Copyright

by

Yonghwee Kim

2007
Probabilistic framework-based history matching algorithm utilizing sub-domain delineation and software ‘Pro-HMS’

by

Yonghwee Kim, B.S

Thesis
Presented to the Faculty of the Graduate School of
The University of Texas at Austin
in Partial Fulfillment
of the Requirements
for the Degree of

Master of Science in Engineering

The University of Texas at Austin
December 2007
Probabilistic framework-based history matching algorithm utilizing sub-domain delineation and software ‘Pro-HMS’

Approved by
Supervising Committee:

______________________________
Steven L. Bryant

______________________________
Sanjay Srinivasan
Dedication

To the readers who acquire useful idea from this thesis for their works. Also, this thesis is dedicated to the Gamma Team leader and members.
Acknowledgements

The work documented in this thesis was initiated since Dr. Steven Bryant appointed me as a graduate research assistant. I thank him for his financial support to the graduate student who hadn’t had any petroleum-related study experience. Dr. Bryant’s supports enabling this work and his comments on the thesis are highly appreciated.

My co-supervisor, Dr. Sanjay Srinivasan, is acknowledged for his expert technical guidance and sincere philosophical advices. It has been a great honor for me to learn geostatistics and stochastic reservoir modeling from him and to work with him. His extensive time and efforts devoted to me is also appreciated.

This work was supported by the Department of Energy grant #DE-FC26-03NT15410. The development of software (Pro-HMS) that highlights this work can be attributed to the efforts of Dr. Sanjay Srinivasan, Dr. Steven Bryant, Dr. Alvaro Barrera, and Kiomars Eskandari. The guidance and supports of fellow graduate students; especially, gamma team members (Aviral Sharma, Pradeep Govind, Juliana Leung, Darrin Madriz, Roy Cook, Louis Forster, Prince Azom, and Cesar Mantillia) are appreciated. Also, Sukkyoon Choi and all members of Korean Petroleum Student Association are also acknowledged.
Abstract

Probabilistic framework-based history matching algorithm utilizing sub-domain delineation and software ‘Pro-HMS’

Yonghwee Kim, M.S.E
The University of Texas at Austin, 2007

Supervisors: Steven L. Bryant, Sanjay Srinivasan

The key idea presented in this thesis is the perturbation of the probability distribution describing the uncertainty in the permeability value within sub-domains of the reservoir using the dynamic information. Probability deformation parameters are defined and optimally established to minimize the deviation of the predicted production response from the observed or measured response. To implement the perturbation method in a parallel computational environment, sub-domains have to be established such that they are the most influential regions and least correlated. In that case the perturbations for establishing the deformation parameters can be done independently in the sub-domains.

In contrast to current history matching algorithms that incur significant computational cost in optimizing permeability for each gridblock in the simulation
model, our approach reduces the optimizing period by employing innovative method such as sub-domain delineation using principal component analysis (PCA) and a reduced parameter set in the form of deformation parameters that have to be optimized. Once the domains are delineated, a fully probabilistic approach to perturb permeability within the delineated zones is implemented. With this method the information inferred from dynamic data is merged with the prior geologic information.

The described process of history matching is effective; however, it can be cumbersome because it combines aspects of stochastic reservoir modeling, flow simulation and iterative optimization. To speed up and enhance the efficiency of history matching process, and to render a streamlined process, an integrated software package Pro-HMS (Probabilistic History Matching Software) was developed. Various synthetic and real field data sets were processed with Pro-HMS, and they show reliable predictions for future reservoir performance.
# Table of Contents

List of Tables ......................................................................................................................... xii

List of Figures ............................................................................................................................ xiii

1. INTRODUCTION 1

1.1 Overview of history matching .................................................................1

1.2 Implemented history matching method .........................................................3

1.3 Thesis outline .................................................................................................6

2. LITERATURE REVIEW 8

2.1 History matching methods .............................................................................9

2.1.1 Gradient based history matching method .............................................9

2.1.2 Streamline sensitivity method ..............................................................10

2.1.3 Global optimization scheme .................................................................10

2.1.4 Gradual deformation method ...............................................................13

2.1.5 Probabilistic approach ........................................................................15

2.2 Sub-domain delineation methods ...............................................................17

2.2.1 Principal component analysis (PCA) approach ....................................17

2.3 Flow simulation in multiple domains .........................................................19

2.3.1 Parallel reservoir simulation environment ............................................19

2.3.2 Domain decomposition for reservoir simulation .................................20

3. HESSIAN MATRIX METHOD FOR SUB-DOMAIN DELINEATION 23

3.1 Motivation ......................................................................................................24

3.2 Background ....................................................................................................25

3.3 Domain delineation using the Hessian matrix ............................................27

3.3.1 Theory ....................................................................................................27

3.3.2 Use of flow simulator module-SimOpt® ..............................................30
3.3.2.1 Pilot points .................................................................31
3.3.2.2 SimOpt® simulation ......................................................33
3.3.3 Examples...........................................................................36
  3.3.3.1 Simple 2D cases............................................................36
  3.3.3.2 3D cases: Basic three related cases............................39
  3.3.3.3 3D cases: Effect of very different initial and reference realizations
                          ..............................................................................46
  3.3.3.4 Discussions ..............................................................56

4. COVARIANCE MATRIX METHOD FOR SUB-DOMAIN DELINEATION
  58

  4.1 Approximate method for sensitivities based on the covariance matrix of
      gridblock pressure responses ..................................................60
    4.1.1 Theory .............................................................................60
    4.1.2 Validation test cases .........................................................65
      4.1.2.1 First case-Permeability field with short range continuity and two
              production wells.................................................................65
      4.1.2.2 Second case-Permeability field with longer range continuity and
              three production wells.......................................................70

  4.2 Comparison of the two methods for sub-domain delineation............74

5. PROBABILISTIC PRUTRUBATION SCHEME ..............................77

  5.1 Motivation ...........................................................................77
  5.2 Basic perturbation scheme ..................................................78
  5.3 Scheme implemented on multiple sub-domains ...........................82
  5.4 History matching case on multiple sub-domains scheme ...............84
    5.4.1 Case example .................................................................84
    5.4.2 Discussion .......................................................................88
6. PROBABILISTIC HISTORY MATCHING SOFTWARE (Pro-HMS) 89

6.1 Motivation ........................................................................................................... 90
6.2 Program architecture ....................................................................................... 91
6.3 Program components ....................................................................................... 95
   6.3.1 Covariance code .................................................................................. 95
   6.3.2 Sub-domain delineation code .................................................................. 96
   6.3.3 Probabilistic perturbation code ............................................................ 98
   6.3.4 Simple validation test case ................................................................. 100
6.4 3D Synthetic test cases .............................................................................. 112
   6.4.1 Purpose ............................................................................................... 112
   6.4.2 3D Synthetic case examples .................................................................. 112
      6.4.2.1 Base case studies for sub-domain option ........................................ 112
      6.4.2.2 Further case studies in conjunction with previous studies .......... 137
      6.4.2.3 Updating of values in new sub-domains using only original “hard”
               data ............................................................................................ 143
      6.4.2.4 Model updating using a reduced set of hard data simulating values
               in the less sensitive regions ....................................................... 146
      6.4.2.5 Final validation ...................................................................... 148
   6.4.3 Discussions ........................................................................................ 151
7. REAL FIELD CASE STUDIES 152

7.1 Characterization of a fluvial reservoir by history matching ................. 153
   7.1.1 Delineation of channel fairways .......................................................... 153
   7.1.2 Prediction study for the validation ....................................................... 161
7.2 Sandstone reservoir field case ................................................................. 167
   7.2.1 Geological setting .............................................................................. 167
   7.2.2 History matching strategy and results ................................................. 169
   7.2.3 Discussions ........................................................................................ 174
7.3 Realistic carbonate reservoir field case ................................................... 175
   7.3.1 Geological background ...................................................................... 175
7.3.2 Realistic reference permeability model .............................................176
7.3.3 Forecasting scenario with an additional well.....................................187
7.3.4 History matching and uncertainty in carbonate reservoir...............192

8. CONCLUSIONS

8.1 Conclusions...............................................................................................195
8.2 Suggested future work ..............................................................................199

Appendix A Description of Pro-HMS Input and Output Files ...................202
Appendix B User’s Manual of Pro-HMS Screens.............................................206
Nomenclature.......................................................................................................235
References............................................................................................................236
Vita .................................................................................................................240
List of Tables

Table 3-1: Results showing that the domains delineated are insensitive to the format of the well production file.................................................................34
Table 3-2: Summarized results of 2D simple test cases.................................................................37
Table 3-3: Summarized results of 3D base case.................................................................41
Table 3-4: Summary of delineated zones when the permeability around the producer P1 is increased in the initial permeability model.........................43
Table 3-5: Summarized results of test cases when the injection well is active..44
Table 3-6: Summarized results of test cases with a large difference between the initial and reference permeability models.........................................48
Table 3-7: Summary of results for cases where the initial model is different from the reference.................................................................51
Table 3-8: Summarized results of test cases corresponding to variations in well operating conditions.................................................................55
Table 4-1: Sensitivity coefficients maps and sub-domains with 50, 75 and 100 initial reservoir models of short range continuity case .....................68
Table 4-2: Sensitivity coefficients maps and sub-domains with 25, 50, 75 and 100 initial reservoir models of longer range continuity case...............71
Table 6-1: The ‘hmissim.par’ generated by Pro-HMS .................................................................118
Table 6-2: The ‘sensregion.par’ generated by Pro-HMS .................................................................120
Table 6-3: The ‘dd.par’ generated by Pro-HMS .................................................................122
Table 7-1: Correlation equation between interparticle porosity and permeability for different lithofacies .................................................................177
Table 7-2: Ranges of permeability for five lithofacies.................................................................178
List of Figures

Figure 3-1: Flow chart of sub-domain delineation using the Hessian matrix......30

Figure 3-2: Flow chart for obtaining the Hessian matrix by SimOpt®; the blue box indicates the output of the SimOpt® simulation, and the rest are input and the procedures for the simulation..................................................35

Figure 3-3: The reference and initial realizations of 2D test case; the black dots indicate the production well location..........................36

Figure 3-4: The initial (top five maps from top to bottom layer) and reference (bottom five maps, from top to bottom layer) realizations case; the black dots indicate the production and injection well locations............40

Figure 3-5: The revised initial (top five maps from top to bottom layer) realizations with higher permeability values near P1 ..................42

Figure 3-6: The initial (top five maps from top to bottom layer) and reference (bottom five from top to bottom layer) realizations; black dots indicate well locations .................................................................47

Figure 3-7: The initial (top five maps from top to bottom layer) and reference (bottom five from top to bottom layer) realizations; black dots indicate well locations .................................................................50

Figure 3-8: The initial (top five maps from top to bottom layer) and reference (bottom five from top to bottom layer) realizations; black dots indicate well locations .................................................................53

Figure 4-1: Schematic illustration of sub-domain delineation using the covariance of grid-block pressures (4×4 reservoir example) .........................64
Figure 4-2: Three realizations of the permeability field; production wells are in white.

Figure 4-3: The upscaled realizations corresponding to three realizations illustrated in Figure 4-2; white dots indicate production wells.

Figure 4-4: The sensitivity coefficients map (right), 40% sub-domains (middle) and 99% sub-domains (left); white dots represent well locations.

Figure 4-5: The first three initial permeability maps for the second test case; the production wells are shown with white dots.

Figure 4-6: The first three initial corresponding upscaled maps for the second test case; the production wells are shown with white dots.

Figure 5-1: Flow chart of implemented algorithm for multiple sub-domains perturbation scheme.

Figure 5-2: Reference permeability model with three production wells (Wells are indicated with black dots).

Figure 5-3: One set of initial permeability model with three production wells (Wells are shown in black dots).

Figure 5-4: Sensitivity coefficient maps for five layers.

Figure 5-5: Two sub-domains after applying 40% threshold value; white dots represent production well locations.

Figure 5-6: History matched permeability model with three production wells for multiple sub-domain case.

Figure 5-7: History matched result of field oil production rate.

Figure 6-1: Schematic of program architecture of Pro-HMS (The arrows in violet color represent the user options).

Figure 6-2: Flow chart of Pro-HMS procedure.
Figure 6-3: The reference model of test case. (From left right, the top section of the reservoir to the bottom).................................................................101

Figure 6-4: The conditional permeability data locations and their values in a color scale..............................................................102

Figure 6-5: One set of initial permeability realizations from top layer to the bottom layer; the black dots indicate the well locations .........................103

Figure 6-6: One set of upscaled initial permeability realizations from top layer to the bottom layer .................................................................104

Figure 6-7: The sensitivity coefficient map of the covariance matrix..........104

Figure 6-8: The sensitivity coefficient map of the covariance matrix..........105

Figure 6-9: The permeability realizations after the first outer loop.............106

Figure 6-10: The permeability realizations after the second outer loop........107

Figure 6-11: The history matched model after three outer loops ...............108

Figure 6-12: The objective function profile of the validation test case. The first dot indicates the objective function value for the initial realization, and the middle two points represent the values for the first and second outer loop result, respectively. The last point indicates the objective function of history matched model.................................................................109

Figure 6-13: History matching results for field pressure and oil production rates in three production wells.........................................................110

Figure 6-14: Reference permeability models from top layer to the bottom (from left to right).................................................................113

Figure 6-15: An initial permeability model from top layer to the bottom (from left to right).................................................................114

Figure 6-16: Sub-domains for tests after applying 40% volume cutoffs.........115
Figure 6-17: The permeability model after three years history matching ..........116
Figure 6-18: History matching result for the base case with sub-domain delineation
.....................................................................................................................................117
Figure 6-19: Well data specification screen .................................................................123
Figure 6-20: Production data specification screen ......................................................124
Figure 6-21: Initial permeability field generation choice screen ............................125
Figure 6-22: Variable specification screen ...............................................................125
Figure 6-23: Threshold and cdf value specification screen .......................................126
Figure 6-24: Grid identification screen .....................................................................127
Figure 6-25: Trimming limit screen .........................................................................127
Figure 6-26: Tail extrapolation and simulated permeability range specification screen
.....................................................................................................................................128
Figure 6-27: Types of kriging screen ........................................................................129
Figure 6-28: Details on Kriging specification screen .................................................130
Figure 6-29: Variogram model specification screen ................................................131
Figure 6-30: Details of variogram mode in each threshold .......................................132
Figure 6-31: Sub-domain option selection screen .....................................................132
Figure 6-32: Sensitivity calculation detail specification screen ..................................133
Figure 6-33: Details on sub-domain performance .....................................................134
Figure 6-34: Perturbation number specification screen ..........................................134
Figure 6-35: The permeability model after three years history matching without sub-
domains ..........................................................................................................................135
Figure 6-36: History match results when the permeability model is perturbed without using sub-domains .................................................................136

Figure 6-37: Sub-domains for the expanded case with two additional wells after applying 40% volume cutoff; gray dots indicate new wells ..........138

Figure 6-38: The permeability models after updating the permeability values in the sensitivity regions corresponding to the two new wells ..........139

Figure 6-39: History matching results corresponding to the update of permeability values in the sensitivity regions corresponding to the two new wells. The updated values in the domains corresponding to the earlier configuration of wells (Figure 6-16) are used as conditioning data for updating the values in the two new sensitivity regions .................................140

Figure 6-40: The permeability models after 10 years history matching with 13000 hard data........................................................................................................141

Figure 6-41: History matching results for the case using 13000 permeability data. History matching is performed for ten years, and the rest of the period is prediction of reservoir performance........................................142

Figure 6-42: The permeability models after history matching using only the original ‘hard’ data for updating the probability distributions within the new sub-domains and using the 19950 simulated values for conditioning the simulated values in the insensitive regions........................................143

Figure 6-43: History matching result for the case where the permeability values in the new sub-regions are only conditioned to the original ‘hard’ data ..145
Figure 6-44: The updated permeability models obtained using a reduced number of conditioning data for simulating the permeability values in the less sensitive regions ................................................................. 146

Figure 6-45: History matching result plots when the permeability values in the less sensitive regions are conditioned to a lesser number of updated permeability values in the sub-domains ........................................ 147

Figure 6-46: The permeability models after ten years history matching with three years matched models as initial models .................................................. 149

Figure 6-47: History matching result plots for the final validation case .......... 150

Figure 7-1: The map of the reservoir for history matching case. Blue dots represent producers, and red ones are the locations where prior permeability values are available from well tests. The black contour lines delineate pay thicknesses. The presence of channel fairways is indicated .... 153

Figure 7-2: Permeability variations in one initial realization. The left realization is the top layer and the fifth right one is the bottom layer. Pink dots indicate the locations of wells. The units of permeability values in the color scale are millidarcies ................................................................. 155

Figure 7-3: The sensitivity maps of the covariance matrix obtained from the upscaled initial realizations. These maps correspond to the diagonal elements of the pressure covariance matrix .............................................. 156

Figure 7-4: Sub-domains for five layers after applying 40% volume cutoff; nine different sensitive regions are shown with different colors .......... 157

Figure 7-5: History matched reservoir models after three outer loop iterations. This model is to be compared against the initial model in Figure 7-2 .... 158
Figure 7-6: History matching results of oil production rates for eight wells; the red dots are actual history, the green line represents the response from the initial model and the blue line is the final history matched result ..160

Figure 7-7: Sensitivity coefficients maps for the further study .........................162

Figure 7-8: Delineated sub-domains for the further study.................................163

Figure 7-9: History matched reservoir models obtained by matching the production history only for 8,640 days. The left realization is the top layer and the very right one is the bottom layer ...................................................163

Figure 7-10: History matching results of oil production rates for 8,640 days and prediction for the remaining production duration (13,080 days in total) for eight wells. The red dots indicates the recorded data, the blue line is the portion of the history matched model, the green line is the initial model response data, the orange dots represents the remaining duration of the historical production data that is used to check the accuracy of the prediction (violet line).....................................................................165

Figure 7-11: The initial permeability model; the dots indicate locations of production wells and black dots with white circles around them represent water injection well converted from production well (Top layer is the top left figure and the bottom layer is the bottom right figure). ...............168

Figure 7-12: The history matched permeability model; the white dots indicate locations of production wells and black dots with white circles around them represent injection wells converted from production wells ...170

Figure 7-13: Three dimensional images of initial and final permeability reservoir models with consideration of topography; the reservoir is tilted to the east and the lifted to the NW direction ..................................................172
Figure 7-14: Plots of history matching results; field pressure, field water cut, and four individual well water cuts; red dots are history records, green dotted-lines indicate initial guess and blue lines are history matched responses

Figure 7-15: The spatial distributions of five lithofacies in the reservoir being studied.
Five black dots indicate production wells (P1, P2, P3, P4 and P5) and one white dot represents water injection well (I1). The wells are named P1 through I1 by proceeding counterclockwise from the top left well.

Figure 7-16: The distributions of permeability data simulated for five different lithofacies; from top to bottom mudstone, wackestone, packstone, grainstone, and macro-dolomite; the simulated permeability data for each lithofacies honors the permeability data range and mean value shown in Table 7-2.

Figure 7-17: The built permeability realizations; the black dots are production wells and the white dot indicates injection well.

Figure 7-18: One set of initial realizations for five layers; the black dots are production wells and the white dot indicates injection well.

Figure 7-19: One set of initial realizations after upscaling with factor of $10 \times 10 \times 5$ for five layers.

Figure 7-20: Sub-domains decomposed based on the pressure response at fourth year.

Figure 7-21: History matched permeability models using four years of production data.
Figure 7-22: Three dimensional space permeability images of reference model (top left), initial model (top right) and history matched model (bottom left) obtained using four years of production data..............................185

Figure 7-23: History matched and forecast profiles of field pressure and oil production rates for five wells; the target is in red, history matched (before fourth years) is in blue, forecast (after fourth year) in blue, and green for initial guess.................................................................................186

Figure 7-24: The bottom layer of history matched permeability model with the new water injection well indicated with white circular line. The black ellipsoid indicates the permeability continuity influenced by water injection from the new well; the dotted black-ellipsoid indicates the perpendicular direction water flow; the right hand side figure is reference bottom permeability model with new injection well. Black arrows represent the permeability connectivity between new injection well and P2........................................................................................................187

Figure 7-25: Prediction curves with new water injection well; the reference case results are in red lines, and the predictions using the history-matched model are shown with blue lines......................................................189

Figure 7-26: The permeability map for the second scenario of new water injection well perforated in the bottom layer indicated with a white circular mark towards the bottom of the model. The figure on the left is the history matched model while that on the right is the corresponding reference slice ..........................................................................................................190
Figure 7-27: Prediction curves with new water injection well; the reference response is in red lines, and the predictions for the new injection well addition are shown with blue lines.................................................................191

Figure 7-28: History matched lithofacies model.......................................................193
CHAPTER 1. INTRODUCTION

1.1 Overview of history matching

Reservoir modeling (including both static and dynamic data) plays a crucial role in estimating oil and gas volumetrics, performing efficient well planning, forecasting reservoir performance and optimizing reservoir depletion schemes. Geological modeling of a reservoir in conjunction with historical dynamic data integration is a critical issue for reservoir engineers and various algorithms have been developed and applied. The two main steps in reservoir modeling are the development of a static model and the adjustment of the established static reservoir model to reflect dynamic data. The static (note that the term ‘static’ is interchangeable with ‘geological’ in this thesis) reservoir model is constructed using information from seismic, well logging, cores, outcrop analysis, sequence stratigraphy, and so forth. The geological reservoir model then undergoes the process of dynamic data integration also known as history matching. During history matching, the reservoir model is adjusted or modified to match the flow responses of real reservoir. After history matching, the reservoir model reflects both geological attributes and dynamic data.

The fundamental components of history matching include the identification of reservoir parameter(s) to be history matched, the definition of a suitable objective function, and the selection of a suitable optimization technique. To determine the most suitable history matching parameter(s) sensitivity analysis among parameters is conducted; however, most of the time the selection of variables is based on past experience. If the historical production data matches the simulated data obtained from the
geological model, then the reservoir model is ready to be used for future reservoir or production management.

History matching is a challenging and ill-posed inverse problem mainly because it deals with both static information such as geological properties (i.e., porosity, permeability, etc) and dynamic information such as field pressures, and production rate. The relationship between static and dynamic data shows high non-linearity. Inevitably, the history matching process is iterative resulting in a computationally intensive process. This makes the optimization technique one of the most important components in any history matching procedure. There are various optimization techniques for history matching and some of them are discussed in Chapter 2 of this thesis.

The final goal of history matching is to generate a reservoir model to provide reliable production forecasts. The future reservoir performance can be simulated using the history matched reservoir model with a certain degree of confidence. The degree of confidence depends on the history matching algorithm adopted because some algorithms do not ensure conformance with the prior geological model as they integrate dynamic data. If the history matched reservoir model represents the heterogeneity of reservoir more accurately, the reliability of future predictions increases. The accuracy or quality of the reservoir model generated by history matching is determined by the degree of consistency between a geological reservoir model and historical production data.
1.2 Implemented history matching method

The method used for conditioning reservoir models to dynamic data in this thesis is probabilistic history matching utilizing sub-domains. As mentioned in the previous section, in order to generate a reliable reservoir model it is required to incorporate geological and production data without sacrificing either one of them as the history matching progresses. The main idea of the implemented probabilistic history matching algorithm is the perturbation of the probability distribution describing uncertainty in the permeability value using both static and dynamic data. It ensures that the reservoir model is updated by dynamic data, and retains consistency with the prior models for reservoir geology.

The initial geological reservoir models are generated conditioned to prior geological knowledge such as well log data, core analysis data, seismic interpretation data, etc. These models are subjected to flow simulations to obtain responses that ultimately are used for sub-domain decomposition. The proposed sub-domain decomposition is a unique technique enabling simultaneous perturbation of conditional probability distributions in multiple regions of the reservoir, using a distributed computational environment. The sub-domains are regions, which are calculated based on the data from simulated flow responses such as gridblock pressures, within the reservoir that are the most sensitive yet least correlated. The two methods for obtaining sub-domains, i) principal component analysis (PCA) of a covariance matrix from an ensemble of initial realizations, ii) PCA of the Hessian matrix from the simulation module called SimOpt®, are presented in this work. Both these methods ensure that the regions are most influential and yet least correlated.
Once the most influential but least correlated regions are decomposed, the perturbation of geological models follows. The main goal of the perturbation scheme is not only to honor the heterogeneous geological model but also to honor flow history by employing a probabilistic approach for gradual deformation of geological reservoir models conditioned to historical dynamic data. The gradual deformation is obtained by perturbing the local conditional permeability distributions with a deformation parameter, $r_n$, and updating the reservoir model using a Markov-chain procedure. The deformation parameter is calibrated by using Dekker-Brent iterative optimization procedure where the objective is to reduce the mismatch between flow response of the simulation and the production history.

