</table>

3.5.2.1.4. Twenty Years of Production

(Figure 3-40) shows the expected NPV as a function of spare capacity volume when the study handles 20 years of production. From the figure, all spare capacity values resulted in negative expected NPV, meaning that there was no spare capacity to acquire.
Figure 3-40. Expected NPV as a Function of Spare Capacity.

3.5.2.1.5. Twenty Five Years of Production

(Figure 3-41) shows the expected NPV as a function of spare capacity volume when the study handles 2 five years of production. From the figure, all spare capacity values resulted in negative expected NPV, indicating that there was no spare capacity to acquire.
3.5.3. **Summary of the Two Price Modeling Approach**

This section compares the optimal spare capacity and optimal expected NPV as a function of production duration for the following approaches:

1. Base demand was based on the first five years, price was forecasted using the MRM, and demand was forecasted using the combined MRM-GBM model.
2. Base demand was based on the first five years, and price and demand were forecasted using the combined MRM-GBM model.
3. Base demand was based on the life of the project, price was forecasted using the MRM, and demand was forecasted using the combined MRM-GBM model.
4. Base demand was based on the life of the project, and price and demand were forecasted using the combined MRM-GBM model.

![Mean NPV Vs. Spare Capacity (25Yrs)](image)
(Table 3-68) and (Figure 3-42) show the optimal spare capacity as a function of production duration for the four scenarios mentioned above. The top blue and green curves assume the first five years to calculate the base demand. The blue curve represents MRM price modeling and the green one represents the combined MRM-GBM price modeling. The bottom red and purple curves assume the life of the project to calculate the base demand. The red curve represents MRM price modeling and the purple one represents the combined MRM-GBM price modeling.

(Table 3-69) and (Figure 3-43) show the optimal expected NPV as a function of production duration for the four scenarios mentioned above. The top blue and green curves assume the first five years to calculate base demand. The blue curve represents MRM price modeling and the green one represents the combined MRM-GBM price modeling. The bottom red and purple curves assume the life of the project to calculate the base demand. The red curve represents MRM price modeling and the purple one represents the combined MRM-GBM price modeling.

From (Figures 3-42 and 3-43), both price and demand modeling assumptions can significantly impact the optimal spare capacity and expected NPV. How to calculate the base demand can significantly impact the shape of the whole function (both spare capacity and expected NPV); the optimal spare capacity and expected NPV can be significantly different based on the base demand calculation. On the other hand the type of the price forecast model shifts the curve up or down. The shift in the price model was larger in cases of expected NPV than in spare capacity. In other words, the type of price forecast can significantly impact the expected NPV and the value of a company; however, it may have a relatively small impact on optimal spare capacity.
In identifying optimal spare capacity, the calculation of base demand was important. Price modeling assumptions and the bases for base demand calculations were important when evaluating the value of a company.

Table 3-68. Optimal Spare Capacity as a Function of Production Duration.

<table>
<thead>
<tr>
<th>Production Duration</th>
<th>MBD</th>
<th>Optimum Spare Capacity</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>MRM Prc MRM_GBM</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Dem 5 Yrs Avg</td>
</tr>
<tr>
<td>5</td>
<td></td>
<td>2,514</td>
</tr>
<tr>
<td>10</td>
<td></td>
<td>3,000</td>
</tr>
<tr>
<td>15</td>
<td></td>
<td>2,974</td>
</tr>
<tr>
<td>20</td>
<td></td>
<td>2,508</td>
</tr>
<tr>
<td>25</td>
<td></td>
<td>2,349</td>
</tr>
</tbody>
</table>

Figure 3-42. Optimum Spare Capacity as a Function of Production Duration.

Table 3-69. Optimal Expected NPV as a Function of Production Duration.

<table>
<thead>
<tr>
<th>Production Duration</th>
<th>MBD</th>
<th>Mean NPV of Optimum Spare Capacity</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>MRM Prc MRM_GBM</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Dem 5 Yrs Avg</td>
</tr>
<tr>
<td>5</td>
<td></td>
<td>3,860</td>
</tr>
<tr>
<td>10</td>
<td></td>
<td>4,577</td>
</tr>
<tr>
<td>15</td>
<td></td>
<td>3,594</td>
</tr>
<tr>
<td>20</td>
<td></td>
<td>2,659</td>
</tr>
<tr>
<td>25</td>
<td></td>
<td>1,950</td>
</tr>
</tbody>
</table>
3.5.4. Sensitivity and Value of Information Analyses

(Figure 3-44) is a tornado chart for the mean NPV and was generated by varying the parameters in the integrated model by +10% and -10% and record the resulting mean NPV. The tornado chart was generated using five years of production and the combined MRM-GBM model for price and demand. From the figure, the long-run equilibrium price $P^*$, and the parameters for the demand forecast model (delta demand, long-run equilibrium demand $Dem^*$, and demand volatility) were the most impacting parameters on the mean NPV. This section presents optimization sensitivity and value of information analyses for those four most impacting parameters, which are delta demand, long-run equilibrium price, long-run equilibrium demand, and demand volatility, on the mean NPV.

Delta demand is an epsilon demand used to calculate the probability of using a specified volume of spare capacity. A small difference (epsilon) was needed to calculate
a probability of an event to happen from the cumulative density function CDF (Ross, 2009); this was basically because the probability of the occurrence of a specific event was zero. Consequently, the delta demand value was used to quantify the probability of using the spare capacity from the CDF of the demand forecast. 800 MBD was the base case delta demand for the study since the spare capacity can be in the millions of barrels.

Long-run equilibrium price $P^*$ is the initial long-run equilibrium price value to which the stochastic price forecasting model reverts. Mean Reversion with Geometric Brownian Motion model was implemented to forecast crude oil prices.

The demand forecasting model was Mean Reversion with Geometric Brownian Motion model, and the required parameters were calculated from historical data for global oil production.
3.5.4.1. Delta Demand Analysis

(Figure 3-45) shows optimization sensitivity for delta demand. In this analysis, the optimum spare capacity and expected NPV were calculated for the range of delta demand between 100 to 1000 MBD. The red dots are the optimal spare capacity and the blue dots are the optimal mean NPV. Note that there was a cutoff point at 500 MBD.
where spare capacity project become profitable. *This signifies on identifying whether the delta demand was greater than or less than 500 MBD.*

(Figure 3-46) illustrates the procedure for the value of information analysis VOI. The VOI identifies the value of acquiring perfect information on the four parameters discussed above. Base and alternate case values of a parameter were specified. Then, the perfect information is acquired or not. If the information is acquired, the mean NPV is optimized for the realized case, and the mean NPV is optimal. However, if the information is not obtained, the optimizer solves the problem for the base case. Then, if the base case is realized, the mean NPV is optimal, but if the alternate case is realized, the mean NPV is suboptimal. The value of the information is the difference between mean NPV of optimal alternate case and suboptimal alternate case. The VOI represent the maximum monetary value a company is willing to pay to mitigate the uncertainty in a parameter. (Figure 3-47) shows the value of information as a function the alternate case delta demand. As the alternate case gets closer to our base case delta demand of 800 MBD, the VOI decreases; this was expected since the optimal mean NPV values of the base and alternate cases are close. The VOI varies between few hundreds millions of dollars to around a billion dollars.
Figure 3-45. Optimization Sensitivity for Delta Demand.

Figure 3-46. Value of Perfect Information Analysis.
3.5.4.2. Long-Run Equilibrium Price Analysis

(Figure 3-48) shows optimization sensitivity for the long-run equilibrium price. In this analysis, the optimum spare capacity and expected NPV were calculated for the range of long-run equilibrium prices between 20 and 200 $/bbl. The red dots indicated the optimal spare capacity and the blue dots indicated the optimal mean NPV. Note the cutoff point at $50/bbl where the spare capacity project became profitable; in other words, it may not be profitable to build spare capacity if prices can drop below 50 $/bbl in the future.

(Figure 3-49) shows the value of information as a function of the alternate case long-run equilibrium price. As the alternate case got closer to our base case delta demand of 88 $/bbl, the VOI decreased; this was expected since the optimal mean NPV values of the base and alternate cases were going to be close. The VOI varied between one and five billion dollars. The impact of the long-run equilibrium price was more significant than the impact of the delta demand or any of the parameters of the demand model as shown below.
Figure 3-48. Optimization Sensitivity for Long-Run Equilibrium Price.

Figure 3-49. Value of Information Analysis for Long-Run Equilibrium Price.

3.5.4.3. Long-Run Equilibrium Demand Analysis

(Figure 3-50) shows optimization sensitivity for the long-run equilibrium demand. In this analysis, the optimum spare capacity and expected NPV were calculated for the range of long-run equilibrium demand between 50 and 130 MMBD. The red dots were the optimal spare capacity and the blue dots were the optimal mean NPV. For the range of long-run equilibrium demand analyzed, acquiring spare capacity was profitable across
the entire range of Dem*. In other words, identifying Dem* can impact the mean NPV resulting from spare capacity; however, spare capacity is profitable regardless of the value of Dem*. (Figure 3-51) shows the value of information as a function of long-run equilibrium demand in the alternate case. As the alternate case got closer to our base case long-run equilibrium demand of 88 MMBD, the VOI decreased; this was expected since the optimal mean NPV values for base and alternate cases were going to be close. The VOI varied within a few hundred millions of dollars.

![Optimization Sensitivity Analysis for LongRun Mean Demand](image)

Figure 3-50. Optimization Sensitivity for Long-Run Equilibrium Demand.

![VOI for LonRun Demand](image)

Figure 3-51. Value of Information Analysis for Long-Run Equilibrium Demand.
3.5.4.4. Demand Volatility Analysis

(Figure 3-52) shows optimization sensitivity to demand volatility. In this analysis, the optimum spare capacity and expected NPV were calculated for the range of demand volatility between 0.01 and 0.15. The red dots indicated the optimal spare capacity and the blue dots indicated the optimal mean NPV. For the range of demand volatility analyzed, acquiring spare capacity was profitable for demand volatility less than 5%. This volatility impacted the probability of using spare capacity and the expected NPV. The parameter of demand volatility had one of the greatest impacts on the optimal decisions.

(Figure 3-53) shows the value of information as a function of alternate case demand volatility. As the alternate case got closer to our base case demand volatility of 0.03, the VOI decreased; this was expected since the optimal mean NPV values of the base and alternate cases were going to be close. The VOI varied within a few hundred millions of dollars.

Figure 3-52. an optimization Sensitivity for Demand Volatility.
Modeling the combined MRM-GBM price and demand forecast model was challenging due to incorporating the two stochastic processes together, resulting in unstable mean NPV and simulation error. The number of iterations, in the Monte Carlo simulation process, was increased to 150,000 to stabilize the mean NPV and minimize the simulation error. Another challenge was solving the optimization problem for this computationally expensive problem. Genetic Algorithm was used with multiple starting point runs to achieve optimized results. Establishing a workflow to estimate the probability of using a specific spare capacity had not been tackled before in the literature.

The results and analysis assumed MRM-GBM behavior in the price and demand forecast. Other forecast models may lead to different results. Calculating the probability of using spare capacity requires the use of delta demand; in other words, the calculated probability was for a small range of spare capacity rather than for a single value.
3.6. Conclusions and Recommendations for Future Work

3.6.1. Conclusions

A workflow was established to identify the optimal spare capacity for a major oil producer to acquire under the uncertainties of price and demand. The problem was a dynamic optimization that maximized the expected NPV that resulted from acquiring the spare capacity. Implementing the proposed scope and models, the impact of price and demand modeling assumptions on the optimal decision and mean NPV was analyzed. The expected NPV is a concave function of spare capacity level which means that there is an optimality. The optimal spare capacity to acquire is a function demand and price modeling assumptions include long-run equilibrium price and demand, and demand volatility. Below are some concluding remarks:

1. The proposed model resulted in a concave mean NPV function as a function of spare capacity. This supports our claim of the existence of an economically optimal spare capacity.

2. Demand modeling parameters, especially delta demand, can significantly impact the optimal volume of spare capacity. Moreover, price modeling parameters have less impact on the optimal spare capacity decision than demand modeling parameters.

3. Price modeling parameters can significantly impact the expected NPV of acquiring spare capacity.

4. Demand modeling parameters can impact the mean NPV, but the impact is less than that of the price modeling parameters.
5. The spare capacity problem is more sensitive to delta demand, long-run equilibrium price, long-run equilibrium demand, and demand volatility.

3.6.2. Recommendations for Future Research

1. Analyze the impact of implementing different demand and price forecast models on the optimal decisions.
2. Conduct a regression analysis to determine the relationship between the optimal decision and other market and field parameters such as crude price, oil demand, and world oil reserves.
3. The procedure implemented in this study can be followed to identify optimal gas storage capacity given the seasonality in demand.
4. Analyze the problem of spare capacity assuming the major oil producer as a price setter. This requires incorporating the game theory concept into the study.

Chapter 4

Integrating Spare Capacity and Capacity Management Studies

4.1. Introduction

This study combined the results of the spare capacity study into the capacity management integrated model. In the capacity management study, the integrated model
identified the optimal production rate allocation for a portfolio of 12 producing fields. The production rate from those 12 fields must meet a daily target rate less than the total potential of the fields. On the other hand, the spare capacity study identified the optimal spare capacity to acquire given the historical behavior of crude oil demand.

This study assigned optimal spare capacity, resulting from the spare capacity study, to the capacity management integrated model. The capacity management model was modified for oil fields since the spare capacity study handled oil fields. Moreover, new development fields were developed to attain the capacity recommended by the spare capacity model. New field parameters, reservoir models, cost models, and price models were developed here. This was a dynamic optimization problem under the uncertainty of crude prices.

4.2. Problem Statement

An oil company is producing 12 oil fields at their maximum capacity. Those fields produce three different types of crude based on crude density as shown in (Table 4-1). The API gravity for the light, medium, and heavy crude are 34, 31, and 27, respectively. The three types of crude control the crude price model since each type has different intrinsic value.

The company’s management is interested in acquiring spare capacity by developing new fields and then maximizing the mean plateau length and mean NPV by optimally allocating the production rate for all fields while maintaining the optimal spare capacity.
4.3. Methodology

This study incorporated the capacity management and spare capacity studies. From the spare capacity study, the optimal spare capacity varied between 2 and 3.5 MMBD depending on demand and price modeling assumptions. For the purposes of this study, 3MMBD was used as optimal spare capacity. Initially, 12 producing fields produced at their maximum potential. Then, three new development fields, one field for each crude type, were added to the portfolio of fields. This study identified the optimal production rate allocation for the new portfolio of fields under the uncertainty of crude price while maintaining spare capacity equivalent to the capacity of the new fields.

4.3.1. Price Model

In this study, the Mean Reversion Model MRM was considered for price forecasting. Historical weekly prices between 1989 and 2010 were obtained from (Bukhari, 2011) for the three crude types considered in this study; these historical data were used to estimate a correlation model among the prices of the three crude types as discussed in the price correlation model section. In the correlation model the price of medium and light was modeled as a function of the price of heavy crude. In other words,
the prices of heavy crude were forecasted using the MRM model; then, the prices of the other two crude types were forecasted using the correlation models. Price correlation models were used rather than modeling the price of each crude type as MRM because it was believed that prices for different densities were correlated, as shown in the price correlation section. The parameters for the MRM heavy price mode were estimated from more recent data of the heavy crude. These monthly data, obtained from the Energy Information Administration, covered from 1985 to 2013 (EIA, 2014).

### 4.3.1.1. Historical Data

(Figure 4-1) shows the historical data for the heavy crude price used to estimate the MRM parameters for the heavy crude price model. (Figure 4-2) shows the weekly historical data for the three types of crude between 1989 and 2010; these historical data were used to build a regression model that correlated the prices for medium and light crude with the heavy crude price.

![Prices for Heavy Crude](image)

Figure 4-1. Historical Data for Heavy Crude Price (1984–2013).
4.3.1.2. Parameters for Heavy MRM Price Model

The concept and process of the MRM model were discussed in the capacity management study. This section presents the parameters used in the MRM heavy crude price model. (Table 4-2) shows the parameters required for that model. The long-run equilibrium price P* and the reversion rate η were estimated from historical data between 2008 and 2013. As claimed by (Xu, 2010), crude prices established new P* starting in 2008, which was why data between 2008 and 2013 were used here. The P* and the η were 94.23 $/bbl and 0.47, respectively. Heavy crude price volatility was estimated from weekly historical data between 1985 and 2013. The volatility for the MRM heavy crude price model was 0.26. The estimation process for these parameters was discussed in the capacity management chapter in the price model section.
4.3.1.3. Price Correlation

Weekly historical data between 1989 and 2010 were used to build the regression correlation models. (Table 4-3) shows the correlation coefficients among the three types of crude; the correlation coefficient shows strong correlations among these types. (Figure 4-3) and (Equation 4-1) shows the regression correlation model between medium and heavy crude prices; the model expresses the price of medium crude as a function of the price of heavy crude. The coefficient for the determination of 99.93% increases confidence in using the model. (Figure 4-4) and (Equation 4-2) show the regression correlation model between light and heavy crude prices; the model expresses the price of light crude as a function of the price of heavy crude. The coefficient for the determination of 99.74% increases confidence in the model’s use. The regression models were developed based on the least squares approach.

Table 4-3. Price Correlation Coefficients.

<table>
<thead>
<tr>
<th>Correlation Factor</th>
<th>Heavy-Medium</th>
<th>Heavy-Light</th>
<th>Medium-Light</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Heavy Crude Price Parameters</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>η (Reversion Speed)</td>
<td>0.47</td>
<td></td>
<td></td>
</tr>
<tr>
<td>P* (Long-Run Mean Price)</td>
<td>94.23</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ln(P*)</td>
<td>4.55</td>
<td></td>
<td></td>
</tr>
<tr>
<td>σ (Volatility)</td>
<td>0.26</td>
<td></td>
<td></td>
</tr>
<tr>
<td>P_min($/bbl)</td>
<td>40.00</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Figure 4-3. Medium and Heavy Crude Price Correlation Model.

\[ \text{Price}_{\text{Medium}} = 1.0158 \times \text{Price}_{\text{Heavy}} + 0.5623 \]  \hspace{1cm} (4-1)

Figure 4-4. Medium and Heavy Crude Price Correlation Model.

\[ \text{Price}_{\text{Light}} = 1.0393 \times \text{Price}_{\text{Heavy}} + 1.0062 \]  \hspace{1cm} (4-2)
4.3.2. Reservoir Model

The reservoir model used here was based on material balance and the Arps empirical relation (Arps, 1945). (Equations 4-3, 4-4, and 4-5) show the Arps empirical formulas for exponential, harmonic, and hyperbolic declines, respectively. The Arps formula is described by three parameters: initial flow rate ($q_i$), decline exponent or shape factor (b), and initial decline rate ($D_i$). $D_i$ the rate at which the flow rate starts to decline where the decline exponent b is the rate at which the initial decline rate $D_i$ changes with time. (Figure 4-5) shows a sample of the three types of decline: exponential in green, harmonic in blue, and hyperbolic in red. Exponential decline is a straight line if plotted in a semi-log plot (Figure 4-6). Researchers attempted to interpret the Arps empirical formula physically (Li and Hore, 2003). An interpretation by (Fetkovich et al., 1994) proposes that the material balance and pseudo-steady state flow equations are the basis of the Arps model; moreover, they proposed a relationship between the parameters of the Arps equation and reservoir rock and fluid properties. The initial decline-rate $D_i$ and decline exponent b are functions of reservoir fluid and rock properties, and are calculated from production data. However, for simplicity they were calculated from (Equations 4-6, 4-7, 4-8, and 4-9) as recommended by (Fetkovich et al., 1994) for single-layer homogenous reservoirs. The $n$ in those equations is the exponent of the back-pressure curve equations (Equations 4-10, 4-11). The value of $n$ varies between 0.5 and 1 for single-layer homogenous reservoirs where $n$ of 1 represents low permeability reservoirs and $n$ of 0.5 represents high permeability reservoirs (Fetkovich et al., 1994). (Table 4-4) summarizes the required parameter for decline curve analysis for the 15 crude oil fields.
We intended to vary the values of $n$ over the 15 fields to analyze its impact on the optimization problem.

\[ q = q_i e^{-D_i t} \]  
\[ q = \frac{q_i}{(1+D_i t)} \]  
\[ q = \frac{q_i}{(1+bD_i t)^{1/b}} \]

\[ Di(Oil) = [(2n + 1)/2](q_i/EUR) \]  
\[ Di(Gas) = 2n(q_i/EUR) \]  
\[ b(Oil) = (2n - 1)/(2n + 1) \]  
\[ b(Gas) = (2n - 1)/2n \]  
\[ q_g = C_g \left( \frac{ar{P}_r}{P_{wf}} \right)^2 \left( \frac{P_{res}}{P_{res}} \right)^n \]  
\[ q_o = J_o \left( \frac{P_r}{P_{res}} \right) \left( \frac{ar{P}_r}{P_{wf}} \right)^2 \left( \frac{P_{res}}{P_{res}} \right)^n \]

Figure 4-5. Mean Reversion Model Sample.
The forecasting model requires reserves, current cumulative production, production rate capacity, and end of plateau expressed as percentage of reserves for each field. In this study, the model started by forecasting the production capacity, which was equal to the maximum production capacity specified for a field until the cumulative production equals the end of plateau value. At that point, the Arps hyperbolic equation was implemented to forecast the capacity. After that, the production rate was assigned by the optimization algorithm. If the production rate assigned was lower than the capacity of the field, the production rate continued at the same rate until it equaled the forecasted production capacity; then, the production rate followed the capacity profile.
4.3.3. Cost Models

The cost model implemented here was the same one implemented in the capacity management study and originally developed by (Kennedy, 1993). However, the cost model here incorporates field development cost (e.g., production facility and pipeline costs). The field development part of the cost model is discussed here. The details about the drilling and maintenance cost can be found in the capacity management chapter under the cost model section. (Table 4-5) shows the drilling costs parameters for the 15 fields.

The field development cost was divided into two parts: production facility and pipeline costs. (Figures 4-7 and 4-8) show the onshore and offshore production facility cost models, respectively. The production facility costs were expressed in millions of dollars as a function flow rate required. (Figures 4-9 and 4-10) show the costs model for onshore and offshore pipelines. The pipeline costs were a function of environment and flow rate. (Table 4-6) shows the general parameters of the development fields for field development costs that include environment, pipeline length, life of the facility, camp base cost, well-site cost, and contingency drilling cost. (Table 4-7) shows the parameters of the development fields for production facility and pipeline costs, including production facility base costs and adjusting factors, and pipeline base costs.
Figure 4-7. Onshore Oil Production Facility Cost.

Figure 4-8. Offshore Oil Production Facility Cost.

Figure 4-9. Offshore Oil Production Facility Cost.
Figure 4-10. Offshore Oil Production Facility Cost.

Table 4-5. Parameters for Drilling Costs.

<table>
<thead>
<tr>
<th>Crude Type</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>Medium</th>
<th>Medium</th>
<th>Medium</th>
<th>Heavy</th>
<th>Heavy</th>
<th>Heavy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Light</td>
<td>11000</td>
<td>12000</td>
<td>14000</td>
<td>16000</td>
<td>18000</td>
<td>20000</td>
<td>22000</td>
<td>24000</td>
<td>26000</td>
<td>28000</td>
<td>30000</td>
<td>32000</td>
</tr>
<tr>
<td>Medium</td>
<td>13756</td>
<td>15000</td>
<td>16500</td>
<td>17500</td>
<td>18500</td>
<td>19500</td>
<td>20500</td>
<td>21500</td>
<td>22500</td>
<td>23500</td>
<td>24500</td>
<td>25500</td>
</tr>
<tr>
<td>Light</td>
<td>72</td>
<td>96</td>
<td>120</td>
<td>144</td>
<td>168</td>
<td>192</td>
<td>216</td>
<td>240</td>
<td>264</td>
<td>288</td>
<td>312</td>
<td>336</td>
</tr>
<tr>
<td>Contingency Drilling Cost (% Total Drilling Cost)</td>
<td>15%</td>
<td>15%</td>
<td>15%</td>
<td>15%</td>
<td>15%</td>
<td>15%</td>
<td>15%</td>
<td>15%</td>
<td>15%</td>
<td>15%</td>
<td>15%</td>
<td>15%</td>
</tr>
</tbody>
</table>

Table 4-6. General Development Parameters.

<table>
<thead>
<tr>
<th>Field</th>
<th>1</th>
<th>2</th>
<th>3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Crude Type</td>
<td>Light</td>
<td>Medium</td>
<td>Heavy</td>
</tr>
<tr>
<td>Light</td>
<td>150</td>
<td>180</td>
<td>200</td>
</tr>
<tr>
<td>Medium</td>
<td>25</td>
<td>25</td>
<td>25</td>
</tr>
<tr>
<td>Heavy</td>
<td>1.448</td>
<td>3.620</td>
<td>3.620</td>
</tr>
<tr>
<td>Wellsite Cost (million $)</td>
<td>0.101</td>
<td>0.087</td>
<td>0.217</td>
</tr>
<tr>
<td>Contingency Drilling Cost (% Total Drilling Cost)</td>
<td>15%</td>
<td>15%</td>
<td>15%</td>
</tr>
</tbody>
</table>
4.3.4. Integrated Optimization Model

The integrated optimization model integrates all models and processes developed in the study to achieve the objective of identifying the production rate allocation that maximizes objective functions. The following objective functions were evaluated in the study: 1) Mean NPV, 2) Plateau length, 3) Mean NPV and plateau length, and 4) Plateau length and average decline rate.

4.3.4.1. Field Parameter Assumptions

(Table 4-8) shows the range of parameters from which the field parameters were assigned. These ranges were assigned by industry experts to reflect actual field data. Relatively large reserve values were assigned to heavy crude oil to reflect the fact that light crude fields have been produced at higher rate because of their higher intrinsic values. End of plateau is the stage of the life of the field when the plateau begins to decline, expressed as a percentage of reserves. Current cumulative production represents the cumulative production at the beginning of the study. Maximum annual depletion rate

<table>
<thead>
<tr>
<th>Field</th>
<th>I1</th>
<th>I2</th>
<th>I3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Crude Type</td>
<td>Light</td>
<td>Medium</td>
<td>Heavy</td>
</tr>
<tr>
<td>Production Facility Base Cost for 100 MBD (MM$)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Remoteness/ Logistics Factor</td>
<td>1.05</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>Construction Difficulty Factor</td>
<td>1.3</td>
<td>2</td>
<td>1.8</td>
</tr>
<tr>
<td>Equipment Complexity Factor</td>
<td>1.25</td>
<td>1.5</td>
<td>1.75</td>
</tr>
<tr>
<td>Enclosing Equipment Factor</td>
<td>1.6</td>
<td>1.8</td>
<td>2</td>
</tr>
<tr>
<td>Pipeline Cost for 100 MBD ($M/km)</td>
<td>491</td>
<td>508</td>
<td>491</td>
</tr>
</tbody>
</table>
sets the production potential for each field. Minimum facility operating rate is the minimum rate required by a production facility for a safe and economical operation. Annual decline rate is a cost parameter selected to determine the number of wells required each year; it is not included in the production forecast model. Additional rates for new wells were estimated from (Figure 4-11); however, a minimum rate of 8 MBD could be added by a newly drilled well. Fixed and variable operating expenditures are related to the operation and maintenance of the field.

Table 4-8. Field Parameter Assumptions.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Light Crude Oil</th>
<th>Medium Crude Oil</th>
<th>Heavy Crude Oil</th>
</tr>
</thead>
<tbody>
<tr>
<td>API Gravity</td>
<td>34</td>
<td>31</td>
<td>27</td>
</tr>
<tr>
<td>Reserves Range</td>
<td>500-15,000</td>
<td>1,000-20,000</td>
<td>2,000-25,000</td>
</tr>
<tr>
<td>End of Plateau</td>
<td>50-70</td>
<td>50-70</td>
<td>50-70</td>
</tr>
<tr>
<td>Current Cumulative Production</td>
<td>25-63</td>
<td>15-58</td>
<td>5-54</td>
</tr>
<tr>
<td>Maximum Annual Depletion Rate</td>
<td>2-8</td>
<td>2-6</td>
<td>2-4</td>
</tr>
<tr>
<td>Min Operating Rate</td>
<td>30</td>
<td>30</td>
<td>30</td>
</tr>
<tr>
<td>Annual Decline Rate of Production</td>
<td>6</td>
<td>5</td>
<td>4</td>
</tr>
<tr>
<td>Depth of Reservoir</td>
<td>10,000-15,000</td>
<td>10,000-15,000</td>
<td>10,000-15,000</td>
</tr>
<tr>
<td>Well Costs</td>
<td>Kennedy’s Models</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Additional Rate from New Wells</td>
<td>Max[ (8), (Add. Rate per Well = -29.31 * Depletion Stage + 26.466)]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fixed OPEX</td>
<td>350-700</td>
<td>500-1000</td>
<td>750-1250</td>
</tr>
<tr>
<td>Variable OPEX</td>
<td>0.7-1.4</td>
<td>1.0-1.7</td>
<td>1.2-2.0</td>
</tr>
</tbody>
</table>

Figure 4-11. Additional Rate from Newly Drilled Wells.
4.3.4.2. Optimization Problem Formulation

The formulation of an optimization problem requires an objective function, decision variable, and constraints. The following objective functions were evaluated in this study:

1. $E[\text{total NPV}]$
2. Total plateau length
3. $E[\text{total NPV}] + \text{plateau length}$
4. Plateau length + Average production decline

The decision variables were the production rates for each field. Three constraints were imposed on the optimization model: 1) Minimum facility operating rate for each field (lower bound), 2) Production capacity for each field (upper bound), and 3) Total target daily rate representing the supply contract commitment. Here is a summary of the optimization problem formulation.