The geological reservoir models are generated based on static reservoir information by sequential indicator simulation. This implies that the available static information is used to derive conditional probability distributions that are then sequentially sampled in order to assign simulated values at grid nodes. The integration of dynamic data within this framework proceeds using the deformation parameters elucidated in the above. The probability conditioned to the dynamic data is derived using Dekker-Brent iterative procedure. After that the permanence of ratio hypothesis suggested by Journel (2002) is implemented to integrate the probability conditioned to geological information and that due to dynamic data in order to derive the joint conditional probability. Permeability realizations can be sampled from the joint conditional probability. Since the relationship between the permeability field and the dynamic data is highly non-linear, it is necessary to repeat the procedure of calibrating the probability conditioned to dynamic data. This iterative process is continued until global convergence to the available historic data is obtained. A significant feature of the
implemented procedure is that it reduces the complex optimization process into a reduced parameter optimization problem, since the goal is to arrive at a set of $r_0$ parameters that affect the permeability outcome at a corresponding set of several independent locations.

The suggested probabilistic perturbation technique is applied to each sub-domain by assigning a suitably established deformation parameter to each sub-domain such that the perturbation process can be done independently and simultaneously using multiple processors. As a result of simultaneous perturbation of conditional probability distributions of permeability within delineated sub-domains, the computational time is reduced. Considering that one of the issues in history matching is the high computational cost on account of a huge number of iterations, the implemented sub-domain delineation procedure proposes a great advantage in saving computational time.

In summary, in contrast to current history matching algorithms that incur significant computational cost in optimizing permeability for each gridblock in the simulation model, the proposed approach reduces the optimizing period by employing innovative method such as domain delineation using principal component analysis and a reduced set of deformation parameters that have to be optimized. Once the domains are delineated, a fully probabilistic approach to perturb permeability within the delineated zones is implemented. With this method the information inferred from dynamic data is merged efficiently with the prior geologic information.
1.3 Thesis outline

The probabilistic history matching algorithm and the software developed based on the proposed algorithm are mainly discussed. The overall algorithm and detail of each component in the algorithm are presented. Based on the theories and algorithms, a user friendly software module was developed that interfaces between the flow simulation software and the indicator simulation algorithm for reservoir model development. A description of the software, as well as its application to real field cases is extensively discussed.

In Chapter 2, a brief review of established history matching algorithms such as gradient-based history matching, global history matching algorithm, gradual deformation method is presented. The advantages and disadvantage of each method are documented. The other sections of the literature review focus on sub-domain delineation, and multi-domain flow simulation.

Chapter 3 investigates the first sub-domain decomposition technique using the Hessian matrix. Extensive examples to decide the optimal pilot points are demonstrated, and the limitation of the Hessian matrix method is discussed. Also, issues and suggestions for using the sensitivity calculation module, such as SimOpt®, are discussed in practical manner.

Chapter 4 proposes the alternative method to the Hessian matrix. The sub-domain delineation method using the covariance matrix of gridblock pressure is documented.
Validation examples reveal the advantages of the method based on covariance matrix such as flow connectivity consideration, cost efficiency, and robustness.

Chapter 5 documents the basic steps of the probability perturbation-based history matching algorithm using perturbation in multiple sub-domains. The schemes introduced in Chapter 4 are integrated into software called Pro-HMS (Probabilistic History Matching Software) which is presented in Chapter 6. An introduction to Pro-HMS (including code specifications) and several related validation cases are presented in the same chapter.

Chapter 7 documents various real field or realistic case studies. In this chapter, three different reservoir history matching case studies are presented. These cases are shown corresponding to different geological systems such as meandering channels, deltaic margins, etc. A further insight on the role of production data for uncertainty assessment of geological reservoir models is also documented.

The thesis ends with a conclusions chapter, Chapter 8, documenting the work done in this research and suggesting some issues for future/further research.
CHAPTER 2. LITERATURE REVIEW

History matching refers to the process of generating geological models that honor the dynamic response of the reservoir. The final goal of history matching is to construct numerical reservoir models that are consistent with all the available information, including both static and dynamic data, and can be used to predict the uncertainty in reservoir performance in the future. History matching may be posed as an optimization process that minimizes a defined objective function that might be for example the deviation of simulated flowrate responses at the wells from the recorded history. There are several methods of optimization to accomplish history matching; for example, gradient based method, global optimization scheme, gradual deformation, and probabilistic approach. In Chapter 2, a brief review of the literature pertaining to history matching, sub-domain delineation, and multi-domain flow simulations is presented.
2.1 History matching methods

2.1.1 Gradient based history matching method

In gradient based methods, the derivative, or gradient, of the response variables with respect to the reservoir parameters is calculated. These sensitivity coefficients are evaluated in flow simulators that solve the non-linear equations yielding the pressure and saturations in each gridblock. After calculating the sensitivity coefficients, the effort would be devoted to iteratively minimizing the objective function. The systematic changes to reservoir parameters are guided by the sensitivity coefficients. There are several algorithms for such minimization, namely the steepest descent direction method, Newton’s method, variable metric method (Yang and Watson, 1987), etc.

The main advantage of gradient based methods is that convergence is faster than the derivative-free approach. On the other hand, one of the limitations of the gradient based method is that the perturbation of the reservoir parameters results in models that do not reflect the underlying geology accurately. One of the other main problems of the gradient based method is that it often converges to a local minimum of the objective function rather than to the global minimum. The problem becomes worse if the number of parameters to be optimized increases. This would result in increased computational cost and worse, the resultant reservoir models may not yield accurate predictions of future performance since they do not conform to the prior geologic model.
2.1.2 Streamline Sensitivity Method

To reduce the computational cost associated with optimization based approaches, methods using analytical sensitivity coefficients have been proposed by Wu et al. (2001) and Wen et al. (2003). Sensitivity coefficients are the first order derivatives of the observable data with respect to the history matching parameters. Datta-Gupta et al. (1998) used the chain rule for differentiation to translate sensitivities of permeability and porosity into tracer concentration and water cut sensitivities and these in turn can be related to time of flight. Owing to the translation from sensitivities of static data to one of dynamic data and that too of time of flight along 1-D streamlines, the sensitivity evaluation problem is reduced into a 1-D integrals solution along streamlines and requires a single simulation run. The advantage of streamline sensitivity method is that it expedites the perturbation process due to the decomposition of the multiple-dimensional flow problem into solution of multiple 1-D problems along streamlines.

2.1.3 Global Optimization Scheme

To avoid some of the problems with gradient-based methods, techniques using global optimization schemes have been presented (Ouenes et al., 1993). These include genetic algorithms, simulated annealing, tunneling method, and hybrid methods, etc. Among these techniques, simulated annealing method is quite popular and is based on the concept of Markov chains. An initial configuration is transformed into a configuration close to the optimum at which the objective function is at a minimum. The simulation process consists of performing a specific number of changes to the model parameters with a specific transition scheme, and for each change, the objective function is evaluated. Variable changes are accepted if they reduce the objective function. Changes that increase the objective function value are accepted or rejected according to
probabilistic criteria (Metropolis et al., 1953). In simulated annealing, the probabilistic criteria for acceptance are based on the Boltzmann distribution, encountered in the study of statistical mechanics of molecular systems. The level of the objective function (energy) and a user specified parameter (temperature) defines the Boltzmann distribution. When the temperature of the system is high, the magnitude of energy as well as the degree of disorder is high such that the probability for accepting a change (even if adverse) is high. On the other hand, as the temperature reduces, meaning that the energy decreases and the system becomes more orderly, there is a small probability that a change will be accepted that results in an increase of the system energy.

This probabilistic feature of simulated annealing allows the system to escape from the solution that corresponds to the local minima of the objective function. However, if the control parameter (temperature) is reduced too fast, the system will reach the local minimum. At each level of the control parameter, the number of iterations or changes must be large enough for the energy function to achieve an equilibrium state. This results in increased computational cost. One more deficient aspect is that that setting optimum control parameter (temperature) decay profile and defining criteria for convergence are difficult. It is frequently non-intuitive and yet they have an enormous influence on the annealing process.

The other global optimization technique which has become popular is genetic algorithm. In the last 20 years, genetic algorithm attracts a lot of attention from various fields such as nuclear reactor management, aircraft design, petroleum production optimization, stochastic reservoir modeling, among others because of its potential as an optimization technique for complex functions (De Jong, 1993).
The algorithm was developed by Holland in 1975 and the fundamental idea relies on Charles Darwin’s theory of evolution. It describes 1) an individual has a tendency to propagate its traits to its offspring, 2) the fittest individuals have tendency to generate superior number of offspring, and 3) the variation results in new species whose traits make them suited to specific environmental niches. The best offspring of the parent solutions are preserved for a next generation of mating such that proceeding in an evolutionary fashion that encourages the survival of the fittest. The best solution in the entire proceeding is recorded and grows to be the applicant proposed by the method for an optimal solution. Thus, natural selection is enabled by the variations that follow from crossover and mutation.

The method has three elements: reproduction, crossover, and mutation (Guerreiro et al., 1998). First, reproduction is the random coupling of individuals from a population to produce one or more offspring from them. Second, crossover identifies the product as gene exchange. The exchange of genes pursues certain rules conventionally encouraged from biological reproduction. These rules must be modified and particularized to different types of combinatorial problems. Finally, mutation is simply the introduction of a random element, often used to amend the result of a gene exchange when the outcome does not successfully meet appropriate restrictions. In this respect, mutation is more likely to be helpful in the application of genetic algorithms than are mutations in biological genetics. The steps involved in a simple genetic algorithm are the following.

1) Build the initial $n$ individual population randomly. The generated initial populations are described as binary strings.
2) Compute the objective function for \( n \) individuals. The objective function in genetic algorithm is called fitness function.

3) Apply “Survival of fitness” concept by selecting probability \( P_r \) as a function of fitness.

4) Crossover is executed to generate new offspring

5) Change some of bits with a certain probability, \( P_n \)

6) Repeat step 1) through 5) \( n \) times for each individual

The advantages of genetic algorithm are the following. First, it handles both continuous and discrete parameters, and hybrid of the two types. Second, the algorithm is free from derivative-related information requirement. Beyond these advantages, genetic algorithm is powerful for the reservoir characterization purpose; the algorithm provides a suite of solutions and they correspond to each different realization of reservoir model such that further investigation of reservoir scenario is enabled. The algorithm is easy to be parallelized, so the computational cost for the reservoir simulation is inexpensive (Romero et al., 2000).

2.1.4 Gradual deformation method

The main feature of the gradual deformation method for history matching (Reis et al., 2000) is that the overall statistical characteristics of the prior reservoir model (such as the histogram and the variogram) are preserved as the reservoir model is perturbed using the reservoir production data. The deformation or updating of model parameters is controlled by a limited number of parameters and the objective is to optimize the set of perturbation parameters using the production information. The reservoir model thus obtained reflects the correct dynamic characteristics.
The main idea proposed by Hu et al. (2001) is the following. Starting from two independent realizations of a Gaussian random field, a new realization is obtained as a linear combination of the two realizations:

\[ Z = \alpha_1 Z_1 + \alpha_2 Z_2 \] (2.1)

In Eq. (2.1), \( Z_1 \) and \( Z_2 \) are the two realizations, and \( \alpha_1 \) and \( \alpha_2 \) are the perturbation parameters. The constraint on the perturbation parameters in order to honor the covariance model is Eq. (2.2).

\[ \sum_{i=1}^{2} \alpha_i^2 = 1 \] (2.2)

Thus, a possible linear combination scheme could be:

\[ Z = \cos(p\pi)Z_1 + \sin(p\pi)Z_2 \] (2.3)

The only parameter \( p \) in Eq. (2.3) is to be optimized such that the objective function defined on the basis of production data is minimized.

The advantages of gradual deformation are that key statistics e.g. variogram and variance identify the target statistics and the 1-D optimization (for \( p \)) is computationally efficient. However, a drawback is that the gradual deformation method is most efficient for multi-Gaussian random fields.
2.1.5 **Probabilistic approach**

In contrast to the other methods, the probability perturbation method, as the name suggests, directly perturbs the conditional distributions depicting the uncertainty in permeability value at a location. Caers (2002) proposed the method and applied it to perturb indicator random fields. Kashib *et al.* (2002) developed a parallel algorithm for continuous random fields and applied it to history matching for several cases.

In the probabilistic approach, a calibration parameter $r_0$ is introduced in order to calibrate the conditional probability of permeability at a location given the dynamic data. The conditional probability of permeability given the prior permeability data and a prior geologic model can be computed using procedures such as indicator kriging/simulation. These conditional probability distributions can subsequently be merged using an approach proposed by Journel (2002). An updated value of permeability is obtained by sampling from the merged probability distribution and the process is repeated at all locations.

In this thesis, probabilistic perturbation approach is utilized. The method include different $r_0$ in regions of the reservoir. Simultaneous optimization of these $r_0$’s require definition of regions that are least correlated. In order to delineate reservoir domains that can be characterized with different $r_0$ parameters, principal component analysis (PCA) of the covariance matrix of pressure response/Hessian matrix has been done. The basic premise of PCA is to isolate the most sensitive and least correlated regions. Some techniques for delineating sub-domains are discussed next. The probabilistic perturbation scheme in multiple sub-domains is presented in Chapter 5, and the prerequisite procedure, sub-domain delineation, which amenable to the simultaneous multiple
calibration parameters-associated probabilistic perturbation, is discussed in Chapter 3 and Chapter 4.
2.2 Sub-domain delineation methods

2.2.1 Principal Component Analysis (PCA) Approach

Principal component analysis (PCA) is a data reduction procedure taking into account similarities or differences between data. Once similarities or difference are observed, it is possible to reduce the complexity of data, by transforming the original data into the principal component space. These reduced set of principal components possess the salient characteristics of the data. PCA technique is a very powerful statistical technique to diminish the high dimensionality of data by recognizing highly significant patterns of data.

The data obtained from petroleum reservoirs are highly diverse and complex, so PCA is widely used in petroleum reservoir data analysis. Both direct application of PCA on data obtained from reservoirs and indirect application of PCA in the process of reservoir model construction are common. For example, PCA clustering technique was utilized to reveal characteristic lithofacies pattern from 3D seismic data (Gilbert et al., 2004). They use PCA and clustering analysis to classify seismic data into hard and soft data. PCA was applied as a pattern recognition tool and only components corresponding to geologic patterns (such as channel) were classified as hard data. The rest of data are clustered and considered as soft data with uncertainty.

Posadas et al. (1993) utilized PC analysis to find the rupture local ellipsoid (RLE) such that the dominant tendencies of fractures can be identified in the seismically active volume. Also, Scheevel et al. (1999) applied PC analysis to 3D seismic amplitude
volume and obtained vectors explaining multiple vertically-adjacent amplitudes for the description of a channellized sand and shale reservoir.

The PCA technique performed in the reservoir region identification for the purpose of history matching is proposed by Yadav et al. (2005). The domains in the reservoir are decomposed by performing PCA of the Hessian matrix. The Hessian matrix represents the sensitivity of the objective function at a given step of the history matching to model parameters. The delineated domains are then assigned to distribute computing environment. Srinivasan et al. (2004, 2005) introduce the domain delineation utilizing streamline density. For the history matching purpose, the regions are defined based on the density of streamline; for example, regions whose streamline is dense are recognized for the parameter perturbation. The key idea indicates that the density of streamline is decision variable for regions that have a significant impact on the observed flow response and that should be adjusted to get a history match.
2.3 Flow simulation in multiple domains

2.3.1 Parallel Reservoir Simulation Environment

Reservoir simulators have been comprehensively used for the evaluation of reservoir flow performance and management. A main issue in performing reservoir flow simulation is the computational cost especially in single CPU computational environments. The computational expenses for solving a linear system of algebraic equation, which describes reservoir multiphase flow, are about 60-80% of the total computational expense (Liu, et al., 2000).

Due to the high computational expenses of reservoir simulators, other problems arise as a result of circumventing the costs such as use of limited number of gridblocks, poor resolution of simulation models, etc. Geologically complex reservoirs require a large number of gridblocks to accurately represent the flow of fluids in the reservoir. The limitation of gridblocks, in other words the problem of size, hinders the spatial resolution of reservoir description; furthermore, if the reservoir simulations involve multi-components and multiphase fluid flows, this problem is even more severe.

The advent of parallel computing systems or distributed computing systems directly addresses these problems. This new generation of parallel computing systems enabling multi-domain or multi-gridblock, multi-scale reservoir simulations dealing with millions of gridblocks (Zhang et al., 2001). To apply these methods, the reservoir needs to be delineated into several pieces such that each sub-domain is simulated on differently assigned CPUs.
Parallel computing systems have had great influence on reservoir simulation, but some challenging issues still remain. The key difficulties are scalability and load balancing (Gratien et al., 2006). The expenses of parallel reservoir simulation are highly dependent on the size of a reservoir model such that it causes scalability problem. The computing load imbalance of among when simulation algorithm adopts domain decomposition process and the computation time associated with solving the flow problem in different domains is different.

2.3.2 Domain Decomposition for Reservoir Simulation

Domain decomposition schemes have been developed to reduce computational expenses and expedite the reservoir simulations process by employing parallel computation environment. The parallel implementation first divides a reservoir into a number of smaller domains, each of which is allocated to a different processor for flow simulation. The non-linear governing equations describing the flow system are partitioned in space and time to be solved in each sub-domain.

Petroleum reservoirs are complex entities that involve related parameters such that the criteria for domain decomposition should have keen consideration for diverse parameters. Since most reservoirs are composed of several different sedimentary classifications, which affect petrophysical properties such as pore size distributions, porosity, permeability, capillary pressure, saturation, etc, decomposed domains should capture distinct differences between these features. Also, well configurations need to be considered while defining the dimensions of each sub-domain especially if coarsening of gridblocks is performed along with domain decomposition (Ma et al., 2004).
In dividing the entire reservoir into several sub-domains, the boundary conditions for each sub-domain have to be carefully considered. Special mortar spaces have to be introduced (Parashar et al., 1998) between adjacent sub-domains. These mortar spaces enable a gradual transition in boundary conditions from one domain to the next. In mortar space upscaling methods, a reservoir is decomposed into a series of sub-domains in which independently constructed numerical gridblocks and possibly different physical models and discretization techniques can be employed in each gridblock.

The techniques of domain decomposition for flow simulation can be categorized as overlapping method and non-overlapping method. Overlapping method implies delineated sub-domains are overlapped such that additional computation is required in the boundary of different sub-domains, but it is robust and uncomplicated to implement (Chan et al., 1994). Implementation of overlapped technique for the thermal simulation of multi-component, multiphase fluid flow in reservoirs is presented by Ma et al. (2004). However, interaction between neighboring overlapped domains are necessary. This implies that processors allocated each domain are required to communicate with each other. In the case of non-overlapping domains, correct specification of boundary conditions at the interface between sub-domains is required.

In this thesis, a viable sub-domain delineation method using pressure response is implemented. The sub-domains are decomposed based on the pressure response of the reservoir such that the connectivity of history matching parameter is well considered; moreover, the sub-domains are not overlapped yet most sensitive as well as least correlated. Thus, the flow simulations can be performed readily in parallel/distributed computation system. Any possible artifacts due to non-overlapped sub-domains are
solved with a conditional stochastic simulation. The orientation of multiple flow simulation for each delineated sub-domain using multiple probabilistic calibration parameters yields a history matching procedure that is more reliable and cost efficient. In Chapter 3 and Chapter 4, the details of algorithm with examples are presented.
CHAPTER 3. HESSIAN MATRIX METHOD FOR SUB-DOMAIN DELINEATION

The previous works performed on sub-domain delineation had been concentrated on testing the basic algorithm. As mentioned in Chapter 2, various methods to delineate sub-domains have been implemented in the past such as using streamline density, sensitivity coefficients, pressure gradients, etc. The algorithm to obtain sub-domains using the Hessian matrix has been researched by Yadav (2005). That work included methods to obtain the Hessian matrix, perform sensitivity analysis, and delineate sub-domains. However, the previous work was not successful in defining a criterion for optimally locating pilot points, and the robustness of the delineated sub-domains remained an issue. Also, the applicability of the method for realistic cases having large number of gridblocks in three dimensional spaces was not adequately demonstrated.

The key issue in using the Hessian matrix method is ‘how do we define optimal pilot points and what would be the resultant computational cost?’ In this chapter, systematic case studies have been performed to investigate the location of optimal pilot points and relevant issues such as the relationship between computational cost and number of pilot points are discussed.
3.1 Motivation

Reservoirs are heterogeneous, and the relationship between geology and flow is complex and non-linear. This implies that reservoir characterization with flow data (e.g. history matching) typically involves solution of complex inverse problems. Inverse problems for non-linear systems typically require intensive computational efforts due to repeated iterations requiring forward flow simulations. Obviously, the choice of optimization technique plays a critical role pointing determining the computational expense. As described in Chapter 2, there are many optimization methods currently being used in history matching and despite the advances, the computational cost is still high.

However, our approach does not only reduce the computational cost of the optimization procedure, but also provides a framework for directly updating uncertainty distributions using innovatively calibrated perturbation parameters. Moreover, to overcome the computational cost the history matching procedure is implemented on parallel computing or distributed computing environment. Any optimization algorithm can be applied, but the algorithm employed should divide the entire reservoir into several sub-domains for simulation on multiple processors (cpu).

The most significant prerequisite for performing flow simulations in parallel processor environment is to obtain regions of the reservoir of interest for which the perturbation parameters can be established on multiple processors simultaneously. In this thesis, sub-domain delineation is implemented to render the history matching procedure more efficient. Two types of domain delineation methods are elucidated in Chapter 3 and Chapter 4, and their implementation within the history matching process is detailed.
3.2 Background

The delineated domains are understood as the most influential and the least correlated sub-domains. They have the biggest impact on the objective function during history matching. Using this type of delineation plays a role in reducing computational cost while one perturbs sub-domains using an iterative method.

The goal of sub-domain delineation procedure is to find the regions within the reservoir that are the most sensitive yet least correlated. It is hypothesized that these sub-domains would permit simultaneous and independent optimization of perturbation parameters (one for each domain). This can be efficiently implemented on a parallel or distributed computing environment thereby resulting in a reduction in computer cost.

The sub-domains should have maximum sensitivity but have minimum relationship between them. This crucial condition needs to be satisfied for perturbing each sub-domain concurrently on different CPUs. The identification of such sub-domains is accomplished by performing principal component analysis (PCA). The multivariate data reduction technique, PCA, projects a set of data onto a reduced set of eigenvectors that are orthogonal to one another. Choosing eigenvectors that correspond to the highest eigenvalues, we partitioned domain into sub-domains that are most sensitive and least correlated. In this work, PCA is applied on matrices representing the sensitivity of the reservoir flow or pressure response at each gridblock to the permeability of the reservoir. Two methods for calculating the sensitivities: i) based on the Hessian matrix calculated by a flow simulator, and ii) based on a covariance matrix calculated using a suite of realizations, are presented.
A module such as SimOpt\textsuperscript{®} in a commercial simulator Eclipse\textsuperscript{®} reports the Hessian matrix, and eigenvalues and corresponding eigenvectors. The post-processing of the SimOpt\textsuperscript{®} output for sub-domain delineation is done within the developed code for history matching. The detailed method and examples are presented in Section 3.3. However, that approach is restricted to situations where a module for reporting the Hessian matrix is available. An alternative way that uses the covariance matrix based on the pressure response in each gridblock can also yield an approximation for the sensitivity matrix. In this approach, several alternate models of the reservoir are processed through a simulator and the grid-block pressures are output. The covariance between the grid-block pressure and the well response is reported. The PCA of the covariance matrix renders the eigenvalues and corresponding eigenvectors which are the most sensitive but least correlated. In Chapter 4, the viability of this alternative method will be extensively discussed.
3.3 Domain delineation using the Hessian matrix

3.3.1 Theory

Sensitivity is defined as the degree to which a physical quantity (or the objective function in the case of an iterative solver) is affected by another physical quantity (permeability). In this specific application of history matching, it describes how the response at a well e.g. bottom-hole pressure varies as the permeability in a specific gridblock is changed.

The traditional approach for determining sensitive regions (i.e., locations where the permeability value has an important influence on the observed flow response) is based on the Hessian matrix that is calculated internally by the flow simulator. The Hessian of a function is the matrix whose components are the second partial derivatives of the function. The function in this case is the objective function measuring the mismatch between the simulated response and history and the partial derivatives are evaluated with respect to permeability. The Hessian matrix is defined as follows in Eq. (3.1).

\[
H = \begin{bmatrix}
\frac{\partial^2 f}{\partial x^2} & \frac{\partial}{\partial x} \left( \frac{\partial f}{\partial y} \right) & \frac{\partial}{\partial x} \left( \frac{\partial f}{\partial z} \right) & \cdots \\
\frac{\partial}{\partial y} \left( \frac{\partial f}{\partial x} \right) & \frac{\partial^2 f}{\partial y^2} & \frac{\partial}{\partial y} \left( \frac{\partial f}{\partial z} \right) & \cdots \\
\cdot & \cdot & \cdot & \cdot \\
\cdot & \cdot & \cdot & \cdot \\
\cdot & \cdot & \cdot & \cdot \\
\end{bmatrix}
\]

In Eq (3.1), \( f \) is an objective function. One parameter, permeability, is dealt with in this thesis thereby \( x, y, z \) are permeabilities at different locations in the simulation.
domain (i.e., pilot points - defined as certain control points in the reservoir designated in order to reduce the dimensionality of the stochastic optimization method; refer Section 3.3.2.1 for the application). Thus, the Hessian matrix is a measure of sensitivity of the objective function to the permeability at each gridblock. The diagonal entries of the Hessian matrix represent the sensitivity of permeability at a particular location. Whereas, the off-diagonal entries in the Hessian (Eq.3.1) measure the redundancy between the sensitivity of the response variable to one variable (or permeability value at one location) and that due to another variable (or the value at another location).

The procedure to obtain the sub-domains based on principal component analysis of the Hessian matrix can be divided in several steps.

1) First of all, the eigenvalues and the corresponding eigenvectors of the Hessian matrix are computed. Eigenvalues represent the contribution of individual sensitivities towards the global objective function. The eigenvectors represent the orthogonal basis on which the original sensitivities can be projected. All pilot points have eigenvalues and corresponding eigenvectors; furthermore, the number of components in an eigenvector is consistent with the dimensionality of the Hessian matrix.

2) The eigenvalues are ranked based on the magnitude of the eigenvalues. A variance cut-off is applied to arrive at a reduced set of eigenvalues and corresponding eigenvectors that explain the observed variability.

3) Eigenvectors are scaled to maintain the magnitude equivalent to their corresponding eigenvalues.
4) The largest scaled eigencomponent (positive or negative) is assigned to a pilot point location. Thus, for example, there are two locations where the largest eigenvector corresponds to the second eigencomponent, and then both these locations receive an index of 2. While if a third location has the largest eigenvector corresponding to the first eigencomponent, that is assigned an index of 1.

5) Finally, a volume-based threshold value (i.e., cut-off value) is applied such that only those locations with eigenvectors greater than the threshold are assigned to be domains. Thus in the preceding example if the magnitude of the maximum scaled eigenvector corresponding to the first two locations is above the specified threshold, then those two regions are assigned to a common sub-domain, while if the maximum scaled eigenvector at the third location is below the threshold, then that location is excluded from sub-domains. By this process, the highest eigenvalues and corresponding eigenvectors, which represent the most sensitive, non-interacting regions, are extracted characterizing the required sub-domains.

A summary of the sub-domain decomposition procedure is illustrated in Figure 3-1. As discussed earlier, the PCA procedure yields the most influential yet least correlated domains. If the regions are bounded by faults or any other geological events such as low permeable streaks, the obtained sub-domains are completely isolated; however, in cases with less obvious heterogeneity, the regions obtained by PCA may exhibit some residual correlation, but are still good enough to make the history matching efficient.
3.3.2 USE OF FLOW SIMULATOR MODULE- SimOpt®

A commercial simulator Eclipse® has been used in this thesis work as part of the history matching module. As listed in Figure 3-1, the first step of the sub-domain delineation procedure is to compute the Hessian matrix and corresponding eigenvalues/eigenvectors. SimOpt® uses a gradient zone method permitting both 2D and 3D applications. In this section, the definition of the Hessian and technical issues related to the delineation of sub-domains with SimOpt® are discussed in practical terms. The major issues are the selection of optimal pilot points, format of files, etc. These technical issues are discussed in the following sections.
3.3.2.1 Pilot Points

The derivative, or gradient, of the objective function with respect to the history matching parameters (permeabilities at each pilot point) are used to calculate the eigenvalues and eigenvectors of the Hessian matrix and identify regions for history matching. The gradients at pilot point locations are interpolated to provide the regions.

To delineate sensitive regions based on gradients it is required to define some sample points for the calculation of the Hessian matrix. If the entire sets of reservoir gridblocks are subjected to gradient analysis, the computational cost would be prohibitive. Since the computation of gradient of all gridblocks is cpu intensive, a minimum set of sample/pilot points have to be carefully chosen. On the other hand, since the interpolation is performed based on gradients at the pilot points, it is important to use an adequate number that yield reliable interpolations. The areas around wells have to be assigned more pilot points in order to observe active fluid flows.

There is thus, the critical issue of balancing computational cost (minimum number of pilot points) as opposed to robust interpolation and consequently physically realistic regions (increased number of pilot points). For example in the SimOpt® calculation module, in the location of pilot points in three dimensional coordinates is specified by the IJK setting. The IJK settings allow definition of the minimum and maximum coordinate ranges and the number of pilot points required. The points are distributed evenly over the range. In SimOpt®, it is also possible to add points manually if required.

The calculation of the Hessian matrix is based on a group of specified points having assigned permeability values. If the history matching considers other parameters
besides permeability, then different regions may be defined on the basis of different parameters. Those different kinds of parameters are referred to as regional parameters.

There is a limitation on the number of locations that can be specified as pilot points. The limitation depends on number of observed data points and number of active data points (time instants at which production data is available). This information can be found for example, in the Observed data | Data information tab in SimOpt® after clicking on one of the observed data section trees. If three active wells exist and each has 60 active production data points, then a maximum of 180 pilot points can be assigned for the calculation of sensitivities.

The optimal IJK parameters (i.e., the optimal number of pilot points) should be one that produces stable sub-domains. Stable sub-domains mean that as the number of pilot points is increased, the sub-domains obtained should be similar and not change much. Heterogeneity has a role in the selection of optimal number of pilot points. Increased heterogeneity in the regions around wells requires greater number of pilot points. However, increased heterogeneity in the entire 3D reservoir model is difficult to handle due to the limitation on the number of pilot points.

An extensive examination of the influence of number of pilot points on the delineated zones is discussed with examples in section 3.3.3.
3.3.2.2 SimOpt® simulation

Basically, the SimOpt® module yields Hessian matrix, eigenvalues and eigenvectors. Eigenvalues and eigenvectors represent sensitivity, and PCA is performed on these quantities. In order to apply SimOpt® the initial guess for the permeability field is loaded first, and then the observed production data file is loaded. There are several different formats of production files that can be loaded. Formats such as Summary Vector Format (*.svf), and RSM (*.rsm) are acceptable to the simulator. Regardless of production file formats, the Hessian matrix obtained from simulator is within 1% error range. To have production file as a Summary Vector Format it is necessary to run the flow simulator using the initial guess for the permeability field and with historical (or reference) production data. Table 3-1 summarizes the results from some validation cases indicating that the production file format does not affect the delineated domains.
Table 3-1: Results showing that the domains delineated are insensitive to the format of the well production file

<table>
<thead>
<tr>
<th>Production File Format loaded in SimOpt®</th>
<th>Results</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Eigenvalues</td>
</tr>
<tr>
<td>Summary Vector Format</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td>RSM</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
</tbody>
</table>

After the observed production file is successfully loaded, data for the calculation of gradients need to be input. This is accomplished using for example, the ‘Gradzone Module Analysis’ window in SimOpt®. Depending on whether the case is 2D or 3D, the parameter type for calculating sensitivities would be either ‘PermX’ or ‘PermXY’. Then, the determination of the number of pilot points using the IJK ranges need to be made. Upon completion of the run, eigenvalues and corresponding eigenvectors are observable through the ‘Gradzone Module Analysis’ Window.

The input and output files of SimOpt® and the procedure to use the software are shown in Figure 3-2.
Generate initial realization with prior geological information

Load initial realization as an include file in simulated data section. Data is automatically loaded from the ‘initial folder’. The file format should be Eclipse® format.

Load production file (or reference data) in the ‘Observed Data Section.’ The objective function is calculated using the reference production data.

In Observed data control section, observation error in the history of each data type is defined.

Define weights to be attached to different output vectors while calculating the objective function

Set the observed variables Active or Inactive; this results in the minimum and maximum number of pilot points.

Define parameters of which sensitivity is to be calculated. If permeability is the only parameter specified, then sensitivity is calculated with permeability data.

Decide number of pilot points and locations of them. ‘Add parameter’ can specifically render the choice of pilot points.

- Hessian matrix, eigenvalues and eigenvectors are the outputs.
- Global as well as well-specific sensitivity coefficients are outputs.
Figure 3-2: The flow chart for obtaining the Hessian matrix by SimOpt®; the blue box indicates the output of the SimOpt® simulation, and the rest are input and the procedures for the simulation.

### 3.3.3 EXAMPLES

The examples are demonstrated to recap the discussion of IJK parameter selection as well as the robustness of domain delineation with the Hessian matrix. 2D and 3D case examples are demonstrated and illustrated with different IJK settings. Seven different 3D cases have been tested to discover the optimal pilot points as well as to see validity of domain delineation process in 3D reservoir scenarios.

#### 3.3.3.1 Simple 2D cases

Simple 2D cases were tested to investigate the effect of pilot point selection on the decomposed sub-domains. The simulated reservoir size is $100 \times 100$, and each gridblock size is 1 ft. One production well located at (41, 81) produces oil for 7.5 years. The initial and reference realizations are synthesized using the indicator simulation algorithm and shown in Figure 3-3.

![Reference and Initial Realizations](image)

Figure 3-3: The reference and initial realizations of 2D test case; the black dots indicate the production well location.
Since the case is two dimensional, the selection of pilot point in the vertical direction is unnecessary. In the IJK selection setting of SimOpt®, K value for this test case is one. The pilot points in x and y directions are varied. The minimum number of pilot points is specified to be 25, and two cases were tested with 90 pilot points. The I and J values were varied for these two cases - one was specified to be (9, 10, 1), while the other was specified to be (10, 9, 1)). Table 3-2 summarizes the applied IJK setting, the five highest eigenvalues, and the corresponding sub-domains.

Table 3-2: Summarized results of 2D simple test cases

<table>
<thead>
<tr>
<th>IJK parameters</th>
<th>Highest five eigenvalues</th>
<th>Sub-domain</th>
</tr>
</thead>
</table>
| (5, 5, 1)      | 1
0.011321
0.000374
6.68×10⁻⁶
1.24×10⁻⁶ | ![Sub-domain](image) |
| (6, 6, 1)      | 1
0.003258
0.000103
6.09×10⁻⁷
2.85×10⁻⁷ | ![Sub-domain](image) |
| (7, 7, 1)      | 1
0.018684
0.000115
3.95×10⁻⁶
5.34×10⁻⁷ | ![Sub-domain](image) |
| (9, 9, 1)      | 1
0.007102
0.000227
2.53×10⁻⁵
2.19×10⁻⁶ | ![Sub-domain](image) |
Table 3-2 continued: Summarized results of 2D simple test cases

<p>| | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>(10, 9, 1)</td>
<td>1</td>
<td>0.001179</td>
</tr>
<tr>
<td></td>
<td></td>
<td>3.87×10⁻⁵</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1.65×10⁻⁶</td>
</tr>
<tr>
<td></td>
<td></td>
<td>9.79×10⁻⁷</td>
</tr>
<tr>
<td>(9, 10, 1)</td>
<td>1</td>
<td>0.02626</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.00103</td>
</tr>
<tr>
<td></td>
<td></td>
<td>4.23×10⁻⁵</td>
</tr>
<tr>
<td></td>
<td></td>
<td>5.92×10⁻⁶</td>
</tr>
</tbody>
</table>

When the IJK setting is (5, 5, 1), the major sub-domain exhibits straight line boundaries. Such lines are unrealistic in the cases of real reservoirs revealing heterogeneity, so it is undesirable; moreover, they are presumably artifacts caused by the limited number of pilot points. Also, the production well is not included in the delineated sub-domain. This is inexplicable since the region around the producing well is sensitive due to large fluid fluxes, and yet, the well is not encompassed by the sub-domains. This indicates the selection of pilot points, (5, 5, 1) is not the best. As the number of pilot points is increased, the obtained sub-domains are more similar. In other words, the decomposed sub-domains stabilize with increasing number of pilot points. The producing well is contained within the sub-domain. Also, the boundary of the sub-domain looks more normal (without the straight-edge seen for the (5, 5, 1) case).

Since one well is implemented in this reservoir model and the number of active production data is 90 (i.e., the 30 days time step for simulation in 7.5 years), the maximum possible number of pilot points in this reservoir case is 90. If larger number of
pilot points is available, the result would be more stable; however, the computational cost to delineate sub-domain obviously increases with increased number of pilot points.

Based on the results of test cases, it can be concluded that realistic or stable sub-domains result with the optimal number of pilot points.

### 3.3.3.2 3D cases: Basic three related cases

The reservoir conditions for these series of test cases are three production wells and one injection well. The location of injection well is different from case to case. The reservoir size is $100 \times 100 \times 5$, and the constraint for the flow simulation is oil production rate.

Case 1 is the base case for the further cases and in this case there is no injection. The locations of wells, P1, P2, P3, and I, are (10, 92), (89, 8), (35, 19) and (76, 91), respectively. The initial and reference realizations are shown in Figure 3-4.
Figure 3-4: The initial (top five maps from top to bottom layer) and reference (bottom five maps, from top to bottom layer) realizations case; the black dots indicate the production and injection well locations.

The configuration of the decomposed sub-domains with four different combinations of IJK parameters are shown in Table 3-3.

Table 3-3: Summarized results for 3D base case

<table>
<thead>
<tr>
<th>Applied IJK parameters</th>
<th>Delineated sub-domains</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Top layer</td>
</tr>
<tr>
<td>(5, 6, 4)</td>
<td>![Image]</td>
</tr>
<tr>
<td>(6, 5, 4)</td>
<td>![Image]</td>
</tr>
<tr>
<td>(7, 6, 3)</td>
<td>![Image]</td>
</tr>
<tr>
<td>(8, 5, 3)</td>
<td>![Image]</td>
</tr>
</tbody>
</table>

There are no regions identified near the producer P1 located at the top left corner of the model. This is especially significant considering that as much oil is produced.
during the period by P1 as P4, but this is not indicated by the sub-domains. The permeability near P4 is similar as one of P1, but the difference between initial and reference realizations near P1 and P4 as observed in Figure 3-4 provides an explanation. The difference in the permeability field is much less near the producer P1 than near P4. Consequently, the SimOpt® calculation indicates the absence of a region around P1 where significant perturbations to the model need to be made. This result implies that the Hessian matrix method is sensitive to the choice of the initial reservoir model.

Since the Hessian matrix is gained from the objective function, it is sensitive to the initial realization. To investigate if the Hessian matrix method is indeed dependent on the initial realization, the permeability near production well P1 is artificially increased as shown in Figure 3-5. The reference model remains the same.
Figure 3-5: The revised initial (top five maps from top to bottom layer) realizations with higher permeability values near P1.

The delineated sub-domains with five different combinations of pilot points are illustrated in Table 3-4.

Table 3-4: Summary of delineated zones when the permeability around the producer P1 is increased in the initial permeability model

<table>
<thead>
<tr>
<th>Applied IJK parameters</th>
<th>Delineated sub-domains</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Top layer</td>
</tr>
<tr>
<td>(6, 3, 5)</td>
<td>![Image]</td>
</tr>
<tr>
<td>(6, 4, 4)</td>
<td>![Image]</td>
</tr>
<tr>
<td>(6, 4, 5)</td>
<td>![Image]</td>
</tr>
<tr>
<td>(6, 5, 4)</td>
<td>![Image]</td>
</tr>
</tbody>
</table>

The result show that P1 is recognized as a sub-domain in all different pilot points cases through five layers. The only change made in this case compared to the previous
case is the permeability of region near P1. This means that different initial realizations result in different sub-domains; in other words, the Hessian method reveals the dependency to the initial realizations. This dependency comes about because the objective function considers both initial and reference permeability models and the objective function in turn influences the sensitivities.

The injection well I located at (76, 91) is shut for the two previous test cases. No sub-domains are detected near injection wells consequently. In the delineated sub-domains summarized in Table 3-5, the injector is turned on. The initial realization is shown in Figure 3-5 and reference realizations are the same (Figure 3-4).

Table 3-5: Summarized results of test cases when the injection well is active

<table>
<thead>
<tr>
<th>Applied IJK parameters</th>
<th>Delineated sub-domains</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Top layer</td>
</tr>
<tr>
<td>(5, 6, 4)</td>
<td>![Image]</td>
</tr>
<tr>
<td>(6, 3, 5)</td>
<td>![Image]</td>
</tr>
<tr>
<td>(6, 4, 4)</td>
<td>![Image]</td>
</tr>
</tbody>
</table>
Based on the results of previous two cases, it is expected that P1 and P4 are recognized as sub-domains because the initial and reference permeability data near those two wells are different. The region around the injection well is also covered by sub-domains since the permeability heterogeneity around the injection well is different between initial and reference realizations. The IJK combinations of pilot point ranges such as (6, 4, 4), (6, 4, 5) and (6, 5, 4) showing similar sub-domains. The issue of optimal pilot point selection is difficult in this case since there are several sub-domains sets and they are all different. The selection of pilot-point locations that yield optimal domain delineation is a trial-and-error process. A common observation based on the results in Table 3-5 is that the domain around the injector increases in size in the bottom layers of the model. This is to be expected because of gravity effects that cause the water to slump to the bottom layers.
3.3.3.3 3D cases: Effect of very different initial and reference realizations

The following three consecutive cases are briefly presented to evaluate the most suitable selection of pilot points. The permeability heterogeneities and the well configurations vary in these cases. Many different selections of pilot points are evaluated before selecting the case with the most sensitive and least correlated sub-domains. The assumption for these test cases is that there is significant uncertainty in modeling the reservoir and so, the initial realization is far from the reference permeability field. This enables us to examine the effect on combinations of pilot points by screening out the effect of difference between initial and reference realizations. For all three cases, the reservoir grid dimension is assumed to be 100×100×5, and the size of each gridblock is 100 ft×100 ft×5 ft. The producers are set to rate constraint, there are three production wells and one injection well, and the simulation duration is 7.5 years with 30 days time steps. Also, all four well are assumed to have penetrated all five layers.

The well locations in the first heterogeneous test case are P1 (50, 92), P2 (11, 11), P3 (67, 77) and I (76, 91). The initial and reference realizations of five layers are illustrated in Figure 3-6. The orientations and permeability ranges are quite different such that the difference between initial and reference realizations are obvious.
Figure 3-6: The initial (top five maps from top to bottom layer) and reference (bottom five from top to bottom layer) realizations; black dots indicate well locations.

Three combinations of IJK parameters are utilized. The number of pilot points in the x-direction increase through the cases. The results of this test are summarized in Table 3-6.

Table 3-6: Summarized results of test cases with a large difference between the initial and reference permeability models

<table>
<thead>
<tr>
<th>Applied IJK parameters</th>
<th>Delineated sub-domains</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Top layer</td>
</tr>
<tr>
<td>(4, 6, 3)</td>
<td><img src="image1" alt="Image" /></td>
</tr>
<tr>
<td>(5, 5, 5)</td>
<td><img src="image6" alt="Image" /></td>
</tr>
<tr>
<td>(6, 4, 3)</td>
<td><img src="image11" alt="Image" /></td>
</tr>
</tbody>
</table>

When the pilot point combination of (4, 6, 3) is applied, the region around the injection well is covered as a sub-domain in only the first (bottom) layer. The case of (5, 5, 5) does not cover all wells through the five layers, but of the case with pilot points in (6, 4, 3) covers the regions around wells. This indicates that even though the number of
pilot points is more in the case with pilot point range (5, 5, 5), the actual location of the pilot points is such that the delineated sub-domains do not cover all regions around wells. It is necessary, therefore, to have some prior information on the reservoir to obtain the optimal pilot point distribution.

In the next case, the reference and initial permeability models have different orientation of permeability continuity; one is 45 degrees (reference) and the other exhibits continuity in 135 degree. The initial and reference realizations and well locations are indicated with black dots in Figure 3-7. The coordinates of wells are P1 (10, 92), P2 (89, 8), P3 (35, 19) and I (76, 91). Unlike the previous examples, the well configuration spans the reservoir model. Also, P2 and P3 are activated midway through the simulation period, and P2 is the last to be put to production. The perforation of P1 is only in the topmost layer. All other wells penetrate all the layers.
Figure 3-7: The initial (top five maps from top to bottom layer) and reference (bottom five from top to bottom layer) realizations; black dots indicate well locations.

Seven different combinations of IJK setting were used and the corresponding sub-domains are illustrated in Table 3-7. The numbers of pilot points selected for all cases were either 14 or 15; however, the number of pilot points in east-west direction increases. Since P1 is perforated in the top layer and produced oil from the beginning of the simulation, the sub-domains delineated should include the region around well P1. P3 and P2 do not open until later in the simulation, and so P2 and P3 may not be contained within the delineated sub-domains. The injection well is open from the beginning of the simulation so that regions around injection well especially in the bottom layers should be observed.

Table 3-7: Summary of results for cases where the initial model is different from the reference

<table>
<thead>
<tr>
<th>Applied IJK parameters</th>
<th>Delineated sub-domains</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Top layer</td>
</tr>
<tr>
<td>(3, 6, 5)</td>
<td><img src="image1.png" alt="Image" /></td>
</tr>
<tr>
<td>(4, 5, 5)</td>
<td><img src="image6.png" alt="Image" /></td>
</tr>
</tbody>
</table>
Table 3-7 continued: Summary of results for cases where the initial model is different from the reference

Based on the test conditions, the delineated sub-domains are best for the location of pilot points in (6, 4, 4) or (6, 3, 5). In both cases, regions around P1 are designated as sub-domain in the top layer. In the bottom layer, the sub-domains include the injection well. P3 is included in the sub-domains corresponding to pilot points in (6, 3, 5), but P2 is never included within the sub-domains. For the pilot points distributed in (3, 6, 5), the region around the injection well in the bottom layer is not covered by the sub-domains. In contrast, the pilot point range (4, 5, 5) that has the same number of pilot points as (3, 6, 5) shows the sub-domain near the injection well in the bottom layer but misses the producer P1 in the top layer. The results indicate that though the effect of difference between initial
and reference realizations is important, other considerations such as the duration of the 
active flow periods and penetration length of wells also have significant influence on the 
delineated zones.

The last set of cases is intended to study the influence of well conditions on the 
delineated sub-domains and the corresponding optimal specification of pilot points. The 
well locations are P1 (10, 92), P2 (35, 19), P3 (89, 8) and I (79, 91). P1, P2 and P3 are 
penetrated through all five layers, but the injection well only intersects the fourth layer. 
P3 is shut in for 7 years and then open for 6 months of production. The initial and 
reference permeability models are illustrated in Figure 3-8.
Figure 3-8: The initial (top five maps from top to bottom layer) and reference (bottom five from top to bottom layer) realizations; black dots indicate well locations.

A various combinations of pilot points are implemented and they are applied based on a systematic increase in the I parameter specifying the range of the pilot points. The results are illustrated in Table 3-8.
Table 3-8: Summarized results of test cases corresponding to variations in well operating conditions

<table>
<thead>
<tr>
<th>Applied IJK parameters</th>
<th>Delineated sub-domains</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Top layer</td>
</tr>
<tr>
<td>(3, 6, 5)</td>
<td><img src="image1.png" alt="Image" /></td>
</tr>
<tr>
<td>(4, 5, 5)</td>
<td><img src="image6.png" alt="Image" /></td>
</tr>
<tr>
<td>(5, 4, 5)</td>
<td><img src="image11.png" alt="Image" /></td>
</tr>
<tr>
<td>(5, 5, 5)</td>
<td><img src="image16.png" alt="Image" /></td>
</tr>
<tr>
<td>(6, 3, 5)</td>
<td><img src="image21.png" alt="Image" /></td>
</tr>
<tr>
<td>(6, 4, 4)</td>
<td><img src="image26.png" alt="Image" /></td>
</tr>
</tbody>
</table>

When the number of pilot points is 15 (i.e., cases for (5, 4, 5) and (5, 5, 5)), two cases delineate unreliable sub-domains. The sub-domains do not include P2 at all through the layers. If the number of pilot points is decreased to 14, various sub-domains scenarios
appear. With an increase in the I parameter setting from four to six, the delineated sub-domains become more reasonable. For the combination of (6, 3, 5), the sub-domains include P1 and P2 in all layers; moreover, the region around the injection well is included in the sub-domains in the top, second and fourth layers reflecting the perforation of the well through all the layers. Since P3 is shut for 7 years and open for 6 months, sub-domains near P3 are not discernible. The case employing the same I parameter setting as six, but with different J and K parameter values (i.e., (6, 4, 4) case) reveal quite different sub-domains; however, looking at the color codes of the identified domains, it can be concluded that these cases have the same eigenvalues (except one identified by the dark blue) for the Hessian matrix. In these cases, given the strongly anisotropic nature of the permeability field, the characteristics of the delineated zones are very sensitive to the specification of the pilot points. Small changes in the configuration (as indicated by the IJK ranges) result in dramatically different sub-domains. In such cases it is imperative that the selection of pilot points and consequently the size and shape of sub-domains be guided by the prior knowledge of the geology.