Maximize:

$E[\text{Total NPV}]$

Total Plateau Length

$E[\text{Total NPV}] + \text{Total Plateau Length}$

Total Plateau Length + Average Production Decline

By Calculating

$Production Rate \in \text{Fields}$

Subject to
Production Rate \leq \text{Production Potential} \forall \text{Fields}

Production Rate \geq \text{Minimum Facility Rate} \forall \text{Fields}

\sum_{f=1}^{F} \text{Production Rate}(f) = \text{Total Target Rate}

\textbf{4.4. Results and Discussion}

The capacity management integrated model and spare capacity study were incorporated here. The optimal spare capacity value, from the spare capacity study, was used in the capacity management integrated model. Three development fields, with total capacity equal to the recommended spare capacity, were added to the portfolio of fields. Then, the optimization algorithm identified the optimal production rate allocation for the portfolio of fields while maintaining recommended spare capacity. The results are discussed below.

\textbf{4.4.1. Initial Non-Optimized Case}

(Table 4-9) shows a non-optimized production allocation that meets the total target daily rate. This case is presented to show the capability of the optimization algorithm to reallocate the production rates to maximize total plateau length and/ or mean total NPV while meeting the total target daily rate. The total plateau length was 1 year, the mean total NPV was $1.373$ trillion, and the standard deviation for mean total NPV was $153$ billion. The average production decline over forty years of production was 184...
MBD/Yr. (Table 4-10) shows the production allocation by crude type. (Figure 4-12) shows the production profile and cumulative production for the entire portfolio of fields. (Table 4-11) shows the fields’ production rates, upper and lower production rate bounds, reserves, initial cumulative production, initial decline rates Di, and decline exponents b. (Figure 4-13) shows the production rate and plateau length for each field.

Table 4-9. Non-Optimized Production Allocation.

<table>
<thead>
<tr>
<th>Field</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
<th>12</th>
<th>13</th>
<th>14</th>
<th>15</th>
</tr>
</thead>
<tbody>
<tr>
<td>Production Rate (MBD)</td>
<td>400</td>
<td>358</td>
<td>548</td>
<td>951</td>
<td>140</td>
<td>483</td>
<td>855</td>
<td>340</td>
<td>551</td>
<td>704</td>
<td>1082</td>
<td>658</td>
<td>877</td>
<td>430</td>
<td>968</td>
</tr>
<tr>
<td>Percentage of Initial Potential Used (%)</td>
<td>40.65%</td>
<td>60.95%</td>
<td>43.69%</td>
<td>61.45%</td>
<td>17.76%</td>
<td>41.03%</td>
<td>86.97%</td>
<td>6.18%</td>
<td>36.93%</td>
<td>59.07%</td>
<td>85.36%</td>
<td>100.00%</td>
<td>100.00%</td>
<td>100.00%</td>
<td>100.00%</td>
</tr>
<tr>
<td>Plateau Length (Years)</td>
<td>1</td>
<td>2</td>
<td>29</td>
<td>14</td>
<td>19</td>
<td>4</td>
<td>41</td>
<td>24</td>
<td>36</td>
<td>13</td>
<td>1</td>
<td>14</td>
<td>3</td>
<td>15</td>
<td></td>
</tr>
<tr>
<td>[TOTAL NPV] ($ Million)</td>
<td>1,372,566</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Standard Deviation of Total NPV ($million)</td>
<td>152,763</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Discount Rate</td>
<td>10%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total Supply Commitment (MBD)</td>
<td>9370</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average Annual Decline (MBD/Yr)</td>
<td>-183.92</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 4-10. Production Allocation by Crude Type for Non-Optimized Case.

<table>
<thead>
<tr>
<th>Crude Type</th>
<th>Initial Production Rate (MBD)</th>
<th>Percentage of Total Supply Commitment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Light</td>
<td>2257</td>
<td>24.09%</td>
</tr>
<tr>
<td>Medium</td>
<td>2368</td>
<td>25.27%</td>
</tr>
<tr>
<td>Heavy</td>
<td>4745</td>
<td>50.64%</td>
</tr>
</tbody>
</table>

Figure 4-12. Non-Optimized Production Profile and Cumulative Production.
Table 4-11. Non-Optimized Production Allocation and Fields’ Properties.

<table>
<thead>
<tr>
<th>Field</th>
<th>Optimum Production Rate (MBD)</th>
<th>Potential Upper Bound MBD</th>
<th>Min. Rate Lower Bound MBD</th>
<th>Production Status</th>
<th>Reserves Size (Trillion STB)</th>
<th>Depletion Stage (% of Reserves)</th>
<th>Decline Rate (D)</th>
<th>Decline Exponent (b)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>400</td>
<td>685</td>
<td>205</td>
<td>5</td>
<td>0.55</td>
<td>0.144</td>
<td>0.13</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>358</td>
<td>493</td>
<td>148</td>
<td>3</td>
<td>0.63</td>
<td>0.180</td>
<td>0.17</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>546</td>
<td>904</td>
<td>271</td>
<td>11</td>
<td>0.25</td>
<td>0.155</td>
<td>0.26</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>951</td>
<td>767</td>
<td>230</td>
<td>6</td>
<td>0.00</td>
<td>0.258</td>
<td>0.12</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>140</td>
<td>539</td>
<td>99</td>
<td>3</td>
<td>0.85</td>
<td>0.104</td>
<td>0.23</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>483</td>
<td>822</td>
<td>247</td>
<td>6</td>
<td>0.58</td>
<td>0.142</td>
<td>0.22</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>855</td>
<td>986</td>
<td>296</td>
<td>12</td>
<td>0.16</td>
<td>0.101</td>
<td>0.26</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>740</td>
<td>986</td>
<td>296</td>
<td>18</td>
<td>0.15</td>
<td>0.075</td>
<td>0.28</td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>704</td>
<td>986</td>
<td>296</td>
<td>6</td>
<td>0.00</td>
<td>0.276</td>
<td>0.28</td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>1082</td>
<td>1205</td>
<td>363</td>
<td>18</td>
<td>0.10</td>
<td>0.059</td>
<td>0.32</td>
<td></td>
</tr>
<tr>
<td>11</td>
<td>658</td>
<td>658</td>
<td>197</td>
<td>22</td>
<td>0.55</td>
<td>0.064</td>
<td>0.33</td>
<td></td>
</tr>
<tr>
<td>12</td>
<td>877</td>
<td>877</td>
<td>263</td>
<td>16</td>
<td>0.30</td>
<td>0.058</td>
<td>0.24</td>
<td></td>
</tr>
<tr>
<td>13</td>
<td>438</td>
<td>438</td>
<td>132</td>
<td>4</td>
<td>0.54</td>
<td>0.141</td>
<td>0.29</td>
<td></td>
</tr>
<tr>
<td>14</td>
<td>986</td>
<td>1096</td>
<td>329</td>
<td>9</td>
<td>0.00</td>
<td>0.129</td>
<td>0.31</td>
<td></td>
</tr>
</tbody>
</table>

Figure 4-13. Non-Optimized Production Allocation and Plateau Length.

4.4.2. Maximize Plateau Length

The total plateau length is maximized here. From (Figure 4-12), the total plateau length increased to eight years; however, the mean total NPV dropped to $1.336 trillion. The standard deviation for mean NPV was $148 billion and the average production decline dropped from 184 to 180 MBD/year. Maximizing the plateau length resulted in the lowest standard deviation for total NPV; accelerating the production rate toward the present time reduced the uncertainty in prices. The allocation in (Figure 4-12) was not a unique solution to maximizing plateau length; other cases could result in the same total plateau length of eight years. From (Table 4-13), the optimizer allocated 44% of the
target daily rate from heavy crude fields. Heavy crude fields were relatively larger and younger than the other two types of crude fields. (Figure 4-14) shows the total production profile and cumulative production. In (Table 4-14), three of the four light crude fields were assigned at minimum rate; those fields were mature and small, and decline fast with time (small decline exponent).

Table 4-12. Production Allocation for Maximizing Total Plateau Length.

<table>
<thead>
<tr>
<th>Field</th>
<th>Production Rate (MBD)</th>
<th>Percentage of Initial Potential Used (%)</th>
<th>Plateau Length (Years)</th>
<th>Total Plateau Length (Yrs)</th>
<th>E[TOTAL NPV] ($ Million)</th>
<th>Standard Deviation of Total NPV ($million)</th>
<th>Discount Rate</th>
<th>Total Supply Commitment (MBD)</th>
<th>Average Annual Decline (MBD/Yr)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>205</td>
<td>0.00%</td>
<td>14</td>
<td>8</td>
<td>1,335,617</td>
<td>148,497</td>
<td>10%</td>
<td>9370</td>
<td>-180.13</td>
</tr>
<tr>
<td>2</td>
<td>148</td>
<td>0.00%</td>
<td>10</td>
<td>8</td>
<td>70.98%</td>
<td>14.14%</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>271</td>
<td>0.00%</td>
<td>41</td>
<td>10</td>
<td>70.98%</td>
<td>94.34%</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>1315</td>
<td>100.00%</td>
<td>10</td>
<td>8</td>
<td>100.00%</td>
<td>46.64%</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>262</td>
<td>91.17%</td>
<td>8</td>
<td>8</td>
<td>100.00%</td>
<td>21.16%</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>328</td>
<td>14.14%</td>
<td>17</td>
<td>8</td>
<td>100.00%</td>
<td>65.85%</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>925</td>
<td>91.17%</td>
<td>14</td>
<td>10</td>
<td>100.00%</td>
<td>25.56%</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>986</td>
<td>70.98%</td>
<td>41</td>
<td>11</td>
<td>100.00%</td>
<td>100.00%</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>618</td>
<td>94.34%</td>
<td>10</td>
<td>11</td>
<td>100.00%</td>
<td>100.00%</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>1205</td>
<td>46.64%</td>
<td>8</td>
<td>12</td>
<td>21.16%</td>
<td>65.85%</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>11</td>
<td>295</td>
<td>21.16%</td>
<td>15</td>
<td>13</td>
<td>25.56%</td>
<td>100.00%</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>12</td>
<td>667</td>
<td>100.00%</td>
<td>15</td>
<td>14</td>
<td>100.00%</td>
<td>100.00%</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>13</td>
<td>210</td>
<td>100.00%</td>
<td>11</td>
<td>11</td>
<td>100.00%</td>
<td>100.00%</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>14</td>
<td>986</td>
<td>100.00%</td>
<td>10</td>
<td>12</td>
<td>21.16%</td>
<td>65.85%</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 4-13. Production Allocation by Crude Type for Maximizing Total Plateau Length.

<table>
<thead>
<tr>
<th>Crude Type</th>
<th>Initial Production Rate (MBD)</th>
<th>Percentage of Total Supply Commitment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Light</td>
<td>1940</td>
<td>20.70%</td>
</tr>
<tr>
<td>Medium</td>
<td>3449</td>
<td>36.81%</td>
</tr>
<tr>
<td>Heavy</td>
<td>3981</td>
<td>42.49%</td>
</tr>
</tbody>
</table>

Figure 4-14. Production Profile and Cumulative Production for Maximizing Total Plateau Length.
Table 4-14. Production Allocation and Fields’ Properties for Maximizing Total Plateau Length.

<table>
<thead>
<tr>
<th>Field</th>
<th>Optimum Production Rate (MBD)</th>
<th>Potential Upper Bound (MBD)</th>
<th>Min. Rate Lower Bound (MBD)</th>
<th>Production Status</th>
<th>Reserves Size (Trillion STB)</th>
<th>Depletion Stage (% of Reserves)</th>
<th>Decline Rate (Di)</th>
<th>Decline Exponent (b)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>205</td>
<td>685</td>
<td>205</td>
<td>Lower_Bound</td>
<td>6</td>
<td>0.55</td>
<td>0.144</td>
<td>0.11</td>
</tr>
<tr>
<td>2</td>
<td>148</td>
<td>493</td>
<td>148</td>
<td>Lower_Bound</td>
<td>3</td>
<td>0.63</td>
<td>0.180</td>
<td>0.17</td>
</tr>
<tr>
<td>3</td>
<td>271</td>
<td>904</td>
<td>271</td>
<td>Lower_Bound</td>
<td>11</td>
<td>0.25</td>
<td>0.135</td>
<td>0.26</td>
</tr>
<tr>
<td>4</td>
<td>1311</td>
<td>767</td>
<td>230</td>
<td>Upper Bound</td>
<td>6</td>
<td>0.00</td>
<td>0.158</td>
<td>0.12</td>
</tr>
<tr>
<td>5</td>
<td>262</td>
<td>329</td>
<td>99</td>
<td>3</td>
<td>0.35</td>
<td>0.104</td>
<td>0.23</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>328</td>
<td>823</td>
<td>297</td>
<td>6</td>
<td>0.58</td>
<td>0.142</td>
<td>0.22</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>925</td>
<td>986</td>
<td>296</td>
<td>12</td>
<td>0.16</td>
<td>0.101</td>
<td>0.26</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>986</td>
<td>986</td>
<td>296</td>
<td>Upper Bound</td>
<td>10</td>
<td>0.15</td>
<td>0.075</td>
<td>0.28</td>
</tr>
<tr>
<td>9</td>
<td>947</td>
<td>986</td>
<td>296</td>
<td>6</td>
<td>0.00</td>
<td>0.276</td>
<td>0.28</td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>618</td>
<td>986</td>
<td>296</td>
<td>18</td>
<td>0.10</td>
<td>0.10</td>
<td>0.276</td>
<td></td>
</tr>
<tr>
<td>11</td>
<td>1305</td>
<td>1205</td>
<td>362</td>
<td>Upper Bound</td>
<td>22</td>
<td>0.35</td>
<td>0.064</td>
<td>0.33</td>
</tr>
<tr>
<td>12</td>
<td>295</td>
<td>618</td>
<td>197</td>
<td>8</td>
<td>0.54</td>
<td>0.064</td>
<td>0.26</td>
<td></td>
</tr>
<tr>
<td>13</td>
<td>692</td>
<td>877</td>
<td>655</td>
<td>16</td>
<td>0.30</td>
<td>0.058</td>
<td>0.24</td>
<td></td>
</tr>
</tbody>
</table>

Figure 4-15. Production Allocation and Plateau Length for Maximizing Total Plateau Length.

4.4.3. Maximize Mean NPV

(Table 4-15) shows the production rate allocation that maximizes the mean total NPV. Unlike the results for capacity management in chapter one, maximizing the mean total NPV does not maximize the plateau length. The resulting mean total NPV was $1.616 trillion, the standard deviation for the total NPV was $184 billion, and the plateau length was 1 year as shown in the table. (Table 4-16) shows the production allocation by crude type—16.49% for light crude, 28.54% for medium crude, and 54.97% for heavy crude. (Figure 4-16) shows the total production profile and cumulative production for the
whole portfolio. Using the figure, the optimizer finds the production allocation that minimizes the production decline for the first 16 years. In the case of maximizing plateau length, the optimizer maximizes the plateau length for eight years; then, the production profile drops at a relatively high rate as shown in (Figure 4-14). From (Table 4-17), the algorithm tends to prioritize the fields with larger decline exponent $b$. Large production rates were assigned to fields with larger $b$ values. The $b$ values are the rates at which the annual decline rate changes—the larger the $b$, the smoother the decline. Moreover, the algorithm prioritized the heavy fields over the lighter crude fields; this could be due to the fact that heavy crude fields were larger and younger than lighter fields. In other words, heavy crude fields have more energy and reserves stored. Heavy crude fields decline at lower rates and have larger reserves. (Figure 4-17) shows the production rate and plateau length for each field.

Table 4-15. Production Allocation for Maximizing Mean Total NPV.

<table>
<thead>
<tr>
<th>Field</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
<th>12</th>
<th>13</th>
</tr>
</thead>
<tbody>
<tr>
<td>Production Rate (MBD)</td>
<td>205</td>
<td>148</td>
<td>797</td>
<td>395</td>
<td>182</td>
<td>247</td>
<td>963</td>
<td>986</td>
<td>296</td>
<td>986</td>
<td>1205</td>
<td>658</td>
<td>877</td>
</tr>
<tr>
<td>Percentage of Initial Potential Used (%)</td>
<td>0.00%</td>
<td>0.00%</td>
<td>83.13%</td>
<td>0.00%</td>
<td>36.11%</td>
<td>0.00%</td>
<td>96.68%</td>
<td>100.00%</td>
<td>0.00%</td>
<td>100.00%</td>
<td>100.00%</td>
<td>100.00%</td>
<td>100.00%</td>
</tr>
<tr>
<td>Plateau Length (Years)</td>
<td>14</td>
<td>8</td>
<td>19</td>
<td>33</td>
<td>10</td>
<td>17</td>
<td>25</td>
<td>41</td>
<td>21</td>
<td>10</td>
<td>1</td>
<td>14</td>
<td>3</td>
</tr>
<tr>
<td>Total Plateau Length (Yrs)</td>
<td>14</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>E[TOTAL NPV] ($ Million)</td>
<td>1,615,602</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Standard Deviation of Total NPV ($ million)</td>
<td>183,559</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
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<td></td>
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<tr>
<td>Discount Rate</td>
<td>10%</td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total Supply Commitment (MBD)</td>
<td>936986%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average Annual Decline (MBD/Yr)</td>
<td>-182.16</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
</tr>
</tbody>
</table>

Table 4-16. Production Allocation by Crude Type for Maximizing Mean Total NPV.

<table>
<thead>
<tr>
<th>Crude Type</th>
<th>Initial Production Rate (MBD)</th>
<th>Percentage of Total Supply Commitment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Light</td>
<td>1545</td>
<td>16.49%</td>
</tr>
<tr>
<td>Medium</td>
<td>2674</td>
<td>28.54%</td>
</tr>
<tr>
<td>Heavy</td>
<td>5151</td>
<td>54.97%</td>
</tr>
</tbody>
</table>
Figure 4-16. Production Profile and Cumulative Production for Maximizing Mean Total NPV.

Table 4-17. Production Allocation and Fields’ Properties for Maximizing Mean Total NPV.

<table>
<thead>
<tr>
<th>Field</th>
<th>Optimum Production Rate (MBD)</th>
<th>Potential Upper Bound MBD</th>
<th>Min. Rate Lower Bound MBD</th>
<th>Production Status</th>
<th>Reserves Size (Trillion STB)</th>
<th>Depletion Stage (% of Reserves)</th>
<th>Decline Rate (Di)</th>
<th>Decline Exponent (b)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>205</td>
<td>685</td>
<td>205</td>
<td>Lower_Bound</td>
<td>5</td>
<td>0.55</td>
<td>0.146</td>
<td>0.13</td>
</tr>
<tr>
<td>2</td>
<td>148</td>
<td>493</td>
<td>146</td>
<td>Lower_Bound</td>
<td>3</td>
<td>0.63</td>
<td>0.180</td>
<td>0.17</td>
</tr>
<tr>
<td>3</td>
<td>797</td>
<td>904</td>
<td>711</td>
<td>Lower_Bound</td>
<td>11</td>
<td>0.25</td>
<td>0.135</td>
<td>0.26</td>
</tr>
<tr>
<td>4</td>
<td>365</td>
<td>767</td>
<td>210</td>
<td>Lower_Bound</td>
<td>6</td>
<td>0.00</td>
<td>0.258</td>
<td>0.12</td>
</tr>
<tr>
<td>5</td>
<td>182</td>
<td>229</td>
<td>99</td>
<td>Lower_Bound</td>
<td>3</td>
<td>0.35</td>
<td>0.104</td>
<td>0.23</td>
</tr>
<tr>
<td>6</td>
<td>247</td>
<td>822</td>
<td>247</td>
<td>Lower_Bound</td>
<td>6</td>
<td>0.58</td>
<td>0.142</td>
<td>0.22</td>
</tr>
<tr>
<td>7</td>
<td>966</td>
<td>986</td>
<td>296</td>
<td>Upper_Bound</td>
<td>12</td>
<td>0.16</td>
<td>0.101</td>
<td>0.26</td>
</tr>
<tr>
<td>8</td>
<td>296</td>
<td>986</td>
<td>296</td>
<td>Lower_Bound</td>
<td>6</td>
<td>0.15</td>
<td>0.075</td>
<td>0.28</td>
</tr>
<tr>
<td>9</td>
<td>966</td>
<td>986</td>
<td>296</td>
<td>Upper_Bound</td>
<td>12</td>
<td>0.10</td>
<td>0.059</td>
<td>0.32</td>
</tr>
<tr>
<td>10</td>
<td>1205</td>
<td>1205</td>
<td>162</td>
<td>Upper_Bound</td>
<td>22</td>
<td>0.35</td>
<td>0.064</td>
<td>0.33</td>
</tr>
<tr>
<td>11</td>
<td>658</td>
<td>658</td>
<td>197</td>
<td>Upper_Bound</td>
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<td>0.54</td>
<td>0.084</td>
<td>0.26</td>
</tr>
<tr>
<td>12</td>
<td>438</td>
<td>438</td>
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<td>Upper_Bound</td>
<td>4</td>
<td>0.54</td>
<td>0.141</td>
<td>0.29</td>
</tr>
<tr>
<td>13</td>
<td>996</td>
<td>1096</td>
<td>329</td>
<td>Upper_Bound</td>
<td>9</td>
<td>0.00</td>
<td>0.129</td>
<td>0.31</td>
</tr>
</tbody>
</table>

Figure 4-17. Production Allocation and Plateau Length for Maximizing Mean Total NPV.
4.4.4. Maximize Plateau Length and Mean NPV

(Table 4-18) shows the production rate allocation that maximized plateau length and mean total NPV. The resulted mean and standard deviation for total NPV and plateau length were $1.543 trillion, $171 billion, and 8 years, respectively. Both the mean total NPV and total plateau length were greater than the ones from the non-optimized case. (Table 4-19) shows the production allocation by crude type; light crude fields accounted for 25.5%, medium crude fields accounted for 33.86%, and heavy crude fields accounted for 40.64%. (Figure 4-18) shows the production profile and cumulative production for the portfolio of fields. According to (Table 4-20), the optimal production allocation was a function of reserves size, depletion stage, and variable OPEX. The optimizer assigned a large production rate to fields with large reserves, young fields, and small variable OPEX. However, the optimizer’s process, when those three parameters vary at the same time, was not clear. When optimizing mean NPV and plateau length, the production rate was assigned first to the fields with least capacity decline per unit produced or to the fields with the largest reserves that were young. (Figure 4-19) shows the production profile and cumulative production for the portfolio of fields.

Table 4-18. Production Allocation for Maximizing Mean Total NPV and Total Plateau Length.

<table>
<thead>
<tr>
<th>Field</th>
<th>Production Rate (MBD)</th>
<th>Percentage of Initial Potential Used (%)</th>
<th>Total Plateau Length (Yrs)</th>
<th>Total Supply Commitment (MBD)</th>
<th>Average Annual Decline (MBD/Yr)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>205</td>
<td>0.00%</td>
<td>14</td>
<td>9370</td>
<td>-186.14</td>
</tr>
<tr>
<td>2</td>
<td>148</td>
<td>0.00%</td>
<td>8</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>721</td>
<td>71.11%</td>
<td>21</td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>1315</td>
<td>100.00%</td>
<td>10</td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>256</td>
<td>68.24%</td>
<td>8</td>
<td></td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>319</td>
<td>12.64%</td>
<td>8</td>
<td></td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>870</td>
<td>12.64%</td>
<td>8</td>
<td></td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>986</td>
<td>83.22%</td>
<td>19</td>
<td></td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>741</td>
<td>100.00%</td>
<td>25</td>
<td></td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>986</td>
<td>64.43%</td>
<td>10</td>
<td></td>
<td></td>
</tr>
<tr>
<td>11</td>
<td>1205</td>
<td>100.00%</td>
<td>14</td>
<td></td>
<td></td>
</tr>
<tr>
<td>12</td>
<td>238</td>
<td>8.89%</td>
<td>14</td>
<td></td>
<td></td>
</tr>
<tr>
<td>13</td>
<td>877</td>
<td>100.00%</td>
<td>11</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>205</td>
<td>100.00%</td>
<td>14</td>
<td></td>
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</tr>
<tr>
<td></td>
<td>296</td>
<td>23.96%</td>
<td>41</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Table 4-19. Production Allocation by Crude Type for Maximizing Mean Total NPV and Total Plateau Length.

<table>
<thead>
<tr>
<th>Crude Type</th>
<th>Initial Production Rate (MBD)</th>
<th>Percentage of Total Supply Commitment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Light</td>
<td>2390</td>
<td>25.50%</td>
</tr>
<tr>
<td>Medium</td>
<td>3173</td>
<td>33.86%</td>
</tr>
<tr>
<td>Heavy</td>
<td>3808</td>
<td>40.64%</td>
</tr>
</tbody>
</table>

Figure 4-18. Production Profile and Cumulative Production for Maximizing Mean Total NPV and Total Plateau Length.

Table 4-20. Production Allocation and Fields’ Properties for Maximizing Mean Total NPV and Total Plateau Length.

<table>
<thead>
<tr>
<th>Field</th>
<th>Optimum Production Rate (MBD)</th>
<th>Potential Upper Bound MBD</th>
<th>Min. Rate Lower Bound MBD</th>
<th>Production Status</th>
<th>Reserves Size (Trillion STB)</th>
<th>Depletion Stage (% of Reserves)</th>
<th>Decline Rate (%)</th>
<th>Decline Exponent (b)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>205</td>
<td>665</td>
<td>205</td>
<td>Lower_Bound</td>
<td>5</td>
<td>0.55</td>
<td>0.134</td>
<td>0.135</td>
</tr>
<tr>
<td>2</td>
<td>148</td>
<td>493</td>
<td>146</td>
<td>Lower_Bound</td>
<td>3</td>
<td>0.63</td>
<td>0.180</td>
<td>0.175</td>
</tr>
<tr>
<td>3</td>
<td>221</td>
<td>504</td>
<td>271</td>
<td>Lower_Bound</td>
<td>11</td>
<td>0.25</td>
<td>0.135</td>
<td>0.26</td>
</tr>
<tr>
<td>11</td>
<td>1335</td>
<td>767</td>
<td>230</td>
<td>Upper_Bound</td>
<td>6</td>
<td>0.00</td>
<td>0.258</td>
<td>0.12</td>
</tr>
<tr>
<td>4</td>
<td>256</td>
<td>529</td>
<td>99</td>
<td>3</td>
<td>0.15</td>
<td>0.194</td>
<td>0.11</td>
<td>0.18</td>
</tr>
<tr>
<td>5</td>
<td>319</td>
<td>832</td>
<td>247</td>
<td>6</td>
<td>0.58</td>
<td>0.142</td>
<td>0.22</td>
<td>0.23</td>
</tr>
<tr>
<td>6</td>
<td>879</td>
<td>986</td>
<td>296</td>
<td>12</td>
<td>0.16</td>
<td>0.101</td>
<td>0.26</td>
<td>0.22</td>
</tr>
<tr>
<td>7</td>
<td>866</td>
<td>986</td>
<td>296</td>
<td>18</td>
<td>0.15</td>
<td>0.075</td>
<td>0.28</td>
<td>0.28</td>
</tr>
<tr>
<td>12</td>
<td>741</td>
<td>986</td>
<td>296</td>
<td>6</td>
<td>0.00</td>
<td>0.176</td>
<td>0.28</td>
<td>0.28</td>
</tr>
<tr>
<td>8</td>
<td>986</td>
<td>986</td>
<td>296</td>
<td>18</td>
<td>0.10</td>
<td>0.059</td>
<td>0.32</td>
<td>0.32</td>
</tr>
<tr>
<td>9</td>
<td>1305</td>
<td>1205</td>
<td>362</td>
<td>Upper_Bound</td>
<td>22</td>
<td>0.35</td>
<td>0.064</td>
<td>0.33</td>
</tr>
<tr>
<td>10</td>
<td>239</td>
<td>658</td>
<td>197</td>
<td>8</td>
<td>0.54</td>
<td>0.064</td>
<td>0.26</td>
<td>0.26</td>
</tr>
<tr>
<td>11</td>
<td>877</td>
<td>877</td>
<td>263</td>
<td>Upper_Bound</td>
<td>16</td>
<td>0.30</td>
<td>0.058</td>
<td>0.24</td>
</tr>
<tr>
<td>12</td>
<td>205</td>
<td>438</td>
<td>132</td>
<td>4</td>
<td>0.54</td>
<td>0.141</td>
<td>0.29</td>
<td>0.29</td>
</tr>
<tr>
<td>13</td>
<td>296</td>
<td>1096</td>
<td>329</td>
<td>9</td>
<td>0.00</td>
<td>0.129</td>
<td>0.31</td>
<td>0.31</td>
</tr>
</tbody>
</table>
4.4.5. Maximize Plateau Length and Minimize Production Decline

(Table 4-21) shows the production allocation for maximizing plateau length and minimizing average production decline rate. The plateau length was eight years, the mean total NPV was $1.327 trillion, and the standard deviation was $147 billion. (Table 4-22) shows the production allocation by crude type; light crude fields accounted for 22.19% of the total rate, medium crude fields accounted for 28%, and heavy crude fields accounted for 49.70%. (Figure 4-20) shows the production profile and cumulative production for the portfolio of fields. According to (Table 4-23), age of the field was the parameter that had the greatest impact on the optimal allocation decision when maximizing plateau length and minimizing average production decline. However, reserve size and decline exponent can impact the allocation as well. First, the algorithm allocates the fields at the lowest depletion stage with maximum capacity; then, the fields with very large reserves and at a relatively large depletion (mature field) stage were preferred over those at a very low
depletion stage and with small reserves. (Figure 4-21) shows the production rate and cumulative production for each field.

Table 4-21. Production Allocation for Maximizing Total Plateau Length and Minimizing Average Production Decline.

<table>
<thead>
<tr>
<th>Field</th>
<th>Production Rate (MBD)</th>
<th>Percentage of Initial Potential Used (%)</th>
<th>Plateau Length (Years)</th>
<th>E[TOTAL NPV] ($ Million)</th>
<th>Standard Deviation of Total NPV ($Million)</th>
<th>Discount Rate</th>
<th>Total Supply Commitment (MBD)</th>
<th>Average Annual Decline (MBD/Yr)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Field 1</td>
<td>205</td>
<td>0.00%</td>
<td>14</td>
<td>1,326,653</td>
<td>147,155</td>
<td>10%</td>
<td>9,370</td>
<td>-167.22</td>
</tr>
<tr>
<td>Field 2</td>
<td>148</td>
<td>0.00%</td>
<td>8</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Field 3</td>
<td>411</td>
<td>22.08%</td>
<td>41</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Field 4</td>
<td>1315</td>
<td>100.00%</td>
<td>10</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Field 5</td>
<td>325</td>
<td>13.66%</td>
<td>16</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Field 6</td>
<td>467</td>
<td>24.73%</td>
<td>8</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Field 7</td>
<td>693</td>
<td>57.47%</td>
<td>16</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Field 8</td>
<td>988</td>
<td>100.00%</td>
<td>41</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Field 9</td>
<td>986</td>
<td>100.00%</td>
<td>10</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Field 10</td>
<td>1205</td>
<td>100.00%</td>
<td>14</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Field 11</td>
<td>344</td>
<td>31.95%</td>
<td>8</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Field 12</td>
<td>877</td>
<td>100.00%</td>
<td>15</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Field 13</td>
<td>258</td>
<td>100.00%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Field 14</td>
<td>988</td>
<td>100.00%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 4-22. Production Allocation by Crude Type for Maximizing Total Plateau Length and Minimizing Average Production Decline.

<table>
<thead>
<tr>
<th>Crude Type</th>
<th>Initial Production Rate (MBD)</th>
<th>Percentage of Total Supply Commitment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Light</td>
<td>2079</td>
<td>22.19%</td>
</tr>
<tr>
<td>Medium</td>
<td>2633</td>
<td>28.11%</td>
</tr>
<tr>
<td>Heavy</td>
<td>4657</td>
<td>49.70%</td>
</tr>
</tbody>
</table>

Figure 4-20. Production Profile and Cumulative Production for Maximizing Total Plateau Length and Minimizing Average Production Decline.
Table 4-23. Production Allocation and Fields’ Properties for Maximizing Total Plateau Length and Minimizing Average Production Decline.

<table>
<thead>
<tr>
<th>Field</th>
<th>Optimum Production Rate (MBD)</th>
<th>Potential Upper Bound MBD</th>
<th>Min. Rate Lower Bound MBD</th>
<th>Production Status</th>
<th>Reserves Size (Trillion STB)</th>
<th>Depletion Stage (% of Reserves)</th>
<th>Decline Rate (Di)</th>
<th>Decline Exponent (b)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>205</td>
<td>685</td>
<td>205</td>
<td>Lower Bound</td>
<td>5</td>
<td>0.55</td>
<td>0.144</td>
<td>0.13</td>
</tr>
<tr>
<td>2</td>
<td>148</td>
<td>493</td>
<td>148</td>
<td>Lower Bound</td>
<td>3</td>
<td>0.63</td>
<td>0.180</td>
<td>0.17</td>
</tr>
<tr>
<td>3</td>
<td>421</td>
<td>504</td>
<td>271</td>
<td>Lower Bound</td>
<td>11</td>
<td>0.15</td>
<td>0.135</td>
<td>0.26</td>
</tr>
<tr>
<td>4</td>
<td>1335</td>
<td>767</td>
<td>230</td>
<td>Upper Bound</td>
<td>6</td>
<td>0.00</td>
<td>0.258</td>
<td>0.12</td>
</tr>
<tr>
<td>5</td>
<td>325</td>
<td>329</td>
<td>99</td>
<td>Upper Bound</td>
<td>3</td>
<td>0.15</td>
<td>0.104</td>
<td>0.23</td>
</tr>
<tr>
<td>6</td>
<td>467</td>
<td>596</td>
<td>296</td>
<td>Upper Bound</td>
<td>6</td>
<td>0.58</td>
<td>0.162</td>
<td>0.22</td>
</tr>
<tr>
<td>7</td>
<td>493</td>
<td>596</td>
<td>296</td>
<td>Upper Bound</td>
<td>6</td>
<td>0.16</td>
<td>0.101</td>
<td>0.26</td>
</tr>
<tr>
<td>8</td>
<td>596</td>
<td>596</td>
<td>296</td>
<td>Upper Bound</td>
<td>6</td>
<td>0.15</td>
<td>0.075</td>
<td>0.28</td>
</tr>
<tr>
<td>9</td>
<td>1205</td>
<td>1205</td>
<td>362</td>
<td>Upper Bound</td>
<td>22</td>
<td>0.15</td>
<td>0.064</td>
<td>0.33</td>
</tr>
<tr>
<td>10</td>
<td>344</td>
<td>658</td>
<td>197</td>
<td>Upper Bound</td>
<td>8</td>
<td>0.54</td>
<td>0.068</td>
<td>0.26</td>
</tr>
<tr>
<td>11</td>
<td>877</td>
<td>877</td>
<td>263</td>
<td>Upper Bound</td>
<td>16</td>
<td>0.30</td>
<td>0.058</td>
<td>0.24</td>
</tr>
<tr>
<td>12</td>
<td>758</td>
<td>438</td>
<td>132</td>
<td>Upper Bound</td>
<td>4</td>
<td>0.14</td>
<td>0.141</td>
<td>0.18</td>
</tr>
<tr>
<td>13</td>
<td>986</td>
<td>1026</td>
<td>329</td>
<td>Upper Bound</td>
<td>9</td>
<td>0.00</td>
<td>0.129</td>
<td>0.31</td>
</tr>
</tbody>
</table>

Figure 4-21. Production Allocation and Plateau Length for Maximizing Total Plateau Length and Minimizing Average Production Decline.

4.4.6. Summary

(Table 4-24) summarizes the results of cases discussed earlier: non-optimized, maximize mean NPV, maximize plateau length, maximize plateau length and minimize average production decline, and maximize mean NPV and plateau length. The highlighted values represent the optimal values among the other cases. Maximizing the mean NPV resulted in a maximum mean NPV of $1,615,602. Maximizing plateau length and maximizing plateau length and minimizing production decline resulted in the least standard deviation of the NPV—$147,155,000. The best plateau length of eight years
resulted from maximizing plateau length, maximizing plateau length & minimizing production decline, and maximizing plateau length and mean NPV. The lowest average production decline resulted from maximizing plateau length and minimizing production decline with average production decline of 167.22 MBD/year.

When maximizing mean total NPV, 55% of the total rate was allocated from heavy crude fields. The optimizer allocated more production from the heavy crude to minimize the decline rate for the first fifteen years; this was because the heavy crude fields possess relatively large reserves, young fields, and have large decline exponents’ b.

Table 4-24. Summary of Results.

<table>
<thead>
<tr>
<th></th>
<th>Mean NPV $million</th>
<th>S.D. of NPV $million</th>
<th>P.L. Yrs</th>
<th>Average Prod. Decline MBD/Year</th>
<th>Light Field Portion of Production</th>
<th>Medium Field Portion of Production</th>
<th>Heavy Field Portion of Production</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial Non-Optimized Case</td>
<td>1,542,903</td>
<td>175214</td>
<td>1</td>
<td>183.92</td>
<td>24%</td>
<td>25%</td>
<td>51%</td>
</tr>
<tr>
<td>Max NPV</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td><strong>1,615,602</strong></td>
<td>183559</td>
<td>1</td>
<td>182.16</td>
<td>16%</td>
<td>29%</td>
<td>55%</td>
</tr>
<tr>
<td>Max PL</td>
<td>1,335,617</td>
<td><strong>148497</strong></td>
<td><strong>8</strong></td>
<td>180.13</td>
<td>21%</td>
<td>37%</td>
<td>42%</td>
</tr>
<tr>
<td>Max PL Min Dec</td>
<td>1,326,653</td>
<td><strong>147155</strong></td>
<td><strong>8</strong></td>
<td><strong>167.22</strong></td>
<td>22%</td>
<td>28%</td>
<td>50%</td>
</tr>
<tr>
<td>Max PL &amp; Mean NPV</td>
<td>1,542,762</td>
<td>170963</td>
<td><strong>8</strong></td>
<td>186.14</td>
<td>26%</td>
<td>34%</td>
<td>41%</td>
</tr>
</tbody>
</table>

An advantage of extending the total plateau length is delaying the development cost of incremental fields required to maintain the total daily target rate. With the time value of money (discounting), this delay can result in significant savings. For example, extending plateau length from one year to eight years can save around $3.3 billion in total NPV, assuming the development field costs 6$ billion over two years ($3 billion each year) at a discount rate of 10%.

(Figure 4-22) shows an optimization sensitivity analysis for the discount rate. The optimizer solves for the optimal decision (maximizing mean NPV) while varying the discount rate between 5% and 50%. According to the figure, the impact of the discount
rate on the optimal decision was minimal. However, the mean NPV for the optimal decision declines as the discount rate increases (Figure 4-23).

Figure 4-22. Impact of Discount Rate on Optimal Decisions.

Figure 4-23. Impact of Discount Rate on Mean NPV.

Solving for the global optimal was a challenge for our optimization problem since the objective function was a nonlinear function of the decision variables. The Genetic Algorithm is a powerful optimization algorithm that can search many areas of the feasible solution at the same time. To increase the chances of finding the global optimal, multi-start points were performed on optimization runs.
4.5. Conclusions and Recommendations for Future Work

4.5.1. Conclusions

This study incorporated capacity management and spare capacity studies. New capacity management integrated models were developed for crude oil that incorporated development fields. The study tackled a dynamic optimization problem that allocated production rates for a portfolio of fields to maximize plateau length and/ or mean total NPV. The optimization problem was further complicated with the following constraints: 1) The field production rate must be greater than or equal to the minimum facility operating rate, 2) The field production rate must be less than or equal to field’s potential, and 3) The spare capacity value recommended by spare capacity study must be maintained. Three fields were developed with a total capacity equal to the required spare capacity. The impact of price and reservoir model assumptions on the optimal allocation decisions was analyzed. Optimal allocation decision is a function of reservoir size and age, and reservoir properties. To maximize portfolio plateau length, young fields with large decline exponents should be prioritized. To maximize total NPV, fields with large decline exponent should be prioritized first; then, fields with large reserves. However, when maximizing both total plateau length and NPV, production from large reservoirs should be prioritized first, then, from young fields with large decline exponents. Below are concluding remarks:

1. The optimal allocation decision that maximized mean NPV or plateau length was a function of reservoir size, age, and properties. Reservoir properties were represented by decline rate Di and decline exponent b.
2. Incorporating oil fields and development fields in the capacity management study changed the behavior of the results. In this study, maximizing mean total NPV did not maximize plateau length. This discrepancy can result from incorporating development fields, the different behaviors of oil fields in comparison to gas fields, or local minima.

3. In maximizing mean total NPV, the optimizer minimized the production decline rate over the first fifteen years. However, in maximizing plateau length and mean NPV, the optimizer minimized the production decline after the eight years of plateau.

4. Extending plateau length can delay development projects required to offset the decline in production. This delay can save billions of dollars in NPV.

5. Extending plateau length added to the reserves with respect to time.

4.5.2. Recommendations for Future Research

1. Construct an expert system that predicts an optimal decision as a function of reservoir and price parameters.

2. Analyze the discrepancy in results between capacity management of gas and oil fields. Possible reasons for the discrepancies identified in this study were the development field or the different behaviors of oil and gas reservoirs.
Appendix A

The Codes for the Expert Systems in Chapter 2

Generating Training Dataset

clear
clc
% load Dy.mat
format long
q = [9000000; 36000000]; % Range of Flow Rates SCFD. gas wells varies between 10 and 30 MMscf/d in reality
Dx = [1300;3300]; % Range of Delta x and y FT.
A = Dx.^2; % Drainage Area in ft.
h = [25;400]; % layer thickness in ft
PHI = [0.08;0.2]; % Reservoir Porosity
k = [8;100]; % Permeability in md
Pi = [2000;5000]; % Initial Reservoir Pressure
num = 20; % number of cases
rand(num,1);

%Creating training dataset using Latin Hyper Cube sampling method
Input_Pred(:,1) = round(A(1) + (A(2)-A(1))*lhsdesign(num,1)); % Drainage Area.
Input_Pred(:,2) = round(q(1) + (q(2)-q(1))*lhsdesign(num,1)); % Plateau Flow Rate
Input_Pred(:,3) = round(h(1) + (h(2)-h(1))*lhsdesign(num,1)); % Thickness of a layer
Input_Pred(:,4) = (PHI(1) + (PHI(2)-PHI(1))*lhsdesign(num,1)); % Porosity
Input_Pred(:,5) = round(k(1) + (k(2)-k(1))*lhsdesign(num,1)); % Permeability in md
Input_Pred(:,6) = round(Pi(1) + (Pi(2)-Pi(1))*lhsdesign(num,1)); % Initial Pressure in psi

% Creating input data for CMG to generate production profiles.
RF(:,1) = Input_Pred(:,2); % Plateau Flow Rate
RF(:,2) = Input_Pred(:,1).^(1/2); % Drainage Area in delta x.
RF(:,3) = Input_Pred(:,3); % Thickness of a layer
RF(:,4) = Input_Pred(:,4); % Porosity
RF(:,5) = Input_Pred(:,5); % Permeability in md
RF(:,6) = Input_Pred(:,6); % Initial Pressure in psi

Input_Pred = Input_Pred';
Preventing Simulation File for Different Combination of Training data

clear all
clc
load RF.mat % Loading the training dataset
nam2 = 'Decline.bat';
fidbatch = fopen(nam2,'w');

% Generate .dat simulation file for different combination of training data
for i=1:size(RF,1) % Looping over cases
    RefDepth(i,1)=RF(i,3)+10000;
    nam = [ 'Dec' num2str(i) ' .dat' ];
    fid = fopen(nam,'w');
    fprintf(fid,'RESULTS SIMULATOR IMEX 201110
');
    fprintf(fid,'
');
    fprintf(fid,'INUNIT FIELD
');
    fprintf(fid,'WSRF WELL 1
');
    fprintf(fid,'WSRF GRID TIME
');
    fprintf(fid,'WSRF SECTOR TIME
');
    fprintf(fid,'OUTSRF WELL LAYER NONE
');
    fprintf(fid,'OUTSRF RES ALL
');
    fprintf(fid,'OUTSRF GRID SO SG SW PRES OILPOT BPP SSPRES WINFLUX
');
    fprintf(fid,'WPRN GRID 0
');
    fprintf(fid,'OUTPRN GRID NONE
');
    fprintf(fid,'OUTPRN RES NONE
');
    fprintf(fid,'**$ Distance units: ft \n');
    fprintf(fid,'RESULTS XOFFSET 0.0000
');
    fprintf(fid,'RESULTS YOFFSET 0.0000
');
    fprintf(fid,'RESULTS ROTATION 0.0000 **$ (DEGREES)
');
    fprintf(fid,'RESULTS AXES-DIRECTIONS 1.0 -1.0 1.0.0
');
    fprintf(fid,'**$ ****************************************************
');
    fprintf(fid,'**$ Definition of fundamental cartesian grid
');
    fprintf(fid,'**$ GRID VARI 1 1 2
');
    fprintf(fid,'KDIR DOWN
');
    fprintf(fid,'DI IVAR \n');
    fprintf(fid,' %d \n', RF(i,2));

fprintf(fid,'DJ JVARM \n');
fprintf(fid,' %d\n', RF(i,2));
fprintf(fid,'DK ALL\n');
fprintf(fid,' %d\n', RF(i,3));
fprintf(fid,'DTRP\n');
fprintf(fid,' 10000\n');
fprintf(fid,'**$ Property: NULL Blocks Max: 1 Min: 1\n');
fprintf(fid,'**$  0 = null block, 1 = active block\n');
fprintf(fid,'NULL CON\n');
fprintf(fid,'**$ Property: Porosity Max: %d Min: %d\n', RF(i,4), RF(i,4));
fprintf(fid,'POR CON %d\n', RF(i,4));
fprintf(fid,'**$ Property: Permeability I (md) Max: %d Min: %d\n', RF(i,5), RF(i,5));
fprintf(fid,'PERMI CON %d\n', RF(i,5));
fprintf(fid,'**$ Property: Permeability J (md) Max: %d Min: %d\n', RF(i,5), RF(i,5));
fprintf(fid,'PERMJ CON %d\n', RF(i,5));
fprintf(fid,'**$ Property: Permeability K (md) Max: %d Min: %d\n', RF(i,5), RF(i,5));
fprintf(fid,'PERMK CON %d\n', RF(i,5));
fprintf(fid,'**$ Property: Pinchout Array Max: 1 Min: 1\n');
fprintf(fid,'**$  0 = pinched block, 1 = active block\n');
fprintf(fid,'PINCHOUTARRAY CON %d\n', RF(i,4));
fprintf(fid,'CPOR 0.000001\n');
fprintf(fid,'MODEL GASWATER\n');
fprintf(fid,'TRES 150\n');
fprintf(fid,'**$ p Eg visg\n');
fprintf(fid,' 14.696  8.1152  0.0117959\n');
fprintf(fid,' 347.05  199.03  0.0122183\n');
fprintf(fid,' 679.403  244.135  0.0128884\n');
fprintf(fid,' 1011.76  380.147  0.0137868\n');
fprintf(fid,' 1344.11  524.135  0.0149293\n');
fprintf(fid,' 1676.46  675.483  0.0163175\n');
fprintf(fid,' 2008.82  824.472  0.0179208\n');
fprintf(fid,' 2341.17  966.242  0.0196788\n');
fprintf(fid,' 2673.52 1096.272  0.0215212\n');
fprintf(fid,' 3005.88 1214.272  0.0233868\n');
fprintf(fid,' 3338.23 1411.242  0.0252308\n');
fprintf(fid,' 3670.59 1567.3  0.0270245\n');
fprintf(fid,' 4002.94 1714.3  0.0287521\n');
fprintf(fid,' 4335.29 1861.49  0.0304066\n');
fprintf(fid,' 4667.65 2008.68  0.0319872\n');
fprintf(fid,' 5000  2161.92  0.033496\n');
fprintf(fid,'DENSITY GAS 5.802166e-002\n');
fprintf(fid,'DENSITY WATER 61.6381\n');
fprintf(fid,'BWI 1.01944\n');
fprintf(fid,'CW 3.1589e-006\n');
fprintf(fid,'VWI 0.47184\n');
fprintf(fid,'CVW 0.0\n');
fprintf(fid,'ROCKFLUID\n');
fprintf(fid,'RPT 1\n');
fprintf(fid,'**$ Sw   krw
');
fprintf(fid,'SWT
');
fprintf(fid,'               0.15  0
');
fprintf(fid,'           0.203125  1.52588e-005
');
fprintf(fid,'            0.25625   0.000244141
');
fprintf(fid,'           0.309375    0.00123596
');
fprintf(fid,'             0.3625    0.00390625
');
fprintf(fid,'           0.415625    0.00953674
');
fprintf(fid,'            0.46875     0.0197754
');
fprintf(fid,'           0.521875     0.0366364
');
fprintf(fid,'              0.575        0.0625
');
fprintf(fid,'           0.628125      0.100113
');
fprintf(fid,'           0.734375      0.223404
');
fprintf(fid,'             0.7875      0.316406
');
fprintf(fid,'           0.840625      0.435806
');
fprintf(fid,'            0.89375      0.586182
');
fprintf(fid,'           0.946875      0.772476
');
fprintf(fid,'                  1             1
');
fprintf(fid,'**$ Sl   krg
');
fprintf(fid,'SLT
');
fprintf(fid,'               0.15        0.85
');
fprintf(fid,'           0.196875    0.656605
');
fprintf(fid,'            0.24375    0.498254
');
fprintf(fid,'           0.290625    0.370435
');
fprintf(fid,'             0.3375    0.268945
');
fprintf(fid,'           0.384375    0.189893
');
fprintf(fid,'            0.43125      0.1297
');
fprintf(fid,'           0.478125      0.085096
');
fprintf(fid,'            0.525      0.053125
');
fprintf(fid,'           0.571875  0.0311409
');
fprintf(fid,'            0.61875  0.0168091
');
fprintf(fid,'           0.665625  0.00810623
');
fprintf(fid,'            0.7125  0.00332031
');
fprintf(fid,'           0.759375  0.00105057
');
fprintf(fid,'            0.80625  0.00020752
');
fprintf(fid,'           0.853125  1.297e-005
');
fprintf(fid,'                0.9           0
');
fprintf(fid,'              0.925           0
');
fprintf(fid,'               0.95           0
');
fprintf(fid,'INITIAL
');
fprintf(fid,'VERTICAL DEPTH_AVE WATER_GAS EQUIL NOTRANZONE
');
fprintf(fid,'REFDEPTH %d
', RefDepth(i,1));
fprintf(fid,'REFPRES %d
', RF(i,6));
fprintf(fid,'DWGC 12000
');
fprintf(fid,'DATUMDEPTH %d INITIAL
', RefDepth(i,1));
fprintf(fid,'NUMERICAL
');
fprintf(fid,'RUN
');
fprintf(fid,'DATE 2013 1 1
');
fprintf(fid,'GROUP ''Prod'' ATTACHTO ''Group-1''
');
fprintf(fid,'**$\n');
fprintf(fid,'**$\n');
fprintf(fid,'WELL ''Well-1'' ATTACHTO ''Prod''
');
fprintf(fid,'PRODUCER ''Well-1''
');
fprintf(fid,'OPERATE MIN BHP 28. CONT\n');
fprintf(fid,'**$ rad geofac wfrac skin\n');
fprintf(fid,'GEOMETRY K 0.25 0.37 1. 0.\n');
fprintf(fid,'PERF GEOA ''Well-1''\n');
fprintf(fid,'**$ UBA ff Status Connection \n');
fprintf(fid,' 1 1 1. OPEN FLOW-TO ''SURFACE''\n');
fprintf(fid,' 1 1 2 1. OPEN FLOW-TO 1\n');
fprintf(fid,'GCONP ''Prod''\n');
fprintf(fid,'TARGET STG %d\n',RF(i,1));
fprintf(fid,'DATE 2015 1 1.00000\n');
fprintf(fid,'DATE 2016 1 1.00000\n');
fprintf(fid,'DATE 2019 1 1.00000\n');
fprintf(fid,'DATE 2025 1 1.00000\n');
fprintf(fid,'DATE 2030 1 1.00000\n');
fprintf(fid,'DATE 2035 1 1.00000\n');
fprintf(fid,'DATE 2040 1 1.00000\n');
fprintf(fid,'DATE 2045 1 1.00000\n');
fprintf(fid,'DATE 2050 1 1.00000\n');
fprintf(fid,'DATE 2053 12 31.00000\n');
fprintf(fid,'DATE 2063 12 31.00000\n');
fprintf(fid,'DATE 2073 12 31.00000\n');
fprintf(fid,'RESULTS RELPERMCORR NUMROCKTYPE 1\n');
fprintf(fid,'RESULTS RELPERMCORR CORRVALS 0.15 0.15 0.05 0.1 1 0.85\n');
fprintf(fid,'RESULTS RELPERMCORR CORRVALS_HONARPOUR -99999 -99999 -99999 -99999 -99999 -99999\n');
fprintf(fid,'RESULTS RELPERMCORR NOSWC false\n');
fprintf(fid,'RESULTS RELPERMCORR CALINDEX 5\n');
fprintf(fid,'RESULTS RELPERMCORR STOP\n');
fprintf(fid,'RESULTS SPEC ''Permeability I''\n');
fprintf(fid,'RESULTS SPEC SPECNOTCALCVAL -99999\n');
fprintf(fid,'RESULTS SPEC REGION ''All Layers (Whole Grid)''\n');
fprintf(fid,'RESULTS SPEC REGIONTYPE ''REGION_WHOLEGRID''\n');
fprintf(fid,'RESULTS SPEC LAYERNUMB 0\n');
fprintf(fid,'RESULTS SPEC PORTYPE 1\n');
fprintf(fid,'RESULTS SPEC CON 50\n');
fprintf(fid,'RESULTS SPEC SPECKEEPMOD ''YES''\n');
fprintf(fid,'RESULTS SPEC STOP\n');
fprintf(fid,'RESULTS SPEC ''Permeability J''\n');
fprintf(fid,'RESULTS SPEC SPECNOTCALCVAL -99999\n');
fprintf(fid,'RESULTS SPEC REGION ''All Layers (Whole Grid)''\n');
fprintf(fid,'RESULTS SPEC REGIONTYPE ''REGION_WHOLEGRID''\n');
fprintf(fid,'RESULTS SPEC LAYERNUMB 0\n');
fprintf(fid,'RESULTS SPEC PORTYPE 1\n');
fprintf(fid,'RESULTS SPEC CON 50\n');
fprintf(fid,'RESULTS SPEC SPECKEEPMOD ''YES''\n');
fprintf(fid,'RESULTS SPEC STOP\n');
fprintf(fid,'\n');
fprintf(fid, '\n');
fprintf(fid, 'RESULTS SPEC ''Permeability K'' \n');
fprintf(fid, 'RESULTS SPEC SPECNOTCALCVAL -99999 \n');
fprintf(fid, 'RESULTS SPEC REGION ''All Layers (Whole Grid)''\n');
fprintf(fid, 'RESULTS SPEC REGIONTYPE ''REGION_WHOLEGRID''\n');
fprintf(fid, 'RESULTS SPEC LAYERNUMB 0\n');
fprintf(fid, 'RESULTS SPEC PORTYPE 1\n');
fprintf(fid, 'RESULTS SPEC CON 50 \n');
fprintf(fid, 'RESULTS SPEC SPECKEEPMOD ''YES''\n');
fprintf(fid, 'RESULTS SPEC STOP\n');
fprintf(fid, '\n');
fprintf(fid, 'RESULTS SPEC ''Porosity'' \n');
fprintf(fid, 'RESULTS SPEC SPECNOTCALCVAL -99999 \n');
fprintf(fid, 'RESULTS SPEC REGION ''All Layers (Whole Grid)''\n');
fprintf(fid, 'RESULTS SPEC REGIONTYPE ''REGION_WHOLEGRID''\n');
fprintf(fid, 'RESULTS SPEC LAYERNUMB 0\n');
fprintf(fid, 'RESULTS SPEC PORTYPE 1\n');
fprintf(fid, 'RESULTS SPEC CON 0.15 \n');
fprintf(fid, 'RESULTS SPEC SPECKEEPMOD ''YES''\n');
fprintf(fid, 'RESULTS SPEC STOP\n');

fclose(fid);
fprintf(fidbatch, '%s', 'C:\Program Files (x86)\CMG\IMEX\2011.10\Win_x64\EXE\mx201110.exe -f '); %office link
fprintf(fidbatch, '%s
', nam);
end
fclose(fidbatch);

%Executing the simulation models
!Decline.bat

Extracting Reservoir Simulation Results

% Loading Input Data
load RF

%% Extracts Data from Simulation Results

for data = ('CMG_rwd.bat');
fidrwd = fopen(fordata, 'wt');

for i=1:length(RF(:,1));

numb = num2str(i);
dataext = ['Recovery', numb '.rwd '];
fid = fopen(dataext, 'wt');
numb = num2str(i);
fprintf(fid, '%s', 'FILE ''Recovery',numb);
fprintf(fid, '%s', '.irf''');

fclose(fid);
fprintf(fidbatch, '%s', 'C:\Program Files (x86)\CMG\IMEX\2011.10\Win_x64\EXE\mx201110.exe -f '); %office link
fprintf(fidbatch, '%s
', nam);
end
fclose(fidbatch);
fprintf(fid,'\nLINES-PER-PAGE 10000\n');
fprintf(fid,'\nTIME ON\n');
fprintf(fid,'\n*TIMES-FOR\n');

% 40 Years with 10 Days increment
for ff=[0:(10):7300];
    if ff==0;
        ff=1;
    end
    fprintf(fid,'%d\n',ff);
end
fprintf(fid,'SPREADSHEET\n');
fprintf(fid,'TABLE-FOR\n');
fprintf(fid,'%s\n', 'COLUMN-FOR *PARAMETERS ''Cumulative Gas SC'' *WELLS ''well-1''');
fprintf(fid,'%s\n', 'COLUMN-FOR *PARAMETERS ''Gas Rate SC'' *WELLS ''well-1''');
fprintf(fid,'%s\n', 'COLUMN-FOR *PARAMETERS ''Well Block Pressure'' *WELLS ''well-1''');
fprintf(fid,'%s\n', 'TABLE-END');
fclose(fid);
fprintf(fidrwd,'%s', 'call "C:\ Program Files\CMG\BR\2011.10\Win_x64\EXE\report.exe" -f "Dec"');
fprintf(fidrwd, num2str(i));
fprintf(fidrwd,'%s', 'TABLE-END');
fprintf(fidrwd,'%s', '.'rwd''');
fprintf(fidrwd,'%s', ' -o "Dec', numb, '.txt'');
fprintf(fidrwd,'%s', '\n');
end
fclose(fidrwd);