3.3.3.4 Discussions

Through the 2D case example, it is possible to observe a trend of delineated sub-domains by applying different combinations of pilot points. In these cases, it is observed that the shape and size of sub-domains exhibit very small changes after some threshold of pilot points is exceeded.

However, it is difficult to observe similar, stable shapes of sub-domains in 3D after increasing the numbers of pilot points. This is especially so in the case of reservoirs exhibiting high degree of heterogeneity. In such cases, it may be necessary to redefine the
regions after a few iterations of history match, so that the permeability models start exhibiting similarity to the reference model and hence some of the wild fluctuations in the definition of sub-domains may be curbed. It may also be a good idea to try some iteration with predefined regions to get a feel for the parameters, before using the gradient analysis in SimOpt®. The difficulty in 3D cases is primarily because of the limitation in the number pilot points that can be specified. The vertical direction in 3D cases requires more pilot points. However, after running a few combinations of pilot points it is possible to apply engineering judgment to rule out cases where the defined sub-domains do not conform to the well or reservoir conditions.

It is concluded that the method for delineation of sub-domains based on gradients cannot always yield good results. The dependency of the sub-domains on the initial realization is especially difficult in situations where the data available for reservoir modeling is sparse. These drawbacks are addressed in the next chapter where an alternate method using an ensemble of realizations is utilized. This method is demonstrated to be independent of the initial realization, and does not use any pilot points.
CHAPTER 4. COVARIANCE MATRIX METHOD FOR SUB-DOMAIN DELINEATION

In Chapter 3, sub-domain delineation method using the Hessian matrix is explained. The Hessian matrix method has some disadvantages; for example, it is heavily dependent on the initial realization, it requires a simulation module such as SimOpt®, and it relies on the engineering judgment to obtain optimal pilot points. Another method that substitutes for the Hessian matrix is necessary in order to achieve the sub-domain delineation method in a more robust manner.

As a viable alternative to the Hessian matrix method for the sub-domain decomposition, a method utilizing the spatial covariance of gridblock pressure responses is presented in this chapter. In the previous work performed by Yadav (2005), the covariance matrix is computed using a suite of initial realizations to represent sensitivity of the reservoir. However, the covariances were not computed for all grid nodes for computational reasons. Instead, the covariances were computed every ten gridblocks. This may incur problems when interpolating calculated covariance values to the unsampled nodes. When the numbers of reservoir gridblocks is over 10,000, the computation of covariance using fifty initial realizations is computationally expensive.

In order to capture the flow connectivity of the reservoir the computation of covariances over the entire domain is necessary. To cope with this key issue, upscaling of the reservoir domain is proposed such that the computation of covariances over the entire domain with multiple initial realizations is enabled.
This method offers the advantage of being independent of the simulator’s capability to calculate and report the Hessian matrix during flow simulation. In addition, it will be demonstrated in this chapter, that this method since it is based on an ensemble of realizations, is independent of the initial guess of the permeability field. Extensive 3D examples with various configurations of number of initial realizations are also demonstrated.
4.1 Approximate method for sensitivities based on the covariance matrix of gridblock pressure responses

4.1.1 THEORY

Consider reservoir models that have been conditioned to prior geological knowledge using sequential indicator simulation. Simulation of flow in these models yields the spatial distribution of pressure (at any given simulation time) corresponding to the input permeability field. The covariance between the pressure at each grid node and every other grid node in the simulation domain can be computed using the series of pressure responses obtained over an ensemble of realizations. When the size of the simulation grid is $n$ gridblocks, the corresponding $n \times n$ covariance matrix of pressure responses is shown in Equation 4.1.

$$C = \begin{pmatrix}
\text{COV}(P_1, P_1) & \text{COV}(P_1, P_2) & \cdots & \text{COV}(P_1, P_{n-1}) & \text{COV}(P_1, P_n) \\
\text{COV}(P_2, P_1) & \text{COV}(P_2, P_2) & \cdots & \text{COV}(P_2, P_{n-1}) & \text{COV}(P_2, P_n) \\
\vdots & \vdots & \ddots & \vdots & \vdots \\
\text{COV}(P_{n-1}, P_1) & \text{COV}(P_{n-1}, P_2) & \cdots & \text{COV}(P_{n-1}, P_{n-1}) & \text{COV}(P_{n-1}, P_n) \\
\text{COV}(P_n, P_1) & \text{COV}(P_n, P_2) & \cdots & \text{COV}(P_n, P_{n-1}) & \text{COV}(P_n, P_n)
\end{pmatrix} \quad (4.1)$$

The gridblock pressures reported by the flow simulator are obtained by solving the finite difference form of flow equations. The pressures, therefore, take into account the connectivity of permeability value at multiple grid locations. At locations close to the wells, the variations in underlying permeability will cause large variations in the corresponding gridblock pressures because of the high fluxes in those regions. At locations far away from the wells, on the other hand, variations in permeability will cause only minor variations in gridblock pressures due to the low flux in those regions. The variances of pressure, which are the diagonal entries of covariance matrix (Eq. 4.1)
computed over a suite of realizations, is therefore a good measure of the sensitivity of the well response to variation in the underlying reservoir properties. As shown for the Hessian matrix, the off-diagonal entries of the sensitivity matrices are measures of joint sensitivity of the response variable to the reservoir variables (permeability) at two locations. Such redundancy is represented in the covariance matrix through the covariance between the pressure values at two different grid-block locations.

The covariance matrix (Eq. (4.1)) is a surrogate to the Hessian matrix in Eq. (3.1). It resembles the Hessian matrix not only in terms of representing the sensitivities but also has the same format (i.e., both matrices are $n \times n$ square matrices). The covariance matrix consists of components that are covariance values between the pressure response of one gridblock and those of the rest of the entire grid, thus, the grid pressure is influenced by the connectivity of permeability. Also, since the covariance is calculated over a suite of realizations, the delineated domains are insensitive to the starting guess (or the initial model). Besides, the covariance matrix can be calculated using any simulator.

The procedure for calculating the sub-domains using the covariance matrix of pressure consists of the following steps.

1) Generate an ensemble of initial reservoir permeability realizations. Sequential indicator simulation is used to get initial models conditioned to static data (i.e. permeability from well test, well logging, etc). The minimum number for the computation of covariance is two realizations, so the number of initial realizations can be any integer above two.
2) Scale up initial reservoir models with a desirable upscale factor such as $10 \times 10 \times \text{Number of layers}$. This procedure prevents excessive computational cost for obtaining sub-domains.

3) Perform flow simulations on the ensemble of upscaled initial realizations. The pressure in each gridblock of each realization is obtained as an output from the flow simulations.

4) Compute the covariance matrix of pressures. The expected value of pressure is calculated over the suite of realizations. The diagonal entries are the variances of pressure at every node using the ensemble of realizations.

5) Perform PCA on the covariance matrix. The factors or groupings of pressure regions are constructed in a way that reduces the overall complexity of the problem and takes advantage of inherent interdependencies in the data. Thus, regions of the reservoir that have a similar behavior in gridblock pressures will be grouped together. The five highest eigenvalues and their corresponding eigenvectors are retained.

6) Scaling and sorting of eigenvalues and eigenvectors.

   6-1) Scale and rank the eigenvalues based on their magnitude

   6-2) Compare the eigenvector components corresponding to the first eigenvalue with the other ones that are obtained corresponding to the rest of the eigenvalues.

   6-3) Mark which eigenvalue has the largest eigen-component for each gridblock.

   6-4) Store eigenvector components and corresponding eigenvalues in an array.

   6-5) Apply a threshold (volume cutoff) to the array in the previous step to define sub-domains. If, for example, the volume cut-off is specified to be
40%, the gridblocks with the highest eigen-components are retained such that they account for 40% of the total reservoir volume.

6-6) The size should be optimal so as to enhance effective perturbation process. If the volume cut-off is specified to be too big, increased interaction between sub-domains is expected. On the other hands, if it is too small, the history matching will be ineffective since only small regions of the reservoir are perturbed.

Some remarks

- Since the sub-domains are obtained by manipulation of the sensitivity matrix (i.e., covariance matrix) and the regions are identified based on the largest eigenvalues, the sub-domains identified are always most sensitive.
- The eigenvectors obtained by PCA are orthogonal (at least in a covariance sense). The physical meaning of orthogonality is that the regions are independent or uncorrelated. Any residual dependence between the identified sub-domains can be removed by performing eigen-rotation procedures.

The schematic illustration of sub-domain delineation utilizing the covariance of grid-block pressures is presented in Figure 4-1. The 2D reservoir size is 4×4. The upscaling factor applied in this example is 2×2 such that the original 16 gridblocks are reduced to 4 gridblocks. Note that the physical size of the reservoir remains the same.
Figure 4-1: The schematic illustration of sub-domain delineation using the covariance of grid-block pressures (4×4 reservoir example).
4.1.2 VALIDATION TEST CASES

The objective was both to validate the method using covariance of grid-block pressures and to observe the sensitivity of the procedure to the number of initial realizations.

Two 2D cases are shown; each case exhibits different permeability continuity (i.e., the major and minor correlation lengths and orientations in variograms are different) and well configuration. All other information such as reservoir size, reservoir petrophysical attributes and operating conditions are assumed to be the same for both cases.

4.1.2.1 First Case-Permeability field with short range continuity and two production wells

The reservoir size is 100×100 and the upscaling factor is 10×10. Two production wells are located at (10, 90) and (80, 80). The major direction of permeability continuity is 0 degree azimuth with range 30 ft and the minor direction is 90 degrees with 15 ft continuity. Sequential indicator simulation generates multiple realizations. In the sensitivity cases, 25, 50, 75 and 100 initial realizations were used in the ensemble. The first three realizations generated by sequential indicator simulation are illustrated in Figure 4-2.
Figure 4-2: Three realizations of the permeability field; production wells are in white.

The initial models are upscaled with a factor of $10 \times 10$. The upscaled reservoir size is $10 \times 10$. The upscaled permeability realizations are shown in Figure 4-3.

Figure 4-3: The upscaled realizations corresponding to three realizations illustrated in Figure 4-2; white dots indicate production wells

Flow simulations were first performed on 25 upscaled realizations. There are twenty five pressure responses for each gridblock at each time step. The pressure values corresponding to the last time step - 720 days were used for subsequent calculations (Note that the final delineated sub-domains are not sensitive to the time step at which the covariance matrix is calculated). The computed covariance matrix has a size of $10 \times 10$. 

66
The diagonal entries of the covariance matrix are the variance of pressure responses at each gridblock and so they are equivalent to single point sensitivity coefficients. The left figure of Figure 4-4 is a map of the diagonal variances (sensitivity coefficient) from the covariance matrix. PCA followed by the scaling of eigenvectors generate the most sensitive and least correlated sub-domains. The proportion of sub-domains is 40% of the entire reservoir. Note that the PCA is performed on the full covariance matrix and not only using the variances (single point sensitivities).

Figure 4-4: The sensitivity coefficients map (right), 40% sub-domains (middle) and 99% sub-domains (left); white dots represent well locations.

The obtained sub-domains are identified in the order of sensitivity; for a given volume threshold, the high sensitivity regions are first grouped into sub-domains. Comparing sensitivity map and delineated sub-domains, sensitivity regions colored red (higher sensitivity) are designated as sub-domains. The sensitivity coefficients show the highest values around two production wells (the well location are (10, 90) and (80, 80)) and the wells are covered by the sub-domains. When the 99% volume cut-off threshold value is applied, the least sensitive region (recognized with blue color in sensitivity coefficients map) in the reservoir is not selected; otherwise, 99% of entire reservoir is
covered within the identified domains. The least sensitive region is the sub-domain with 99% threshold, shown in the left of Figure 4-4.

The domain delineation exercise was repeated with different numbers of initial realizations. The test results of sensitivity coefficients maps and delineated sub-domains are summarized in Table 4-1.

Table 4-1: Sensitivity coefficients maps and sub-domains with 50, 75 and 100 initial reservoir models of short range continuity case

<table>
<thead>
<tr>
<th>Number of initial realizations</th>
<th>Sensitivity coefficients map</th>
<th>Sub-domain(s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>50</td>
<td><img src="image" alt="Sensitivity Coe." /></td>
<td><img src="image" alt="Sub-domain" /></td>
</tr>
<tr>
<td>75</td>
<td><img src="image" alt="Sensitivity Coe." /></td>
<td><img src="image" alt="Sub-domain" /></td>
</tr>
</tbody>
</table>
The results reveal that the number of initial realization affects the smoothness and continuity of the identified sub-domains; however, that effect is minimal. The sensitivity maps do not reveal any inconsistency by increasing the number of realizations. Maximum sensitivity is observed near the two production wells regardless of how many initial realizations are utilized. However, the isolated patches of high-sensitivity observed corresponding to 50 realizations are not present when the number of realizations is increased to 100. This implies that more realizations render the results more reliable. The process of generating more initial realizations is not time consuming if the reservoir size is small; however, a large number of multiple realizations with millions of gridblock may increase computational cost. Even though the location of the maximum sensitivity regions and the magnitude of the sensitivity values may become more reliable with more realizations, the delineated domains, regardless of the number of initial realizations, correctly identify the region around wells to be the most sensitive. The shapes of delineated sub-domains are similar for all cases; moreover, the delineated regions around
wells are almost the same. It is therefore asserted that the covariance matrix method can yield reliable delineation of sensitive yet least correlated regions without incurring expensive computational cost.

4.1.2.2 Second Case–Permeability field with longer range continuity and three production wells

In this case, the test conditions are the same as in the first case but the well configuration and permeability heterogeneity are different. The major direction of permeability anisotropy is still 0 degree but the ranges in the major and minor direction of continuity are increased to 60 ft and 20 ft, respectively. The locations of the three production wells are (10, 90), (90, 10) and (90, 90). The first three initial permeability realizations and the corresponding upscaled maps with a factor of $10 \times 10$ are illustrated in Figure 4-5 and Figure 4-6, respectively.

Figure 4-5: The first three initial permeability maps for the second test case; the production wells are shown with white dots.
Figure 4-6: The first three initial corresponding upscaled maps for the second test case; the production wells are shown with white dots.

The results of sensitivity maps and delineated sub-domains with different number of initial realizations are tabulated in Table 4-2.

Table 4-2: Sensitivity coefficients maps and sub-domains with 25, 50, 75 and 100 initial reservoir models of longer range continuity case

<table>
<thead>
<tr>
<th>Number of initial realizations</th>
<th>Sensitivity coefficients map</th>
<th>Sub-domain(s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>25</td>
<td><img src="image" alt="Sensitivity Co." /></td>
<td><img src="image" alt="Sub-domain" /></td>
</tr>
</tbody>
</table>
Table 4-2 continued: Sensitivity coefficients maps and sub-domains with 25, 50, 75 and 100 initial reservoir models of longer range continuity case
The results shown in Table 4-2 satisfy two requirements. Firstly, the three production wells are all covered by sub-domains. The sensitivity maps reveal the highest degree of sensitivity near the three wells. As the number of initial realizations increase, the region around the production well at (10, 90) is more obviously recognized as high sensitivity area. As noted in the earlier case, the number of initial realizations does not significantly alter the sub-domains in terms of covering wells. The choice of the number of initial realizations should be made on a case-by-case basis; however, 25 realizations are adequate in most cases to describe sensitivity and render stable sub-domains.
4.2 Comparison of the two methods for sub-domain delineation

To evaluate whether the methods properly represent the sensitivity, it is necessary to observe whether wells are covered by delineated sub-domains. Since regions near wells are most sensitive due to larger flux of fluids than the rest of regions, decomposed regions should include area around wells. The method using the Hessian matrix is suitable most of the time depending on the number of pilot points. If the number of pilot points is not enough, the delineated sub-domains are not sufficient to cover all wells; in other words, this method depends on the number of pilot points such that engineering judgment or well knowledge of the investigated reservoir are required. To gain the physically stable sub-domains the number of pilot points should be a maximum. The key drawback of the Hessian matrix method is it causes high computational cost; more pilot points require more gradient calculations so that it costs more computational expenses. This is an adverse effect to the purpose of performing sub-domain delineation. Initially, the sub-domain decomposition is employed to enhance computationally inexpensive procedure. Even if the expenses for obtaining sub-domains is less than that for traditional history matching procedure, it is less likely favorable when we consider the cost for setting up parallel computing systems.

Beyond the issue of the cpu expensive procedure of the Hessian matrix, the other one for the use of the Hessian for domain delineation is that not all commercial simulators have the facility to output the Hessian matrix. An additional drawback in using the Hessian matrix as a measure of sensitivity is that the pressure response is assumed to be sensitive to the permeability values only at two locations. The connectivity of permeability is thus ignored while calculating the sensitivities. When the Hessian matrix
calculation is available in simulator module, and profound when knowledge of the reservoir is at hand, the utility of the Hessian matrix is efficient; however, it has limitations due to its two-points sensitivity calculation dependency, expensive computation cost, and undefined technique to select pilot points.

The covariance matrix method, on the other hand, has more sound theoretical and practical utility background than the Hessian matrix method. It is an analogy of the Hessian matrix, and it is $n \times n$ just like the Hessian. The covariance matrix (Eq. 4-1) consists of components that are covariance values between the pressure response of one gridblock and those of the rest of the entire grid; hence the connectivity of permeability can be represented. Also, since the covariance is calculated over a suite of realizations, the delineated domains are insensitive to the starting guess (or the initial model). Besides, the covariance matrix can be calculated using any simulator. The computational cost is not expensive since it adopts a scale up procedure and the number of realizations is not important in deciding delineated sub-domains.

One more perspective in the difference of the methods is the Hessian matrix represents the sensitivity of permeability to objective function whereas the covariance matrix represents sensitivity of pressures responses based on the initial permeabilities. To obtain the Hessian matrix thereby the computation of the objective function is required. However, the covariance matrix is based on initial permeability fields providing pressure responses from the flow simulator, such that the procedure is independent of the reference model. This enables the history matching to be more feasible for the cases in which real reservoir knowledge is limited. If the reservoir is not studied enough for the history matching, the Hessian matrix method is not the best choice due to its objective
dependency (i.e. it depends on the reference model to calculate the Hessian matrix). This also results in the computational cost; the calculation of objective function and the gradient with respect to permeabilities is more computationally costly than the generation of an ensemble of realizations and performance of flow simulations on upscaled realizations.
CHAPTER 5. PROBABILISTIC PERTURBATION SCHEME

5.1 Motivation

Geological reservoir models are a key component of reservoir engineering for prediction of oil and gas production rates and reservoir management. The accuracy of reservoir models representing underlying geological features and petrophysical attributes is a key consideration in reservoir characterization. To build reliable reservoir models, a production history matching procedure is generally implemented.

There have been several approaches that have been presented to condition reservoir models to dynamic data. As documented in Chapter 2, common perturbation algorithms are gradient-based methods (Yeh et al., 1986), pilot point method (de Marsily et al., 1995), Markov chain Monte Carlo method (Omre et al., 1996) and gradual deformation method (Hu et al., 1998). However, some of these methods are not efficient for honoring the prior geologic model while integrating dynamic flow data, while others are restricted to parameter fields that exhibit Gaussian characteristics. Dynamic flow data such as field pressure, bottom hole pressure, oil or gas production rate are strongly dependent on petrophysical attributes such as permeability and porosity and yet these properties are uncertain, given the scarcity of conditioning data. This motivates a scheme for systematic perturbation of the underlying uncertainty (probability) distributions characterizing these attributes.
5.2 Basic perturbation scheme

The final goal of probabilistic framework-based perturbation proposed in this thesis is the development of history matched reservoir models that are geologically consistent as well as yield production profiles that closely match historical field data. For this purpose, the combination of the efficiency of sequential indicator simulation for modeling uncertainty distributions, within an iterative non-stationary Markov chain for updating permeability realizations is implemented. The probability distributions are updated using a 1-D optimization procedure until the model sampled from the updated probability distribution is history matched.

In the implemented approach, permeability values are sampled from the probability distribution conditioned to static and dynamic data. The joint conditional probability \( P(A|B,C) \) needs to be evaluated. ‘A’ represents the simulation event such as permeability at a particular location in the reservoir; ‘B’ represents static or geological information that influences the simulation event A, and ‘C’ is the dynamic information influencing the simulation event A. The permanence of ratio hypothesis (Eq. 5-1) proposed by Journel (2002) approximates the joint conditional probability as the combination of elemental probabilities \( P(A) \), \( P(A|B) \), and \( P(A|C) \). The conditional probability \( P(A|B) \) represents the probability of the event A given the data event B, and \( P(A|C) \) means the probability of occurrence of A given the dynamic data event C.

\[
\frac{x}{b} = \frac{c}{d}
\]  

(5-1)

The parameters of Eq. (5-1) are listed in below:
\[ a = \frac{1 - P(A)}{P(A)} , \quad b = \frac{1 - P(A \mid B)}{P(A \mid B)} , \quad c = \frac{1 - P(A \mid C)}{P(A \mid C)} , \text{ and } \quad x = \frac{1 - P(A \mid B, C)}{P(A \mid B, C)} \] such that the joint conditional probability can be expressed as \[ P(A \mid B, C) = \frac{a}{a + bc} \]. An interpretation of quantities \( a, b, c \) and \( x \) in the framework of the information theory is interpreted as follows. The \( x \) quantity represents the relative distance to occurrence of event \( A \) conditioned event \( B \) and \( C \) occurrence. Likewise \( a, b, \) and \( c \) are also interpreted as relative distances to the occurrence of event \( A \). The ratio, \( \frac{x}{b} \), shown in Eq. (5-1) represents the relative contribution of the event \( C \) towards the event \( A \) occurrence, conditioned to the occurrence of event \( B \). The ratio, \( \frac{c}{a} \), represents the relative contribution of \( C \) to towards \( A \) occurring prior to \( B \); therefore, the permanence of ratio hypothesis indicates the relative contribution of the data event \( C \) to the event \( A \) occurrence is independent to occurrence of event \( B \).

The perturbation process is now focused on how to obtain the elemental conditional probabilities. The prior probability \( P(A) \) is known from the geological information. The conditional probability \( P(A \mid B) \) is obtained from the sequential indicator simulation, where an indicator is identified as:

\[
I(u, z) = \begin{cases} 
1 & \text{if } k(u) \leq z_i, \forall i = 1, ..., N \\
0 & \text{if } k(u) > z_i 
\end{cases}
\] (5-2)

In indicator kriging (simulation) the conditional probability \( P(A \mid B) \) is expressed as the expected value of the indicator, estimated as a linear combination of the indicator coded data:
\[ I'(u_o; z_i|n) = F_k(z_i|n) = \sum_{i=1}^{n} \lambda(u) \cdot \{i(u_o; z_i) - p_i\} \]  \hspace{1cm} (5-3) 

, where \( p_i \) is the prior probability corresponding to \( z_i \)

In contrast, the evaluation of \( P(A|C) \) is exigent due to the complex relationship between static data such as permeability and dynamic data, oil production rate. The proposed approach is to use a calibration parameter \( r_D \). This dynamic factor is an optimization factor used to minimize deviation from target response. In a Markov chain context, it controls the probability of transitioning from existing category, \( i'(u) = k \), to a new category, \( i'^{+1}(u) = k' \), in an \( L \) step iterative conditioning process:

\[
P\{i'\equiv1(u) = k' \mid i'(u) = k, P, C\} = r_D \cdot P\{i(u) = k' \} \hspace{1cm} \forall k' \neq k
\]

\[
P\{i'\equiv1(u) = k \mid i'(u) = k, P, C\} = 1 - \sum_{i=1}^{\infty} r_D \cdot P\{i(u) = k\}
\]

\( r_D \in [0,1] \)

\( P\{i(u) = k\} \) is the probability of static data, previously denoted as \( P(A) \), corresponding to the \( k^{th} \) category of permeability field. \( P(A|C) \) (i.e., the left hand side terms of the first two equations in Eq. (5-4)) is being sought as the convergence of objective function proceeds. A 1-D iterative process is designed for the selection of optimal \( r_D \). The procedure comprises of the following steps:

1) Start from an initial guess for \( r_D \in [0,1] \) and an initial realization generated by sequential indicator simulation, \( i'(u) \).
2) Compute Eq. (5-4) so as to obtain \( P(A|C) \)
3) Evaluate \( P(A|B,C) \) by using the permanence of ratio’s hypothesis
4) Draw realization of permeability field
5) Compute the objective function (See Eq. (5-5)) describing the difference from the simulated response to the target response

\[
\Delta OF^i(r_D) = \left| f_{i_{\text{true}}}(t) - f^i(r_D, t) \right|^2
\]  

(5-5)

, where superscript \(i\) represents the number of iterations

6) Perform 1-D optimization of \(r_D\) until the objective function is minimized.

Once the inner \(r_D\) loop has converged, it yields the updated model that might still not be globally optimal. The next inner loop is then commenced with the initial realization of the permeability field replaced by the updated model from the previous outer loop. Thus, the main scheme of perturbation proposed in this thesis utilizes two loops in order to minimize objective function as well as honoring both permeability and production responses.
5.3 Scheme implemented on multiple sub-domains

The preceding description of the probability perturbation approach assumed that the conditional probability distribution at all locations in the reservoir can be perturbed using a single \( r_D \) parameter. While, that results in a 1-D parameter optimization problem, it is conceivable that in reservoirs exhibiting geologic complexity and in situations were the wells exhibit wide variations in operating conditions, history matching using a single perturbation parameter might be inefficient and in some cases, infeasible. In this section, a modification to the earlier procedure to exploit the most sensitive and least correlated sub-domains identified using the domain delineation procedure is described.

In the case of multiple \( r_D \) parameters, the same procedure as explained in the Section 5.1 is carried but this time perturbing only the distributions within the sub-domain, and each sub-domain has its own \( r_D \) parameter.

The conditional probability in regions outside sub-domains are frozen to be the \( P(A \mid B) \) derived from indicator kriging or simulation. The optimization of \( r_D \) within a sub-domain is performed independent of the \( r_D \) value in other sub-domains. This is permitted since the delineated domains are least correlated.

The flow chart describing the details of the perturbation scheme implemented over several sub-domains is shown in Figure 5-1. Also, the computer code written in C++ for sequential perturbation scheme in multiple sub-domains is elucidated in Section 6.3.3.
Figure 5-1: The flow chart of implemented algorithm for multiple perturbation scheme
5.4 History matching case on multiple sub-domains scheme

5.4.1 CASE EXAMPLE

In this section, a 3D representative synthetic case is demonstrated. This case is an exemplary history matching case having multiple sub-domains to elucidate the procedure shown in Figure 5-1. The reference reservoir is illustrated in Figure 5-2. It has three production wells located at P1 (20, 90), P2 (10, 50) and P3 (50, 10). The history matching duration is ten years.

Figure 5-2: Reference permeability model with three production wells (Wells are indicated with black dots).
Fifty initial realizations are generated by sequential indicator simulation, and one set of them is illustrated in Figure 5-3. The reservoir gridblocks are $100 \times 100 \times 5$.

![Figure 5-3: One set of initial permeability model with three production wells (Wells are shown in black dots).](image)

The next step is to compute covariances of pressure responses from the fifty upscaled permeability models obtained after applying an upscaling factor of $10 \times 10 \times 5$. Covariances are computed such that sensitivity matrix is obtained. The diagonal entries of covariance matrix representing sensitivities at each gridblock are illustrated in Figure 5-4.
Figure 5-4: Sensitivity coefficient maps for five layers

Then, calculation of eigenvalues and eigenvectors of covariance matrix is initiated. After that PCA and the scaling procedure is performed; consequently, the most sensitive yet least correlated sub-domains are obtained with 40% volume cut-off value. The obtained sub-domains are shown in Figure 5-5.

Figure 5-5: Two sub-domains after applying 40% threshold value; white dots represent production well locations.

Since there are two sub-domains, sequential probabilistic perturbation is required. First, the perturbation of probability distributions within the blue regions is initiated using optimal calibration parameter (i.e., $r_{D1_{opt}}$). Then, permeability probability distributions in red regions are perturbed with another optimal calibration parameter (i.e., $r_{D2_{opt}}$). Once sequential perturbation procedure using $r_{D1_{opt}}$ and $r_{D2_{opt}}$ is finished, indicator simulation for the non-sub-domain region conditioned perturbed permeability data is performed. Two iterations of outer loop are performed to achieve the final history matched permeability model shown in Figure 5-6.
Figure 5-6: History matched permeability model with three production wells for multiple sub-domain case.

Also, field oil production rate is history matched as illustrated in Figure 5-7.
5.4.2 DISCUSSION

In this section, a simple 3D history matching example is demonstrated for the multiple perturbation scheme using multiple deformation parameters. As observed in results from the case, the implemented multiple sub-domains method is robust.

In the next chapter, an integrated software implementing the demonstrated algorithm is discussed. Extensive test cases utilizing the developed software are studied and show more details on the proposed multiple sub-domain perturbation algorithm.
CHAPTER 6. PROBABILISTIC HISTORY MATCHING SOFTWARE (PRO-HMS)

The method of probabilistic history matching is explained with two main focuses; one for sub-domain delineation and the other one for probabilistic perturbation with multiple perturbation parameters. This method is efficient not only in honoring consistent geological features but in reducing computational expenses. The continuous computational process avoids interruption of the work flow by having to use several different software. Thus, it can make the history matching more feasible in terms of computational cost and work flow. In Chapter 6, the integrated software developed based on the algorithm suggested in the previous chapters is documented. The necessity and goal, details on the software, and the validation example and some synthetic 3D examples are discussed.
6.1 Motivation

Integrated software for history matching are not readily available because the history matching procedure utilizes various steps from the selection of history matching parameters to the optimization of selected parameter with historical dynamic data. However, the utility of history matching software arises from the high computational cost requirement of history matching. In this thesis work, a software called Pro-HMS, Probabilistic History Matching Software, is developed, and the fundamental goal for Pro-HMS is described.

The described procedure of history matching in this thesis is effective; however, it combines several aspects of stochastic reservoir modeling, flow simulation and iterative optimization such that it is a cumbersome task requiring additional effort and time in managing different features. To speed up and enhance the efficiency of history matching and to render a streamlined process, the development of integrated software based on the methods described earlier was executed. The software enables users to specify reservoir related information and choose a simulator. Then, the software automatically produces a history matched model. The software provides reliable prediction of reservoir performance for test cases; moreover, it reduces the computational cost significantly.
6.2 Program architecture

The software modules are themselves developed in C++. The software interface is written in Qt programming language to render it feasible to execute Pro-HMS in Mac, PC and Unix/Linux environments.

The algorithms written in C++ have three main programs. They are ‘covariance code’, ‘sub-domain delineation code’, and ‘probabilistic perturbation code’. Each section of programs is executed by the input data of the users through graphical user interface (GUI). The user input reservoir information is loaded through the screen developed in Qt programming language such that the internal C++ codes are executed based on the input data. The generation of initial realizations and utilization of flow simulator is performed by Gslib and Eclipse®. C++ codes render feasibility to utilize those external software whenever they are required during the history matching procedure.

By launching Pro-HMS, users provide specific information on the history matching data through the GUI. The GUI generates three parameter files as output files of the GUI. The output files are parameter files for the main three C++ codes. Each code is executed with corresponding parameter files and the resultant files generated by previous code. The schematic of program architecture of Pro-HMS is illustrated in Figure 6-1.
Figure 6-1: The schematic of program architecture of Pro-HMS (The arrows in violet color represent the user options)

The flow chart showing the procedure of Pro-HMS is presented in Figure 6-2. The users input all the information that they want; then the GUI program generates parameter files depending on the data the users entered. If the sub-domain delineation scheme is not used, only parameters for single domain perturbation code are generated. Three parameter files are generated if users utilize sub-domain delineation method. These are ‘sensregion.par’, ‘dd.par’, and ‘hsissim.par’. They are output files from the GUI yet input files for three different codes that are used in Pro-HMS.

An option permits users to provide delineated region indices file for the multiple perturbation schemes. If the region indices file is provided, Pro-HMS does not execute
the covariance calculation code and sub-domain delineation code. If users neither provide region indices nor an option for the covariance matrix calculation, Pro-HMS performs the perturbation process for the entire reservoir.
• Input information on the reservoir being studied
• Specify the data files (i.e., upscaled data file for sub-domain delineation and perturbation file) and conditions for the flow simulation

Sub-domain delineation is utilized?

No

Yes

Generate three parameter files which are used for input files in the main C++ codes

Sub-domain delineation parameter file

Covariance code parameter file

Probabilistic perturbation parameter file

Covariance code

Covariance code output files: eigenvalues and eigenvectors

Sub-domain delineation code

Sub-domain delineation code output file: sub-domain indices

Update probabilistic perturbation parameter file

Probabilistic perturbation code

History matched results

Figure 6-2: The flow chart of Pro-HMS procedure
6.3 Program components

6.3.1 COVARIANCE CODE

The covariance code is designed ultimately to obtain eigenvalues and corresponding eigenvectors after performing PCA on covariance matrix. This is an alternative method when no commercial simulator module such as SimOpt® is available to compute the sensitivity matrix equivalent to the Hessian matrix. The code performs three main computations; generation of initial permeability realizations, upscaling of the gridblock, and PCA of the obtained eigenvalues from covariance matrix. These three features are written in C++ and the detail of each is explained in the following.

Generation of initial reservoir models

The covariance code has the ability to generate initial geological model such as permeability and porosity. It combines the generation of geological model data parameter file and the use of sequential indicator simulation which is one module of Gslib. The covariance code generates an ensemble of initial realizations conditioning prior geological information. The number of realizations generated as initial realizations depend on the user decision. In most cases, 25 or 50 realizations are enough to obtain reasonable results.

Upscaling of reservoir gridblocks

If the reservoir has 10,000 gridblocks (e.g., 100 × 100 × 1 case), then the covariance matrix would be 10,000 × 10,000 (i.e., 10^8 entries). The computer cost for handling hundred million values is expensive. To solve this problem upscaling of the gridblock is implemented. The covariance code can take upscale factor specified by the
user and perform flow–based upscaling. The user can specify what size they want to use as up-scaling factor (e.g., $10 \times 10 \times 1$ instead of using $100 \times 100 \times 1$). The advantage of this methodology in covariance code is that it reduces the flow simulation cost. The covariance code uses $10 \times 10 \times 1$ data file instead of using $100 \times 100 \times 1$ reservoir simulations with Eclipse®; the number of executions of flow simulation equals the number of initial realizations such that reduction of number of gridblocks is very beneficial.

**PCA of eigenvalues and corresponding eigenvectors**

The upscaled initial realizations are submitted to the flow simulator. The covariance code obtains the pressure responses of the upscaled initial realizations and arranges those values in arrays. According to the users’ specified time, the covariance code computes the covariances at each location. The covariances are obtained at all the locations and the covariance matrix is constructed. The diagonal entries of the covariance matrix are sensitivity coefficients, and they are illustrated in a 2D figure (Refer to Figure 4-1). The final action of covariance code is to perform PCA after obtaining eigenvalues and corresponding eigenvectors from the covariance matrix.

**6.3.2 SUB-DOMAIN DELINEATION CODE**

The purpose of the sub-domain code is to render the region indices as positive or negative integers. These numbers are the indices for the most sensitive yet least correlated regions. The code takes its input data from the resultant file from covariance code. The highest eigenvalues and their corresponding eigenvectors achieved from the
covariance matrix are subjected to be scaled in the sub-domain code. After that scaling procedure, the code renders region indices as its output.

**Scaling of highest eigenvalues and corresponding eigenvectors**

The number of eigenvalues is the same as that of gridblocks of the reservoir. In the covariance code, the PCA render the highest five eigenvalues and corresponding eigenvectors. They are the most sensitive eigenvalues yet least correlated ones. The sub-domain code generates array values and sorts each eigenvector entry at every gridblock. Another array is prepared to mark where the highest eigenvector entry originated. For instance, if the first entry of the eigenvector obtained from the first eigenvalue is greater than that from the second eigenvalue, the sub-domain code assigns the first eigenvalue correspondent index. The negative and positive notation represents the sign of the selected eigenvector’s entry.

**Volumetric threshold application**

The array constructed with highest eigenvalue indices is as large as the number of the gridblock. The users can apply a suitable threshold value for the size of the sub-domain. The threshold value is applied such that the volume of delineated sub-domain is the same as the threshold value specified. It can vary from 0 to 100. The optimal choice of the threshold value depends on the reservoir being studied. For the various test cases, it is recommended that 40% of threshold value is reasonable in most cases. If 40% threshold is applied, the sub-domain code performs sorting of the highest eigenvector entries and corresponding eigenvalue values in each gridblock obtained in the previous
step. It then applies cut-off value as 40 according to the highest absolute values of the eigenvector entries in an array, and then renders 40% region indices.

6.3.3 Probabilistic perturbation code

The fundamental scheme of perturbation code is based on the theory described in Chapter 5. The main feature of the perturbation code in the Pro-HMS is that it accommodates the perturbation scheme within delineated sub-domains. The use of sub-domain perturbation or entire reservoir perturbation is a choice for the user. Pro-HMS can perform both cases. Also, the number of inner loops, Dekker-Brent optimizations, and outer loops for the update the reservoir model are selected by the user. The perturbation code uses the parameter file which is the same in terms of reservoir information as used in the covariance matrix code. It uses stochastic reservoir model building module, sequential indicator simulation (SISIM) in Gslib, and flow simulator, Eclipse®.

Perturbation procedures of probabilistic perturbation code

1) Call sequential indicator simulation code to generate an initial realization for the actual reservoir model.

2) Compute the local probability distributions conditioned to prior static data set in all gridblocks. If multiple sub-domains exist, the local probability distributions are generated only in the gridblocks within the first sub-domain. After perturbation algorithm of the first sub-domain is performed, the next sub-domain is perturbed in the same manner.
3) Initiate Markov chain iterative updating algorithm with initial realization. The updating algorithm includes the following subsequent steps illustrated in 4) to 8).

4) Build newly defined random paths and random draws to sample from the local distributions.

5) Call a flow simulator to evaluate different $r_D$ values by computing objective functions.

6) Choose the $r_D$ value showing the minimum objective function value.

7) Initiate Dekker-Brent loop to calibrate $r_D$ value by incorporating dynamic flow data. The number of inner loops continues until the maximum number that user specified.

8) Obtain $r_{D_{opt}}$ value and update the geological model.

9) Repeat step from 3) to 8) as many times as the maximum user-specified outer loop number.

10) Repeat step 2) to 9) for the rest of sub-domains if applicable.

11) Obtain history matched model and generate output files

**Sequential perturbation scheme**

The most challenging issue of perturbation of the sub-domain zones is the artifacts around the boundaries of the sub-domains. This may be a critical issue if the perturbations of the sub-domains are independently performed and the merging of the separate perturbed models is required. The merging of the reservoir models may incur artifacts, and result in additional computational cost due to another perturbation procedure for the merged reservoir model. To resolve this issue a sequential perturbation procedure is implemented in Pro-HMS. The perturbation algorithm is applied to each
sub-domain sequentially, and the perturbed regions remain the same as the other sub-domains being perturbed. After all different sub-domains are perturbed, the non-sub-domain regions are simulated by conditioning with prior geological information and perturbed data. The Dekker-Brent inner optimization is used in each sub-domain perturbation; on the other hand, the outer loop is used after the entire reservoir is perturbed to update the model.

6.3.4 SIMPLE VALIDATION TEST CASE

The simple test case is presented in this section to validate the procedure that Pro-HMS utilizes. The test conditions and results are documented according to the different codes.

Test conditions

The 3D case is designed with size of $100 \times 100 \times 5$. There are three production wells and one injection well, and they are all active for the entire simulation time. The locations of four wells are P1 (30, 90), P2 (90, 50), P3 (90, 90) and I (80, 80). The flow simulation time step is 30 days and the entire simulation duration is 1260 days. The reference permeability fields are illustrated in Figure 6-3.
Figure 6-3: The reference model of test case. (From left right, the top section of the reservoir to the bottom)

Also, the prior permeability data available are shown in Figure 6-4.
Figure 6-4: The conditional permeability data locations and their values in a color scale

Covariance code results

The covariance code generate 15 realizations by sequential indicator simulation based on the conditional data, and inferred variograms from the prior permeability data. The Figure 6-5 illustrates the one realization out of 15 realizations.
Figure 6-5: One set of initial permeability realizations from top layer to the bottom layer; the black dots indicate the well locations

The covariance code performs flow-based upscaling on 15 initial realizations to reduce the number of gridblocks. Initially the number of gridblock in each realization is 50,000, but the upscaled gridblocks are 500 due to the application of $10 \times 10 \times 5$ upscaling factor. As mentioned in Section 6.3, the main goal for the upscaling is to diminish computational cost consumed by the flow simulator. The upscaling factor is a user option, but in most cases the one tenth of the initial reservoir size renders reliable results. For this test case, the result is shown in Figure 6-6.
Figure 6-6: One set of upscaled initial permeability realizations from top layer to the bottom layer

The covariance code calls flow simulator, Eclipse® and performs flow simulation on upscaled 15 realizations. The output of flow simulations is pressure responses according to time steps for all gridblocks. The pressure responses for all gridblock at the last time step (at 1260 day) is obtained and used for the covariance matrix construction. The diagonal entries of the covariance matrix are the sensitivity coefficients representing the variances of the covariance matrix. The sensitivity realization of the covariance matrix is unique. It is illustrated in Figure 6-7.

Figure 6-7: The sensitivity coefficient map of the covariance matrix; high sensitivity is in red and blue is for low sensitivity

Since the sub-domains are the most sensitive region, the delineated sub-domains in the next step should be very similar to high values area in the sensitivity map. Then,
covariance code computes the eigenvectors and corresponding eigenvalues of obtained covariance matrix. The PCA is performed on eigenvalues such that highest five eigenvalues and corresponding eigenvectors are generated as its output files.

**Sub-domain delineation code results**

Sub-domain delineation code performs scaling of the highest five eigenvalues and corresponding eigenvectors. It then stores sorted data in an array. The 40% volumetric threshold is applied so that the code selects the highest 40% values from the array. By using the sub-domain delineation code, the sub-domains for each layer, which are shown in Figure 6-8, are obtained. It is consistent with the result of sensitivity coefficient map in the sense that the sub-domains are where sensitivity coincides with regions.

![Figure 6-8: The sensitivity coefficient map of the covariance matrix.](image)

For this case only one sub-domain is delineated. All region indices for nodes within sub-domains are identical (i.e., only blue is illustrated in Figure 6-8) indicating they come from one eigenvalue.

**Probabilistic perturbation code results**

The probabilistic perturbation code initially evaluates the optimal perturbation parameters. The inner loop, Dekker-Brent optimization, calibrates the perturbation such
that it decides \( r_{D_{\text{opt}}} \). Thus, it perturbs the initial permeability realization using \( r_{D_{\text{opt}}} \). The outer loop procedure is followed by the perturbation of permeability distribution within the sub-domain. The result for the first outer loop is shown in Figure 6-9.

![Figure 6-9: The permeability realizations after the first outer loop](image)

The realization after one outer loop fades out high permeability near regions away from wells. The result obtained after ten iterations of flow simulations shows high degree changes in permeability such that the objective function value is diminished over 15 times; however, the continuity of the permeability still almost remains similar to the initial realizations. In Figure 6-10, the result of second outer loop is illustrated. The continuity of the permeability is increased compared to that of first outer loop case such
that it more closely resembles the reference case. This realization is obtained after 34 flow simulations.

Figure 6-10: The permeability realizations after the second outer loop

After each outer loop, the probabilistic perturbation code performs sequential indicator simulation for the non-sub-domain region conditioning the original conditional data and perturbed sub-domain permeability data. The final reservoir history matched model is illustrated in Figure 6-11. The permeability data within sub-domain almost remains the same compared to Figure 6-10; the minor changes are observed due to the third outer loop procedure. The third outer loop result has such a small updating impact that the objective function change between two loops is less than 1% (See Figure 6-12).
Figure 6-11: The history matched model after three outer loops.

The objective function profile is shown in Figure 6-12. The objective function decreases significantly in the first outer loop. The change of objective function values from the second loop resultant model to the final model is very small as observed in the permeability realizations.
Figure 6-12: The objective function profile of the validation test case. The first dot indicates the objective function value for the initial realization, and the middle two points represent the values for the first and second outer loop result, respectively. The last point indicates the objective function of history matched model.

**History matching results**

As illustrated in Figure 6-13, the history match result show high-quality matching between simulated and historical data. The matching is performed for field pressure, production wells.
Figure 6-13: Results of the history match for field pressure, three production wells

Discussion

The history matching algorithm implemented in Pro-HMS is tested in this case. In this case, the Pro-HMS use sub-domain delineation option such that the permeability distribution perturbation is done only within the delineated sub-domains. For the comparison and the assessment of the usefulness of the sub-domain option in Pro-HMS, the case without sub-domains also tested. The quality of the matching is similar based on the same test conditions (such as inner and outer loops iteration numbers) but the computational cost is different. For sub-domain case, the total computation cost is about
six hours; whereas, entire perturbation procedure requires about seven hours. The computational time reduction is enhanced approximately 14%.

In terms of the programming component and architecture, each component code of Pro-HMS is validated with result as shown in the test cases; moreover, the systematic code correlation and internal responses between codes are well correlated such that it is stable.
6.4 3D synthetic test cases

6.4.1 PURPOSE

Further validation of the developed software is necessary. From the base case defined for the further tests, the modification of the history matching conditions to test the ability of Pro-HMS is required. The test cases are designed not only to test technical programming codes validation of Pro-HMS but also to assess the robustness of the algorithm that Pro-HMS utilizes. In this sense, some portions of code revision were required to demonstrate the feasibility of the probabilistic perturbation utilizing sub-domain delineation algorithm.

6.4.2 3D SYNTHETIC CASE EXAMPLES

In Section 6.4.2, several different synthetic cases, which are related from the base case, are studied. The screenshots of the first case (base case) study is shown in Figures from 6-19 to 6-33, and Tables from 6-1 to 6-3.

6.4.2.1 Base case studies for sub-domain option

Objective

Two cases are shown to demonstrate the usefulness of the sub-domain delineation as well as the accuracy of the reservoir models obtained using Pro-HMS. The sequential perturbation of the permeability probability distribution within the sub-domains is implemented to see the resultant reservoir permeability map for each step.
The flow simulator used by Pro-HMS in this example is ECLIPSE-100 (©Schlumberger-Geoquest Inc.) For comparison, the results obtained without using sub-domains is also presented to demonstrate the effectiveness of the Pro-HMS Algorithm. One case uses a sub-domain perturbation and the other does not.

**Test conditions**

Reference and initial models are generated based on the following conditions. The reference reservoir models are generated by sequential indicator simulation. The dimension of the reservoir is 100×100×5, and each grid is 50ft×50ft×10ft. Three wells are located at grid locations (30, 30), (50, 50), and (70, 70). One injector is at (90, 90). Figure 6-14 illustrates slices of the reference permeability model.
Figure 6-14: Reference permeability models from top layer to the bottom (from left to right); production wells are in black and an injection well is in white.

Pro-HMS generates an ensemble of initial models in order to get sub-domains. Figure 6-15 shows slices from one of the initial models.

Figure 6-15: An initial permeability model from top layer to the bottom (from left to right); production wells are in black and an injection well is in white.

**Sub-domain option: History matching with limited duration data**

The first test is intended to demonstrate the history matching capability of Pro-HMS. The production data over a three year period was used for the history matching.
The sub-domains, which are the most influential yet least correlated regions, are obtained by covariance matrix calculation and principle component analysis (PCA). The sub-domains obtained for this case after 40% volume cutoffs are show in Figure 5-16.

![Sub-domains for tests after applying 40% volume cutoffs.](image)

Figure 6-16: Sub-domains for tests after applying 40% volume cutoffs.

The final history matched permeability reservoir models are shown in Figure 6-17. Note that the reference model exhibits varying angles of anisotropy in the different layers. The limited duration of the production data matched, is insufficient for imparting the correct variations in permeability anisotropy to the different layers.
The results indicate that the representation of spatial heterogeneity has improved in the vicinity of the production wells. However, the permeability distributions in regions away from three wells do not resemble that observed in the reference models. Predictions of future performance for wells in those regions are therefore likely to be inaccurate. Figure 6-18 shows the matches to the production data observed at the wells. As is evident, the initial model exhibits production response that is distinctly different from the reference response. The final model matches the reference response closely.
Figure 6-18: History matching result for the base case with sub-domain delineation
The generated parameter files from Pro-HMS for this case are shown in Tables 6-5, 6-6, and 6-7.