% Converting simulation results into .txt
!CMG_rwd.bat

Calculating Parameters Required for Training (i.e. Decline Parameters)

clear all
cle
files= dir ('*.txt');
NumCase=numel(files); % Number of Cases
TimeDec=0; % Initializing variable
RateDec=0; % Initializing variable
SD=1000000; % Initializing variable
RemovedCase=0; % Initializing variable
RemovedCase2=0; % Initializing variable
%% Extracting Simulation Data (Time, Rate, and Cum).

```matlab
for i = 1:numel(files)
    fileName=['Recovery',num2str(i),'.txt'];
    A=importdata(fileName);
    B = getfield(A,'data');
    Cum(i,:)=B(1:731,2);  % Cumulative production
    Rate(i,:)=B(1:731,3);  % Production rate
    Time(i,:)=B(1:731,1); % Time
    Block_Pressure(i,:)=B(1:731,4);
end

[NumCase, TimeStep]=size(Rate);

%% Removing cases without decline
for i=NumCase:-1:1
    if i<=NumCase;
        if floor(Rate(i,1)/1000)==floor(Rate(i,TimeStep-4)/1000) ||
            floor(Rate(i,1)/1000)-floor(Rate(i,TimeStep-4)/1000)<150; %comparing
            with 4 steps before because decline for 3 periods is not
            representative.
                Cum(i,:)=[];
                Time(i,:)=[];
                Rate(i,:)=[];
                Block_Pressure(i,:)=[];
                RemovedCase(i)=i;
                NumCase=NumCase-1;
            end
    end
end
RemovedCase(RemovedCase==0)=[];

[NumCase, TimeStep]=size(Rate);
TimeDecFit=zeros(NumCase,1);
RateDecFit=zeros(NumCase,1);
TimeDecMod=zeros(1,NumCase);
ATime=zeros(NumCase,1); %initializing ATime
PL=zeros(NumCase,1); %initializing Plateau Length Counting

%% Identifying Length of Plateau and the life of the field.
for h=1:1:NumCase; %loop over each case
    count=1;
    SD=1000000;
    for j=1:1:length(sum(Rate)); %loop over time steps
        % Identifying the time when rate starts to decline
        if count==1;
            if Rate(h,j)>Rate(h,j+1) && Rate(h,j+1)>Rate(h,j+2) &&
                Rate(h,j+2)>Rate(h,j+3) && Rate(h,j+3)~=0;
                SD=j;
            end
        end
```
if j>=SD && Rate(h,j)==0; %the second condition is to eliminate the recording of the time while the rate =0 at abandonment.
    TimeDec(h,j)=Time(h,j);
    RateDec(h,j)=Rate(h,j);
    TimeDecFit(h,count)=Time(h,j);
    RateDecFit(h,count)=Rate(h,j);
    count=count+1;
end
%
end

%Plateau Length in Days
PL(h)=TimeDecFit(h,1);
TimeDecStart(h)=PL(h);

%% Identifying Decline parameters (qi, Di, b) using the non-linear least square approach.
qi(h,1)=Rate(h,1); %initial Rate for each case
TimeDecFit1=TimeDecFit(h,:);
RateDecFit1=RateDecFit(h,:);
TimeDecFit1(TimeDecFit1==0)=[]; %removing zeros since not all cases have the same length of time.
RateDecFit1(RateDecFit1==0)=[];
TimeDecFit2=TimeDecFit1;

%Adjusting the Time, so that the decline time start from zero.
if TimeDecStart(h)~=1;
    TimeDecFit2=TimeDecFit1-TimeDecStart(h);
end

%% EZYFIT Curve fitting. Fitting decline part of production profile through a hyperbolic decline model.
if max(TimeDecFit2)>0
    time=TimeDecFit2;
    gasrate=RateDecFit1;
    tic
    options = optimset ('MaxFunEvals',2000,'TolX',1e-10,
    'TolFun',1e-15, 'MaxIter', 2000);
    f = ezfit(time,gasrate,'hyperbolic',options);
    toc
    hyperbolic_output(1,h) = f(1,1).m(1,1);
    hyperbolic_output(2,h) = f(1,1).m(1,2);
    hyperbolic_output(3,h) = f(1,1).m(1,3);
    hyperbolic_output(4,h) = f(1,1).r(1,1);

    DecPrm(1,h)=hyperbolic_output(1,h); %qi
    DecPrm(2,h)=hyperbolic_output(2,h); %b*Di
    DecPrm(3,h)=hyperbolic_output(3,h); %1/b
DecPrm_R2(1,h)=hyperbolic_output(4,h); \%R^2 (the godness of the hyperbolic fitted curve.
else
    DecPrm(:,h)=zeros(3,1);
    DecPrm_R2(1,h)=0;

    hyperbolic_output(:,h)=0;
end

%% Removing input data for cases without decline
load RF1
RF1=RF1';
q_Plateau= RF1(1,:); \% Production Plateau Rate in SCFD
AD= RF1(2,:).^2; \% Drainage Area in ft2
AF= 12000*8000; \% Field Area
WellNum= ceil(AF./AD); \% number of wells required to develop the field
Thickness= RF1(3,:); \% Layer Thickness in ft.
POR= RF1(4,:); \% Average Porosity
Perm= RF1(5,:); \% Average Permeability in md
Pi= RF1(6,:); \% Initial Pressure in psi

%Removing the cases without decline
for i=length(RemovedCase):-1:1;
    q_Plateau(RemovedCase(i))=[];
    AD(RemovedCase(i))=[];
    WellNum(RemovedCase(i))=[];
    Thickness(RemovedCase(i))=[];
    POR(RemovedCase(i))=[];
    Perm(RemovedCase(i))=[];
    Pi(RemovedCase(i))=[];
    RF1(:,RemovedCase(i))=[];
end

% Removing the cases with poor fit (R^2<98%) or is the decline parameter is negative.
for i=length(hyperbolic_output(4,:)):-1:1; \%looping over Cases
    if hyperbolic_output(4,i)<0.98
        Cum(i,:)=[];
        Time(i,:)=[];
        Rate(i,:)=[];
        PL(i,:)=[];
        qi(i,:)=[];
        Block_Pressure(i,:)=[];
        DecPrm(:,i)=[];
        DecPrm_R2(:,i)=[];
        RemovedCase2(i)=i;
        NumCase=NumCase-1;
    end
end
end
end

RemovedCase2(RemovedCase2==0)=[];
if RemovedCase2>0;
    for i=length(RemovedCase2):-1:1;
        q_Plateau(RemovedCase2(i))=[];
        AD(RemovedCase2(i))=[];
        WellNum(RemovedCase2(i))=[];
        Thickness(RemovedCase2(i))=[];
        POR(RemovedCase2(i))=[];
        Perm(RemovedCase2(i))=[];
        Pi(RemovedCase2(i))=[];
        RF1(:,RemovedCase2(i))=[];
    end
end
RF1_M=RF1; % saving new RF after removing cases w/o decline

%% Calculate Abandonment Time (Assuming q_ab=1,800,000 SCFD).
q_ab=ones(1,NumCase)*1800000; %Specifying Abandonment Rate in SCFD
Time_ab=zeros(1,NumCase);
Time_ab_index=zeros(1,NumCase);
Cum_ab=zeros(1,NumCase);
for ijk=1:NumCase;
    count2=1;
    for jki=1:TimeStep;
        if Rate(ijk,jki)<=q_ab(1,1) && count2==1;
            Time_ab(1,ijk)=Time(ijk,jki);
            Time_ab_index(1,ijk)=jki;
            Cum_ab(1,ijk)=Cum(ijk,jki);
            count2=count2+1;
        end
    end
end
qi=qi';
ATime=ATime';
PL=PL';
DecStart=PL;
Rate=Rate';
Rate_tot=Rate_tot';
Time=Time';
TimeDecFit=TimeDecFit';
RateDecFit=RateDecFit';
Cum=Cum';
Block_Pressure=Block_Pressure';
qPlateau_qab=q_Plateau./q_ab;
qPlateau_Area=q_Plateau./AD;
Rate_98=Rate;
Time_98=Time;
for j=1:length(Perm(1,:)) %Looping over cases
\text{eigValMax}(1,j) = \max(\text{abs}(\text{eig}([\text{Perm}(1,j),\text{Thickness}(1,j); \text{AD}(1,j),q_{\text{Plateau}}(1,j)]))));

\text{eigValMin}(1,j) = \min(\text{abs}(\text{eig}([\text{Perm}(1,j),\text{Thickness}(1,j); \text{AD}(1,j),q_{\text{Plateau}}(1,j)]))));

\text{end}

\text{Input1}_98 = \{\text{AD}; q_{\text{Plateau}}; \text{Thickness}; \text{POR}; \text{Perm}; \Pi; \text{eigValMax}\}; % \text{ANN Input}
\text{Output1}_98 = \{\text{PL}; \text{DecPrm}; \text{Cum}_{\text{Dec}}; q_{\text{Plateau\_Area}}; \text{Perm}.\ast \text{Thickness};
\text{Thickness}.\ast \text{POR}; \text{POR}.\ast \text{Perm}; \text{Pi}.\ast \text{AD}; \text{AD}.\ast \text{Perm}.\ast \text{DecPrm}(2,:)\;
\Pi.\ast \text{DecPrm}(3,:).\ast \text{POR}; 
\text{Thickness}.\ast \text{DecPrm}(3,:); q_{\text{Plateau\_Area}}.\ast \text{DecPrm}(3,:); q_{\text{Plateau\_Area}}.\ast \text{DecPrm}(2,:); 
\text{Perm}.\ast \text{Thickness}.\ast \text{DecPrm}(3,:); \text{Perm}.\ast \text{Thickness}.\ast \text{DecPrm}(3,:); \text{Thickness}.\ast \text{POR}.\ast \text{DecPrm}(3,:); \text{POR}.\ast \text{DecPrm}(3,:); \text{POR}.\ast \text{DecPrm}(2,:); 
\text{Perm}.\ast \text{DecPrm}(3,:); \text{DecPrm}(2,:).\ast \text{DecPrm}(3,:);\}; % \text{ANN Output, using Cum, decline parameters and as functional links}

\text{save RFl}_98\_M.\text{mat RF1}\_M
\text{save Thickness.}\text{mat Thickness}
\text{save POR.}\text{mat POR}
\text{save Perm.}\text{mat Perm}
\text{save Pi.}\text{mat Pi}
\text{save Time}\_\text{ab.}\text{mat Time}\_\text{ab}
\text{save Cum}\_\text{ab.}\text{mat Cum}\_\text{ab}
\text{save Time}\_\text{ab\_index.}\text{mat Time}\_\text{ab\_index}
\text{save Cum}\_\text{Dec.}\text{mat Cum}\_\text{Dec}
\text{save q1.}\text{mat q1}
\text{save DecPrm.}\text{mat DecPrm}
\text{save DecPrm}\_R2.\text{mat DecPrm}\_R2
\text{save hyperbolic output.}\text{mat hyperbolic output}
\text{save Block}\_\text{Pressure.}\text{mat Block}\_\text{Pressure}
\text{save AD.}\text{mat AD}
\text{save q}_{\text{Plateau\_tot.}}\text{mat q}_{\text{Plateau\_tot}}
\text{save WellNum.}\text{mat WellNum}
\text{save Input1}_98.\text{mat Input1}_98
\text{save Output1}_98.\text{mat Output1}_98
\text{save Cum.}\text{mat Cum}
\text{save Rate1}_98.\text{mat Rate1}_98
\text{save Time1}_98.\text{mat Time1}_98
\text{save PL.}\text{mat PL}
\text{save ATime.}\text{mat ATime}

\textbf{Code for Artificial Neural Network Training}

\text{clear}
\text{close all}
\text{clc}
\text{format long}

\% Loading input and output dataset for training
load Input
load Output

%% manipulating and normalizing training dataset
P = log(Input); %each case is a column, so either enter them as column,
or as row then transpose.
P(4,:) = P(4,:) * -1; %multiplying the fourth parameter (PHI) of output by -1
because it is in negative

T = log(Output); %taking the logarithm of output data to reduce the
difference in magnitude between the values
T([7,:]) = T([7,:]) * -1; %multiplying the third parameter of output by -1
because it is in negative
T([3:4,11,:]) = asinh(exp(T([3:4,11,:]))); %tanking sinh of cumulative
and rate/area.

[m,n] = size(P);
[m1,n1] = size(T);

[P2,ps2] = removeconstantrows(P);

%normalising the data
[Ps] = mapminmax(P2,-1,1); % gives all values between -1 & 1 for
efficiency
[Ts] = mapminmax(T,-1,1); % gives all values between -1 & 1 for
efficiency

[mi,ni] = size(Pn);
[mo,mo] = size(Tn);

for i=29:60 % Running different number of neurons
    %The data is divided randomly between training, testing, and
validating
    % 94% of the data is assigned for training, 30% for testing and 30%
    % for validation.
    [Pn_train,Pn_val,Pn_test,trainInd,valInd,testInd] =
    dividerand(Pn,0.94,0.03,0.03);
    [Tn_train,Tn_val,Tn_test] = divideind(Tn,trainInd,valInd,testInd);

    val.T = Tn_val;
    val.P = Pn_val;
    test.T = Tn_test;
    test.P = Pn_test;

    %Initiating network parameters
    % Number of neurons in each of the hidden layer
    NNeu0 = i; % Number of neurons in the first hidden layer
    NNeu1 = i; % Number of neurons in the second hidden layer
    NNeu2 = i; % Number of neurons in the third hidden layer
net = newcf(Pn,Tn,[NNeu0,NNeu1,NNeu2],{'tansig','tansig','tansig'},'trainscg','learngdm','msereg');

%setting training parameters for the network
net.trainParam.epochs = 8000; % number of iteration sets
net.trainParam.mu = 0.005; % Marquardt adjustment
net.trainParam.mu_dec = 0.1; %Decrease factor for mu
net.trainParam.mu_inc = 10; %Increase factor for mu
net.trainParam.mu_max = 1e11; %Maximum value for mu
net.trainParam.show = 1; %Epochs between displays (NaN for no displays)
net.trainParam.showCommandLine = 0; % Generate command-line output
net.trainParam.showWindow = 1; % Show training GUI
net.trainParam.goal = 0.0001; %accuracy within this range
net.trainParam.time = inf; %Maximum time to train in seconds
net.trainParam.min_grad = 1e-8; %Minimum performance gradient
net.trainParam.max_fail = 1000; %Maximum validation failures
net.trainParam.mem_reduc = 60; %to reduce memory requirements

% Training the network
[net,tr] = train(net,Pn_train,Tn_train,[],[],test,val);

% Retrieving data using trained network-------------------------
Tn_train_ann = sim(net,Pn_train);
Tn_test_ann = sim(net,Pn_test);
Tn_val_ann = sim(net,Pn_val);

[m_Te,n_Te] = size(Tn_test);
NP_test = 1:n_Te;

%denormalising the data sets obtained
%output reversal
T_train = mapminmax('reverse',Tn_train,ts);
T_test = mapminmax('reverse',Tn_test,ts);
T_train_ann = mapminmax('reverse',Tn_train_ann,ts);
T_test_ann = mapminmax('reverse',Tn_test_ann,ts);

T_val = mapminmax('reverse',Tn_val,ts);
T_val_ann = mapminmax('reverse',Tn_val_ann,ts);

%input reversal
P_train = mapminmax('reverse',Pn_train,ps);
P_val = mapminmax('reverse',Pn_val,ps);
P_test = mapminmax('reverse', Pn_test, ps);

%############################
% Getting the values back out of log
T_train_N=T_train;
T_train_N([7],:)=T_train([7],:)*-1;
T_train_N=exp(T_train_N);
T_train_N([3:4,11],:)=sinh(log(T_train_N([3:4,11],:)));

T_test_N=T_test;
T_test_N([7],:)=T_test([7],:)*-1;
T_test_N=exp(T_test_N);
T_test_N([3:4,11],:)=sinh(log(T_test_N([3:4,11],:)));

T_train_ann_N=T_train_ann;
T_train_ann_N([7],:)=T_train_ann([7],:)*-1;
T_train_ann_N=exp(T_train_ann_N);
T_train_ann_N([3:4,11],:)=sinh(log(T_train_ann_N([3:4,11],:)));

T_test_ann_N=T_test_ann;
T_test_ann_N([7],:)=T_test_ann([7],:)*-1;
T_test_ann_N=exp(T_test_ann_N);
T_test_ann_N([3:4,11],:)=sinh(log(T_test_ann_N([3:4,11],:)));

T_val_N=T_val;
T_val_N([7],:)=T_val([7],:)*-1;
T_val_N=exp(T_val_N);
T_val_N([3:4,11],:)=sinh(log(T_val_N([3:4,11],:)));

T_val_ann_N=T_val_ann;
T_val_ann_N([7],:)=T_val_ann([7],:)*-1;
T_val_ann_N=exp(T_val_ann_N);
T_val_ann_N([3:4,11],:)=sinh(log(T_val_ann_N([3:4,11],:)));

P_train_N=P_train;
P_train_N(4,:)=P_train(4,:)*-1;
P_train_N=exp(P_train_N);

P_val_N=P_val;
P_val_N(4,:)=P_val(4,:)*-1;
P_val_N=exp(P_val_N);

P_test_N=P_test;
P_test_N(4,:)=P_test(4,:)*-1;
P_test_N=exp(P_test_N);

%% error estimation
errors_test=(mean(mean(abs(T_test_ann_N(1:2,:)-T_test_N(1:2,:))/T_test_N(1:2,:))));
error_test_max=(max(max(abs(T_test_ann_N(1:2,:)-T_test_N(1:2,:))/T_test_N(1:2,:))));
error_test_min=(min(min(abs(T_test_ann_N(1:2,:)-T_test_N(1:2,:)))./T_test_N(1:2,:)))
errors_train=(mean(mean(abs(T_train_ann_N(1:2,:)-T_train_N(1:2,:)))./T_train_N(1:2,:)))

name = ['ZLLT' '_' num2str(errors_test) '_' num2str(errors_train)'.mat'];
save(name)
end

Code for Genetic Programming Training

function gp=my_config2(gp);
%Configuration file for multiple gene symbolic regression.

% Main run control parameters
%Define population size, number of generations, fitness function name and
%optimisation type.
gp.runcontrol.pop_size=500;
gp.runcontrol.num_gen=1000;
gp.fitness.minimisation=true;
gp.runcontrol.verbose=20; % Set to n to display run information to screen every n generations

% Selection method options
%-------------------------
gp.selection.method='tour'; % Only tournament selection is currently supported.
gp.selection.tournament.size=7;
gp.selection.tournament.lex_pressure=true; % True to use Luke & Panait's plain lexicographic tournament selection
gp.selection.elite_fraction=0.05;

% Fitness function specification
%-------------------------------
gp.fitness.fitfun=@regressmulti_fitfun; % Function handle to name of the user's fitness function (filename with no .m extension).
gp.fitness.minimisation=true; % Set to true if you want to minimise the fitness function (if false it is maximised).
gp.fitness.terminate=true; % terminate run if fitness below achieved
gp.fitness.terminate_value=0.0000001;

% Set up user data

% Load the variables xtrain, ytrain, xtest, ytest and assign to gp structure
load data
% Randomly Dividing the Data
[gp.userdata.xtrain, gp.userdata.xval, gp.userdata.xtest, 
trainInd, valInd, testInd] = dividerand(Input, 0.75, 0.15, 0.10);
[gp.userdata.ytrain, gp.userdata.yval, gp.userdata.ytest] = 
divideind(Output, trainInd, valInd, testInd);

% Transposing the data, so each variable is a column
gp.userdata.xtrain = gp.userdata.xtrain';
gp.userdata.xval = gp.userdata.xval';
gp.userdata.xtest = gp.userdata.xtest';
gp.userdata.ytrain = gp.userdata.ytrain'
   gp.userdata.yval = gp.userdata.yval'
   gp.userdata.ytest = gp.userdata.ytest'

% Taking Natural Log of Input and Output to bring the number into close % magnitude
gp.userdata.xtrain = log(gp.userdata.xtrain);
gp.userdata.xval = log(gp.userdata.xval);
gp.userdata.xtest = log(gp.userdata.xtest);
gp.userdata.ytrain = log(gp.userdata.ytrain);
gp.userdata.yval = log(gp.userdata.yval);
gp.userdata.ytest = log(gp.userdata.ytest);

% scale data to zero mean and unit variance
 gp = gpscale(gp);

 gp.userdata.datasampling = true;
gp.userdata.user_fcn = @regressmulti_fitfun_validate; % enables hold out validation set

% Input configuration
% -------------------

% Define the number of inputs
gp.nodes.inputs.num_inp = size(gp.userdata.xtrain, 2); % This sets the number of inputs (i.e. the size of the terminal set NOT including constants)
gp.nodes.const.range = [-10 10]; % The range that constant nodes are generated from uniform probability.
gp.nodes.const.p_ERC = 0.2; % Probability that a constant node, rather than an input node, will be generated when adding a terminal node to a tree.

%% Tree build options

 gp.treedef.max_depth = 10; % Maximum depth of trees
 gp.treedef.build_method = 3; % Tree building algorithm to use. 1 = full, 2 = grow, 3 = ramped 1/2 and 1/2.
gp.treedef.max_nodes = inf; % Maximum number of nodes per tree
gp.treedef.max_mutate_depth=10; % Maximum depth of sub-trees created by mutation operator

%% Multiple gene settings

% Enable multiple gene mode and set max number of genes per individual.
gp.genes.multigene=true; % Set to true to use multigene individuals and false to use ordinary single gene individuals.
gp.genes.max_genes=11; % The absolute maximum number of genes allowed in an individual.
gp.genes.max_depth=10;
gp.genes.operators.p_cross_hi = 0.30; %if multigene is enabled, this is the proportion of crossover events that are high level gene crossovers.

%% Genetic Operators (All must add to 1)
gp.operators.mutation.p_mutate = 0.1; %Probability of GP tree Mutation
gp.operators.crossover.p_cross = 0.85; %Probability of GP tree crossover
gp.operators.directrepro.p_direct = 0.05; %Probability of GP tree direct copy.

%% Mutation Settings

gp.operators.mutation.mutate_par = [0.87 0.05 0.05 0.01 0.01 0.01]; %Probabilities of mutation type N occuring is the Nth entry in this vector. Types can be found in Manual page 24.

%% Define functions

% ----------------
% (Below are some definitions of functions that have been used for symbolic regression problems)
% Function name Number of arguments
% (must be an mfile on the path)

gp.nodes.functions.name{1}='times' ;
gp.nodes.functions.name{2}='minus' ;
gp.nodes.functions.name{3}='plus' ;
gp.nodes.functions.name{4}='rdivide' ; % unprotected divide (may cause NaNs)
gp.nodes.functions.name{5}='psqroot' ; % protected sqrt
gp.nodes.functions.name{6}='plog' ; % protected natural log
gp.nodes.functions.name{7}='square' ; % .^2 square
gp.nodes.functions.name{8}='tanh' ; % tanh function
gp.nodes.functions.name{9}='pdivide' ; % protected divide function
gp.nodes.functions.name{10}='iflte' ; % IF-THEN-ELSE function
gp.nodes.functions.name{11}='sin' ;
gp.nodes.functions.name{12}='cos' ;
gp.nodes.functions.name{13}='exp';

% Active functions
% ------------------
% Manually setting a function node to inactive allows you to exclude a
% function node in a
% particular run.
gp.nodes.functions.active(1)=1;
gp.nodes.functions.active(2)=1;
gp.nodes.functions.active(3)=1;
gp.nodes.functions.active(4)=0;
gp.nodes.functions.active(5)=1;
gp.nodes.functions.active(6)=1;
gp.nodes.functions.active(7)=1;
gp.nodes.functions.active(8)=1;
gp.nodes.functions.active(9)=0;
gp.nodes.functions.active(10)=0;
gp.nodes.functions.active(11)=1;
gp.nodes.functions.active(12)=1;
gp.nodes.functions.active(13)=1;
Appendix B

The Graphical User Interface (GUI) for the Expert Systems in Chapter 2

This appendix presents the codes for the graphical user interface (GUI) that were constructed for the two prediction systems developed in chapter 2. The two systems were developed using artificial neural network and genetic programming learning techniques. In other words, each prediction expert system has two prediction models (one with ANN and the other with GP). The GUI starts by specifying which system to launch as shown in (Figure B-1). The first expert system predicts plateau length and production decline parameters for a given reservoir properties and production rate. The second system predicts the drainage area required to achieve plateau length and flow rate for a given reservoir. (Figure B-2) shows the GUI for the first expert system. The cells on the left hand side are the input for the system. Once the button calculate is pressed the constructed expert system is used to predict the output for the given set of input. As shown, there are two sets of outputs for ANN and GP. Moreover, the GUI includes plotting capability to check the accuracy of the results against the reservoir simulator. (Figure B-3) shows the GUI for the second expert system. To check the accuracy of the predicted drainage area, the drainage area with the given reservoir properties are used to build a reservoir simulation model. Then, the resulted plateau length is check against the specified plateau length in the input data as shown in (Figure B-3).
Figure B-1. The Main Window for the GUI

Figure B-2. The GUI for the Forward-Looking Expert System to Predict Decline Parameters and Plateau Length
Figure B-3. The GUI for the Inverse-Looking Expert System to Predict Drainage Area

The Code

Code for the main window GUI

```matlab
function varargout = ExpertSys_Combined(varargin)
% EXPERTSYS_COMBINED MATLAB code for ExpertSys_Combined.fig
% EXPERTSYS_COMBINED, by itself, creates a new EXPERTSYS_COMBINED
% or raises the existing
% singleton*.
%
% H = EXPERTSYS_COMBINED returns the handle to a new
% EXPERTSYS_COMBINED or the handle to
% the existing singleton*.
%
% EXPERTSYS_COMBINED('CALLBACK',hObject,eventData,handles,...)
calls the local
% function named CALLBACK in EXPERTSYS_COMBINED.M with the given
% input arguments.
%
% EXPERTSYS_COMBINED('Property','Value',...) creates a new
% EXPERTSYS_COMBINED or raises the
% existing singleton*. Starting from the left, property value
% pairs are
% applied to the GUI before ExpertSys_Combined_OpeningFcn gets
% called. An
% unrecognized property name or invalid value makes property
% application
% stop. All inputs are passed to ExpertSys_Combined_OpeningFcn
% via varargin.
```
*See GUI Options on GUIDE's Tools menu. Choose "GUI allows only one instance to run (singleton)."