Table 6-1: The ‘hmissim.par’ generated by Pro-HMS

<table>
<thead>
<tr>
<th>Variable</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>VariableType</td>
<td>1</td>
</tr>
<tr>
<td>NumThresholds/Categories</td>
<td>7</td>
</tr>
<tr>
<td>ThresholdV/CategoriesValues</td>
<td>0.55 0.9 2.5 7.55 26.85 84.2 157.95</td>
</tr>
<tr>
<td>PriorCDF/PDF</td>
<td>0.05 0.1 0.25 0.5 0.75 0.9 0.95</td>
</tr>
<tr>
<td>CondDataFile</td>
<td>Conditional.txt</td>
</tr>
<tr>
<td>CondFileDescr</td>
<td>1 2 3 4</td>
</tr>
<tr>
<td>SoftDataFile</td>
<td>direct.ik</td>
</tr>
<tr>
<td>SoftFileDescr</td>
<td>1 2 3 4 5 6 7 8 9 10</td>
</tr>
<tr>
<td>Markov-Bayes</td>
<td>0</td>
</tr>
<tr>
<td>Mark-BCalibBs</td>
<td>0.61 0.61 0.61 0.61 0.61 0.61 0.61</td>
</tr>
<tr>
<td>TrimmingLimits</td>
<td>-1.0e21 1.0e21</td>
</tr>
<tr>
<td>Min/MaxDataVal</td>
<td>0.005 500</td>
</tr>
<tr>
<td>LowerTailOpt</td>
<td>1 0.005</td>
</tr>
<tr>
<td>MiddleOption</td>
<td>1 1</td>
</tr>
<tr>
<td>UpperTailOpt</td>
<td>1 500</td>
</tr>
<tr>
<td>TabulatedValFile</td>
<td>cluster.dat</td>
</tr>
<tr>
<td>TabFileDescr</td>
<td>4 0</td>
</tr>
<tr>
<td>DebuggingLevel</td>
<td>0</td>
</tr>
<tr>
<td>DebuggingFile</td>
<td>sisim.dbg</td>
</tr>
<tr>
<td>IncSimPermFile</td>
<td>PERM.DAT</td>
</tr>
<tr>
<td>ProdHistFile</td>
<td>ProdHistory.txt</td>
</tr>
<tr>
<td>GridDescrX</td>
<td>100 0.5 1</td>
</tr>
<tr>
<td>GridDescrY</td>
<td>100 0.5 1</td>
</tr>
<tr>
<td>GridDescrZ</td>
<td>5 0.5 1</td>
</tr>
<tr>
<td>RandomSeedVal</td>
<td>93984</td>
</tr>
<tr>
<td>MaxCondDataKrig</td>
<td>12</td>
</tr>
</tbody>
</table>
MaxSimDataKrig: 12
MaxSoftDataKrig: 1
AssignCondData: 1
MultiGridOpt: 0 3
NumDataPerOct: 0
MaxSearchRadii: 1000 1000 200
SearchAngles: 341 0 0
Full/MedianK: 0 50
Simple/Ordinary: 1
InitRealizOpt: 0
InitRealizFile: InitRealiz.dat
SubdomainsOpt
SubdomainFile: RegionIndices.txt
InnerLoopIter: 3
OuterLoopIter: 4
1-st Variogram: 1 0
  1 1 45 0 0
  16 8 2
2-nd Variogram: 1 0
  1 1 45 0 0
  16 8 2
3-rd Variogram: 1 0
  1 1 45 0 0
  16 8 2
4-th Variogram: 1 0
  1 1 45 0 0
  16 8 2
5-th Variogram: 1 0
  1 1 45 0 0
  16 8 2
6-th Variogram: 1 0
  1 1 45 0 0
16 8 2
7-th Variogram 1 0
1 1 45 0 0
16 8 2

Table 6-1 continued: The ‘hmissim.par’ generated by Pro-HMS

Table 6-2: The ‘sensregion.par’ generated by Pro-HMS

<table>
<thead>
<tr>
<th>'sensregion.par'</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>- 1 = continuous(cdf), 0 = categorical(pdf)</td>
</tr>
<tr>
<td>7</td>
<td>- number of thresholds/categories</td>
</tr>
<tr>
<td>0.55 0.9 2.5 7.55 26.85 84.2 157.95</td>
<td>- thresholds / categories</td>
</tr>
<tr>
<td>0.05 0.1 0.25 0.5 0.75 0.9 0.95</td>
<td>- global cdf / pdf</td>
</tr>
<tr>
<td>highcluster.dat</td>
<td>- file with data</td>
</tr>
<tr>
<td>1 2 3 4</td>
<td>- columns for X,Y,Z, and variable</td>
</tr>
<tr>
<td>direct.ik</td>
<td>- file with soft indicator input</td>
</tr>
<tr>
<td>1 2 3 4 5 6 7 8 9 10</td>
<td>- columns for X,Y,Z, and indicators</td>
</tr>
<tr>
<td>0</td>
<td>- Markov-Bayes simulation (0=no, 1=yes)</td>
</tr>
<tr>
<td>0.61 0.61 0.61 0.61 0.61 0.61 0.61</td>
<td>- calibration B(z) values</td>
</tr>
<tr>
<td>-1.0e21 1.0e21</td>
<td>- trimming limits</td>
</tr>
<tr>
<td>0.005 500</td>
<td>- minimum and maximum data values</td>
</tr>
<tr>
<td>1 0.005</td>
<td>- lower tail option and parameter</td>
</tr>
<tr>
<td>1 1</td>
<td>- middle tail option and parameter</td>
</tr>
<tr>
<td>1 500</td>
<td>- upper tail option and parameter</td>
</tr>
<tr>
<td>highcluster.dat</td>
<td>- file with tabulated values</td>
</tr>
<tr>
<td>3 0</td>
<td>- columns for variable, weight</td>
</tr>
<tr>
<td>0</td>
<td>- debugging level: 0,1,2,3</td>
</tr>
<tr>
<td>sisim.dbg</td>
<td>- debugging file for debugging output</td>
</tr>
<tr>
<td>sisim.out</td>
<td>- file for simulation output</td>
</tr>
<tr>
<td>100 0.5 1</td>
<td>- nx, xmn, xsiz</td>
</tr>
</tbody>
</table>
100 0.5 1 - ny, ymn, ysz
5 0.5 1 - nz, zmn, zsz
93984 - random number seed
12 - maximum original data for each kriging
12 - maximum previous nodes for each kriging
1 - maximum soft indicator nodes for kriging
1 - assign data to nodes? (0=no, 1=yes)
0 3 - multiple grid search? (0=no, 1=yes), num
0 -maximum per octant (0=not used)
1000 1000 200 - maximum search radii
341 0 0 - angles for search ellipsoid
51 51 11 - size of covariance lookup table
0 50 - 0=full IK, 1=median approx. (cutoff)
1 - 0=SK, 1=OK
1 0 -1 nst, nugget effect
1145000 - it,cc,ang1,ang2,ang3
16 8 2 - a_hmax, a_hmin, a_vert
1 0 -2 nst, nugget effect
1145000 - it,cc,ang1,ang2,ang3
16 8 2 - a_hmax, a_hmin, a_vert
1 0 -3 nst, nugget effect
1145000 - it,cc,ang1,ang2,ang3
16 8 2 - a_hmax, a_hmin, a_vert
1 0 -4 nst, nugget effect
1145000 - it,cc,ang1,ang2,ang3
16 8 2 - a_hmax, a_hmin, a_vert
1 0 -5 nst, nugget effect
1145000 - it,cc,ang1,ang2,ang3
16 8 2 - a_hmax, a_hmin, a_vert
1 0 -6 nst, nugget effect
1145000 - it,cc,ang1,ang2,ang3
16 8 2 - a_hmax, a_hmin, a_vert
The following series of Pro-HMS screenshots (from Figure 6-19 to Figure 6-33) are for this case. They show some key various input parameters.

The name of the file with the conditioning ‘hard’ data is specified as ‘Conditional.txt’ as shown in Figure 6-19. The conditional hard data are used when Pro-
HMS does sequential indicator simulation. In the conditional file, the format of the columns are specified as $x,y,z$ coordinates and permeability data.

Figure 6-19: Well data specification screen

Figure 6-20 represents the screen that production file specification. Since the total numbers of wells are four and the name of file is ‘ProdHistory.txt’, they are specified accordingly.
The multiple initial permeability realizations are generated based on the sequential indicator simulation such that the ‘Sequential Indicator Simulation’ is selected as shown in Figure 6-21. One set of the ensemble initial realizations is illustrated in Figure 6-15.
Figure 6-21: Initial permeability field generation choice screen

Figure 6-22 is for the specification of the variable type. The history matching parameter in this case is permeability such that continuous variable; therefore, ‘Continuous (CDF)’ option is selected. Also, the number of thresholds in permeability field is seven so that ‘7’ is specified in Figure 6-22.
Figure 6-22: Variable specification screen

The threshold values are obtained from the cdf of conditional data. The specified threshold and cdf values are shown in Figure 6-23.

![Figure 6-23: Threshold and cdf value specification screen]

In Figure 6-24, the grid cells in x, y, and z, direction as 100, 100, and 5, the minimum grid offset (0.5), and the cell size as one in the last column.
The trimming limits for the conditioning data are specified. The default maximum and minimum values are used in this case as shown in Figure 6-25.

Figure 6-24: Grid identification screen

Figure 6-25: Trimming limit screen
As shown in Figure 6-26, in each tail option specification section, values are specified; for upper tail, 1 and 500, for middle tail, 1 and 1, and for lower tail 1 and 0.005. On the other hand, the simulated permeability values range from 0.005 to 500 milidarcies.

---

Figure 6-26: Tail extrapolation and simulated permeability range specification screen

---

Figure 6-27 shows the screen for the Kriging option. The full ordinary indicator Kriging is used for permeability field generation.
Figure 6-27: Types of kriging screen

Figure 6-28 illustrate the screen for the additional Kriging option. The ‘Maximum original data’ is the maximum number of the original well data (conditional data) to be used to simulate the value at a grid node in sequential indicator simulation, and in this base case the default values is used. ‘Maximum previous nodes’ is the maximum number of previously simulated nodes to be used for constructing the local probability distribution at a node. Also, the default value is used. ‘Assign data to nodes’ is an option for assigning data at a node. ‘Yes’ is selected such that the data are relocated to grid nodes and a spiral search is used; the parameters of Maximum original data are not taken into consideration. ‘Maximum number of soft data’ restricts the number of soft data when an exhaustive secondary variable informs all grid nodes. This option is basically maximum number of soft data at node locations that will be used for the simulation of a node. It is set as one. ‘Maximum Search Radius’ specifies the size of the search ellipsoid in the horizontal direction and vertical direction. ‘Angles for ellipsoid’ is the angle parameters that describe the orientation of the search ellipsoid. The entered
values are observed in Table 6-1 as following. ‘MaxSearchRadii’ are 1000, 1000, and 200, and ‘SearchAngles’ are 341, 0, and 0.

Figure 6-28: Details on Kriging specification screen

As illustrated in Figure 6-29, each threshold has one structure of variogram model and zero nugget effect.
Figure 6-29: Variogram model specification screen

Seven consecutive screens are automatically shown for the specifications of type of structure, sill contribution and anisotropy angles. (i.e., the screen similar to Figure 6-30 will be shown for seven times due to the seven threshold values). The numbers of these screens are shown in Table 6-1.
Figure 6-30: Details of variogram mode in each threshold

The base case utilizes the sub-domain delineation, so the volumetric threshold for the sub-domain is entered as 0.4 as shown in Figure 6-31.

Figure 6-31: Sub-domain option selection screen
To obtain pressure responses 50 multiple realizations are generated such that ‘50’ is specified in the top box in Figure 6-32. The pressure responses are obtained from the responses of the last time step of entire flow simulations, so ‘1260 day’ is inserted in the bottom box.

Figure 6-32: Sensitivity calculation detail specification screen

The upscaling factor is designated as 10, 10 and 1 in $x$, $y$, $z$ direction, respectively. Also, in Figure 6-33, the Eclipse data file for the upscaled flow simulation is loaded named as ‘Data.DAT.’
The number of Dekker-Brent inner loop optimization is three and outer loop is four. They are specified in Figure 6-34.
Non-sub-domain option: History matching with limited duration data

The importance of domain delineation for developing robust history matched reservoir models is demonstrated in this second case. The perturbations of local conditional distributions are performed in all gridblocks. The result is shown in Figure 6-35. Compared to Figure 6-17, the permeability values far away from wells are also perturbed. This results in increased computational cost and also poor convergence to the target reservoir responses as evident in Figure 6-36.

Figure 6-35. The permeability model after three years history matching without subdomains; production wells are in black and an injection well is in white
Figure 6-36: History match results when the permeability model is perturbed without using sub-domains
6.4.2.2 Further case studies in conjunction with previous studies

**Objective**

It was observed in Figure 6-17 that though the production data is matched well by the updated models, the spatial characteristics of the permeability field in regions far away from wells are not consistent with the reference model. This can result in poor predictions of the reservoir performance in the future. To improve the characteristics of the reservoir models in regions away from existing wells and to test the efficacy of the software to handle addition of new wells on future dates, the following cases were attempted.

**Test conditions**

These further cases have not been done with Pro-HMS itself, but with customized versions of Pro-HMS. The only change made in the codes for these cases is to alter the definition of conditioning data for simulating further nodes. These cases have been demonstrated in order to see the robustness of the Pro-HMS. Since all the other procedures are the same, it is possible to test the effectiveness of Pro-HMS with these further cases.

Based on the result of three years history matching reservoir models, two more wells are drilled at locations (40, 90) and (90, 10). After the sensitivity test, the sub-domains are obtained and they are shown in Figure 6-37.
Expanded case with 2 additional wells and 3 years of production data

In this case including additional wells, the permeability values within the two new sub-domains are perturbed conditioned to the previously perturbed regions in the first case shown in Section 6.4.1.2. The local conditional distributions at locations inside the two new sensitivity regions are obtained conditioned to the updated permeability values in the sensitivity regions identified for the base case.

The result after the updating process is shown in Figure 6-38. This result is compared with the one obtained from the base case, and it can be seen that the new sub-domains area are perturbed such that the high permeability values observed in Figure 6-17 are reduced to low permeability values. This is to be expected since the updated permeability values in the earlier sensitivity regions (base case) are all medium valued (corresponding to the green regions in the map) and that data conditions the probability distributions in the two new sensitivity regions. These smooth updated reservoir models lead to fair reproduction of the historic as evident from Figure 6-39.
Figure 6-38: The permeability models after updating the permeability values in the sensitivity regions corresponding to the two new wells. (Note that permeability change near two additional wells)
Figure 6-39: History matching results corresponding to the update of permeability values in the sensitivity regions corresponding to the two new wells. The updated values in the domains corresponding to the earlier configuration of wells (Figure 6-16) are used as conditioning data for updating the values in the two new sensitivity regions.
**Test the effect of the number of available hard data**

The test condition is ten years of production history matching and prediction of oil production and field pressure for with three years with 13000 available hard data. This test is comparable with the one using 19950 conditional data. This test is revised from the previous case to see the difference of the number of hard data as conditional data (hard data). The available permeability data is reduced in 35%. The result is show in Figure 6-40, and the results are almost the same as those used 19950 hard data.

![Figure 6-40](image)

Figure 6-40: The permeability models after 10 years history matching with 13000 hard data

Figure 6-41 shows the history matched plots for this case. Compared with previous case, the degree of mismatch becomes higher because this case has less hard data. However, some plots show better results in a certain period of time so that the effect
of number of hard data is neither meaningful over the entire reservoir nor all production wells. The number of hard data can result in better matching or poorer matching.

Figure 6-41: History matching results for the case using 13000 permeability data. History matching is performed for ten years, and the rest of the period is prediction of reservoir performance.
6.4.2.3 Updating of values in new sub-domains using only original “hard” data

In this case, the conditional probability distributions at locations only within the two new sub-domains are obtained using only the original ‘hard’ data. The sequential indicator simulated permeability values in the less-sensitive regions are however obtained conditional to the values in the updated sub-domains.

The main feature of this case is that the computational time is tremendously reduced compared to the case shown in Section 6.4.2.2. The updated reservoir models are shown in Figure 6-42.
Figure 6-42: The permeability models after history matching using only the original ‘hard’ data for updating the probability distributions within the new sub-domains and using the 19950 simulated values for conditioning the simulated values in the insensitive regions.

The permeability values near new wells are not similar to those for the case presented in Section 6.4.2.2. The permeability values are higher. This can be attributed to the conditioning of values in the new sub-domains to the original data histogram that is not affected by the distribution of values within the previous sub-domains.

Figure 6-43 below indicates that much better reproduction of the production history information is possible using this approach.
Figure 6-43: History matching result for the case where the permeability values in the new sub-regions are only conditioned to the original ‘hard’ data.
6.4.2.4 Model updating using a reduced set of hard data simulating values in the less sensitive regions

This test uses the same procedures as for the case shown in Section 6.4.2.3, but the number of conditioning data from previously history matched sub-domains for simulating the values in the less sensitive regions is reduced from 19950 to 13000.

The results are illustrated in Figure 6-44 and Figure 6-45. Reducing the number of conditioning data has minimal effect on the reproduction of the production history information.

Figure 6-44: The updated permeability models obtained using a reduced number of conditioning data for simulating the permeability values in the less sensitive regions
Figure 6-45: History matching result plots when the permeability values in the less sensitive regions are conditioned to a lesser number of updated permeability values in the sub-domains.
6.4.2.5 Final Validation

The final case is intended to observe the cross check the validity of the Pro-HMS. The initial permeability realizations are used from the result of the base case history matched result. The expected results are very low degrees of mismatch for three years in three production wells, P1, P2, and P3; moreover, the prediction of future production rate is expected to be more reliable. From the history matching period results, it is evident that the previous test cases are reasonably history matched.

The history matched permeability model resembles the result of base case shown in Figure 6-17. Also, the history matched plots are exactly the same as the result of the base case (Figure 6-18). For three production wells initially existing in the base case, after three years the prediction shows good matching. The results obtained from this case are shown in Figure 6-45, and Figure 6-46.
Figure 6-46: The permeability models after ten years history matching with three years matched models as initial models
Figure 6-47: History matching result plots for the final validation case
6.4.3 Discussions

The cases presented in Section 6.4 are designed with various conditions to test the robustness of the Pro-HMS and its algorithm. Seven related cases are effectively demonstrates the usefulness of sub-domain delineation algorithm, and cost competitive Pro-HMS property due to sub-domain delineation. Also, probabilistic perturbation algorithm is proved to have ability in perturbing specific permeability distribution within the sub-domains and in updating permeability model honoring prior permeability data. A few key conclusions from the test cases are the following.

- Sequential perturbation of the conditional probability distributions representing the uncertainty in reservoir attributes using the dynamic data has been demonstrated.
- Procedure employs a unique domain delineation method that yields sub-domains that are most sensitive and least correlated. This renders the procedure amenable to distributed computing.
- Sequential perturbation zones taking into account data from new wells is possible. Previously history matched regions remain unperturbed.
- Pro-HMS is an efficient software package and reduces computational costs.
CHAPTER 7. REAL FIELD CASE STUDIES

The matching of production data for a number of real fields were performed using the Pro-HMS software. In Chapter 6, some of the results for some synthetic cases were shown, and it was demonstrated that the implemented method gave reliable predictions of future reservoir production rate as well as field pressures for the reservoir management.

Real reservoir history matching is quite challenging due to the following reasons. First of all, availability of relevant data for constructing the reservoir model is an important issue. In most cases, lack of sufficient field data results in large uncertainty in the reservoir model and that in turn leads to questions about the validity of the history matched model. The quality or reliability of data is another factor determining the success of history matching. Issues such as inadequately documented well operating conditions influence the reliability of the production data. Lastly, in order to render the history matching process meaningful, predictions for reservoir performance have to be continually assessed against actual recorded measurements and based on the mismatch, the process of updating has to be applied at periodic intervals. This necessitates current production data for model updating or validation.

In this chapter, three different challenging field applications with Pro-HMS are documented. In Section 7.1, the history matching with very limited data was processed and the accurate characterization of channels in a fluvial sandstone reservoir is demonstrated. The next case presented is for a fluvial-deltaic sandstone reservoir, and the last history matching case was performed on a carbonate reservoir that was constructed based on actual field data.
7.1 Characterization of a fluvial reservoir by history matching

7.1.1 DELINEATION OF CHANNEL FAIRWAYS

Actual oil production data is used for demonstrating the history matching procedure using Pro-HMS. The area of the reservoir for history matching is about 1499 acres, and the thickness of the pay interval is 2,100 feet. The total duration of the history matching data is 13,080 days and permeability is the only parameter perturbed for history matching. The reservoir is split into $100 \times 100 \times 5$ gridblocks. The areal map of the reservoir prepared by the field geologist has a few distinct channel fairways as shown in Figure 7-1. The size of the reservoir in x, y, and z directions are 6,141.5 feet, 10,630 feet, and 2,100 feet, respectively.

![Figure 7-1: The map of the reservoir for history matching case. Blue dots represent producers, and red ones are the locations where prior permeability values are available from well tests. The black contour lines delineate pay thicknesses. The presence of channel fairways is indicated.](image)
Ideally conditioning information for modeling the permeability field is obtained from well tests and core analysis of the drilled wells. As indicated in Figure 7-1, wells where permeability data are obtained are different from those where production profiles are recorded. Prior permeabilities were obtained for the wells which are indicated with red in Figure 7-1; however, production information was not available in those wells. Furthermore, this case study is challenging in the sense that the only prior geologic information we have are nine permeability values; moreover, the only available dynamic data are oil production rates and bottom hole pressures for some wells recorded over limited duration.

The variogram required for performing indicator simulation was inferred and modeled from the limited permeability data (nine permeabilities) available. Fifty initial permeability fields are generated, and the variation in permeability on one of the initial realization is shown in Figure 7-2. Even if the available permeability data is sparse, the inferred variograms can be effective such that the distributions of channels in all layers are observed. The permeability histogram is discretized using five thresholds, and so there are five indicator semi-variograms characterizing the permeability field.
Figure 7-2: Permeability variations in one initial realization. The left realization is the top layer and the fifth right one is the bottom layer. Pink dots indicate the locations of wells. The units of permeability values in the color scale are millidarcies.

The topography of the reservoir is also important for modeling its flow performance. The available 27 well tops information in the reservoir were used to infer a semi-variogram; and subsequently, ordinary kriging based on the 27 tops values was performed. The resultant model for the topography of the reservoir being studied is included in the simulation data files for history matching.

The upscaling factor is $10 \times 10 \times 5$ so that the total number of gridblocks for the sub-domain calculation was 500. The computation of pressure response for the sensitivity
matrix is performed corresponding to the last flow simulation time step (13080 days). The sensitivity maps are illustrated in Figure 7-3.

![Sensitivity Maps](image)

Figure 7-3: The sensitivity maps of the covariance matrix obtained from the upscaled initial realizations. These maps correspond to the diagonal elements of the pressure covariance matrix; red color represents greater sensitivity than blue color.

The continuity in sensitivity regions shown in Figure 7-3 has an orientation in about 35 to 45 degree azimuth; however, the channels in the initial models (Figure 7-2) are oriented in NS direction. Since oil production from the wells indicated as low sensitive regions are relatively less than those represented as higher sensitive regions, higher degree of sensitivity is observed in regions where two corners of the reservoir meet and the lower sensitive regions appear continuous. For this reason, the continuity directions in the sensitivity map and channels are obviously different, but the channel orientation maintained in NS direction.

The pressure responses of initial realizations are obtained from flow simulation, and then the sensitivity analysis along with PCA gives sub-domains as illustrated in Figure 7-4. The volumetric cutoff for the sub-domains is 40%.
Figure 7-4: Sub-domains for five layers after applying 40% volume cutoff; nine different sensitive regions are shown with different colors.

The most sensitive yet least correlated regions are shown with different colors in Figure 7-4. There are seven colors representing seven regional indices combining positive or negative signed eigenvalues. Also, the delineated sub-domains designate the regions where high sensitivity coefficients (Figure 7-3) are assigned. The sub-domains are observed only where relative sensitivity is higher than other regions, and they are based on the volumetric threshold value. Since the fluid flux is relatively higher in regions where sub-domains are delineated than those where sub-domains are not observed with a criterion of 40% volumetric cut-off value, some wells located in the middle-low sensitive regions are not observed as sub-domains. However, if the sub-domain cut-off value is increased, the regions that are not shown as sub-domains in Figure 7-4 would be recognized as sub-domains.

Next, sequential perturbation of each sub-domain is performed. Finally, sequential indicator simulation is performed in regions not covered by sub-domains to eliminate artifacts around the boundaries of sensitive regions. This simulation at the end uses the perturbed data in the sub-domains as well as the nine original permeability data for
conditioning. The history matched permeability reservoir models are shown in Figure 7-5.

![Reservoir Models](image)

Figure 7-5: History matched reservoir models after three outer loop iterations. This model is to be compared against the initial model in Figure 7-2.

The history matched models are obviously different from the initial ones. The first layer of the initial model has a channel in the middle of the reservoir, whereas the final model reveals one channel in the right margin of the reservoir; in addition, some broken low permeability channels are shown near left margin of the reservoir. These probably indicate channel features that are undulating in the vertical direction. The initial model of third layer shows two channels that are fairly connected and one channel with short connectivity; however, the probabilistic perturbation procedure results in a model with a
series of broken high permeability zones (shown with yellowish or red colors in Figure 7-5) indicating that the channels may actually be more heterogeneous in pay quality than initially represented. The fourth and fifth layers illustrate more interesting results. In the initial realization of the fourth layer, two distinctive channels are observed; one channel with higher permeability is located near the right side of the reservoir, and the other channel with lower permeability is located to the left side of the reservoir. The history matched model of this layer, on the other hand, shows three distinctive channels, and the high permeability channel is located in the left margin of the reservoir. In the fifth layer, the final history matched realization has no channels and shows the lowest permeability zone among the five layers, whereas the initial model has channels and high permeability zones. The model obtained subsequent to the history match is consistent with the isopach maps (Figure 7-1) that have been drawn for the reservoir that indicate a gradation in pay thickness through the channel cross-section, with the flanks of the channel being thinner than the spine.

The geological reservoir models after history matching provide an idea how the actual reservoir would be like; however, since the reference reservoir is unknown in this case, one way to assess the accuracy of the models would be to assess the quality of the match of the fluid flow response. The history matching of oil production rates of eight wells are shown in Figure 7-6.
Figure 7-6: History matching results of oil production rates for eight wells; the red dots are the actual history, the green line represents the response from the initial model and the blue line is the final history matched result.

For the production well, P1, the final history match result in blue passes through the middle of the scatter of red dots representing historical production rate. The final matched profile for P2 also passes through the scatter of the historic data; in addition, it can also be observed that the production profile corresponding to the initial guess is far from the history during the first 8000 days. The scatter observed in the actual production history is attributable to measurement noise and fluctuations in well operating conditions. The matching result for production wells, P3, P5, and P7 are excellent. The remaining deviations between the history matched result and the actual history are, as mentioned before, due to the lack of any information about how the wells were operated. In conventional history matching, the rates of the wells for flow simulation would be set equal to the historic rates and the attempt would be to match the pressure. However, in this case since very sparse pressure data was available, the history matching was done by setting a fixed minimum well bottom-hole pressure and observing the rates. Despite these constraints, the reasonable match of rates is indicative of the robustness of the algorithm implemented in Pro-HMS.

7.1.2 PREDICTION STUDY FOR THE VALIDATION

A further check on the validity of the history matching procedure would be to history match the permeability field using data for a reduced duration and subsequently checking the predictions made using the history-matched model against the remaining duration of the production data. History matching was performed using the data for a reduced duration (8640 days) and the predictions from the history matched model were
compared to the remainder of the prediction data. In contrast to the previous results, the flow responses achieved from the simulator in this case are constrained by the bottom hole pressures in the recorded data.

The initial reservoir models are the same as shown in Figure 7-2. The same procedures were followed to obtain the sub-domains. After applying upscaling factor of $10 \times 10 \times 5$ and computing the sensitivity of the pressure responses achieved at 8640 days, sensitivity coefficients maps are obtained as illustrated in Figure 7-7.

![Sensitivity Coefficients Maps for the Further Study](image)

**Figure 7-7:** Sensitivity coefficients maps for the further study; red indicates greater sensitivity than blue

The sub-domains are illustrated in Figure 7-8; corresponding to a volume threshold of 40%. This case illustrates different configuration of sub-domains from the one shown in Figure 7-4; however, the middle part of the reservoir is not covered with sub-domains as before due to the lower fluid flux.
Figure 7-8: Delineated sub-domains for the further study

The history matched models for 8,640 days are shown in Figure 7-9.

Figure 7-9: History matched reservoir models obtained by matching the production history only for 8,640 days. The left realization is the top layer and the very right one is the bottom layer.
We observe that the models are different from the initial models in Fig. 6-2. The thin channel in the top layer of initial realization is located in the middle of the reservoir. In the final model of this case, channels have a tendency to be located towards the right edge of the reservoir and the permeability within the channels is more discontinuous. There are some resemblances of the final model with that obtained after constraining to the full 13,080 days of production data. For example, the channel located in the right margin of the reservoir is retained even in the model obtained after constraining to the lesser duration data. Similar observations are observed in the other layers as well.

The prediction of oil production rates shown in Figure 7-10 demonstrates a high-quality matching with target response. P1 and P4 are shut in after 8,000 days, so no prediction is made. The flow rate performance of all the other wells have been predicted very accurately. As noted earlier, the actual operational data of wells is unavailable and so exact prediction is impossible. Despite this major shortcoming, the prediction for wells P3, P5, and P8 are exceptionally good. Also, P2, P6, and P7 predict the average behavior of the historical production rate.
Figure 7-10: History matching results of oil production rates for 8,640 days and prediction for the remaining production duration (13,080 days in total) for eight wells. The red dots indicates the recorded data, the blue line is the portion of the history matched model, the green line is the initial model response data, the orange dots represents the remaining duration of the historical production data that is used to check the accuracy of the prediction (violet line).

In summary, in the test cases demonstrated in this section, accurate models for reservoir heterogeneity are generated that could provide reliable prediction of future reservoir performance.
7.2 Sandstone reservoir field case

7.2.1 GEOLOGICAL SETTING

A fluvial-deltaic sandstone reservoir deposited in a shallow-marine environment is history matched with Pro-HMS. The pay thickness of the formation is 2500 feet, and the total study area is approximately 1,700 acres. The reservoir has been produced for about 43 years, using forty two production and injection wells. The porosity values obtained from cores range from 8% to 25%. The water-oil contact depth is 6,530 feet, and the reference depth of the pay interval is 6,300 feet. Oil production wells and water injection wells are rate-controlled.

Geological features reported in this reservoir are fluvial channels in the top layers, whereas delta plains are predominant near the bottom of the pay thickness (Mijares et al., 2001). Pressure responses reveal that inter-layer connectivity is poor such that separate pools exist. The deposition environment involves transgress and retrogressive processes resulting in the lowermost part of the deposits to be differentiated from the uppermost deposits. The presence of reverse faults results in the formation being compartmentalized, representing separate zones with several productive sands zones. Reservoir heterogeneity was modeled using ten layers; the top layers are the most prolific hydrocarbon production zones.

The initial permeability reservoir model was constructed based on permeability data from core data and well logs obtained from 42 wells. The initial permeability models were generated using indicator variograms inferred on the basis of conditional (hard) permeability data as illustrated in Figure 7-11.
Figure 7-11: The initial permeability model; the dots indicate locations of production wells and black dots with white circles around them represent water injection well converted from production well. Clearly mark, which are the top layers and which are the bottom layers (Top layer is the top left figure and the bottom layer is the bottom right figure)

The spatial permeability distribution varies from four millidarcies to about 1,200 millidarcies. The upper layers (top four layers) have higher permeability than lower part of the pay zones (bottom three layers). Also, channels are speculated to be more prevalent in the top layer. The continuity of higher permeability channels diminish in the lower layers. Although it is difficult to model channel connectivity using indicator variograms,
the relative higher proportion of high permeability facies in the top layers is correctly represented in the initial models (Figure 7-11).

7.2.2 HISTORY MATCHING STRATEGY AND RESULTS

The total flow simulation gridblocks are $135 \times 78 \times 10$, and the size of each gridblock is $101 \, ft \times 101 \, ft$ in the x and y directions. The since the layers are undulating, the blocks have variable thickness. (Refer to Figure 7-13 for the three dimensional image). Thirteen production wells were implemented and two of them were converted into injection wells as indicated in Figure 7-11. Simulation of the initial 15 years of production were performed with four production wells and the following 25 years of waterflood were performed with nine additional producers; the first two initial producers were converted to injectors. The history matching parameter is permeability, and the production responses for history matching are field pressure, field water cut, and water cuts of four wells. The perturbation of permeability probability distributions of all gridblocks is performed.

The degree of uncertainty in the initial geological model is very high due to limited permeability data available compared to the size of the reservoir model to be history matched. Also, variogram based indicator simulation may be inadequate for representing the spatial distribution of channels. This necessitates more iterations of the probability perturbation approach; the number of outer loop is set twice higher (six) than the synthetic cases presented earlier that had more congenial geology. The perturbation scheme used in this case is to perturb all the gridblocks.
The history match results are shown in Figures 6-12, 13 and 14; Figure 7-12 illustrates the history matched permeability model, and Figure 7-14 represents the history matched results of field pressure, field water cut, and individual well water cuts.

![Final Perm. Model Layer 1 - 10](image)

Figure 7-12: The history matched permeability model; the white dots indicate locations of production wells and black dots with white circles around them represent injection wells converted from production wells.

The final history matched permeability model shows that areas with higher permeability values are located near the center of the reservoir where most wells are located. The higher permeability zones are concentrated in the center area and the rest of the area has relatively lower permeability. Compared to initial model in terms of
geological features, the top two layers show distinct channel with less continuity of permeability values in the minor directions. The initial top permeability model shows an amorphous high permeability zone in 135 degree azimuth direction from which it is difficult to detect the shape and extent of individual channels. In contrast, the history matched model retains the 135 degree oriented channel but shows thinner channel fairways in that direction. In the second layer of the history matched model, the channel is observed with the same orientation of heterogeneity. The permeability values in the bottom four layers are reduced from the corresponding values in the initial model. This is in good agreement with the geological information indicating the bottom pools are relatively less productive than the upper pools. Overall permeability distribution in the upper zones is higher than in the lower parts in the final model.

The three dimensional permeability model of the reservoir is illustrated in Figure 7-13. The geological structure of the reservoir is lifted to the NW and tilted to the east.
Figure 7-13: Three dimensional images of initial and final permeability reservoir models with consideration of topography; the reservoir is tilted to the east and the lifted to the NW direction.

Finally, the history matched dynamic data responses need to be examined to assess the quality of the history matching. Figure 7-14 shows the history matching results.
Figure 7-14: Plots of history matching results; field pressure, field water cut, and four individual well water cuts; red dots are history records, green dotted-lines indicate initial guess and blue lines are history matched responses.

The field pressure response matching is exceptional for the first 10 years. The improved history matching for field pressure can be observed; the field pressures
corresponding to the initial model is far from the actual field data. The field water cut matching is the best matching result. The final history matching responses follow the trace of history records with very small error considering that the data is for a real field. Also, the individual water cut matching results illustrates high quality matching.

### 7.2.3 DISCUSSIONS

In this field case, the challenge to model permeability is the limited number of hard data available. The limitation of the indicator modeling methodology also inhibits accurate modeling of the permeability field. This also results in an increase in the number of iterations required to obtain a reliable history matched model. The number of conditioning data used in this case is approximately hundred. This number is relatively very small considering that the size of the reservoir is 1,700 acres. In spite of the concerns listed, the history matching results are quite impressive in the sense that the final permeability model fairly represents underlying geological features such as channels, and non-connected interlayer sand sequences.
7.3 Realistic carbonate reservoir field case

7.3.1 GEOLOGIC BACKGROUND

Carbonate reservoirs, which are often created in marine environment, are most of times elephant fields and provide approximately 40% of total oil production (M. Akbar et al., 1995), so the characterization of carbonate reservoirs is of paramount importance to the industry. However, uncertainty of carbonates reservoir modeling is much higher than terrigenous clastic reservoirs due to the diagenesis of carbonates such that the characterization of carbonate reservoirs is not straightforward. The primary step for the delineation of carbonate reservoir is to establish the static geological model. Reliable model of facies architectures is critical for the success of carbonate reservoir modeling.

A common classification of carbonate rocks is based on textural features; the presence of mud, the degree of grain abundance, and clues of binding grains (R. Dunham, 1962). Dunham’s classification, which is fundamentally based on the depositional texture, have two categories; ‘depositional texture recognizable’ and ‘depositional texture not recognizable’. Within these two categories, carbonates are divided into several rock types. There are five rock types in ‘depositional texture recognizable’ category. They are mudstone, wackestone, packstone, grainstone, and boundstone. Mudstone and wackestone are both mud-supported type. Packstone also contains mud, but it is grain-supported. Grainstone is grain-supported and includes no mud. On the other hand, the rest of carbonates are categorized as ‘depositional texture not recognizable’. It is not possible to observe the depositional texture, so they are called as crystalline carbonate.
Lucia (1995) also introduced new classification based on the Dunham’s classification. He divided packstone as mud-dominated packstone and grain-dominated packstone for the purpose of better description of pore space distribution in carbonate reservoir characterization. In summary, the lithofacies of carbonates classification are generally identified by the depositional texture of rocks (rock fabrics) and types of rock including mudstone, wackestone, packstone, and grainstone.

Diagenesis is common in carbonates is common and imparts a great degree of uncertainty in petrophysical properties. Often times it is very difficult to understand and model diagenesis since it takes place irregularly and does not impart in any systematic variations in rock properties. Petrophysical properties such as porosity and permeability are altered to a great degree by the diagenesis process; they might be increased or decreased. The main parameter representing diagenesis is secondary porosity or vug porosity.

7.3.2 REALISTIC REFERENCE PERMEABILITY MODEL

A realistic reservoir permeability data generated by stochastic simulation is used for this last field case study. Actual data are available for the lithofacies model as shown in Figure 7-15. There are five lithofacies in the reservoir model - mudstone, wackestone, packstone, grainstone, and macro-dolomite. The macro-dolomite lithofacie in this field data is defined as rocks whose crystal size is larger than 100 microns such that the innercrystalline pore spaces are larger than any other lithofacies. Note that this lithofacie term, macro-dolomite, is not the same as that used in the Lucia’s classification (Lucia, 1995). It can be the same as large crystalline dolostones regarded as class I in Lucia’s rock fabric classification.
In addition to the lithofacies model, total porosity as well as secondary porosity data are acquired. The secondary porosity in this case is assumed as vug porosity induced by diagenesis. The interparticle porosity values are obtained by subtracting vug porosity from total porosity. The interparticle porosity data are utilized to estimate permeability using porosity-permeability relationship based on rock-fabric petrophysical class proposed by J. Lucia (1995 and 1999). From the given porosity data and corresponding lithofacies, the range of permeability and its mean value for each lithofacies were obtained. The average interparticle porosity values are 4.5%, 5.5%, 7%, 9.5%, and 14.3% for mudstone, wackestone, packstone, grainstone, and macro-dolomite, respectively. The correlation equation for each lithofacies is shown in Eqs. (7-1), (7-2) and (7-3) in Table 7-1. The corresponding permeability ranges and mean values are summarized in Table 7-2.

Table 7-1: Correlation equation between interparticle porosity and permeability for different lithofacies

<table>
<thead>
<tr>
<th>Class</th>
<th>Correlation Equation</th>
<th>Permeability Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Class 1 (Macro-dolomite and grainstone)</td>
<td>[ k = (45.35 \times 10^8) \times \phi_{ip}^{8.537} ]</td>
<td>(7-1)</td>
</tr>
<tr>
<td>Class 2 (Packstone)</td>
<td>[ k = (2.04 \times 10^6) \times \phi_{ip}^{6.38} ]</td>
<td>(7-2)</td>
</tr>
<tr>
<td>Class 3 (Wackestone and mudstone)</td>
<td>[ k = (2.884 \times 10^3) \times \phi_{ip}^{4.275} ]</td>
<td>(7-3)</td>
</tr>
</tbody>
</table>

The available porosity and obtained permeability data have agreement with the experimental data demonstrated by P. Enos and L. Sawatsky (1981) who postulated that porosity and permeability are inversely proportional to each other.
Table 7-2: Ranges of permeability for five lithofacies

<table>
<thead>
<tr>
<th>Lithofacie</th>
<th>Data.MIN</th>
<th>Permeability (md)</th>
<th>Data.MAX</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mudstone</td>
<td>8.0</td>
<td>8.364</td>
<td>9.67</td>
</tr>
<tr>
<td>Wackestone</td>
<td>7.32</td>
<td>7.634</td>
<td>7.999</td>
</tr>
<tr>
<td>Packstone</td>
<td>11.27</td>
<td>11.69</td>
<td>12.07</td>
</tr>
<tr>
<td>Grainstone</td>
<td>15.56</td>
<td>15.96</td>
<td>16.29</td>
</tr>
<tr>
<td>Macro-dolomite</td>
<td>14.8</td>
<td>15.214</td>
<td>15.56</td>
</tr>
</tbody>
</table>

The obtained permeability data shows very low values. It is most likely that there are some micro-fractures that enhance the permeability.

Reference permeability realization is generated using the following procedure.

1) Five indicator variograms showing corresponding spatial correlation of the five lithofacies (i.e., each lithofacie has one indicator variogram) were inferred from a Gulf of Mexico carbonate data set. The lithofacies indicator variograms were used to populate the permeability field shown in Figure 7-15.
Figure 7-15: The spatial distributions of five lithofacies in the reservoir being studied. Five black dots indicate production wells (P1, P2, P3, P4 and P5) and one white dot represents water injection well (I1). The wells are named P1 through I1 by proceeding counterclockwise from the top left well.

2) The permeability data ranges obtained from correlation equations (Eq (7-1), (7-2) and (7-3)) were utilized. The ranges of the permeability data shown in Table 7-2 were used to generate permeability distribution for each lithofacies, as illustrated in Figure 7-16. These permeability histograms along with the previous facies indicator variograms were used to simulate spatial variations in permeability values for each facies.
Figure 7-16: The distributions of permeability data simulated for five different lithofacies; from top to bottom mudstone, wackestone, packstone, grainstone, and macro-dolomite; the simulated permeability data for each lithofacies honors the permeability data range and mean value shown in Table 7-2.
3) All gridblocks in the lithofacies model are assigned with permeability data generated by five different sequential indicator simulations for five lithofacies. Knowing the lithofacies at a particular gridblock location, the corresponding gridblock value of permeability is obtained from the permeability realization for that facies.

4) Repeat step 3) for all gridblocks. Cutting and pasting permeability values according to the lithofacies indices for each gridblock ensures consistency between the facies and permeability models.

5) Obtain one permeability realization (Figure 7-17) that considers the spatial correlation of lithofacies as well as permeability ranges shown in Table 7-2.

Figure 7-17: The built permeability realizations; the black dots are production wells and the white dot indicates injection well
The relative permeability curve for typical carbonate reservoirs were studied by M. Esfahani and M. Haghighi (2004), and that data was input into the simulator in order to obtain field pressure, and oil production rate. The total area of the reservoir is 14 km², discretized using $100 \times 100 \times 5$ gridblocks with individual block dimensions of $70 \text{m} \times 70 \text{m}$. The thickness of the gridblocks are variable based on the seismic horizons. Production and water injection are controlled by rates.

Fifty initial permeability reservoir models were generated in order to perform subdomain delineation using pressure responses. One set of initial realizations are illustrated in Figure 7-18. Also, the corresponding set of upscaled permeability maps are shown in Figure 7-19.
Figure 7-18: One set of initial realizations for five layers; the black dots are production wells and the white dot indicates injection well

Figure 7-19: One set of initial realizations after upscaling with factor of $10 \times 10 \times 5$ for five layers

The pressure response obtained at fourth year are used to compute sub-domains occupying 40% of the reservoir volume. The delineated sub-domains are illustrated in Figure 7-20. The different shape of sub-domains in the fourth and bottom layers are due to the water injection wells. The perforation for water injection well is made in the bottom two layers such that different shapes of sub-domains are achieved in the last two layers; however, the color for the delineated sub-domain is the same through the all layer indicating all sub-domains are corresponding to the same eigenvalue.

Figure 7-20: Sub-domains decomposed based on the pressure response at fourth year

History matching was performed for four years using the field pressure and oil production rate for production wells. After that prediction of future reservoir performance was made. The history matched permeability model is shown in Figure 7-21. The results
represent different spatial heterogeneity from initial models; the high permeability zones are more homogeneous within the respective facies in the initial reservoir models, but the final history matched models illustrates that the high permeability zones are less homogeneous. As a result, the continuity of the permeability model is better represented. This spatial distribution resembles the reference permeability models. Also, the areas which are delineated as sub-domains in the fourth and fifth layers are well perturbed and consequently the representation of heterogeneity within sub-domains is exceptional.

![Figure 7-21: History matched permeability models using four years of production data.](image)

The reservoir being studied has several horizons that determine vertical intervals of the reservoir. Horizons are established by seismic data, a geological time sequence, and a variation of data interpreted from a suite of well-logs. The available horizon data obtained from the seismic were used as conditional data to simulate topography of the
entire field. The obtained reservoir topography with permeability data is shown in Figure 7-22. The production and injection wells are located near area where the reservoir shows anticline.

Figure 7-22: Three dimensional space permeability images of reference model (top left), initial model (top right) and history matched model (bottom left) obtained using four years of production data.

Figure 7-23 illustrates the history matched profiles for field pressure, oil production rate for five wells. Since the initial permeability model (Figure 7-18) is not representative of the permeability heterogeneity seen in the reference model (Figure 7-17), the initial profiles indicated with green colored lines in Figure 7-23 are far away from the history profiles colored in red. The history matching profiles using the data for the first four years show good matches for field pressure, oil production rates in P1, P2, and P5. The discrepancy shown in the P4 and P3 is less than 10% or less. The history matched model was used to predict the performance of the reservoir. The forecast profile
is obtained by maintaining the well production rates constant at the last rate for the history matched period. The forecast for all the cases are exceptional indicating that the history matching is performed successfully.
7.3.3 Forecasting Scenario with an Additional Well

To assess the quality of history matching described in Section 6.3.2, a further realistic forecast scenario is simulated. A new injection well is drilled at location (65, 70) indicated in Figure 7-24. Water injection is activated for about three years in the bottom layer. The new water injection well notated as I2 is located in the region where relatively higher permeability continuity is observed in the 45 degree direction (black ellipsoid in Figure 7-24) such that the flow of water for displacing the oil is facilitated.

The forecast of field pressure and oil production rates after drilling one more water injection well is shown in Figure 7-25 with the blue line. The corresponding profile...
for the reference model is shown in red. In both cases, the first four years production profiles correspond to two injectors. It can be seen that the prediction for field pressure and the profiles for P3 and P5 are excellent. A comparison of the mismatch obtained at the end of the history-match period and that at the end of prediction reveals that in the history matching period, mismatch in field pressure and P1 oil production rate is negligible, and the quality of history match of P1 is better than P5; however, the mismatch of P1 is greater than that for P5 for the prediction case. This may due to the location of the new water injection well; P5 may be more influenced by the new water injection well because P5 is located in the higher permeability connectivity zone in 135 degree direction (illustrated by the dotted black-ellipsoid in Figure 7-24). Whereas, P1 is located at the farther end of the connectivity zone, and consequently has less influence.

The overall mismatch in the new well addition scenario is relatively small (less than 30 STB/Day on any given day). This confirms that the history matching performed by Pro-HMS is reliable and the final permeability model is reliable for reservoir management purposes.
Figure 7-25: Prediction curves with new water injection well; the reference case results are in red lines, and the predictions using the history-matched model are shown with blue lines.

Even though the overall matching is acceptable, the mismatch in P2 is quite significant compared to other wells. Further investigation of the possible reasons for this mismatch was studied. Connectivity of permeability between the new injection well and
P2 is not observed in the reference model whereas in the history matched model, that region has high permeability connectivity, as shown in Figure 7-24. Consequently, the water injected in the new well is diverted from the injection well to P2 in the history matched model, but the same amount of flow is not expected in the reference model. This results in the relatively significant mismatch in P2.

When the new injection well (I2) is located at the bottom part of the reservoir so as to not preferentially influence any of the existing wells as shown in Figure 7-26, the prediction of P2 would be improved.

Figure 7-26: The permeability map for the second scenario of new water injection well perforated in the bottom layer indicated with a white circular mark towards the bottom of the model. The figure on the left is the history matched model while that on the right is the corresponding reference slice.

The results as shown in the following plots indicate a good match for P2 as expected.
Figure 7-27: Prediction curves with new water injection well; the reference response is in red lines, and the predictions for the new injection well addition are shown with blue lines.
7.3.4 History Matching and Uncertainty in Carbonate Reservoir

As mentioned in the earlier discussion, since a significant amount of world-wide hydrocarbon reserves resides in carbonate reservoirs, accurate characterization of carbonate reservoirs is important. Reservoir modeling of static attributes including depositional heterogeneity, lithofacies architecture and petrophysical attributes becomes important. The overall heterogeneity of the carbonate reservoirs are often governed by diagenesis. It occurs randomly such that uncertainty in the modeling of carbonate reservoirs is high.

Facies architecture defines macro-heterogeneity, whereas modeling of petrophysical attributes allows definition of micro-heterogeneity. Even if the model for lithogy model (or distribution of lithofacies types) is relatively dependent on the depositional environment (such as surface, platform, basin, etc) for carbonate reservoirs (Grammer et al., 2001), the uncertainty associated with such a lithofacies model and corresponding key petrophysical attributes (porosity, permeability and water saturation) is still high due to diagenesis effects. The approach presented to update the prior geological reservoir model by integrating dynamic data in effect reduces the uncertainty in the reservoir model. The proposed history matching updates the reservoir permeability model by integrating well oil production rates and field pressure response.

The sub-domain delineation method as shown in the realistic field cases effectively designate areas of the reservoir that require more attention since they are the most influential regions in terms of flow. Also, the probabilistic history matching scheme using multiple calibration parameters renders the reservoir permeability model consistent with geology and facilitates the history matching process. Figure 7-28 represents the
lithofacies model obtained by transforming the continuous permeability values to corresponding lithofacies indices using thresholds that are consistent with carbonate facies (Table 7-2).