See also: GUIDE, GUIDATA, GUIHANDLES

Edit the above text to modify the response to help ExpertSys_Combined

Last Modified by GUIDE v2.5 15-Sep-2014 21:46:31

Begin initialization code - DO NOT EDIT

```matlab
% gui_Singleton = 1;
% gui_State = struct('gui_Name', mfilename, ...
%     'gui_Singleton', gui_Singleton, ...
%     'gui_OpeningFcn', ...
%     @ExpertSys_Combined_OpeningFcn, ...
%     'gui_OutputFcn', @ExpertSys_Combined_OutputFcn, ...
%     'gui_LayoutFcn', [], ...
%     'gui_Callback', []);
if nargin && ischar(varargin{1})
    gui_State.gui_Callback = str2func(varargin{1});
end
if nargout
    varargin{1:nargout} = gui_mainfcn(gui_State, varargin{:});
else
    gui_mainfcn(gui_State, varargin{:});
end
% End initialization code - DO NOT EDIT

% --- Executes just before ExpertSys_Combined is made visible.
function ExpertSys_Combined_OpeningFcn(hObject, eventdata, handles, varargin)
% This function has no output args, see OutputFcn.
% hObject    handle to figure
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)
% varargin   command line arguments to ExpertSys_Combined (see VARARGIN)

% Choose default command line output for ExpertSys_Combined
handles.output = hObject;

% Update handles structure
guidata(hObject, handles);

% UIWAIT makes ExpertSys_Combined wait for user response (see UIRESUME)
% uiwait(handles.figure1);

% --- Outputs from this function are returned to the command line.
function varargout = ExpertSys_Combined_OutputFcn(hObject, eventdata, handles)
% varargout cell array for returning output args (see VARARGOUT);
% hObject    handle to figure
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)

% Get default command line output from handles structure
varargout{1} = handles.output;

% --- Executes on button press in expsys1.
function expsys1_Callback(hObject, eventdata, handles)
% hObject    handle to expsys1 (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)
ExpertSys1_V2 % Name of the file for the first expert system

% --- Executes on button press in expsys2.
function expsys2_Callback(hObject, eventdata, handles)
% hObject    handle to expsys2 (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)
ANNExpertSys2_V2 % Name of the file for the second expert system

Code for the First Expert System GUI

function varargout = ExpertSys1_V2(varargin)
% EXPERTSYS1_V2 MATLAB code for ExpertSys1_V2.
% EXPERTSYS1_V2, by itself, creates a new EXPERTSYS1_V2 or raises the existing singleton*.
% EXPERTSYS1_V2 returns the handle to a new EXPERTSYS1_V2 or the handle to the existing singleton*.
% EXPERTSYS1_V2('CALLBACK',hObject,eventData,handles,...) calls the local function named CALLBACK in EXPERTSYS1_V2.M with the given input arguments.
% EXPERTSYS1_V2('Property','Value',...) creates a new EXPERTSYS1_V2 or raises the existing singleton*. Starting from the left, property value pairs are applied to the GUI before ExpertSys1_V2_OpeningFcn gets called.
unrecognized property name or invalid value makes property application stop. All inputs are passed to ExpertSys1_V2_OpeningFcn via varargin.

"See GUI Options on GUIDE's Tools menu. Choose "GUI allows only one instance to run (singleton)."

See also: GUIDE, GUIDATA, GUIHANDLES

% Edit the above text to modify the response to help ExpertSys1_V2

% Last Modified by GUIDE v2.5 14-Sep-2014 15:49:03

% Begin initialization code - DO NOT EDIT

if nargin && ischar(varargin{1})
    gui_State.gui_Callback = str2func(varargin{1});
end

if nargout
    [varargout{1:nargout}] = gui_mainfcn(gui_State, varargin{:});
else
    gui_mainfcn(gui_State, varargin{:});
end

% End initialization code - DO NOT EDIT

% --- Executes just before ExpertSys1_V2 is made visible.
function ExpertSys1_V2_OpeningFcn(hObject, eventdata, handles, varargin)

% This function has no output args, see OutputFcn.
% hObject    handle to figure
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)
% varargin   command line arguments to ExpertSys1_V2 (see VARARGIN)

% Choose default command line output for ExpertSys1_V2
handles.output = hObject;

% Update handles structure
guidata(hObject, handles);

% UIWAIT makes ExpertSys1_V2 wait for user response (see UIRESUME)
% uiwait(handles.figure1);
% --- Outputs from this function are returned to the command line.
function varargout = ExpertSys1_V2_OutputFcn(hObject, eventdata, handles)
% varargout  cell array for returning output args (see VARARGOUT);
% hObject    handle to figure
% eventdata  reserved - to be defined in a future version of MATLAB
% handles   structure with handles and user data (see GUIDATA)

% Get default command line output from handles structure
varargout{1} = handles.output;

function area_ann_Callback(hObject, eventdata, handles)
% hObject    handle to area_ann (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)

% Hints: get(hObject,'String') returns contents of area_ann as text
%        str2double(get(hObject,'String')) returns contents of area_ann
% as a double

% --- Executes during object creation, after setting all properties.
function area_ann_CreateFcn(hObject, eventdata, handles)
% hObject    handle to area_ann (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    empty - handles not created until after all CreateFcns
called

% Hint: edit controls usually have a white background on Windows.
% See ISPC and COMPUTER.
if ispc && isequal(get(hObject,'BackgroundColor'),
                   get(0,'defaultUicontrolBackgroundColor'))
    set(hObject,'BackgroundColor','white');
end

function rate_ann_Callback(hObject, eventdata, handles)
% hObject    handle to rate_ann (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles   structure with handles and user data (see GUIDATA)

% Hints: get(hObject,'String') returns contents of rate_ann as text
%        str2double(get(hObject,'String')) returns contents of rate_ann
% as a double

% --- Executes during object creation, after setting all properties.
function rate_ann_CreateFcn(hObject, eventdata, handles)
% hObject    handle to rate_ann (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles   structure with handles and user data (see GUIDATA)

% Hints: get(hObject,'String') returns contents of rate_ann as text
%        str2double(get(hObject,'String')) returns contents of rate_ann
% as a double
function h_ann_Callback(hObject, eventdata, handles)
    % hObject    handle to h_ann (see GCBO)
    % eventdata  reserved - to be defined in a future version of MATLAB
    % handles    structure with handles and user data (see GUIDATA)

    % Hints: get(hObject,'String') returns contents of h_ann as text
    %        str2double(get(hObject,'String')) returns contents of h_ann as a double

    % --- Executes during object creation, after setting all properties.
    function h_ann_CreateFcn(hObject, eventdata, handles)
    % hObject    handle to h_ann (see GCBO)
    % eventdata  reserved - to be defined in a future version of MATLAB
    % handles    empty - handles not created until after all CreateFcns called

    % Hints: edit controls usually have a white background on Windows.
    %        See ISPC and COMPUTER.
    if ispc && isequal(get(hObject,'BackgroundColor'),
                      get(0,'defaultUicontrolBackgroundColor'))
        set(hObject,'BackgroundColor','white');
    end

function phi_ann_Callback(hObject, eventdata, handles)
    % hObject    handle to phi_ann (see GCBO)
    % eventdata  reserved - to be defined in a future version of MATLAB
    % handles    structure with handles and user data (see GUIDATA)

    % Hints: get(hObject,'String') returns contents of phi_ann as text
    %        str2double(get(hObject,'String')) returns contents of phi_ann as a double

    % --- Executes during object creation, after setting all properties.
    function phi_ann_CreateFcn(hObject, eventdata, handles)
    % hObject    handle to phi_ann (see GCBO)
% eventdata reserved - to be defined in a future version of MATLAB
% handles empty - handles not created until after all CreateFcns called

% Hint: edit controls usually have a white background on Windows.
%       See ISPC and COMPUTER.
if ispc && isequal(get(hObject,'BackgroundColor'),
get(0,'defaultUicontrolBackgroundColor'))
    set(hObject,'BackgroundColor','white');
end

function k_ann_Callback(hObject, eventdata, handles)
% hObject    handle to k_ann (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)

% Hints: get(hObject,'String') returns contents of k_ann as text
%        str2double(get(hObject,'String')) returns contents of k_ann as a double

% --- Executes during object creation, after setting all properties.
function k_ann_CreateFcn(hObject, eventdata, handles)
% hObject    handle to k_ann (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    empty - handles not created until after all CreateFcns called

% Hint: edit controls usually have a white background on Windows.
%       See ISPC and COMPUTER.
if ispc && isequal(get(hObject,'BackgroundColor'),
get(0,'defaultUicontrolBackgroundColor'))
    set(hObject,'BackgroundColor','white');
end

function pi_ann_Callback(hObject, eventdata, handles)
% hObject    handle to pi_ann (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)

% Hints: get(hObject,'String') returns contents of pi_ann as text
%        str2double(get(hObject,'String')) returns contents of pi_ann as a double

% --- Executes during object creation, after setting all properties.
function pi_ann_CreateFcn(hObject, eventdata, handles)
% hObject    handle to pi_ann (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    empty - handles not created until after all CreateFcns called
function edit12_Callback(hObject, eventdata, handles)
% hObject    handle to edit12 (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)

% Hints: get(hObject,'String') returns contents of edit12 as text
%       str2double(get(hObject,'String')) returns contents of edit12 as a double

% --- Executes during object creation, after setting all properties.
function edit12_CreateFcn(hObject, eventdata, handles)
% hObject    handle to edit12 (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    empty - handles not created until after all CreateFcns called

% Hint: edit controls usually have a white background on Windows.
%       See ISPC and COMPUTER.
if ispc && isequal(get(hObject,'BackgroundColor'),
                   get(0,'defaultUicontrolBackgroundColor'))
    set(hObject,'BackgroundColor','white');
end

function edit11_Callback(hObject, eventdata, handles)
% hObject    handle to edit11 (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)

% Hints: get(hObject,'String') returns contents of edit11 as text
%        str2double(get(hObject,'String')) returns contents of edit11 as a double

% --- Executes during object creation, after setting all properties.
function edit11_CreateFcn(hObject, eventdata, handles)
% hObject    handle to edit11 (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    empty - handles not created until after all CreateFcns called

% Hint: edit controls usually have a white background on Windows.
%       See ISPC and COMPUTER.
if ispc && isequal(get(hObject,'BackgroundColor'),
                   get(0,'defaultUicontrolBackgroundColor'))
    set(hObject,'BackgroundColor','white');
end
function c_ann_Callback(hObject, eventdata, handles)
    % hObject    handle to c_ann (see GCBO)
    % eventdata  reserved - to be defined in a future version of MATLAB
    % handles    structure with handles and user data (see GUIDATA)

    % Hints: get(hObject,'String') returns contents of c_ann as text
    %        str2double(get(hObject,'String')) returns contents of c_ann as a double

    % --- Executes during object creation, after setting all properties.
    function c_ann_CreateFcn(hObject, eventdata, handles)
        % hObject    handle to c_ann (see GCBO)
        % eventdata  reserved - to be defined in a future version of MATLAB
        % handles    empty - handles not created until after all CreateFcns called

        % Hint: edit controls usually have a white background on Windows.
        % See ISPC and COMPUTER.
        if ispc && isequal(get(hObject,'BackgroundColor'),
                get(0,'defaultUicontrolBackgroundColor'))
            set(hObject,'BackgroundColor','white');
        end

function b_ann_Callback(hObject, eventdata, handles)
    % hObject    handle to b_ann (see GCBO)
    % eventdata  reserved - to be defined in a future version of MATLAB
    % handles    structure with handles and user data (see GUIDATA)

    % Hints: get(hObject,'String') returns contents of b_ann as text
    %        str2double(get(hObject,'String')) returns contents of b_ann as a double

    % --- Executes during object creation, after setting all properties.
    function b_ann_CreateFcn(hObject, eventdata, handles)
        % hObject    handle to b_ann (see GCBO)
        % eventdata  reserved - to be defined in a future version of MATLAB
        % handles    empty - handles not created until after all CreateFcns called

        % Hint: edit controls usually have a white background on Windows.
        % See ISPC and COMPUTER.
        if ispc && isequal(get(hObject,'BackgroundColor'),
                get(0,'defaultUicontrolBackgroundColor'))
            set(hObject,'BackgroundColor','white');
        end

% eventdata reserved - to be defined in a future version of MATLAB
% handles empty - handles not created until after all CreateFcns called

% Hint: edit controls usually have a white background on Windows.
% See ISPC and COMPUTER.
if ispc && isequal(get(hObject,'BackgroundColor'),
                get(0,'defaultUicontrolBackgroundColor'))
    set(hObject,'BackgroundColor','white');
end
function a_ann_Callback(hObject, eventdata, handles)
    % hObject    handle to a_ann (see GCBO)
    % eventdata  reserved - to be defined in a future version of MATLAB
    % handles    structure with handles and user data (see GUIDATA)

    if ispc && isequal(get(hObject,'BackgroundColor'),
        get(0,'defaultUicontrolBackgroundColor'))
        set(hObject,'BackgroundColor','white');
    end

function pl_ann_Callback(hObject, eventdata, handles)
    % hObject    handle to pl_ann (see GCBO)
    % eventdata  reserved - to be defined in a future version of MATLAB
    % handles    structure with handles and user data (see GUIDATA)

    if ispc && isequal(get(hObject,'BackgroundColor'),
        get(0,'defaultUicontrolBackgroundColor'))
        set(hObject,'BackgroundColor','white');
    end

function pl_ann_CreateFcn(hObject, eventdata, handles)
    % hObject    handle to pl_ann (see GCBO)
    % eventdata  reserved - to be defined in a future version of MATLAB
    % handles    structure with handles and user data (see GUIDATA)

    if ispc && isequal(get(hObject,'BackgroundColor'),
        get(0,'defaultUicontrolBackgroundColor'))
        set(hObject,'BackgroundColor','white');
    end
% eventdata reserved - to be defined in a future version of MATLAB
% handles empty - handles not created until after all CreateFcns
called

% Hint: edit controls usually have a white background on Windows.
% See ISPC and COMPUTER.
if ispc && isequal(get(hObject,'BackgroundColor'),
    get(0,'defaultUicontrolBackgroundColor'))
    set(hObject,'BackgroundColor','white');
end

% --- Executes on button press in calculate_ann.
function calculate_ann_Callback(hObject, eventdata, handles)
% hObject handle to calculate_ann (see GCBO)
% eventdata reserved - to be defined in a future version of MATLAB
% handles structure with handles and user data (see GUIDATA)

%% **************Start of the code for ANN
Technique***********************

area_ann = (str2double(get(handles.area_ann,'String'))); % Obtain
drainage area value from user input.
rate_ann = (str2double(get(handles.rate_ann,'String'))); % Obtain flow
rate value from user input.
phi_ann = (str2double(get(handles.phi_ann,'String'))); % Obtain
porosity value from user input.
k_ann = (str2double(get(handles.k_ann,'String'))); % Obtain
permeability value from user input.
pi_ann = (str2double(get(handles.pi_ann,'String'))); % Obtain
initial reservoir pressure value from user input.
h_ann = (str2double(get(handles.h_ann,'String'))); % Obtain
reservoir thickness value from user input.

% ---------------------Warning Messages---------------------
% The GUI flag warning messages if the values of the input properties
% are outside the training ranges.
if area_ann > 10890000 || area_ann < 1690000
    set(handles.area_ann,'ForegroundColor','red')
    uiwait(msgbox('Out of range! Specify value between 1,690,000 and
10,890,000','Warning','modal'))
else
    set(handles.area_ann,'ForegroundColor','black')
end

if rate_ann > 36000000 || rate_ann < 9000000
    set(handles.rate_ann,'ForegroundColor','red')
end
uiwait(msgbox('Out of range! Specify value between 9,000,000 and 36,000,000', 'Warning', 'modal'))
else
    set(handles.rate_ann, 'ForegroundColor', 'black')
end

if phi_ann > 0.20 || phi_ann < 0.08
    set(handles.phi_ann, 'ForegroundColor', 'red')
    uiwait(msgbox('Out of range! Specify value between 0.08 and 0.20', 'Warning', 'modal'))
else
    set(handles.phi_ann, 'ForegroundColor', 'black')
end

if k_ann > 100 || k_ann < 8
    set(handles.k_ann, 'ForegroundColor', 'red')
    uiwait(msgbox('Out of range! Specify value between 8 and 100', 'Warning', 'modal'))
else
    set(handles.k_ann, 'ForegroundColor', 'black')
end

if pi_ann > 5000 || pi_ann < 2000
    set(handles.pi_ann, 'ForegroundColor', 'red')
    uiwait(msgbox('Out of range! Specify value between 2000 and 5000', 'Warning', 'modal'))
else
    set(handles.pi_ann, 'ForegroundColor', 'black')
end

if h_ann > 800 || h_ann < 50
    set(handles.h_ann, 'ForegroundColor', 'red')
    uiwait(msgbox('Out of range! Specify value between 50 and 800', 'Warning', 'modal'))
else
    set(handles.h_ann, 'ForegroundColor', 'black')
end

%------------------------------------------------
% The constructed ANN model is called to predict the plateau length and decline parameters.
% Input = [Area; q_Plateau; Thickness/2; POR; Perm; Pi]

INPUT_P1 = [area_ann; rate_ann; h_ann/2; phi_ann; k_ann; pi_ann];
answer_ann = ANN_Pred(INPUT_P1);

% the output values are assigned to the output boxes in the GUI
set(handles.pl_ann, 'String', num2str(answer_ann(1,1)));
set(handles.a_ann, 'String', num2str(answer_ann(2,1)));
set(handles.b_ann, 'String', num2str(answer_ann(3,1)));
set(handles.c_ann, 'String', num2str(answer_ann(4,1)));
%% ************* runing reservoir simulation model to check the accuracy of the expert system.

% --- Executes on button press in plot_ann.
function plot_ann_Callback(hObject, eventdata, handles)
    % hObject    handle to plot_ann (see GCBO)
    % eventdata  reserved - to be defined in a future version of MATLAB
    % handles    structure with handles and user data (see GUIDATA)

    % Obtainig the input properties from the input boxes in the GUI
    area = (str2double(get(handles.area_ann,'String')));
    rate = (str2double(get(handles.rate_ann,'String')));
    phi = (str2double(get(handles.phi_ann,'String')));
    k = (str2double(get(handles.k_ann,'String')));
    pi = (str2double(get(handles.pi_ann,'String')));
    h = (str2double(get(handles.h_ann,'String')));

    % ---------------------- Warning Messages ----------------------
    if area > 10890000 || area < 1690000
        set(handles.area_ann,'ForegroundColor','red')
        uiwait(msgbox('Out of range! Specify value between 1,690,000 and 10,890,000', 'Warning', 'modal'))
    else
        set(handles.area_ann,'ForegroundColor','black')
    end

    if rate > 36000000 || rate < 9000000
        set(handles.rate_ann,'ForegroundColor','red')
        uiwait(msgbox('Out of range! Specify value between 9,000,000 and 36,000,000', 'Warning', 'modal'))
    else
        set(handles.rate_ann,'ForegroundColor','black')
    end

    if phi > 0.20 || phi < 0.08
        set(handles.phi_ann,'ForegroundColor','red')
        uiwait(msgbox('Out of range! Specify value between 0.08 and 0.20', 'Warning', 'modal'))
    else
        set(handles.phi_ann,'ForegroundColor','black')
    end

    if k > 100 || k < 8
        set(handles.k_ann,'ForegroundColor','red')
        uiwait(msgbox('Out of range! Specify value between 8 and 100', 'Warning', 'modal'))
    else
        % Code continues here...
set(handles.k_ann,'ForegroundColor','black')

end

if pi > 5000 || pi < 2000
    set(handles.pi_ann,'ForegroundColor','red')
    uiwait(msgbox('Out of range! Specify value between 2000 and 5000', 'Warning', 'modal'))
else
    set(handles.pi_ann,'ForegroundColor','black')
end

if h > 800 || h < 500
    set(handles.h_ann,'ForegroundColor','red')
    uiwait(msgbox('Out of range! Specify value between 50 and 800', 'Warning', 'modal'))
else
    set(handles.h_ann,'ForegroundColor','black')
end

%---------------Simulation Model-----------------------
INPUT_P1=[area;rate;h/2;phi;kr;pi];
answer_ann=ANN_Pred(INPUT_P1); %Predict plateau length and decline parameters using the expert system.

% Dividing the thickness over two layers.
h=h/2;
nam2 = 'Dec_ann.bat';
fidbatch = fopen(nam2,'w'); %Creating a batch file run the simulation model.
RefDepth= h+10000;

nam = ['Dec_ann.dat'];
fid = fopen(nam,'w');

fprintf(fid,'RESULTS SIMULATOR IMEX 201110\n');
fprintf(fid,'\n');
fprintf(fid,'INUNIT FIELD\n');
fprintf(fid,'WSRF WELL 1\n');
fprintf(fid,'WSRF GRID TIME\n');
fprintf(fid,'WSRF SECTOR TIME\n');
fprintf(fid,'OUTSRF WELL LAYER NONE\n');
fprintf(fid,'OUTSRF RES ALL\n');
fprintf(fid,'OUTSRF GRID SO SG SW PRES OILPOT BPP SSPRES WINFLUX\n');
fprintf(fid,'WPRN GRID 0\n');
fprintf(fid,'OUTPRN GRID NONE\n');
fprintf(fid,'OUTPRN RES NONE\n');
fprintf(fid,'***$ Distance units: ft \n');
fprintf(fid,'RESULTS XOFFSET 0.0000\n');
fprintf(fid,'RESULTS YOFFSET 0.0000\n');
fprintf(fid,'RESULTS ROTATION 0.0000 **$ (DEGREES)\n');
fprintf(fid,'RESULTS AXES-DIRECTIONS 1.0 -1.0 1.0\n');
fprintf(fid,'***$ Definition of fundamental cartesian grid\n');
fprintf(fid, '***$ ******************************************************
' ***
\nGRID VARI 1 1 2
\nfprintf(fid, 'KDIR DOWN
\nfprintf(fid, 'DIVAR
\nfprintf(fid, ' %d
\nfprintf(fid, 'DJ JVAR
\nfprintf(fid, ' %d
\nfprintf(fid, 'DK ALL
\nfprintf(fid, ' 2*%d
\nh); fprintf(fid, 'DTOP
\nfprintf(fid, ' 10000\n'); fprintf(fid, '***$ Property: NULL Blocks Max: 1 Min: 1\n'); fprintf(fid, '***$ 0 = null block, 1 = active block\n'); fprintf(fid, 'NULL CON
\nfprintf(fid, '***$ Property: Porosity Max: %d Min: %d\n', phi, phi); fprintf(fid, 'POR CON %d
\nfprintf(fid, '***$ Property: Permeability I (md) Max: %d Min: %d\n', k, k); fprintf(fid, 'PERMI CON %d
\nfprintf(fid, '***$ Property: Permeability J (md) Max: %d Min: %d\n', k, k); fprintf(fid, 'PERMJ CON %d
\nfprintf(fid, '***$ Property: Permeability K (md) Max: %d Min: %d\n', k, k); fprintf(fid, 'PERMK CON %d
\nfprintf(fid, '***$ Property: Pinchout Array Max: 1 Min: 1\n'); fprintf(fid, '***$ 0 = pinched block, 1 = active block\n'); fprintf(fid, 'PINCHOUTARRAY CON 1\n'); fprintf(fid, 'CPOR 0.000001
\nfprintf(fid, 'MODEL GASWATER \n'); fprintf(fid, 'TRES 150\n'); fprintf(fid, 'PVTG EG 1\n'); fprintf(fid, '\n'); fprintf(fid, '***$ p Eg visg\n'); fprintf(fid, ' 14.696 4.81152 0.0117959\n'); fprintf(fid, ' 347.05 119.03 0.0122183\n'); fprintf(fid, ' 679.403 244.135 0.0128884\n'); fprintf(fid, ' 1011.76 380.147 0.0137868\n'); fprintf(fid, ' 1344.11 525.33 0.0149293\n'); fprintf(fid, ' 1676.46 675.483 0.0163175\n'); fprintf(fid, ' 2008.82 824.472 0.0179208\n'); fprintf(fid, ' 2341.17 966.242 0.0196786\n'); fprintf(fid, ' 2673.52 1096.72 0.0215212\n'); fprintf(fid, ' 3005.88 1214.25 0.0233230\n'); fprintf(fid, ' 3338.23 1318.89 0.0251208\n'); fprintf(fid, ' 3670.59 1411.69 0.0270245\n'); fprintf(fid, ' 4002.94 1494.01 0.0287521\n'); fprintf(fid, ' 4335.29 1567.3 0.0304066\n'); fprintf(fid, ' 4667.65 1632.86 0.0319872\n'); fprintf(fid, ' 5000 1691.92 0.033496\n'); fprintf(fid, ' 5332.41 1758.75 0.0350538\n'); fprintf(fid, ' 5664.76 1825.6 0.0366132\n'); fprintf(fid, ' 6007.11 1892.45 0.0381882\n'); fprintf(fid, ' 6339.46 1959.3 0.0397692\n'); fprintf(fid, ' 6671.81 2026.16 0.0413660\n'); fprintf(fid, ' 7004.16 2093.01 0.0430793\n'); fprintf(fid, ' 7336.51 2159.87 0.0448087\n'); fprintf(fid, ' 7668.86 2226.72 0.0465551\n'); fprintf(fid, ' 8001.21 2293.58 0.0483187\n'); fprintf(fid, ' 8333.56 2360.44 0.0501009\n'); fprintf(fid, ' 8665.91 2427.3 0.0519025\n'); fprintf(fid, ' 9008.26 2494.16 0.0537247\n'); fprintf(fid, ' 9340.61 2561.02 0.0555768\n'); fprintf(fid, ' 9672.96 2627.88 0.0574594\n'); fprintf(fid, ' 10005.31 2694.74 0.0593725\n'); fprintf(fid, ' 10337.66 2761.6 0.0613259\n'); fprintf(fid, 'DENSITY GAS 5.802166e-002
\nfprintf(fid, 'DENSITY WATER 61.6381
\n');
fprintf(fid, 'BWI 1.01944\n');
fprintf(fid, 'CW 3.1589e-006\n');
fprintf(fid, 'VWI 0.47184\n');
fprintf(fid, 'CVW 0.0\n');
fprintf(fid, 'ROCKFLUID\n');
fprintf(fid, 'RPT 1\n');
fprintf(fid, '***$ Sw krw\n');
fprintf(fid, 'SWT\n');
fprintf(fid, '               0.15           0\n');
fprintf(fid, '           0.203125  1.52588e-005\n');
fprintf(fid, '            0.25625   0.000244141\n');
fprintf(fid, '           0.309375   0.00123596\n');
fprintf(fid, '             0.3625    0.00390625\n');
fprintf(fid, '           0.415625   0.00953674\n');
fprintf(fid, '            0.46875    0.0197754\n');
fprintf(fid, '           0.521875   0.0366364\n');
fprintf(fid, '              0.575     0.0625\n');
fprintf(fid, '           0.628125   0.100113\n');
fprintf(fid, '           0.68125    0.223404\n');
fprintf(fid, '           0.734375   0.316406\n');
fprintf(fid, '             0.7875    0.435806\n');
fprintf(fid, '           0.840625   0.586182\n');
fprintf(fid, '           0.89375    0.772476\n');
fprintf(fid, '                1     1\n');
fprintf(fid, '***$ Sl krg\n');
fprintf(fid, 'SLT\n');
fprintf(fid, '               0.15        0.85\n');
fprintf(fid, '           0.196875    0.656605\n');
fprintf(fid, '            0.24375    0.498254\n');
fprintf(fid, '           0.290625    0.370435\n');
fprintf(fid, '             0.3375    0.268945\n');
fprintf(fid, '           0.384375    0.189893\n');
fprintf(fid, '            0.43125     0.1297\n');
fprintf(fid, '           0.478125    0.085096\n');
fprintf(fid, '            0.525    0.053125\n');
fprintf(fid, '           0.571875    0.031149\n');
fprintf(fid, '            0.61875    0.0168091\n');
fprintf(fid, '           0.665625    0.00810623\n');
fprintf(fid, '            0.7125    0.00332031\n');
fprintf(fid, '           0.759375    0.00105057\n');
fprintf(fid, '            0.80625    0.00020752\n');
fprintf(fid, '           0.853125   1.297e-005\n');
fprintf(fid, '          0.9        0\n');
fprintf(fid, '          0.925        0\n');
fprintf(fid, '          0.95        0\n');
fprintf(fid, 'INITIAL\n');
fprintf(fid, 'VERTICAL DEPTH_AVE WATER_GAS EQUIL NOTRANZONE\n');
fprintf(fid, 'REFDEPTH %d\n', RefDepth);
fprintf(fid, 'REFPRES %d\n', pi);
fprintf(fid, 'DWGC 12000\n');
fprintf(fid, 'DATUMDEPTH %d INITIAL\n', RefDepth);
fprintf(fid, 'NUMERICAL\n');
fprintf(fid, 'RUN\n');
fprintf(fid,'DATE 2013 1 1\n');
fprintf(fid,'GROUP ''Prod'' ATTACHTO ''Group-1''\n');
fprintf(fid,'***$\n');
fprintf(fid,'***$\n');
fprintf(fid,'WELL ''Well-1'' ATTACHTO ''Prod''\n');
fprintf(fid,'OPERATE MIN BHP 28. CONT\n');
fprintf(fid,'**$\n');
fprintf(fid,'**$\n');
fprintf(fid,'WELL  ''Well-1'' ATTACHTO ''Prod''\n');
fprintf(fid,'PRODUCER ''Well-1''\n');
fprintf(fid,'OPERATE  MIN  BHP  28. CONT\n');
fprintf(fid,'**$          rad  geofac  wfrac  skin\n');
fprintf(fid,'GEOMETRY  K  0.25  0.37  1.  0.\n');
fprintf(fid,'PERF GEOA  ''Well-1''\n');
fprintf(fid,'**$ UBA     ff  Status  Connection \n');
fprintf(fid,'    1 1 1  1.  OPEN  FLOW-TO  ''SURFACE''\n');
fprintf(fid,'    1 1 2  1.  OPEN    FLOW-TO  1\n');
fprintf(fid,'GCONP ''Prod''\n');
fprintf(fid,'    TARGET   STG      %d\n',rate);
fprintf(fid,'DATE 2015 1  1.00000\n');
fprintf(fid,'DATE 2016 1 1.00000\n');
fprintf(fid,'DATE 2019 1  1.00000\n');
fprintf(fid,'DATE 2025 1 1.00000\n');
fprintf(fid,'DATE 2030 1  1.00000\n');
fprintf(fid,'DATE 2035 1  1.00000\n');
fprintf(fid,'DATE 2040 1 1.00000\n');
fprintf(fid,'DATE 2045 1  1.00000\n');
fprintf(fid,'DATE 2050 1  1.00000\n');
fprintf(fid,'DATE 2053 12 31.00000\n');
fprintf(fid,'DATE 2063 12 31.00000\n');
fprintf(fid,'DATE 2073 12 31.00000\n');
fprintf(fid,'RESULTS RELPERMCORR NUMROCKTYPE 1\n');
fprintf(fid,'RESULTS RELPERMCORR CORRVALS 0.15 0.15 0.05 0.1 0.85 4 4\n');
fprintf(fid,'RESULTS RELPERMCORR CORRVALS_HONARPOUR -99999 -99999 -99999 -99999 -99999 -99999\n');
fprintf(fid,'RESULTS RELPERMCORR NOSWC false\n');
fprintf(fid,'RESULTS RELPERMCORR CALINDEX 5\n');
fprintf(fid,'RESULTS RELPERMCORR STOP\n');
fprintf(fid,'RESULTS SPEC ''Permeability I''\n');
fprintf(fid,'RESULTS SPEC SPECNOTCALCVAL -99999\n');
fprintf(fid,'RESULTS SPEC REGION ''All Layers (Whole Grid)''\n');
fprintf(fid,'RESULTS SPEC REGIONTYPE ''REGION_WHOLEGRID''\n');
fprintf(fid,'RESULTS SPEC LAYERNUMB 0\n');
fprintf(fid,'RESULTS SPEC PORTYPE 1\n');
fprintf(fid,'RESULTS SPEC CON 50\n');
fprintf(fid,'RESULTS SPEC SPECKEEPROM ''YES''\n');
fprintf(fid,'RESULTS SPEC STOP\n');
fprintf(fid,'RESULTS SPEC ''Permeability J''\n');
fprintf(fid,'RESULTS SPEC SPECNOTCALCVAL -99999\n');
fprintf(fid,'RESULTS SPEC REGION ''All Layers (Whole Grid)''\n');
fprintf(fid,'RESULTS SPEC REGIONTYPE ''REGION_WHOLEGRID''\n');
fprintf(fid,'RESULTS SPEC LAYERNUMB 0\n');
fprintf(fid,'RESULTS SPEC PORTYPE 1\n');
fprintf(fid,'RESULTS SPEC CON 50\n');
fprintf(fid,'RESULTS SPEC SPECKEEPMOD ''YES''\n');
fprintf(fid,'RESULTS SPEC STOP\n');
fprintf(fid,'\n');
fprintf(fid,'RESULTS SPEC ''Permeability K'' \n');
fprintf(fid,'RESULTS SPEC SPECMONTCALCVAL -99999 \n');
fprintf(fid,'RESULTS SPEC REGION ''All Layers (Whole Grid)''\n');
fprintf(fid,'RESULTS SPEC REGIONTYPE ''REGION_WHOLEGRID''\n');
fprintf(fid,'RESULTS SPEC LAYERNUMB 0\n');
fprintf(fid,'RESULTS SPEC PORTYPE 1\n');
fprintf(fid,'RESULTS SPEC CON 50 \n');
fprintf(fid,'RESULTS SPEC SPECKEEPMOD ''YES''\n');
fprintf(fid,'RESULTS SPEC STOP\n');
fprintf(fid,'\n');
fprintf(fid,'RESULTS SPEC ''Porosity'' \n');
fprintf(fid,'RESULTS SPEC SPECMONTCALCVAL -99999 \n');
fprintf(fid,'RESULTS SPEC REGION ''All Layers (Whole Grid)''\n');
fprintf(fid,'RESULTS SPEC REGIONTYPE ''REGION_WHOLEGRID''\n');
fprintf(fid,'RESULTS SPEC LAYERNUMB 0\n');
fprintf(fid,'RESULTS SPEC PORTYPE 1\n');
fprintf(fid,'RESULTS SPEC CON 0.15 \n');
fprintf(fid,'RESULTS SPEC SPECKEEPMOD ''YES''\n');
fprintf(fid,'RESULTS SPEC STOP\n');
fclose(fid);
fprint(fidbatch,'%s','"C:\Program Files (x86)\CMG\IMEX\2011.10\Win_x64\EXE\mx201110.exe" -f"); %office link
fclose(fidbatch);

% Executing the batch file to run the simulation model.
!Dec_ann.bat

% Extracts Data from CMG Results into text file
for data = ('Dec_RWD.bat');
fidrwd = fopen(fordata,'wt');
dataext = ['Dec_ann.rwd'];
fid = fopen(dataext,'wt');
fprint(fid,'%s','FILE '''Dec_ann''');
fprint(fid,'%s','.irf''');

fprint(fid,'\nLINES-PER-PAGE 10000\n');
fprint(fid,'\nTIME ON\n');
fprintf(fid, '\n*TIMES-FOR\n');

% generating time steps between 1 and 14600 days with 10 days
% increments.
for ff=[0:(10):14600];
    if ff==0;
        ff=1;
    end
    fprintf(fid, '%d\n', ff);
end
fprintf(fid, 'SPREADSHEET\n'); % Specify the parameters to extract
from the simulation results
fprintf(fid, 'TABLE-FOR\n');
fprintf(fid, '%s', 'COLUMN-FOR *PARAMETERS ''Cumulative Gas SC'' *WELLS ''well-1''');
fprintf(fid, '%s\n', 'COLUMN-FOR *PARAMETERS ''Gas Rate SC'' *WELLS ''well-1''');
fprintf(fid, '%s\n', 'COLUMN-FOR *PARAMETERS ''Well Block Pressure'' *WELLS ''well-1''');
fprintf(fid, '%s\n', 'TABLE-END');
close(fid);

fprintf(fidrwd, '%s', 'call "C:\Program Files (x86)\CMG\BR\2011.10\Win_x64\EXE\report.exe" -f "Dec_ann"');%office link
% fprintf(fidrwd, '1');
fprintf(fidrwd, '%s', '.rwd');
fprintf(fidrwd, '%s', '-o "Dec_ann.txt"');
fprintf(fidrwd, '\n');
close(fidrwd);

%Executing the batch file to convert the .rwd file to .txt
!Dec_RWD.bat

% Extracting Data From the Text File
files= dir ('*.txt');

fileName=['Dec_ann.txt'];
A=importdata(fileName);
B = getfield(A, 'data');
Cum(1,:)=B(1:731,2); % discarding time array% transposing Cum array
Rate(1,:)=B(1:731,3); % Production data
Time(1,:)=B(1:731,1); % production time
Block_Pressure(1,:)=B(1:731,4);

Rate=Rate';
Time=Time';
% ---Plotting ANN results Vs. CMG results---

% number of Time steps:
TS=length(Time(:,1));

% Generating Flow Rate Profile from the deline parameters
JJ=1; % One Case

% Calculating the time when flow rate equals the plateau rate, in case
% of fitted qi is greater than plateau rate.
t_qi_ann(1,JJ)=((answer_ann(2,JJ)/rate)^(1/answer_ann(4,JJ))-
1)*(1/answer_ann(3,JJ));
PL_mod_ann(1,JJ)=t_qi_ann(1,JJ)+answer_ann(1,JJ);

% Forecasting Production Profile using decline parameters.
for mm=1:TS
    if Time(mm,JJ)<=PL_mod_ann(1,JJ)
        q_ann(mm,JJ) = rate;
    else
        q_ann(mm,JJ)=answer_ann(2,JJ)./((1+answer_ann(3,JJ).*(Time(mm,JJ)-
answer_ann(1,JJ))).^(answer_ann(4,JJ)));
    end
end
II=1;
plot(handles.plot1,Time(1:TS,1),q_ann(1:TS,II),Time(1:TS,1),Rate(1:TS,II),'
--r')
title(handles.plot1,'Artificial Neural Network Results');
xlabel(handles.plot1,'Time (Days)');ylabel(handles.plot1,'Gas Rate
(ft3/D)'); grid(handles.plot1,'on')
hleg1 = legend(handles.plot1,'DecPrm ANN','CMG Data');

% Starting the Genetic Programming GP Code
function c_gp_Callback(hObject, eventdata, handles)
% hObject handle to c_gp (see GCBO)
% eventdata reserved - to be defined in a future version of MATLAB
% handles structure with handles and user data (see GUIDATA)

% Hints: get(hObject,'String') returns contents of c_gp as text
%    str2double(get(hObject,'String')) returns contents of c_gp as a double
% --- Executes during object creation, after setting all properties.
function c_gp_CreateFcn(hObject, eventdata, handles)
% hObject    handle to c_gp (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    empty - handles not created until after all CreateFcns called

% Hint: edit controls usually have a white background on Windows.
% See ISPC and COMPUTER.
if ispc && isequal(get(hObject,'BackgroundColor'),
    get(0,'defaultUicontrolBackgroundColor'))
    set(hObject,'BackgroundColor','white');
end

function b_gp_Callback(hObject, eventdata, handles)
% hObject    handle to b_gp (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)

% Hints: get(hObject,'String') returns contents of b_gp as text
%        str2double(get(hObject,'String')) returns contents of b_gp as a double

% --- Executes during object creation, after setting all properties.
function b_gp_CreateFcn(hObject, eventdata, handles)
% hObject    handle to b_gp (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    empty - handles not created until after all CreateFcns called

% Hint: edit controls usually have a white background on Windows.
% See ISPC and COMPUTER.
if ispc && isequal(get(hObject,'BackgroundColor'),
    get(0,'defaultUicontrolBackgroundColor'))
    set(hObject,'BackgroundColor','white');
end

function a_gp_Callback(hObject, eventdata, handles)
% hObject    handle to a_gp (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)

% Hints: get(hObject,'String') returns contents of a_gp as text
%        str2double(get(hObject,'String')) returns contents of a_gp as a double
function a_gp_CreateFcn(hObject, eventdata, handles)
% hObject    handle to a_gp (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    empty - handles not created until after all CreateFcns
called

% Hint: edit controls usually have a white background on Windows.
% See ISPC and COMPUTER.
if ispc && isequal(get(hObject,'BackgroundColor'),
    get(0,'defaultUicontrolBackgroundColor'))
    set(hObject,'BackgroundColor','white');
end

function pl_gp_Callback(hObject, eventdata, handles)
% hObject    handle to pl_gp (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)

% Hints: get(hObject,'String') returns contents of pl_gp as text
%       str2double(get(hObject,'String')) returns contents of pl_gp as a
double

function area_gp_Callback(hObject, eventdata, handles)
% hObject    handle to area_gp (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)

% Hints: get(hObject,'String') returns contents of area_gp as text
%       str2double(get(hObject,'String')) returns contents of area_gp as a
double
function area_gp_CreateFcn(hObject, eventdata, handles)
% hObject    handle to area_gp (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    empty - handles not created until after all CreateFcns
called

% Hint: edit controls usually have a white background on Windows.
%       See ISPC and COMPUTER.
if ispc && isequal(get(hObject, 'BackgroundColor'),
    get(0, 'defaultUicontrolBackgroundColor'))
    set(hObject, 'BackgroundColor', 'white');
end

function rate_gp_Callback(hObject, eventdata, handles)
% hObject    handle to rate_gp (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)

% Hints: get(hObject,'String') returns contents of rate_gp as text
%        str2double(get(hObject,'String')) returns contents of rate_gp
% as a double

% --- Executes during object creation, after setting all properties.
function rate_gp_CreateFcn(hObject, eventdata, handles)
% hObject    handle to rate_gp (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    empty - handles not created until after all CreateFcns
called

% Hint: edit controls usually have a white background on Windows.
%       See ISPC and COMPUTER.
if ispc && isequal(get(hObject, 'BackgroundColor'),
    get(0, 'defaultUicontrolBackgroundColor'))
    set(hObject, 'BackgroundColor', 'white');
end

function h_gp_Callback(hObject, eventdata, handles)
% hObject    handle to h_gp (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)

% Hints: get(hObject,'String') returns contents of h_gp as text
%        str2double(get(hObject,'String')) returns contents of h_gp as a double

% --- Executes during object creation, after setting all properties.
function h_gp_CreateFcn(hObject, eventdata, handles)
% hObject    handle to h_gp (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    empty - handles not created until after all CreateFcns called

% Hint: edit controls usually have a white background on Windows.
%       See ISPC and COMPUTER.
if ispc && isequal(get(hObject,'BackgroundColor'),
    get(0,'defaultUicontrolBackgroundColor'))
    set(hObject,'BackgroundColor','white');
end

function phi_gp_Callback(hObject, eventdata, handles)
% hObject    handle to phi_gp (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)

% Hints: get(hObject,'String') returns contents of phi_gp as text
%        str2double(get(hObject,'String')) returns contents of phi_gp as a double

% --- Executes during object creation, after setting all properties.
function phi_gp_CreateFcn(hObject, eventdata, handles)
% hObject    handle to phi_gp (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    empty - handles not created until after all CreateFcns called

% Hint: edit controls usually have a white background on Windows.
%       See ISPC and COMPUTER.
if ispc && isequal(get(hObject,'BackgroundColor'),
    get(0,'defaultUicontrolBackgroundColor'))
    set(hObject,'BackgroundColor','white');
end

function k_gp_Callback(hObject, eventdata, handles)
% hObject    handle to k_gp (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)

% Hints: get(hObject,'String') returns contents of k_gp as text
%        str2double(get(hObject,'String')) returns contents of k_gp as a double

% --- Executes during object creation, after setting all properties.
function k_gp_CreateFcn(hObject, eventdata, handles)
% hObject    handle to k_gp (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    empty - handles not created until after all CreateFcns
% called

% Hint: edit controls usually have a white background on Windows.
% See ISPC and COMPUTER.
if ispc && isequal(get(hObject,'BackgroundColor'),
                get(0,'defaultUicontrolBackgroundColor'))
    set(hObject,'BackgroundColor','white');
end

function pi_gp_Callback(hObject, eventdata, handles)
% hObject    handle to pi_gp (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)

% Hints: get(hObject,'String') returns contents of pi_gp as text
%        str2double(get(hObject,'String')) returns contents of pi_gp as a double

% --- Executes during object creation, after setting all properties.
function pi_gp_CreateFcn(hObject, eventdata, handles)
% hObject    handle to pi_gp (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    empty - handles not created until after all CreateFcns
% called

% Hint: edit controls usually have a white background on Windows.
% See ISPC and COMPUTER.
if ispc && isequal(get(hObject,'BackgroundColor'),
                get(0,'defaultUicontrolBackgroundColor'))
    set(hObject,'BackgroundColor','white');
end

% Start of the GP GUI Code
% --- Executes on button press in calculate_gp.
function calculate_gp_Callback(hObject, eventdata, handles)
% hObject    handle to calculate_gp (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)

% Obtain the input values from the input boxes in the GUI
area_gp = (str2double(get(handles.area_ann,'String')));
rate_gp = (str2double(get(handles.rate_ann,'String')));
phi_gp = (str2double(get(handles.phi_ann,'String')));
k_gp = (str2double(get(handles.k_ann,'String')));
pi_gp = (str2double(get(handles.pi_ann,'String')));
h_gp = (str2double(get(handles.h_ann,'String')));
% ------------------Warning Messages------------------

% The GUI flag warning messages if the values of the input properties are outside the training ranges.

if area_gp > 10890000 || area_gp < 1690000
    set(handles.area_ann,'ForegroundColor','red')
    uiwait(msgbox('Out of range! Specify value between 1,690,000 and 10,890,000','Warning','modal'))
else
    set(handles.area_ann,'ForegroundColor','black')
end

if rate_gp > 36000000 || rate_gp < 9000000
    set(handles.rate_ann,'ForegroundColor','red')
    uiwait(msgbox('Out of range! Specify value between 9,000,000 and 36,000,000','Warning','modal'))
else
    set(handles.rate_ann,'ForegroundColor','black')
end

if phi_gp > 0.20 || phi_gp < 0.08
    set(handles.phi_ann,'ForegroundColor','red')
    uiwait(msgbox('Out of range! Specify value between 0.08 and 0.20','Warning','modal'))
else
    set(handles.phi_ann,'ForegroundColor','black')
end

if k_gp > 100 || k_gp < 8
    set(handles.k_ann,'ForegroundColor','red')
    uiwait(msgbox('Out of range! Specify value between 8 and 100','Warning','modal'))
else
    set(handles.k_ann,'ForegroundColor','black')
end

if pi_gp > 5000 || pi_gp < 2000
    set(handles.pi_ann,'ForegroundColor','red')
    uiwait(msgbox('Out of range! Specify value between 2000 and 5000','Warning','modal'))
else
    set(handles.pi_ann,'ForegroundColor','black')
end

if h_gp > 800 || h_gp < 50
    set(handles.h_ann,'ForegroundColor','red')
    uiwait(msgbox('Out of range! Specify value between 50 and 800','Warning','modal'))
else
    set(handles.h_ann,'ForegroundColor','black')
end
Using the GP Model to predict the output

%Input=[Area,q_Plateau,Thickness/2,POR,Perm,Pl]

INPUT_P1=[area_gp,rate_gp,h_gp/2,phi_gp,k_gp,pi_gp];

answer_gp=GP_Pred(INPUT_P1);

% Assign the predicted values to the output boxes in the GUI
set(handles.pl_gp, 'String', num2str(answer_gp(1,1)));
set(handles.a_gp, 'String', num2str(answer_gp(1,2)));
set(handles.b_gp, 'String', num2str(answer_gp(1,3)));
set(handles.c_gp, 'String', num2str(answer_gp(1,4)));

%% ###** Running Simulation model and check the predicted results
###***
%--- Executes on button press in plot_gp.
function plot_gp_Callback(hObject, eventdata, handles)
% hObject    handle to plot_gp (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)

% obtaining the input values from the input boxes in the GUI
area = (str2double(get(handles.area_ann,'String')));
rate = (str2double(get(handles.rate_ann,'String')));
phi = (str2double(get(handles.phi_ann,'String')));
k = (str2double(get(handles.k_ann,'String')));
pi = (str2double(get(handles.pi_ann,'String')));
h = (str2double(get(handles.h_ann,'String')));

% ---------------------- Warning Messages-------------------------------%
% The GUI flag warning messages if the values of the input props are
% outside the traning ranges.
if area > 10890000 || area < 1690000
    set(handles.area_ann,'ForegroundColor','red')
    uiwait(msgbox('Out of range! Specify value between 1,690,000 and 10,890,000', 'Warning','modal'))
else
    set(handles.area_ann,'ForegroundColor','black')
end

if rate > 36000000 || rate < 9000000
    set(handles.rate_ann,'ForegroundColor','red')
    uiwait(msgbox('Out of range! Specify value between 9,000,000 and 36,000,000', 'Warning','modal'))
else
    set(handles.rate_ann,'ForegroundColor','black')
end
if phi > 0.20 || phi < 0.08
    set(handles.phi_ann,'ForegroundColor','red')
    uiwait(msgbox('Out of range! Specify value between 0.08 and 0.20','Warning','modal'))
else
    set(handles.phi_ann,'ForegroundColor','black')
end

if k > 100 || k < 8
    set(handles.k_ann,'ForegroundColor','red')
    uiwait(msgbox('Out of range! Specify value between 8 and 100','Warning','modal'))
else
    set(handles.k_ann,'ForegroundColor','black')
end

if pi > 5000 || pi < 2000
    set(handles.pi_ann,'ForegroundColor','red')
    uiwait(msgbox('Out of range! Specify value between 2000 and 5000','Warning','modal'))
else
    set(handles.pi_ann,'ForegroundColor','black')
end

if h > 800 || h < 50
    set(handles.h_ann,'ForegroundColor','red')
    uiwait(msgbox('Out of range! Specify value between 50 and 800','Warning','modal'))
else
    set(handles.h_ann,'ForegroundColor','black')
end

%--------Predict the output value using the GP model------------
INPUT_P1=[area,rate,h/2,phi,k,pi];
anwer_gp=GP_Pred(INPUT_P1);

% The start of the simulation model
% Dividing the thickness over two layers.
h=h/2;
nam2 = 'Dec_gp.bat';
fidbatch = fopen(nam2,'w');
RefDepth= h+10000;

nam = ['Dec_gp.dat'];
fid = fopen(nam,'w');
fprintf(fid,'RESULTS SIMULATOR IMEX 201110\n');
fprintf(fid,'\n');
fprintf(fid,'**$ Distance units: ft \n');
fprintf(fid,'RESULTS XOFFSET           0.0000\n');
fprintf(fid,'RESULTS YOFFSET           0.0000\n');
fprintf(fid,'RESULTS ROTATION           0.0000 **$ (DEGREES)\n');
fprintf(fid,'**$ Property: NULL Blocks  Max: 1  Min: 1\n');
fprintf(fid,'**$ 0 = null block, 1 = active block\n');
fprintf(fid,'**$ Property: Porosity  Max: %d  Min: %d\n');
fprintf(fid,'**$ Property: Permeability I (md)   Max: %d  Min: %d\n');
fprintf(fid,'**$ Property: Permeability J (md)   Max: %d  Min: %d\n');
fprintf(fid,'**$ Property: Permeability K (md)   Max: %d  Min: %d\n');
fprintf(fid,'**$ Property: Pinchout Array  Max: 1  Min: 1\n');
fprintf(fid,'**$ p        Eg       visg\n');
fprintf(fid,'14.696   4.81152  0.0117959\n');
fprintf(fid,' 0.665625  0.00810623\n');
fprintf(fid,' 0.7125   0.00332031\n');
fprintf(fid,' 0.759375  0.00105057\n');
fprintf(fid,' 0.80625   0.00020752\n');
fprintf(fid,' 0.853125  1.297e-005\n');
fprintf(fid,'   0.9       0\n');
fprintf(fid,' 0.925     0\n');
fprintf(fid,' 0.95     0\n');
fprintf(fid,'INITIAL\n');
fprintf(fid,'VERTICAL DEPTH_AVE WATER_GAS EQUIL NOTRANZONE\n');
fprintf(fid,'REFDEPTH %d\n', RefDepth);
fprintf(fid,'REFPRES %d\n', pi);
fprintf(fid,'DWGC 12000\n');
fprintf(fid,'DATUMDEPTH %d INITIAL\n', RefDepth);
fprintf(fid,'NUMERICAL\n');
fprintf(fid,'RUN\n');
fprintf(fid,'DATE 2013 1 1\n');
fprintf(fid,'GROUP ''Prod'' ATTACHTO ''Group-1''\n');
fprintf(fid,'**$\n');
fprintf(fid,'**$\n');
fprintf(fid,'WELL ''Well-1'' ATTACHTO ''Prod''\n');
fprintf(fid,'OPERATE MIN BHP 28. CONT\n');
fprintf(fid,'**$\n');
fprintf(fid,'**$\n');
fprintf(fid,'GEOMETRY K 0.25 0.37 1. 0.\n');
fprintf(fid,'PERF GEOA ''Well-1''\n');
fprintf(fid,'***$ UBA ff Status Connection \
');
fprintf(fid,'    1 1 1 1. OPEN FLOW-TO ''SURFACE''\n');
fprintf(fid,'    1 1 2 1. OPEN FLOW-TO 1\n');
fprintf(fid,'GCONP ''Prod''\n');
fprintf(fid,'    TARGET STG %d\n', rate);
fprintf(fid,'\n');
fprintf(fid,'DATE 2015 1 1.00000\n');
fprintf(fid,'DATE 2016 1 1.00000\n');
fprintf(fid,'DATE 2019 1 1.00000\n');
fprintf(fid,'DATE 2025 1 1.00000\n');
fprintf(fid,'DATE 2030 1 1.00000\n');
fprintf(fid,'DATE 2035 1 1.00000\n');
fprintf(fid,'DATE 2040 1 1.00000\n');
fprintf(fid,'DATE 2045 1 1.00000\n');
fprintf(fid,'DATE 2050 1 1.00000\n');
fprintf(fid,'DATE 2053 12 31.00000\n');
fprintf(fid,'DATE 2063 12 31.00000\n');
fprintf(fid,'DATE 2073 12 31.00000\n');

fprintf(fid,'RESULTS RELPERMCORR NUMROCKTYPE 1\n');
fprintf(fid,'RESULTS RELPERMCORR CORRVALS 0.15 0.15 0.05 0.1 1 0.85 4\n');
fprintf(fid,'RESULTS RELPERMCORR CORRVALS_HONARPOUR -99999 -99999 -99999 -99999 -99999 -99999 -99999\n');
fprintf(fid,'RESULTS RELPERMCORR NOSWC false
');
fprintf(fid,'RESULTS RELPERMCORR CALINDEX 5
');
fprintf(fid,'RESULTS RELPERMCORR STOP
');
fprintf(fid,'
');
fprintf(fid,'RESULTS SPEC ''Permeability I''
');
fprintf(fid,'RESULTS SPEC SPECNOTCALCVAL -99999
');
fprintf(fid,'RESULTS SPEC REGION ''All Layers (Whole Grid)''
');
fprintf(fid,'RESULTS SPEC REGIONTYPE ''REGION_WHOLEGRID''
');
fprintf(fid,'RESULTS SPEC LAYERNUMB 0
');
fprintf(fid,'RESULTS SPEC PORTYPE 1
');
fprintf(fid,'RESULTS SPEC CON 50
');
fprintf(fid,'RESULTS SPEC SPECKEEPMOD ''YES''
');
fprintf(fid,'RESULTS SPEC STOP
');
fprintf(fid,'
');
fprintf(fid,'RESULTS SPEC ''Permeability J''
');
fprintf(fid,'RESULTS SPEC SPECNOTCALCVAL -99999
');
fprintf(fid,'RESULTS SPEC REGION ''All Layers (Whole Grid)''
');
fprintf(fid,'RESULTS SPEC REGIONTYPE ''REGION_WHOLEGRID''
');
fprintf(fid,'RESULTS SPEC LAYERNUMB 0
');
fprintf(fid,'RESULTS SPEC PORTYPE 1
');
fprintf(fid,'RESULTS SPEC CON 50
');
fprintf(fid,'RESULTS SPEC SPECKEEPMOD ''YES''
');
fprintf(fid,'RESULTS SPEC STOP
');
fprintf(fid,'
');
fprintf(fid,'RESULTS SPEC ''Porosity''
');
fprintf(fid,'RESULTS SPEC SPECNOTCALCVAL -99999
');
fprintf(fid,'RESULTS SPEC REGION ''All Layers (Whole Grid)''
');
fprintf(fid,'RESULTS SPEC REGIONTYPE ''REGION_WHOLEGRID''
');
fprintf(fid,'RESULTS SPEC LAYERNUMB 0
');
fprintf(fid,'RESULTS SPEC PORTYPE 1
');
fprintf(fid,'RESULTS SPEC CON 0.15
');
fprintf(fid,'RESULTS SPEC SPECKEEPMOD ''YES''
');
fprintf(fid,'RESULTS SPEC STOP
');
fclose(fid);
fprintf(fidbatch,'%s','"C:\Program Files (x86)\CMG\IMEX\2011.10\Win_x64\EXE\mx201110.exe" -f '); %office link
fprintf(fidbatch,'%s\n',nam);
fclose(fidbatch);
% Executing the simulation model
!Dec_gp.bat

% Extracts Data from CMG Results into text file

fordata = ('DecGP_RWD.bat');
fidrwd = fopen(fordata, 'wt');

dataext = ['Dec_gp.rwd'];
fid = fopen(dataext, 'wt');
fprintf(fid, '%s', 'FILE ''Dec_gp''');
fprintf(fid, '%s', '.irf''');

fprintf(fid, '\nLINES-PER-PAGE 10000\n');
fprintf(fid, '\nTIME ON\n');
fprintf(fid, '\n*TIMES-FOR\n');

for ff=[0:(10):14600];
  if ff==0;
    ff=1;
  end
  fprintf(fid, '%d\n', ff);
end

fprintf(fid, 'SPREADSHEET\n');   %GIVES ONLY ONE TABLE AND STRING DATA
  IS WRITTEN ONLY ONCE(FIVE LINES)
  fprintf(fid, 'TABLE-FOR\n');
  fprintf(fid, '%s\n', 'COLUMN-FOR *PARAMETERS ''Cumulative Gas SC'' *WELLS ''well-1''');
  fprintf(fid, '%s\n', 'COLUMN-FOR *PARAMETERS ''Gas Rate SC'' *WELLS ''well-1''');
  fprintf(fid, '%s\n', 'COLUMN-FOR *PARAMETERS ''Well Block Pressure'' *WELLS ''well-1''');

fprintf(fid, '%s\n', 'TABLE-END');
fclose(fid);

fprintf(fidrwd, '%s', 'call "C:\Program Files (x86)\CMG\BR\2011.10\Win_x64\EXE\report.exe" -f "Dec_gp"');
link
%   fprintf(fidrwd, '1');
fprintf(fidrwd, '%s', '.rwd''');
fprintf(fidrwd, '%s', '-o "Dec_gp.txt"');
fprintf(fidrwd, '
');

fclose(fidrwd);
DecGP_RWD.bat

!DecGP_RWD.bat

% Extracting Data From Text File
files= dir ('*.txt');

fileName=['Dec_gp.txt'];
A=importdata(fileName);
B = getfield(A,'data');
Cum(1,:)=B(1:731,2); % discarding time array
Rate(1,:)=B(1:731,3); % Production data
Time(1,:)=B(1:731,1); % production time
Block_Pressure(1,:)=B(1:731,4);
Rate=Rate';
Time=Time';

% Plotting gp results Vs. CMG results

% number of Time steps:
TS=length(Time(:,1));

% Generating Flow Rate Profile from the deline parameters
JJ=1; % One Case

% Calculating the time when flow rate equals the plateau rate, in case of fitted qi is greater than plateau rate.
t_qi_gp(1,JJ)=((answer_gp(JJ,2)/rate)^((1/answer_gp(JJ,4))-1))*(1/answer_gp(JJ,3));
PL_mod_gp(1,JJ)=t_qi_gp(1,JJ)+answer_gp(JJ,1);

%Forecasting Production Profile using decline parameters.
for mm=1:TS
    if Time(mm,JJ)<=PL_mod_gp(1,JJ)
        q_gp(mm,JJ) = rate;
    else
        q_gp(mm,JJ)=answer_gp(JJ,2)./(1+answer_gp(JJ,3).*(Time(mm,JJ)-answer_gp(JJ,1)).^answer_gp(JJ,4));
    end
end

II=1;
plot(handles.plot2,Time(1:TS,1),q_gp(1:TS,II),Time(1:TS,1),Rate(1:TS,II),'-r');
title(handles.plot2,'Genetic Programming Results');
xlabel(handles.plot2,'Time (Days)');ylabel(handles.plot2,'Gas Rate (ft3/D)'); grid(handles.plot2,'on');
hleg1 = legend(handles.plot2,'DecPrm GP','CMG Data');
% --- Executes on button press in clear2.
function clear2_Callback(hObject, eventdata, handles)
% hObject    handle to clear2 (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)
cla(handles.plot2, 'reset');
set(handles.p1_gp, 'String', '');
set(handles.a_gp, 'String', '');
set(handles.b_gp, 'String', '');
set(handles.c_gp, 'String', '');

% --- Executes on button press in clear1.
function clear1_Callback(hObject, eventdata, handles)
% hObject    handle to clear1 (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)
cla(handles.plot1, 'reset');
set(handles.p1_ann, 'String', '');
set(handles.a_ann, 'String', '');
set(handles.b_ann, 'String', '');
set(handles.c_ann, 'String', '');

Code for the Second Expert System GUI

function varargout = ANNExpertSys2_V2(varargin)
% ANNEXPERTSYS2_V2 MATLAB code for ANNExpertSys2_V2.fig
%    ANNEXPERTSYS2_V2, by itself, creates a new ANNEXPERTSYS2_V2 or
% raises the existing
%    singleton*.
%    %
%    H = ANNEXPERTSYS2_V2 returns the handle to a new
ANNEXPERTSYS2_V2 or the handle to
%    the existing singleton*.
%    %
%    ANNEXPERTSYS2_V2('CALLBACK',hObject,eventData,handles,...) calls
the local
%    function named CALLBACK in ANNEXPERTSYS2_V2.M with the given
input arguments.
%    %
%    ANNEXPERTSYS2_V2('Property','Value',...) creates a new
ANNEXPERTSYS2_V2 or raises the
%    existing singleton*. Starting from the left, property value
pairs are
%    applied to the GUI before ANNExpertSys2_V2_OpeningFcn gets
called. An
%    unrecognized property name or invalid value makes property
application
% stop. All inputs are passed to ANNExpertSys2_V2_OpeningFcn via varargin.
% "See GUI Options on GUIDE's Tools menu. Choose "GUI allows only one
% instance to run (singleton)".
% See also: GUIDE, GUIDATA, GUIDATA
% Edit the above text to modify the response to help ANNExpertSys2_V2
% Last Modified by GUIDE v2.5 11-Sep-2014 11:27:07

% Begin initialization code - DO NOT EDIT
gui_Singleton = 1;
gui_State = struct('gui_Name', mfilename, ...
    'gui_Singleton', gui_Singleton, ...
    'gui_OpeningFcn', @ANNExpertSys2_V2_OpeningFcn, ...
    'gui_OutputFcn', @ANNExpertSys2_V2_OutputFcn, ...
    'gui_LAYOUTFcn', [], ...
    'gui_Callback', []);
if nargin && ischar(varargin{1})
    gui_State.guicallback = str2func(varargin{1});
end

if nargout
    [varargout{1:nargout}] = gui_mainfcn(gui_State, varargin{:});
else
    gui_mainfcn(gui_State, varargin{:});
end
% End initialization code - DO NOT EDIT

% --- Executes just before ANNExpertSys2_V2 is made visible.
function ANNExpertSys2_V2_OpeningFcn(hObject, eventdata, handles, varargin)
% This function has no output args, see OutputFcn.
% hObject    handle to figure
% eventdata   reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)
% varargin   command line arguments to ANNExpertSys2_V2 (see VARARGIN)

% Choose default command line output for ANNExpertSys2_V2
handles.output = hObject;

% Update handles structure
guidata(hObject, handles);

% UIWAIT makes ANNExpertSys2_V2 wait for user response (see UIRESUME)
% uiwait(handles.figure1);

% --- Outputs from this function are returned to the command line.
function varargout = ANNExpertSys2_V2_OutputFcn(hObject, eventdata, handles)
% varargout  cell array for returning output args (see VARARGOUT);
% hObject    handle to figure
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)

% Get default command line output from handles structure
varargout{1} = handles.output;

function area_Callback(hObject, eventdata, handles)
% hObject    handle to area (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)

% Hints: get(hObject,'String') returns contents of area as text
%        str2double(get(hObject,'String')) returns contents of area as a double

% --- Executes during object creation, after setting all properties.
function area_CreateFcn(hObject, eventdata, handles)
% hObject    handle to area (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    empty - handles not created until after all CreateFcns called

% Hint: edit controls usually have a white background on Windows.
% See ISPC and COMPUTER.
if ispc && isequal(get(hObject,'BackgroundColor'),
get(0,'defaultUicontrolBackgroundColor'))
    set(hObject,'BackgroundColor','white');
end

function sim_pl_Callback(hObject, eventdata, handles)
% hObject    handle to sim_pl (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)

% Hints: get(hObject,'String') returns contents of sim_pl as text
%        str2double(get(hObject,'String')) returns contents of sim_pl as a double

% --- Executes during object creation, after setting all properties.
function sim_pl_CreateFcn(hObject, eventdata, handles)
% hObject    handle to sim_pl (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
function rate_Callback(hObject, eventdata, handles)
    % hObject    handle to rate (see GCBO)
    % eventdata  reserved - to be defined in a future version of MATLAB
    % handles    structure with handles and user data (see GUIDATA)

    % Hints: get(hObject,'String') returns contents of rate as text
    %        str2double(get(hObject,'String')) returns contents of rate as a double

    % --- Executes during object creation, after setting all properties.
    function rate_CreateFcn(hObject, eventdata, handles)
        % hObject    handle to rate (see GCBO)
        % eventdata  reserved - to be defined in a future version of MATLAB
        % handles    empty - handles not created until after all CreateFcns called

        % Hint: edit controls usually have a white background on Windows.
        %       See ISPC and COMPUTER.
        if ispc && isequal(get(hObject,'BackgroundColor'),
                           get(0,'defaultUicontrolBackgroundColor'))
            set(hObject,'BackgroundColor','white');
        end

function phi_Callback(hObject, eventdata, handles)
    % hObject    handle to phi (see GCBO)
    % eventdata  reserved - to be defined in a future version of MATLAB
    % handles    structure with handles and user data (see GUIDATA)

    % Hints: get(hObject,'String') returns contents of phi as text
    %        str2double(get(hObject,'String')) returns contents of phi as a double

    % --- Executes during object creation, after setting all properties.
    function phi_CreateFcn(hObject, eventdata, handles)
        % hObject    handle to phi (see GCBO)
        % eventdata  reserved - to be defined in a future version of MATLAB
% handles  empty - handles not created until after all CreateFcns
called

% Hint: edit controls usually have a white background on Windows.
%       See ISPC and COMPUTER.
if ispc & & isequal(get(hObject,’BackgroundColor’),
get(0,’defaultUicontrolBackgroundColor’))
    set(hObject,’BackgroundColor’,’white’);
end

function k_Callback(hObject, eventdata, handles)
% hObject    handle to k (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)

% Hints: get(hObject,’String’) returns contents of k as text
%        str2double(get(hObject,’String’)) returns contents of k as a
double

% --- Executes during object creation, after setting all properties.
function k_CreateFcn(hObject, eventdata, handles)
% hObject    handle to k (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    empty - handles not created until after all CreateFcns
called

% Hint: edit controls usually have a white background on Windows.
%       See ISPC and COMPUTER.
if ispc & & isequal(get(hObject,’BackgroundColor’),
get(0,’defaultUicontrolBackgroundColor’))
    set(hObject,’BackgroundColor’,’white’);
end

function pi_Callback(hObject, eventdata, handles)
% hObject    handle to pi (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)

% Hints: get(hObject,’String’) returns contents of pi as text
%        str2double(get(hObject,’String’)) returns contents of pi as a
double

% --- Executes during object creation, after setting all properties.
function pi_CreateFcn(hObject, eventdata, handles)
% hObject    handle to pi (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles  empty - handles not created until after all CreateFcns called

% Hint: edit controls usually have a white background on Windows.
%       See ISPC and COMPUTER.
if ispc && isequal(get(hObject,'BackgroundColor'),
    get(0,'defaultUicontrolBackgroundColor'))
    set(hObject,'BackgroundColor','white');
end

function h_Callback(hObject, eventdata, handles)
% hObject    handle to h (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)

% Hints: get(hObject,'String') returns contents of h as text
%        str2double(get(hObject,'String')) returns contents of h as a double

% --- Executes during object creation, after setting all properties.
function h_CreateFcn(hObject, eventdata, handles)
% hObject    handle to h (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    empty - handles not created until after all CreateFcns called

% Hint: edit controls usually have a white background on Windows.
%       See ISPC and COMPUTER.
if ispc && isequal(get(hObject,'BackgroundColor'),
    get(0,'defaultUicontrolBackgroundColor'))
    set(hObject,'BackgroundColor','white');
end

function pl_Callback(hObject, eventdata, handles)
% hObject    handle to pl (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)

% Hints: get(hObject,'String') returns contents of pl as text
%        str2double(get(hObject,'String')) returns contents of pl as a double

% --- Executes during object creation, after setting all properties.
function pl_CreateFcn(hObject, eventdata, handles)
% hObject    handle to pl (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    structure with handles and user data (see GUIDATA)
% handles   empty - handles not created until after all CreateFcns
% called

% Hint: edit controls usually have a white background on Windows.
% See ISPC and COMPUTER.
if ispc && isequal(get(hObject,'BackgroundColor'),
get(0,'defaultUicontrolBackgroundColor'))
    set(hObject,'BackgroundColor','white');
end

%% Start of GUI Code
% --- Executes on button press in calculate.
function calculate_Callback(hObject, eventdata, handles)
  % hObject    handle to calculate (see GCBO)
  % eventdata  reserved - to be defined in a future version of MATLAB
  % handles    structure with handles and user data (see GUIDATA)

  % Obtain input data from the input boxes in the GUI
  rate = (str2double(get(handles.rate,'String')));
  phi = (str2double(get(handles.phi,'String')));
  k  = (str2double(get(handles.k,'String')));
  pi = (str2double(get(handles.pi,'String')));
  h  = (str2double(get(handles.h,'String')));
  pl = (str2double(get(handles.pl,'String')));

  %-------------------------------Warning Messages------------------------
  --
  % The GUI flag warning messages if the values of the input properteis are
  % outside the traning ranges.
  if rate > 36000000 || rate < 9000000
    set(handles.rate,'ForegroundColor','red')
    uiwait(msgbox('Out of range! Specify value between 9,000,000 and
36,000,000','Warning','modal'))
  else
    set(handles.rate,'ForegroundColor','black')
  end

  if phi > 0.20 || phi < 0.08
    set(handles.phi,'ForegroundColor','red')
    uiwait(msgbox('Out of range! Specify value between 0.08 and
0.20','Warning','modal'))
  else
    set(handles.phi,'ForegroundColor','black')
  end

  if k > 100 || k < 8
    set(handles.k,'ForegroundColor','red')
    uiwait(msgbox('Out of range! Specify value between 8 and
100','Warning','modal'))
  else

set(handles.k,'ForegroundColor','black')

end

if pi > 5000 || pi < 2000
    set(handles.pi,'ForegroundColor','red')
    uiwait(msgbox('Out of range! Specify value between 2000 and 5000','Warning','modal'))
else
    set(handles.pi,'ForegroundColor','black')
end

if h > 800 || h < 50
    set(handles.h,'ForegroundColor','red')
    uiwait(msgbox('Out of range! Specify value between 50 and 800','Warning','modal'))
else
    set(handles.h,'ForegroundColor','black')
end

if pl > 7120 || pl < 40
    set(handles.pl,'ForegroundColor','red')
    uiwait(msgbox('Out of range! Specify value between 40 and 7120','Warning','modal'))
else
    set(handles.pl,'ForegroundColor','black')
end

%----------------------Predict output using ANN------------------------

%Input=[q_Plateau;Thickness/2;POR;Perm;Pi;PL]
INPUT_P1=[rate;h/2;phi;k;pi;pl];
AREA=ANN_Pred_Area(INPUT_P1);

% Assigning output value to the output box in the GUI
% set(handles.area,'String',num2str(round(T_ann_N(1))));
set(handles.area, 'String', num2str(AREA));

% Simulation Model
% --- Executes on button press in simulate.
function simulate_Callback(hObject, eventdata, handles)
    hObject handle to simulate (see GCBO)
    eventdata reserved - to be defined in a future version of MATLAB
    handles structure with handles and user data (see GUIDATA)

    % Obtain input data from the input boxes in the GUI
    rate = (str2double(get(handles.rate,'String')));
    phi = (str2double(get(handles.phi,'String')));
    k = (str2double(get(handles.k,'String')));
    pi = (str2double(get(handles.pi,'String')));
    h = (str2double(get(handles.h,'String')));
    pl = (str2double(get(handles.pl,'String')));
INPUT_P1=[rate;h/2;phi;k;pi;pl];
AREA=ANN_Pred_Area(INPUT_P1);

% ------------------------Warning Messages------------------------
% The GUI flag warning messages if the values of the input properties are
% outside the training ranges.

if rate > 36000000 || rate < 9000000
    set(handles.rate,'ForegroundColor','red')
    uiwait(msgbox('Out of range! Specify value between 9,000,000 and
36,000,000','Warning','modal'))
else
    set(handles.rate,'ForegroundColor','black')
end

if phi > 0.20 || phi < 0.08
    set(handles.phi,'ForegroundColor','red')
    uiwait(msgbox('Out of range! Specify value between 0.08 and
0.20','Warning','modal'))
else
    set(handles.phi,'ForegroundColor','black')
end

if k > 100 || k < 8
    set(handles.k,'ForegroundColor','red')
    uiwait(msgbox('Out of range! Specify value between 8 and
100','Warning','modal'))
else
    set(handles.k,'ForegroundColor','black')
end

if pi > 5000 || pi < 2000
    set(handles.pi,'ForegroundColor','red')
    uiwait(msgbox('Out of range! Specify value between 2000 and
5000','Warning','modal'))
else
    set(handles.pi,'ForegroundColor','black')
end

if h > 800 || h < 50
    set(handles.h,'ForegroundColor','red')
    uiwait(msgbox('Out of range! Specify value between 50 and
800','Warning','modal'))
else
    set(handles.h,'ForegroundColor','black')
end

if pl > 7120 || pl < 40
    set(handles.pl,'ForegroundColor','red')
    uiwait(msgbox('Out of range! Specify value between 40 and
7120','Warning','modal'))
else
    set(handles.pl, 'ForegroundColor', 'black')
end

% Dividing the thickness over two layers.

h = h/2;
nam2 = 'Area.bat';
fidbatch = fopen(nam2, 'w');
RefDepth = h + 10000;

nam = ['Area.dat'];
fid = fopen(nam, 'w');

fprintf(fid, 'RESULTS SIMULATOR IMEX 201110
');
fprintf(fid, 'INUNIT FIELD
');
fprintf(fid, 'WSRF WELL 1
');
fprintf(fid, 'WSRF GRID TIME
');
fprintf(fid, 'WSRF SECTOR TIME
');
fprintf(fid, 'OUTSRF WELL LAYER NONE
');
fprintf(fid, 'OUTSRF RES ALL
');
fprintf(fid, 'OUTSRF GRID SO SG SW PRES OILPOT BPP SSPRES WINFLUX
');
fprintf(fid, 'WFRN GRID 0
');
fprintf(fid, 'OUTPRN GRID NONE
');
fprintf(fid, 'OUTPRN RES NONE
');

fprintf(fid, 'GRID VARI 1 1 2
');
fprintf(fid, 'KDIR DOWN
');
fprintf(fid, 'DI I VAR
');
fprintf(fid, ' %d
', sqrt(AREA));
fprintf(fid, 'DJ J VAR
');
fprintf(fid, ' %d
', sqrt(AREA));
fprintf(fid, 'DK ALL
');
fprintf(fid, ' 2*%d
', h);
fprintf(fid, 'DTOP
');
fprintf(fid, ' 10000
');

fprintf(fid, 'RESULTS XOFFSET           0.0000
');
fprintf(fid, 'RESULTS YOFFSET           0.0000
');
fprintf(fid, 'RESULTS ROTATION           0.0000 **$ (DEGREES)
');
fprintf(fid, 'RESULTS AXES-DIRECTIONS 1.0 -1.0 1.0
');
fprintf(fid, '**$ Property: NULL Blocks  Max: 1  Min: 1
');
fprintf(fid, '**$ 0 = null block, 1 = active block
');
fprintf(fid, 'NULL CON            1
');
fprintf(fid, '**$ Property: Porosity  Max: %d  Min: %d
', phi, phi);
fprintf(fid, 'POR CON          %d
', phi);
fprintf(fid, '**$ Property: Permeability I (md)   Max: %d  Min: %d
', k, k);
fprintf(fid,'PERMI CON %d\n', k);
fprintf(fid,'***$ Property: Permeability J (md) Max: %d Min: %d\n', k, k);
fprintf(fid,'PERMJ CON %d\n', k);
fprintf(fid,'***$ Property: Permeability K (md) Max: %d Min: %d\n', k, k);
fprintf(fid,'PERMK CON %d\n', k);
fprintf(fid,'***$ Property: Pinchout Array Max: 1 Min: 1\n');
fprintf(fid,'PINCHOUTARRAY CON %d\n', 1);
fprintf(fid,'CPOR 0.000001\n');
fprintf(fid,'MODEL GASWATER \n');
fprintf(fid,'TRES 150\n');
fprintf(fid,'PVTG EG 1\n');
fprintf(fid,'***$ p Eg visg\n');
fprintf(fid,'14.696 4.81152 0.0117959\n');
fprintf(fid,'347.05 380.147 0.0137868\n');
fprintf(fid,'547.403 424.135 0.0128884\n');
fprintf(fid,'747.795 464.132 0.0122183\n');
fprintf(fid,'948.187 504.13 0.0115579\n');
fprintf(fid,'1148.579 544.127 0.0110186\n');
fprintf(fid,'1349.971 584.124 0.0105995\n');
fprintf(fid,'1550.363 624.121 0.0102127\n');
fprintf(fid,'1750.755 664.118 0.0098379\n');
fprintf(fid,'1951.147 704.115 0.0094872\n');
fprintf(fid,'2151.539 744.112 0.0091508\n');
fprintf(fid,'2351.931 784.109 0.0088274\n');
fprintf(fid,'2552.323 824.106 0.0085178\n');
fprintf(fid,'2752.715 864.103 0.0082207\n');
fprintf(fid,'2953.107 904.1 0.0079359\n');
fprintf(fid,'3153.499 944.1 0.0076628\n');
fprintf(fid,'3353.891 984.1 0.0074014\n');
fprintf(fid,'3554.283 1024.1 0.0071419\n');
fprintf(fid,'3754.675 1064.1 0.0068938\n');
fprintf(fid,'4055.067 1104.1 0.0066571\n');
fprintf(fid,'4255.459 1144.1 0.0064217\n');
fprintf(fid,'4455.851 1184.1 0.0061876\n');
fprintf(fid,'4656.243 1224.1 0.0059547\n');
fprintf(fid,'4856.635 1264.1 0.0057229\n');
fprintf(fid,'5057.027 1304.1 0.0054923\n');
fprintf(fid,'DENSITY GAS 5.802166e-002\n');
fprintf(fid,'REFPW 14.696\n');
fprintf(fid,'DENSITY WATER 61.6381\n');
fprintf(fid,'BWI 1.01944\n');
fprintf(fid,'CW 3.1589e-006\n');
fprintf(fid,'VWI 0.47184\n');
fprintf(fid,'CVW 0.0\n');
fprintf(fid,'ROCKFLUID\n');
fprintf(fid,'RPT 1\n');
fprintf(fid,'***$ Sw krw\n');
fprintf(fid,'SWT\n');
fprintf(fid,'0.15 0\n');
fprintf(fid,'0.203125 1.52588e-005\n');
fprintf(fid,'0.25625 0.000244141\n');
fprintf(fid,'0.309375 0.00123596\n');
fprintf(fid,'0.3625 0.00390625\n');
fprintf(fid,'0.415625 0.00953674\n');
fprintf(fid,'0.46875 0.0197754\n');
fprintf(fid,'0.521875 0.0366364\n');
fprintf(fid,'0.575 0.0625\n');
fprintf(fid,'0.628125 0.100113\n');
fprintf(fid,'0.734375 0.223404\n');
fprintf(fid,'   0.7875     0.316406
');
fprintf(fid,'   0.840625     0.435806
');
fprintf(fid,'   0.946875     0.772476
');
fprintf(fid,'             1             1
');
fprintf(fid,'**$        Sl       krg
');
fprintf(fid,'SLT
');
fprintf(fid,'   0.15        0.85
');
fprintf(fid,'   0.196875    0.656605
');
fprintf(fid,'   0.24375    0.498254
');
fprintf(fid,'   0.290625    0.370435
');
fprintf(fid,'   0.3375    0.268945
');
fprintf(fid,'   0.384375    0.189893
');
fprintf(fid,'   0.43125    0.1297
');
fprintf(fid,'   0.478125    0.085096
');
fprintf(fid,'   0.525    0.053125
');
fprintf(fid,'   0.571875   0.0311409
');
fprintf(fid,'   0.61875    0.0168091
');
fprintf(fid,'   0.665625    0.00810623
');
fprintf(fid,'   0.7125    0.00332031
');
fprintf(fid,'   0.759375    0.00020752
');
fprintf(fid,'   0.853125 1.297e-005
');
fprintf(fid,'   0.9           0
');
fprintf(fid,'              0.911
');
fprintf(fid,'   0.95           0
');
fprintf(fid,'INITIAL
');
fprintf(fid,'VERTICAL DEPTH_AVE WATER_GAS EQUIL NOTRAN ZONE
');
fprintf(fid,'
');
fprintf(fid,'REFDEPTH %d
', RefDepth);
fprintf(fid,'REFPRES %d
', pi);
fprintf(fid,'DWGC 12000
');
fprintf(fid,'
');
fprintf(fid,'DATE 2013 1 1
');
fprintf(fid,'GROUP ''Prod'' ATTACHTO ''Group-1''
');
fprintf(fid,'**$
');
fprintf(fid,'**$
');
fprintf(fid,'WELL ''Well-1'' ATTACHTO ''Prod''
');
fprintf(fid,'OPERATE MIN BHP .28. CONT
');
fprintf(fid,'GCONP ''Prod''
');
fprintf(fid,'TARGET STG %d
',rate);
fprintf(fid, 'DATE 2015 1 1.00000
');
fprintf(fid, 'DATE 2016 1 1.00000
');
fprintf(fid, 'DATE 2019 1 1.00000
');
fprintf(fid, 'DATE 2025 1 1.00000
');
fprintf(fid, 'DATE 2040 1 1.00000
');
fprintf(fid, 'DATE 2045 1 1.00000
');
fprintf(fid, 'DATE 2050 1 1.00000
');
fprintf(fid, 'DATE 2053 12 31.00000
');
fprintf(fid, 'DATE 2063 12 31.00000
');
fprintf(fid, 'DATE 2073 12 31.00000
);

fprintf(fid, 'RESULTS RELPERMCORR NUMROCKTYPE 1
');
fprintf(fid, 'RESULTS RELPERMCORR CORRVALS 0.15 0.15 0.05 0.1 1 0.85 4
');
fprintf(fid, 'RESULTS RELPERMCORR CORRVALS_HONARPOUR -99999 -99999 -99999 -99999 -99999 -99999 -99999
');
fprintf(fid, 'RESULTS RELPERMCORR NOSWC false
');
fprintf(fid, 'RESULTS RELPERMCORR CALINDEX 5
');
fprintf(fid, 'RESULTS RELPERMCORR STOP
');
fprintf(fid, '
');
fprintf(fid, 'RESULTS SPEC ''Permeability I''
');
fprintf(fid, 'RESULTS SPEC SPECNOTCALCVAL -99999
');
fprintf(fid, 'RESULTS SPEC REGION ''All Layers (Whole Grid)''
');
fprintf(fid, 'RESULTS SPEC REGIONTYPE ''REGION_WHOLEGRID''
');
fprintf(fid, 'RESULTS SPEC LAYERNUMB 0
');
fprintf(fid, 'RESULTS SPEC PORTYPE 1
');
fprintf(fid, 'RESULTS SPEC CON 50
');
fprintf(fid, 'RESULTS SPEC SPECKEEPMOD ''YES''
');
fprintf(fid, 'RESULTS SPEC STOP
');
fprintf(fid, '
');
fprintf(fid, 'RESULTS SPEC ''Permeability J''
');
fprintf(fid, 'RESULTS SPEC SPECNOTCALCVAL -99999
');
fprintf(fid, 'RESULTS SPEC REGION ''All Layers (Whole Grid)''
');
fprintf(fid, 'RESULTS SPEC REGIONTYPE ''REGION_WHOLEGRID''
');
fprintf(fid, 'RESULTS SPEC LAYERNUMB 0
');
fprintf(fid, 'RESULTS SPEC PORTYPE 1
');
fprintf(fid, 'RESULTS SPEC CON 50
');
fprintf(fid, 'RESULTS SPEC SPECKEEPMOD ''YES''
');
fprintf(fid, 'RESULTS SPEC STOP
');
fprintf(fid, '
');
fprintf(fid, 'RESULTS SPEC ''Permeability K''
');
fprintf(fid, 'RESULTS SPEC SPECNOTCALCVAL -99999
');
fprintf(fid, 'RESULTS SPEC REGION ''All Layers (Whole Grid)''
');
fprintf(fid, 'RESULTS SPEC REGIONTYPE ''REGION_WHOLEGRID''
');
fprintf(fid, 'RESULTS SPEC LAYERNUMB 0
');
fprintf(fid, 'RESULTS SPEC PORTYPE 1
');
fprintf(fid, 'RESULTS SPEC CON 50
');
fprintf(fid, 'RESULTS SPEC SPECKEEPMOD ''YES''
');
fprintf(fid, 'RESULTS SPEC STOP
');
fprintf(fid, '
');
fprintf(fid, '
');
fprintf(fid,'RESULTS SPEC ''Porosity'' \n');
fprintf(fid,'RESULTS SPEC SPECNOTCALCVAL -99999 \n');
fprintf(fid,'RESULTS SPEC REGION ''All Layers (Whole Grid)'' \n');
fprintf(fid,'RESULTS SPEC REGIONTYPE ''REGION_WHOLEGRID'' \n');
fprintf(fid,'RESULTS SPEC LAYERNUMB 0\n');
fprintf(fid,'RESULTS SPEC PORTYPE 1\n');
fprintf(fid,'RESULTS SPEC CON 0.15 \n');
fprintf(fid,'RESULTS SPEC SPECKEEPMOD ''YES'' \n');
fprintf(fid,'RESULTS SPEC STOP\n');

close(fid);
fprintf(fidbatch,'%s','"C:\Program Files (x86)\CMG\IMEX\2011.10\Win_x64\EXE\mx201110.exe" -f '); %office link
fprintf(fidbatch,'%s
',nam);
fclose(fidbatch);

%Executing the simulation model
!Area.bat

% Extracts Data from CMG Results
for data = ('CMG_RWD.bat');
fidrwd = fopen(for data,'wt');

dataext = ['Area.rwd'];
fid = fopen(dataext,'wt');
fprintf(fid,'%s', 'FILE ''Area''');
fprintf(fid,'%s', '.irf''');

fprintf(fid, '\nLINES-PER-PAGE 10000\n');
fprintf(fid, '\nTIME ON\n');
fprintf(fid, '\n*TIMES-FOR\n');

for ff=[0:(10):14600];
    if ff==0;
        ff=1;
    end
    fprintf(fid,'%d\n',ff);
end
fprintf(fid,'SPREADSHEET\n'); %GIVES ONLY ONE TABLE AND STRING DATA IS WRITTEN ONLY ONCE(FIVE LINES)
fprintf(fid,'TABLE-FOR\n');
fprintf(fid,'%s\n','COLUMN-FOR *PARAMETERS ''Cumulative Gas SC'' *WELLS ''well-1''');
fprintf(fid,'%s\n','COLUMN-FOR *PARAMETERS ''Gas Rate SC'' *WELLS ''well-1''');
fprintf(fid,'%s
', 'COLUMN-FOR *PARAMETERS ''Well Block Pressure'' *WELLS ''well-1''');

fprintf(fid,'%s
', 'TABLE-END');
fclose(fid);

fprintf(fidrwd,'%s','call "C:\Program Files (x86)\CMG\BR\2011.10\Win_x64\EXE\report.exe" -f "Area' );
% office link
% fprintf(fidrwd,'1');
fprintf(fidrwd,'%s',' ');% Calculating Plateau length
fprintf(fidrwd,'%s', '.rwd');
fprintf(fidrwd,'%s','-o "Area.txt"');
fclose(fidrwd);

fclose(fidrwd);

% Converting the simulation results into .txt
!CMG_RWD.bat
% Calculating Plateau length
files=dir ('*.txt');

fileName=['Area.txt'];
A=importdata(fileName);
B = getfield(A,'data');
Cum(1,:)=B(1:731,2); % discarding time array% transposing Cum array
Rate(1,:)=B(1:731,3); % Production data
Time(1,:)=B(1:731,1); % production time
Block_Pressure(1,:)=B(1:731,4);

%% Identifying Length of Plateau and the life of the field.
% for i=1:1:NumCase; %loop over each case
i=1; %one case
count=1;
SD=1000000;
for j=1:1:length(Rate); %loop over time steps
%Calculating the End of Production Time.
% Identifying the time when rate starts to decline
if count==1;
    if Rate(i,j)>Rate(i,j+1) && Rate(i,j+1)>Rate(i,j+2) && Rate(i,j+2)>Rate(i,j+3) && Rate(i,j+3)==0;
        SD=j;
    end
end

if j>=SD && Rate(i,j)==0; %the second condition is to eliminate the recording of the time while the rate =0 at abandonment.
    TimeDec(i,j)=Time(i,j);
    RateDec(i,j)=Rate(i,j);
    TimeDecFit(i,count)=Time(i,j);
RateDecFit(i,count)=Rate(i,j);

count=count+1;
end

% Plateau Length in Days
PL(i)=TimeDecFit(i,1);
set(handles.sim_pl, 'String', num2str(PL));


%% """
%%% #####GP Code Starts#####
function sim_pl_gp_Callback(hObject, eventdata, handles)
% hObject handle to sim_pl_gp (see GCBO)
% eventdata reserved - to be defined in a future version of MATLAB
% handles structure with handles and user data (see GUIDATA)

% Hints: get(hObject,'String') returns contents of sim_pl_gp as text
% str2double(get(hObject,'String')) returns contents of
sim_pl_gp as a double

% --- Executes during object creation, after setting all properties.
function sim_pl_gp_CreateFcn(hObject, eventdata, handles)
% hObject handle to sim_pl_gp (see GCBO)
% eventdata reserved - to be defined in a future version of MATLAB
% handles empty - handles not created until after all CreateFcns called

% Hint: edit controls usually have a white background on Windows.
% See ISPC and COMPUTER.
if ispc && isequal(get(hObject,'BackgroundColor'),
get(0,'defaultUicontrolBackgroundColor'))
    set(hObject,'BackgroundColor','white');
end

function area_gp_Callback(hObject, eventdata, handles)
% hObject handle to area_gp (see GCBO)
% eventdata reserved - to be defined in a future version of MATLAB
% handles structure with handles and user data (see GUIDATA)

% Hints: get(hObject,'String') returns contents of area_gp as text
% str2double(get(hObject,'String')) returns contents of area_gp as a double

% --- Executes during object creation, after setting all properties.
function area_gp_CreateFcn(hObject, eventdata, handles)
function rate_gp_Callback(hObject, eventdata, handles)
    % hObject    handle to rate_gp (see GCBO)
    % eventdata  reserved - to be defined in a future version of MATLAB
    % handles    structure with handles and user data (see GUIDATA)
    % Hints: get(hObject,'String') returns contents of rate_gp as text
    % str2double(get(hObject,'String')) returns contents of rate_gp
    % as a double

    if ispc && isequal(get(hObject,'BackgroundColor'),
                  get(0,'defaultUicontrolBackgroundColor'))
        set(hObject,'BackgroundColor','white');
    end

function phi_gp_Callback(hObject, eventdata, handles)
    % hObject    handle to phi_gp (see GCBO)
    % eventdata  reserved - to be defined in a future version of MATLAB
    % handles    structure with handles and user data (see GUIDATA)
    % Hints: get(hObject,'String') returns contents of phi_gp as text
    % str2double(get(hObject,'String')) returns contents of phi_gp
    % as a double

    if ispc && isequal(get(hObject,'BackgroundColor'),
                  get(0,'defaultUicontrolBackgroundColor'))
        set(hObject,'BackgroundColor','white');
    end

% --- Executes during object creation, after setting all properties.
function rate_gp_CreateFcn(hObject, eventdata, handles)
    % hObject    handle to rate_gp (see GCBO)
    % eventdata  reserved - to be defined in a future version of MATLAB
    % handles    empty - handles not created until after all CreateFcns
called

    if ispc && isequal(get(hObject,'BackgroundColor'),
                  get(0,'defaultUicontrolBackgroundColor'))
        set(hObject,'BackgroundColor','white');
    end

function phi_gp_CreateFcn(hObject, eventdata, handles)
    % hObject    handle to phi_gp (see GCBO)
    % eventdata  reserved - to be defined in a future version of MATLAB
    % handles    empty - handles not created until after all CreateFcns
called

    if ispc && isequal(get(hObject,'BackgroundColor'),
                  get(0,'defaultUicontrolBackgroundColor'))
        set(hObject,'BackgroundColor','white');
    end
% hObject    handle to phi_gp (see GCBO)
% eventdata reserved - to be defined in a future version of MATLAB
% handles empty - handles not created until after all CreateFcns called

% Hint: edit controls usually have a white background on Windows.
% See ISPC and COMPUTER.
if ispc && isequal(get(hObject,'BackgroundColor'),
    get(0,'defaultUicontrolBackgroundColor'))
    set(hObject,'BackgroundColor','white');
end

function k_gp_Callback(hObject, eventdata, handles)
% hObject    handle to k_gp (see GCBO)
% eventdata reserved - to be defined in a future version of MATLAB
% handles structure with handles and user data (see GUIDATA)

% Hints: get(hObject,'String') returns contents of k_gp as text
%        str2double(get(hObject,'String')) returns contents of k_gp as a double

% --- Executes during object creation, after setting all properties.
function k_gp_CreateFcn(hObject, eventdata, handles)
% hObject    handle to k_gp (see GCBO)
% eventdata reserved - to be defined in a future version of MATLAB
% handles empty - handles not created until after all CreateFcns called

% Hint: edit controls usually have a white background on Windows.
% See ISPC and COMPUTER.
if ispc && isequal(get(hObject,'BackgroundColor'),
    get(0,'defaultUicontrolBackgroundColor'))
    set(hObject,'BackgroundColor','white');
end

function pi_gp_Callback(hObject, eventdata, handles)
% hObject    handle to pi_gp (see GCBO)
% eventdata reserved - to be defined in a future version of MATLAB
% handles structure with handles and user data (see GUIDATA)

% Hints: get(hObject,'String') returns contents of pi_gp as text
%        str2double(get(hObject,'String')) returns contents of pi_gp as a double

% --- Executes during object creation, after setting all properties.
function pi_gp_CreateFcn(hObject, eventdata, handles)
function h_gp_Callback(hObject, eventdata, handles)
% hObject    handle to h_gp (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    empty - handles not created until after all CreateFcns called

% Hint: edit controls usually have a white background on Windows.
%       See ISPC and COMPUTER.
if ispc && isequal(get(hObject,'BackgroundColor'),
get(0,'defaultUicontrolBackgroundColor'))
set(hObject,'BackgroundColor','white');
end

function pl_gp_Callback(hObject, eventdata, handles)
% hObject    handle to pl_gp (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    empty - handles not created until after all CreateFcns called

% Hint: edit controls usually have a white background on Windows.
%       See ISPC and COMPUTER.
if ispc && isequal(get(hObject,'BackgroundColor'),
get(0,'defaultUicontrolBackgroundColor'))
set(hObject,'BackgroundColor','white');
end

% --- Executes during object creation, after setting all properties.
function h_gp_CreateFcn(hObject, eventdata, handles)
% hObject    handle to h_gp (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    empty - handles not created until after all CreateFcns called

% Hint: edit controls usually have a white background on Windows.
%       See ISPC and COMPUTER.
if ispc && isequal(get(hObject,'BackgroundColor'),
get(0,'defaultUicontrolBackgroundColor'))
set(hObject,'BackgroundColor','white');
end

function pl_gp_CreateFcn(hObject, eventdata, handles)
% hObject    handle to pl_gp (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles    empty - handles not created until after all CreateFcns called

% Hint: edit controls usually have a white background on Windows.
%       See ISPC and COMPUTER.
if ispc && isequal(get(hObject,'BackgroundColor'),
get(0,'defaultUicontrolBackgroundColor'))
set(hObject,'BackgroundColor','white');
end

% --- Executes during object creation, after setting all properties.
function pl_gp_CreateFcn(hObject, eventdata, handles)
% hObject    handle to pl_gp (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles   empty - handles not created until after all CreateFcns
called

% Hint: edit controls usually have a white background on Windows.
% See ISPC and COMPUTER.
if ispc && isequal(get(hObject,'BackgroundColor'),
    get(0,'defaultUicontrolBackgroundColor'))
    set(hObject,'BackgroundColor','white');
end

% --- Executes on button press in calculate_gp.
function calculate_gp_Callback(hObject, eventdata, handles)
% hObject    handle to calculate_gp (see GCBO)
% eventdata  reserved - to be defined in a future version of MATLAB
% handles   structure with handles and user data (see GUIDATA)

% Obtain input data from the input boxes in the GUI
rate_gp = (str2double(get(handles.rate,'String')));
phi_gp = (str2double(get(handles.phi,'String')));
k_gp = (str2double(get(handles.k,'String')));
pi_gp = (str2double(get(handles.pi,'String')));
h_gp = (str2double(get(handles.h,'String')));
pl_gp = (str2double(get(handles.pl,'String')));

% ---------------------- Warning Messages ----------------------
% The GUI flag warning messages if the values of the input properties are
% outside the training ranges.
if rate_gp > 36000000 || rate_gp < 9000000
    set(handles.rate,'ForegroundColor','red')
    uiwait(msgbox('Out of range! Specify value between 9,000,000 and
36,000,000', 'Warning', 'modal'))
else
    set(handles.rate,'ForegroundColor','black')
end

if phi_gp > 0.20 || phi_gp < 0.08
    set(handles.phi,'ForegroundColor','red')
    uiwait(msgbox('Out of range! Specify value between 0.08 and
0.20', 'Warning', 'modal'))
else
    set(handles.phi,'ForegroundColor','black')
end

if k_gp > 100 || k_gp < 8
    set(handles.k,'ForegroundColor','red')
    uiwait(msgbox('Out of range! Specify value between 8 and
100', 'Warning', 'modal'))

else
    set(handles.k,'ForegroundColor','black')
end

if pi_gp > 5000 || pi_gp < 2000
    set(handles.pi,'ForegroundColor','red')
    uiwait(msgbox('Out of range! Specify value between 2000 and 5000','Warning','modal'))
else
    set(handles.pi,'ForegroundColor','black')
end

if h_gp > 800 || h_gp < 50
    set(handles.h,'ForegroundColor','red')
    uiwait(msgbox('Out of range! Specify value between 50 and 800','Warning','modal'))
else
    set(handles.h,'ForegroundColor','black')
end

if pl_gp > 7120 || pl_gp < 40
    set(handles.pl,'ForegroundColor','red')
    uiwait(msgbox('Out of range! Specify value between 40 and 7120','Warning','modal'))
else
    set(handles.pl,'ForegroundColor','black')
end

%%%% Predict Output using the GP model------------------------

%Input=[q_Plateau;Thickness/2;POR;Perm;Pi;PL]

INPUT_P1=[rate_gp,h_gp/2,phi_gp,k_gp,pi_gp,pl_gp];
AREA_gp=GP_Pred2(INPUT_P1);

% set(handles.area,'String',num2str(round(T_ann_N(1))));
set(handles.area_gp,'String',num2str(AREA_gp));

%%%% Simulation model
% --- Executes on button press in simulate_gp.
function simulate_gp_Callback(hObject, eventdata, handles)
    rate_gp = (str2double(get(handles.rate,'String')));
    phi_gp = (str2double(get(handles.phi,'String')));
    k_gp = (str2double(get(handles.k,'String')));
pi_gp = (str2double(get(handles.pi,'String')));
pl_gp = (str2double(get(handles.pl,'String')));
INPUT_P1=[rate_gp,h_gp/2,phi_gp,k_gp,pi_gp,pl_gp];
AREA_gp=GP_Pred2(INPUT_P1);

% ------------------------Warning Messages------------------------------- --
% The GUI flag warning messages if the values of the input properties are
% outside the training ranges.

if rate_gp > 36000000 || rate_gp < 9000000
    set(handles.rate,'ForegroundColor','red')
    uiwait(msgbox('Out of range! Specify value between 9,000,000 and 36,000,000','Warning','modal'))
else
    set(handles.rate,'ForegroundColor','black')
end

if phi_gp > 0.20 || phi_gp < 0.08
    set(handles.phi,'ForegroundColor','red')
    uiwait(msgbox('Out of range! Specify value between 0.08 and 0.20','Warning','modal'))
else
    set(handles.phi,'ForegroundColor','black')
end

if k_gp > 100 || k_gp < 8
    set(handles.k,'ForegroundColor','red')
    uiwait(msgbox('Out of range! Specify value between 8 and 100','Warning','modal'))
else
    set(handles.k,'ForegroundColor','black')
end

if pi_gp > 5000 || pi_gp < 2000
    set(handles.pi,'ForegroundColor','red')
    uiwait(msgbox('Out of range! Specify value between 2000 and 5000','Warning','modal'))
else
    set(handles.pi,'ForegroundColor','black')
end

if h_gp > 800 || h_gp < 50
    set(handles.h,'ForegroundColor','red')
    uiwait(msgbox('Out of range! Specify value between 50 and 800','Warning','modal'))
else
    set(handles.h,'ForegroundColor','black')
end

if pl_gp > 7120 || pl_gp < 40
set(handles.pl,'ForegroundColor','red')
uiwait(msgbox('Out of range! Specify value between 40 and 7120', 'Warning', 'modal'))
else
    set(handles.pl,'ForegroundColor','black')
end

% Dividing the thickness over two layers.
h_gp=h_gp/2;

nam2 = 'Area_gp.bat';
fidbatch = fopen(nam2,'w');
RefDepth= h_gp+10000;

nam = ['Area_gp.dat'];
fid = fopen(nam,'w');

fprintf(fid,'RESULTS SIMULATOR IMEX 201110\n');
fprintf(fid,'\n');
fprintf(fid,'INUNIT FIELD\n');
fprintf(fid,'WSRF WELL 1\n');
fprintf(fid,'WSRF GRID TIME\n');
fprintf(fid,'WSRF SECTOR TIME\n');
fprintf(fid,'OUTSRF WELL LAYER NONE\n');
fprintf(fid,'OUTSRF RES ALL\n');
fprintf(fid,'OUTSRF GRID SO SG SW PRES OILPOT BPP SSPRES WINFLUX\n');
fprintf(fid,'WFRN GRID 0\n');
fprintf(fid,'OUTPRN GRID NONE\n');
fprintf(fid,'OUTPRN RES NONE\n');
fprintf(fid,'***$ Distance units: ft \n');
fprintf(fid,'RESULTS XOFFSET 0.0000\n');
fprintf(fid,'RESULTS YOFFSET 0.0000\n');
fprintf(fid,'RESULTS ROTATION 0.0000 ***$ (DEGREES)\n');
fprintf(fid,'RESULTS AXES-DIRECTIONS 1.0 -1.0 1.0\n');
fprintf(fid,***$ ****************************************************
');
fprintf(fid,'***$ Definition of fundamental cartesian grid\n');
fprintf(fid,***$ ****************************************************
');
fprintf(fid,'GRID VARI 1 1 2\n');
fprintf(fid,'KDIR DOWN\n');
fprintf(fid,'DI IVAR \n');
fprintf(fid,'%d\n', sqrt(AREA_gp));
fprintf(fid,'DJ JVAR \n');
fprintf(fid,'%d\n', sqrt(AREA_gp));
fprintf(fid,'DK ALL\n');
fprintf(fid,'2*%d\n', h_gp);
fprintf(fid,'DTOP\n');
fprintf(fid,'10000\n');
fprintf(fid,***$ Property: NULL Blocks Max: 1 Min: 1\n');
fprintf(fid,***$ 0 = null block, 1 = active block\n');
fprintf(fid,'NULL CON 1\n');
fprintf(fid, '**$ Property: Porosity  Max: %d  Min: %d\n', phi_gp, phi_gp);
fprintf(fid, 'POR CON          %d\n', phi_gp);
fprintf(fid, '**$ Property: Permeability I (md)   Max: %d  Min: %d\n', k_gp, k_gp);
fprintf(fid, 'PERMI CON          %d\n', k_gp);
fprintf(fid, '**$ Property: Permeability J (md)   Max: %d  Min: %d\n', k_gp, k_gp);
fprintf(fid, 'PERMJ CON          %d\n', k_gp);
fprintf(fid, '**$ Property: Permeability K (md)   Max: %d  Min: %d\n', k_gp, k_gp);
fprintf(fid, 'PERMK CON          %d\n', k_gp);
fprintf(fid, '**$ Property: Pinchout Array  Max: 1  Min: 1\n');
fprintf(fid, 'PINCHOUTARRAY CON            1\n');
fprintf(fid, 'CPOR 0.000001\n');
fprintf(fid, 'MODEL GASWATER \n');
fprintf(fid, 'TRES 150\n');
fprintf(fid, 'PVTG EG 1\n');
fprintf(fid, '        p        Eg       visg\n');
fprintf(fid, '       14.696   4.81152  0.0117959\n');
fprintf(fid, '       347.05   119.03   0.0122183\n');
fprintf(fid, '      679.403   244.135  0.0128883\n');
fprintf(fid, '      1011.76   380.147  0.0137868\n');
fprintf(fid, '      1344.11   525.33   0.0149293\n');
fprintf(fid, '      1676.46   675.483  0.0163175\n');
fprintf(fid, '      2008.82   824.472  0.0179208\n');
fprintf(fid, '      2341.17   966.242  0.0196788\n');
fprintf(fid, '      2673.52  1096.72   0.0215212\n');
fprintf(fid, '      3005.88   1214.25  0.0233868\n');
fprintf(fid, '      3338.23   1318.89  0.0252308\n');
fprintf(fid, '      3670.59   1411.69  0.0270245\n');
fprintf(fid, '      4002.94   1567.3   0.0304066\n');
fprintf(fid, '      4335.29   1632.88  0.0319872\n');
fprintf(fid, '      4667.65   1702.63  0.0335152\n');
fprintf(fid, '      5000   1691.92   0.033496\n');
fprintf(fid, 'DENSITY GAS 5.802166e-002\n');
fprintf(fid, 'REFPW 14.696e\n');
fprintf(fid, 'DENSITY WATER 61.6381\n');
fprintf(fid, 'BWI 1.01944\n');
fprintf(fid, 'CW 3.1589e-006\n');
fprintf(fid, 'VWI 0.47184\n');
fprintf(fid, 'CVW 0.0\n');
fprintf(fid, 'ROCKFLUID\n');
fprintf(fid, 'RPT 1\n');
fprintf(fid, '**$ Sw       krw\n');
fprintf(fid, 'SWT\n');
fprintf(fid, '               0.15             0\n');
fprintf(fid, '           0.203125  1.52588e-005\n');
fprintf(fid, '            0.25625   0.000244141\n');
fprintf(fid, '           0.309375    0.00123596\n');
fprintf(fid, '             0.3625    0.00390625\n');
fprintf(fid, '           0.415625    0.00953674\n');
fprintf(fid, '            0.46875     0.0197754
');
fprintf(fid, '           0.521875     0.0366364
');
fprintf(fid, '              0.575        0.0625
');
fprintf(fid, '           0.628125      0.100113
');
fprintf(fid, '           0.734375      0.223404
');
fprintf(fid, '             0.7875      0.316406
');
fprintf(fid, '           0.840625      0.435806
');
fprintf(fid, '            0.89375      0.586182
');
fprintf(fid, '           0.946875      0.772476
');
fprintf(fid, '                  1             1
');
fprintf(fid, '**$        Sl       krg
');
fprintf(fid, 'SLT
');
fprintf(fid, '               0.15        0.85
');
fprintf(fid, '           0.196875  0.656605
');
fprintf(fid, '            0.24375    0.498254
');
fprintf(fid, '           0.290625    0.370435
');
fprintf(fid, '             0.3375    0.268945
');
fprintf(fid, '           0.384375    0.189893
');
fprintf(fid, '            0.43125      0
');
fprintf(fid, '           0.478125    0.085096
');
fprintf(fid, '              0.525    0.053125
');
fprintf(fid, '           0.571875  0.0311409
');
fprintf(fid, '           0.61875  0.0168091
');
fprintf(fid, '           0.665625  0.00810623
');
fprintf(fid, '           0.7125  0.00332031
');
fprintf(fid, '           0.759375  0.00105057
');
fprintf(fid, '           0.80625  0.00020752
');
fprintf(fid, '           0.853125  1.297e-005
');
fprintf(fid, '               0.9      0
');
fprintf(fid, '               0.925      0
');
fprintf(fid, '               0.95      0
');
fprintf(fid, 'INITIAL
');
fprintf(fid, 'VERTICAL DEPTH_AVE WATER_GAS EQUIL NOTRANZONE
');
fprintf(fid, 'REFDEPTH %d
', RefDepth);
fprintf(fid, 'REFPRES %d
', pi_gp);
fprintf(fid, 'DWGC 12000
');
fprintf(fid, 'DATUMDEPTH %d
', RefDepth);
fprintf(fid, 'NUMERICAL
');
fprintf(fid, 'RUN
');
fprintf(fid, 'DATE 2013 1 1
');
fprintf(fid, 'GROUP ''Prod'' ATTACHTO ''Group-1''
');
fprintf(fid, 'OPERATE MIN BHP 28. CONT
');
fprintf(fid, 'WELL ''Well-1'' ATTACHTO ''Prod''
');
fprintf(fid, 'PRODUCER ''Well-1''
');
fprintf(fid, 'PERF GEOA ''Well-1''
');
fprintf(fid, 'UBA     ff  Status  Connection
');
fprintf(fid, '    1 1 1  1.  OPEN    FLOW-TO ''SURFACE''
');
fprintf(fid, '    1 1 2  1.  OPEN    FLOW-TO 1
');
fprintf(fid,'GCONP ''Prod''
');
fprintf(fid,'    TARGET   STG      %d
',rate_gp);

fprintf(fid,'DATE 2015 1  1.00000
');
fprintf(fid,'DATE 2016 1  1.00000
');
fprintf(fid,'DATE 2019 1  1.00000
');
fprintf(fid,'DATE 2025 1  1.00000
');
fprintf(fid,'DATE 2030 1  1.00000
');
fprintf(fid,'DATE 2035 1  1.00000
');
fprintf(fid,'DATE 2040 1  1.00000
');
fprintf(fid,'DATE 2045 1  1.00000
');
fprintf(fid,'DATE 2050 1  1.00000
');
fprintf(fid,'DATE 2053 12  31.00000
');
fprintf(fid,'DATE 2063 12  31.00000
');
fprintf(fid,'DATE 2073 12  31.00000
');

fprintf(fid,'RESULTS RELPERMCORR NUMROCKTYPE 1
');
fprintf(fid,'RESULTS RELPERMCORR CORRVALS 0.15 0.15 0.05 0.1 1 0.85 4 4
');
fprintf(fid,'RESULTS RELPERMCORR CORRVALS_HONARPOUR -99999 -99999 -99999 -99999 -99999 -99999 -99999
');
fprintf(fid,'RESULTS RELPERMCORR NOSWC false
');
fprintf(fid,'RESULTS RELPERMCORR CALINDEX 5\n');
fprintf(fid,'RESULTS RELPERMCORR STOP\n');
fprintf(fid,'\n');
fprintf(fid,'RESULTS SPEC ''Permeability I'' \n');
fprintf(fid,'RESULTS SPEC SPECNOTCALCVAL -99999 \n');
fprintf(fid,'RESULTS SPEC REGION ''All Layers (Whole Grid)''\n');
fprintf(fid,'RESULTS SPEC REGIONTYPE ''REGION_WHOLEGRID''\n');
fprintf(fid,'RESULTS SPEC LAYERNUMB 0\n');
fprintf(fid,'RESULTS SPEC PORTYPE 1\n');
fprintf(fid,'RESULTS SPEC CON 50 \n');
fprintf(fid,'RESULTS SPEC SPECKEEPMOD ''YES''\n');
fprintf(fid,'RESULTS SPEC STOP\n');
fprintf(fid,'\n');
fprintf(fid,'RESULTS SPEC ''Permeability J'' \n');
fprintf(fid,'RESULTS SPEC SPECNOTCALCVAL -99999 \n');
fprintf(fid,'RESULTS SPEC REGION ''All Layers (Whole Grid)''\n');
fprintf(fid,'RESULTS SPEC REGIONTYPE ''REGION_WHOLEGRID''\n');
fprintf(fid,'RESULTS SPEC LAYERNUMB 0\n');
fprintf(fid,'RESULTS SPEC PORTYPE 1\n');
fprintf(fid,'RESULTS SPEC CON 50 \n');
fprintf(fid,'RESULTS SPEC SPECKEEPMOD ''YES''\n');
fprintf(fid,'RESULTS SPEC STOP\n');
fprintf(fid,'\n');
fprintf(fid,'RESULTS SPEC ''Permeability K'' \n');
fprintf(fid,'RESULTS SPEC SPECNOTCALCVAL -99999 \n');
fprintf(fid,'RESULTS SPEC REGION ''All Layers (Whole Grid)''\n');
fprintf(fid,'RESULTS SPEC REGIONTYPE ''REGION_WHOLEGRID''\n');
fprintf(fid,'RESULTS SPEC LAYERNUMB 0\n');
fprintf(fid,'RESULTS SPEC PORTYPE 1\n');
fprintf(fid,'RESULTS SPEC CON 50 \n');
fprintf(fid,'RESULTS SPEC SPECKEEPMOD "YES"\n');
fprintf(fid,'RESULTS SPEC STOP\n');
fprintf(fid,'\n');
fprintf(fid,'RESULTS SPEC ''Porosity'' \n');
fprintf(fid,'RESULTS SPEC SPECNOTCALCVAL -99999 \n');
fprintf(fid,'RESULTS SPEC REGION ''All Layers (Whole Grid)''\n');
fprintf(fid,'RESULTS SPEC REGIONTYPE ''REGION_WHOLEGRID''\n');
fprintf(fid,'RESULTS SPEC LAYERNUMB 0\n');
fprintf(fid,'RESULTS SPEC PORTYPE 1\n');
fprintf(fid,'RESULTS SPEC CON 0.15 \n');
fprintf(fid,'RESULTS SPEC SPECKEEPMOD "YES"\n');
fprintf(fid,'RESULTS SPEC STOP\n');

fclose(fid);
fprintf(fidbatch,'%s','"C:\Program Files (x86)\CMG\IMEX\2011.10\Win_x64\EXE\mx201110.exe" -f ');
fclose(fidbatch,'%s\n',nam);

fclose(fidbatch);
fprintf(fidbatch,'%s','"Area_gp.bat"');

% Execute the simulation model
!Area_gp.bat

% Extracts Data from CMG Results
for data = ('CMG_RWD_gp.bat');
fidrwd = fopen(for data,'wt');

dataext = ['Area gp.rwd'];
 fid = fopen(dataext,'wt');
fprintf(fid,'%s','FILE ''Area_gp''');
fprintf(fid,'%s','.irf''');

fprintf(fid,'\nLINES-PER-PAGE 10000\n');
fprintf(fid,'\nTIME ON\n');
fprintf(fid,'\n*TIMES-FOR\n');

% looping over time steps.
for ff=[0:(10):14600];
  if ff==0;
    ff=1;
  end
  fprintf(fid,'%d\n',ff);
end

fprintf(fid,'SPREADSHEET\n');

fclose(fid);
fprintf(fid,'TABLE-FOR\n');
fprintf(fid,'%s
','COLUMN-FOR *PARAMETERS ''Cumulative Gas SC'' *WELLS ''well-1''');
fprintf(fid,'%s
','COLUMN-FOR *PARAMETERS ''Gas Rate SC'' *WELLS ''well-1''');
fprintf(fid,'%s
','COLUMN-FOR *PARAMETERS ''Well Block Pressure'' *WELLS ''well-1''');

fprintf(fid,'%s
','TABLE-END');
fclose(fid);

fprintf(fidrwd,'%s','call "C:\Program Files (x86)\CMG\BR\2011.10\Win_x64\EXE\report.exe" -f "Area_gp'');

fclose(fidrwd);

fclose(fidrwd);

% Converting the simulation results to .txt
!CMG_RWD_gp.bat

% Calculating Plateau length
files= dir ('*.txt');

fileName=['Area_gp.txt'];
A=importdata(fileName);
B = getfield(A,'data');
Cum(:,2)=B(1:731,2); % discarding time array% transposing Cum array
Rate(:,3)=B(1:731,3); % Production data
Time(:,1)=B(1:731,1); % production time
Block_Pressure(:,1)=B(1:731,4);

% Identifying Length of Plateau and the life of the field.
% for i=1:1:NumCase; %loop over each case
i=1; %one case
count=1;
SD=1000000;
for j=1:1:length(Rate); % loop over time steps
%Calculating the End of Production Time.

% Identifying the time when rate starts to decline
if count==1;
 if Rate(i,j)>Rate(i,j+1) && Rate(i,j+1)>Rate(i,j+2) &&
 Rate(i,j+2)>Rate(i,j+3) && Rate(i,j+3)>Rate(i,j+4) &&
 SD=|j|;
 end
end
\begin{verbatim}
if j>=SD && Rate(i,j)~=0; %the second condition is to eliminate the recording of the time while the rate =0 at abandonment.
    TimeDec(i,j)=Time(i,j);
    RateDec(i,j)=Rate(i,j);
    TimeDecFit(i,count)=Time(i,j);
    RateDecFit(i,count)=Rate(i,j);
    count=count+1;
end
end

% Assigning the simulation result into the GUI box
% Plateau Length in Days
PL_gp(i)=TimeDecFit(i,1);
set(handles.sim_pl_gp, 'String', num2str(PL_gp));
\end{verbatim}
Bibliography

Chapter 1


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Chapter 2


Chapter 3


Chapter 4


VITA

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Abdulwahab Abdullatif Bukhari was born in Jeddah, Saudi Arabia. He was sponsored by Saudi ARAMCO to pursue his bachelor degree in petroleum engineering between 2001 and 2005 from Louisiana State University. After that, he worked for Saudi ARAMCO for four years in different petroleum engineering disciplines including development planning, production engineering, reservoir engineering and reservoir simulation engineering. He earned his master’s degree in petroleum engineering from The University of Texas at Austin in 2011. He earned his PhD degree from The Pennsylvania State University in petroleum engineering in 2014.

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