Figure 7-28: History matched lithofacies model

Comparing to the reference lithofacies model in Figure 7-15, it can be concluded that the updating of the lithofacies model is effectively performed with the probabilistic history matching process using sub-domains.
CHAPTER 8. CONCLUSIONS

In this thesis, a history matching software built around the probability perturbation method, Pro-HMS is developed, and tested on synthetic and real field cases. The main algorithm of Pro-HMS comprises of geological reservoir modeling, sub-domain delineation and probabilistic history matching. The algorithm implemented in Pro-HMS emphasizes sub-domain delineation. A method using covariance of gridblock pressures calculated over an ensemble of initial realizations is demonstrated. An extensive set of synthetic and field cases are demonstrated using Pro-HMS to validate the capability of the probabilistic history matching algorithm utilizing sub-domain delineation. In this chapter, a summary of the key findings of this study and some key conclusions are documented. In addition, recommended future research directions are proposed.
8.1 Conclusions

The probabilistic history matching method has been researched further for the purpose of making the process more efficient and increasing the reliability of the resultant geological model for making future predictions of reservoir performance. The main idea is to perturb the permeability distributions within the delineated sub-domains such that the history matching procedure is amenable to a parallel computing environment. The key components of the procedure are petrophysical (permeability) modeling consistent with prior geological information, sub-domain delineation, and perturbation of local conditional probability distributions describing the uncertainty in permeability.

Two methods for the sub-domain delineation, one using the Hessian matrix method and the other one using the covariance of gridlock pressures have been studied extensively in this thesis. These methods originally proposed by Yadav (2005), have been further fine-tuned and rendered more efficient in this thesis. Furthermore the robustness of the method using covariance of pressures has been demonstrated over a suite of real field examples. It is also pointed out that the covariance matrix method has some critical advantages over the Hessian matrix method. It is computationally less expensive and independent of the advanced capabilities of commercial flow simulator; moreover, it is insensitive to the initial guess of the permeability field. Furthermore, unlike the Hessian that considers the sensitivity of the flow response to each gridblock permeability, the covariance of gridblock pressure considers the connectivity of the permeability field. This is because the pressure in a gridblock is affected by the connectivity of the permeability field in the vicinity of that gridblock. Last but not the least; the method does not require
identifying an optimal pilot points. As demonstrated in this thesis, optimal locations of pilot points require the accurate prior knowledge of the reservoir being studied. The covariance matrix method using pressure responses computed on an upscaled grid avoids many of the issues that the Hessian matrix method encounters. Systematic validation cases shown in Chapter 4, 6 and 7 reveal the sub-domain delineation method using pressure responses to be a robust scheme.

In some situations, it may not be necessary to delineate the reservoir into sub-domains. In that case, the user can choose to perturb the probability distributions over the entire domain using a single perturbation parameter. The selection of the sub-domain delineation option accounts for the uncertainty of the prior geological/petrophysical information through the ensemble of realizations using which the covariances of grid-block pressures are calculated. Geological modeling relies on the indicator variogram model built with available hard data. The variogram model is assumed invariant during the perturbation process of permeability distribution thereby ensuring that the history matched model exhibits similar spatial heterogeneity as the initial model. In that sense, the history matching process is sensitive to the prior reservoir model. When the sub-domain method is chosen, the delineation of sub-domains is affected by the well configuration and the flow characteristics near wells. However, when the reservoir size is considerably big with features exhibiting long correlation lengths, a large number of initial realizations are required for the domain delineation process. Failing that, the process may result in ineffective sub-domains thereby rendering the history match process more CPU intensive.
The upscaling of high-resolution geological models prior to calculation of the pressure covariance matrix renders the domain delineation method computationally efficient. The software Pro-HMS integrates the steps for geological modeling, upscaling, covariance matrix calculation and PCA of eigenvalues/eigenvectors of the covariance matrix for delineating sub-domains such that the computational time to obtain sub-domain is not an obstacle to using this method.

Probabilistic perturbation method enables the prior geological information to be retained while the production data is being integrated into the reservoir model. The deformation parameter integrates the geological information and dynamic data such that the final history matched model honors both types of data. Multiple deformation parameters are accounted for with multiple delineated sub-domains. This method enables the perturbation scheme to be implemented in multiple cpu environment thereby reducing the computational cost for history matching.

History matching for both synthetic and realistic field cases are performed. The synthetic cases mainly focus on the validation of the proposed algorithm as well as explore its sensitivity to various parameters. The extended real field cases demonstrate the applicability of Pro-HMS to a wide variety of geological environments and field operating conditions. All demonstrated case studies support the main idea of this thesis work: retain the geological information and reduce the computational time for history matching.

In summary, the main accomplishment of this thesis is the development of an integrated software named Pro-HMS that performs geostatistical simulation, flow
simulation, domain delineation and stochastic optimization within a reasonable computational time. The sensitivity analysis required for sub-domain delineation is carried out in Pro-HMS by calculation of the pressure covariance matrix. Upscaled reservoir models are generated for this purpose. The sub-domain delineation procedure results in sub-domains that are sensitive and yet least correlated with one another so that the optimal deformation parameters for each region are established independent of other regions. This renders the procedure amenable to distributed computing.
8.2 Suggested future work

Further research on the following topics is recommended to investigate the applicability of the software and the algorithm for a variety of geological modeling applications.

1. A significant fraction of petroleum reservoirs worldwide are naturally fractured. Fracture patterns are difficult to characterize and yet have a profound influence on the flow of fluids. The issue of fractured reservoir characterization using production data with the implementation of sub-domain delineation method needs to be studied. It is conjectured that the production data can provide valuable information about fracture density and orientation. The identification of fracture density in the reservoir is useful for the future drilling and production plan. The sub-domain delineation method will specify regions with higher density of fractures using pressure responses of the fractured reservoir.

2. Flow of fluids is controlled by the connectivity of geological features. Study on the degree or level of flow connectivity embedded within the Hessian matrix method or the pressure-covariance method for delineating domains needs to be assessed. It was concluded in Chapter 4 that flow connectivity is somewhat considered in the covariance matrix method that employs gridblock pressures. This is because the grid block pressures are themselves affected by the connectivity of the permeability field. To rigorously prove this statement, systematic case studies are needed using geological models exhibiting different
levels of permeability connectivity and analyzing sub-domains obtained by the
two different methods.

3. Although Pro-HMS has the capability to perform history matching on several
nodes of a cpu cluster, all the cases presented in this thesis were performed on
single cpu machines. The cost comparison of performing history matching on
single cpu machine considering the perturbation of the entire permeability field
using a single $r_D$ parameter and that performed within delineated sub-domains is
valuable. In addition, evaluation of the perturbation scheme implemented on
multiple cpu environments is crucial to test if sub-domain delineation meets its
stated objectives. It is expected that the computational cost for multiple cpu
environment is less than that for single cpu framework; nevertheless it will be
constructive to evaluate the efficiency enhancement due to the sub-domain
delineation method on parallel computing system.

4. A key issue for implementing the domain delineation method using the Hessian
matrix is how to determine optimal pilot point locations without depending too
much on engineering judgment? An approach could be to start from a simple base
case with known reference optimal pilot points and corresponding sub-domain,
and then perform a perturbation of pilot points such that a suite of corresponding
delineated sub-domains are obtained. A sensitivity analysis between pilot points
and corresponding sub-domains can reveal how IJK parameters affect on the
delineated sub-domains. An optimal configuration of control points can then be
specified accounting for the uncertainty in flow induced by the variations in the
shapes and size of the delineated domains.
5. One might argue that if geological information is not sufficient or hard data is not enough to depict the initial petrophysical model accurately, a more effective history matching procedure would be to perturb entire the permeability probability distribution of all grid blocks rather than perturb permeability within uncertain sub-domains. The domain delineation method using an ensemble of grid-block pressure realizations is more robust in the face of uncertainty in the prior model. However, it is essential to evaluate exhaustively that this sub-domain method is universally valid for all reservoir modeling scenarios with different quantity of available information.

Also, a semi-sub-domain method needs to be researched in order to delineate sub-domains only for specific layers. The current algorithm of sub-domain delineation decomposes volumetric percentage-based regions of the entire reservoir being studied (i.e., the sum of the volumetric percentage of the delineated sub-domains through all layers are equal to the threshold value that is applied for the sub-domain delineation). The delineated sub-domains vary from layer to layer with small variability. However, if geological features are completely different from the top to bottom layers, an effective sub-domain delineation scheme would be to not delineate regions based on the entire reservoir but to identify domains based on certain layers of the reservoir. For instance, if the bottom layer of the reservoir is geologically so complex that perturbation is necessitated for all gridblocks of the bottom layer. In that case, sub-domain delineation for the bottom layer is not required. However, the overall history matching algorithm still utilizes sub-domain algorithm for other layers thereby enhancing the computational efficiency of the procedure.
### Appendix A: Description of Pro-HMS Input and Output Files

#### Pro-HMS User Input Files

<table>
<thead>
<tr>
<th>File name</th>
<th>Format</th>
<th>Instruction</th>
</tr>
</thead>
<tbody>
<tr>
<td>Conditional.txt</td>
<td>Conditional Data</td>
<td>User specified conditioning data file. The column numbers of relevant data needs to be specified. If rank or weights for data are not specified, data are assumed equal weighted.</td>
</tr>
<tr>
<td></td>
<td>5</td>
<td></td>
</tr>
<tr>
<td></td>
<td>X</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Y</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Z</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Perm</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Rank</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>21 43 5 1.40405 0.05</td>
<td></td>
</tr>
<tr>
<td></td>
<td>27 64 5 4.73353 0.05</td>
<td></td>
</tr>
<tr>
<td></td>
<td>54 41 1 1.05201 0.05</td>
<td></td>
</tr>
<tr>
<td></td>
<td>35 88 1 223.917 0.05</td>
<td></td>
</tr>
<tr>
<td>Prodhistory.txt</td>
<td>Primary Production History</td>
<td>It is mandatory for the user to provide this file. There is no maximum on the number of variables that can be included in the objective function.</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td></td>
</tr>
<tr>
<td></td>
<td>T</td>
<td></td>
</tr>
<tr>
<td></td>
<td>FPR</td>
<td></td>
</tr>
<tr>
<td></td>
<td>WOPR-PI</td>
<td></td>
</tr>
<tr>
<td></td>
<td>43</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0 7006.199 0 0.05</td>
<td></td>
</tr>
<tr>
<td></td>
<td>30 6851.058 3190.944</td>
<td></td>
</tr>
<tr>
<td></td>
<td>60 6738.524 3019.498</td>
<td></td>
</tr>
<tr>
<td></td>
<td>90 6643.017 2917.788</td>
<td></td>
</tr>
<tr>
<td>RegionIndices.txt</td>
<td>-9999</td>
<td>It is generated by Pro-HMS only if the user wants to have sub-domains. If a user wants to provide this file, the name should always be ‘RegionIndices.txt’</td>
</tr>
<tr>
<td></td>
<td>-9999</td>
<td></td>
</tr>
<tr>
<td></td>
<td>-9999</td>
<td></td>
</tr>
<tr>
<td></td>
<td>-9999</td>
<td></td>
</tr>
<tr>
<td></td>
<td>1</td>
<td></td>
</tr>
<tr>
<td></td>
<td>-5</td>
<td></td>
</tr>
<tr>
<td></td>
<td>-9999</td>
<td></td>
</tr>
<tr>
<td></td>
<td>-2</td>
<td></td>
</tr>
<tr>
<td></td>
<td>-9999</td>
<td></td>
</tr>
<tr>
<td></td>
<td>3</td>
<td></td>
</tr>
<tr>
<td>BASE.DAT</td>
<td>It should be consistent with the data file used for covariance matrix calculation.</td>
<td>Simulator data file for perturbation</td>
</tr>
<tr>
<td>DATA.DAT</td>
<td>It should be consistent with the data file used for perturbation. The only difference occurs in</td>
<td>Simulator data file for covariance</td>
</tr>
</tbody>
</table>
the reservoir size. matrix calculation

Pro-HMS Output Files

Parameter files

<table>
<thead>
<tr>
<th>File name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>sensregion.par</td>
<td>Parameter file for covariance matrix calculation</td>
</tr>
<tr>
<td>dd.par</td>
<td>Parameter file for domain delineation</td>
</tr>
<tr>
<td>hmissim.par</td>
<td>Parameter file for perturbation</td>
</tr>
</tbody>
</table>

[Note]

- The order of sub-domains perturbations is fixed in such a way that Pro-HMS perturbs sub-domains in the sequence of region indices.

For example, if the format of ‘RegionIndices.txt’ is

-9999
-2
3
1
.
.
.

, then Pro-HMS will perturb sub-domains whose indices are -2, 3, and 1 sequentially.

- If the perturbation order is to be changed, it is possible to change the order in ‘hmissim.par’ directly.

For example, if ‘hmissim.par’ has format(38th line) such as

SubdomainsOpt  -2 3 1 -9999
then Pro-HMS will perturb sub-domains whose indices are -2, 3, and 1 sequentially. However, if the sequence of perturbation has to be 1, then -2, and finally 3, then the 38th line has to be changed as
When loading a previously existing ‘hmissim.par’ file into Pro-HMS, the file should follow the format of the sample file. The default ‘hmissim.par’ file has only the key word ‘SubdomainsOpt’. This corresponds to performing the sub-domain perturbations in the order of indices in ‘RegionIndices.txt’. If the sequence is to be changed, the new sequence has to be entered into ‘hmissim.par’ by opening it in a text editor and adding the sequence following the keyword SubdomainsOpt as in above.

### Covariance matrix related files

<table>
<thead>
<tr>
<th>File name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>sisim.dbg</td>
<td>Debug file from SISIM</td>
</tr>
<tr>
<td>sisim.out</td>
<td>Ensemble of permeability values</td>
</tr>
<tr>
<td>sisim.par</td>
<td>Parameter file for generating multiply reservoir models</td>
</tr>
<tr>
<td>PR#1L#1.ps</td>
<td>Postscript permeability maps for one realization. One map per layer is generated.</td>
</tr>
<tr>
<td>upsc-por.out</td>
<td>Porosity data for upscaling</td>
</tr>
<tr>
<td>upscaledperm.out</td>
<td>Effective permeability data after upscaling</td>
</tr>
<tr>
<td>upscaler.par</td>
<td>Parameter file for upscaling the realizations</td>
</tr>
<tr>
<td>wholeoutput.out</td>
<td>Gridblock Pressure values extracted from flow simulation output file (*.PRT file in case of Eclipse)</td>
</tr>
<tr>
<td>perminclude.inc</td>
<td>Upscaled permeability values to be used in flow simulation.</td>
</tr>
<tr>
<td>upscaledpermX.out</td>
<td>Absolute permeability data after upscaling</td>
</tr>
<tr>
<td>upscalK #1Layer1.ps</td>
<td>Upscaled permeability map corresponding to the first realization. One map per upscaled layer will be generated.</td>
</tr>
<tr>
<td>covariance.out</td>
<td>File with computed covariance matrix</td>
</tr>
<tr>
<td>pressurearrays.out</td>
<td>Pressure data corresponding to the time specified by the user for covariance matrix calculation</td>
</tr>
<tr>
<td>covdiagonal.out</td>
<td>The diagonal terms of covariance matrix</td>
</tr>
<tr>
<td>sensitivitco L# 1.ps</td>
<td>The map of sensitivity coefficients. The region with high sensitivity coefficient will be the basis for defining sub-domains.</td>
</tr>
<tr>
<td>tridiagmat.out</td>
<td>Reduced tri-diagonal matrix to get eigenvalues</td>
</tr>
<tr>
<td>eigenvalue.out</td>
<td>Eigenvalues of the tri-diagonal matrix</td>
</tr>
<tr>
<td>eigenvectors.out</td>
<td>Eigenvectors of the tri-diagonal matrix</td>
</tr>
<tr>
<td>1wellflowev1.txt</td>
<td>Eigenvector corresponding to the first eigenvalue</td>
</tr>
<tr>
<td>1wellflowev2.txt</td>
<td>Eigenvector corresponding to the second eigenvalue</td>
</tr>
<tr>
<td>File name</td>
<td>Description</td>
</tr>
<tr>
<td>---------------------------</td>
<td>------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>1wellflowev3.txt</td>
<td>Eigenvector corresponding to the third eigenvalue</td>
</tr>
<tr>
<td>1wellflowev4.txt</td>
<td>Eigenvector corresponding to the fourth eigenvalue</td>
</tr>
<tr>
<td>1wellflowev5.txt</td>
<td>Eigenvector corresponding to the fifth eigenvalue</td>
</tr>
<tr>
<td>1wellflowevalue.txt</td>
<td>Eigenvector after Principal Component Analysis(PCA) listed in their magnitudes</td>
</tr>
<tr>
<td>sortedeigenvalues.out</td>
<td>Sorted eigenvalues according to their magnitude</td>
</tr>
</tbody>
</table>

### Domain Delineation related files

<table>
<thead>
<tr>
<th>File name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Output.txt</td>
<td>Highest eigenvector component and its position of occurrence</td>
</tr>
<tr>
<td>RegionIndices.txt</td>
<td>Region indices of the reservoir -9999 means not sensitive regions. Minus means negative eigenvector component. Plus sign indicates positive eigenvector component.</td>
</tr>
</tbody>
</table>

### Perturbation related files

<table>
<thead>
<tr>
<th>File name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>ReadData.txt</td>
<td>The conditional data that is reading for perturbation</td>
</tr>
<tr>
<td>ReadParameter.txt</td>
<td>The parameters that is read from parameter file by Pro-HMS</td>
</tr>
<tr>
<td>PERM.DAT</td>
<td>Permeability data used as an include file for perturbation</td>
</tr>
<tr>
<td></td>
<td>Overwriting on the same file.</td>
</tr>
<tr>
<td>PermMap_after_OuterLoop.out</td>
<td>Permeability data after each outer loop</td>
</tr>
<tr>
<td></td>
<td>Overwriting on the same file.</td>
</tr>
<tr>
<td>PermOptResult.txt</td>
<td>Permeability data after perturbations of each outer loop for each sub-domains</td>
</tr>
<tr>
<td></td>
<td>Overwriting on the same file.</td>
</tr>
<tr>
<td>ProdOptResult.txt</td>
<td>Production matching result after each outer loop for each sub-domains</td>
</tr>
<tr>
<td>RDout.txt</td>
<td>Objective function information after outer loop for each sub-domains</td>
</tr>
</tbody>
</table>
Appendix B: User’s Manual of Pro-HMS Screens

This is the opening screen when Pro-HMS is launched. Pro-HMS is composed is of five sections:

1. Reservoir Information: Basic data such as grid size, dimensions etc. are specified.
2. Initial Realizations Information: Ensemble size, conditioning data etc. are specified.
3. Sub-domain Information: Option to calculate or specify sub-domains, method for calculating sub-domains can be specified here.
5. Flow Information: Simulator type, data file, flow variables to match etc.

There is an option in this screen which is ‘Load Input File’. If you have parameter files generated by this software already, that option is clicked to load the files instead of going through all the screens.
Section 1 is for reservoir information of the reservoir that is to be history matched. The starting guess (initial realization), the number and location of wells and the details of the reservoir production history are specified here.
The name of the file with the conditioning “hard” data is specified. The conditional hard data are used when Pro-HMS does sequential indicator simulation.

Click ‘Browse’ button to locate the appropriate well data file. Indicate column numbers for data location. The variable means the column number for the data. The format of the file should be the coordinates of the data location in columns and corresponding data value also in a column. (See Appendix 1: Description of Pro-HMS Input and Output Files)
In this screen, the production history (that you want to match with) file and the number of wells whose history are to be matched are specified.
The column for the production variables for a particular well is specified. There are as many screens as the number of wells. The column numbers for well pressure data, production time and well production rates are specified.
This screen is the introduction to section 2. Section 2 provides information for the initial realization. To obtain an initial guess for the history matching process, sequential indicator simulation is performed. The inputs for that initial SISIM realization are specified in this section.
An option for the initial realization is provided. Either a sequential indicator simulation generated internally within the program can be used or an initial guess can be read in from an external file. If the latter option is selected, the format of the external file should be compatible with the simulator’s include files.
The first screen for sequential indicator simulation - the variable type is selected first. If the variable type is continuous, the number of thresholds has to be specified. If the variable type is categorical, the number of categories has to be specified.
The second screen for sequential indicator simulation:

If the variable type is specified to be continuous then the indicator threshold values have to be specified in the first column and the corresponding cumulative density function (cdf) values in the second column.

If the variable type has been chosen as categorical in the previous screen, the indicator categories have to be specified in the first column and the corresponding probability density function (pdf) values in the second column.
The size of the reservoir is specified in this third screen - the first column is the number of grid cells, the second column is the minimum grid offset, and the last column is the cell size.
The fourth screen of the sequential indicator simulation:

The trimming limits for the conditioning data are specified. There are maximum and minimum data values that are used in the simulation.
The preference for tail extrapolation of the distribution is specified here. Options for the interpolation of the upper and lower tail of the distribution as well as the middle part of the distribution have to be specified.

**Upper tail:**
If the option is chosen to be ‘1’, then Pro-HMS implements linear interpolation to the upper limit.
If the option is chosen to be ‘2’, then it implements power model interpolation.
If the option is chosen to be ‘3’, then it implements linear interpolation between tabulated quantile values.
If the option is chosen to be ‘4’, then it implements hyperbolic model extrapolation. This option ‘4’ is only available for continuous variables.
If the option is selected to be 2 or 4, the power law parameters are specified under the parameter heading.

**Middle tail:**
- **Option 1** implements linear interpolation
- **Option 2** implements power model interpolation
- **Option 3** linear interpolation between tabulated quantile values (only for continuous
variables).

**Lower Tail:** specify the extrapolation in the lower tail:

- `lower tail`=1 implements linear interpolation to the lower limit
- `lower tail`=2 power model interpolation to the lower limit
- `lower tail`=3 linear interpolation between tabulated quantiles (only for continuous variables).

‘Range of Simulated Values’ is the range of permeability data in the simulated initial model. The numbers that can be input are any real numbers.
The sixth screen of sequential indicator simulation:

If ‘Full’ indicator kriging option is selected, then the variogram models corresponding to each threshold/category is used to establish the local conditional probability corresponding to that threshold. On the other hand, if ‘Median’ indicator kriging is opted, then the median approximation is used, i.e., a single variogram (corresponding to the median threshold) is used for all categories/threshold.

The bottom box is for the choice of kriging. Either ordinary or simple kriging can be selected. If simple kriging is selected, the global mean value has to be entered.
Maximum original data is the maximum number of the original well data (conditional data) to be used to simulate the value at a grid node in sequential indicator simulation.

Maximum previous nodes is the maximum number of previously simulated nodes to be used for constructing the local probability distribution at a node.

Assign data to nodes is an option for assigning data at a node. If ‘Yes’ is selected, then the data are relocated to grid nodes and a spiral search is used; the parameters of Maximum original data are not taken into consideration. If ‘no’ is selected, then the data and previously simulated grid nodes are searched separately: the data are searched with a super block search and the previously simulated nodes are searched with a spiral search.

Maximum number of soft data: it restricts the number of soft data when an exhaustive secondary variable informs all grid nodes. This option is basically maximum number of soft data at node locations that will be used for the simulation of a node.

Maximum Search Radius specifies the size of the search ellipsoid in the horizontal direction and vertical direction.

Angles for ellipsoid are the angle parameters that describe the orientation of the search ellipsoid.
This screen is for variogram specifications. The number of structures and nugget effect for each threshold is specified.
One such screen appears for each threshold. The screen will have as many rows as ‘Number of Structure’ indicated in the previous screen. Each screen requires to be filled up with the following information.

**types of structure**: 1 is for Spherical model, 2 is for Exponential model, 3 is Gaussian Model, and 4 is for Power model.

**sill contribution**: sill contribution of each structure

**ang1, ang2, ang3**: the angles defining the geometric anisotropy

**aa_hmax**: the maximum horizontal range

**aa_hmin**: the minimum horizontal range

**aa_vert**: the vertical range.

Note: Each semivariogram model refers to the corresponding indicator transform. A Gaussian variogram with a small nugget constant is not a legitimate variogram model for a discontinuous indicator function. There is no need to standardize the parameters to a sill of one since only the relative shape affects the kriging weights.

In the case of median indicator kriging, only the variogram corresponding to the median threshold needs to be specified.
A debug level between 0 and 3 can be specified. The higher the debugging level (the larger number) is the more information will be provided (e.g. kriging matrices, weights assigned to data at each simulation location). The ‘Debug Log’ output file in the folder can be checked for the debug outputs.
The name of output file generated by sequential indicator simulation has to be specified. The random number seed for ordering the random path through the nodes as well as for drawing values from the local probability distributions has to be specified. The seed should be a large odd integer.
Section 3 is for specifying sub-domain calculation options. The user has the option to use sub-domains or not for the perturbation step.

If the option for calculating/using sub-domains is selected, then there is another option for calculating sub-domains using Principal Component Analysis of sensitivity values or for loading a file with region indices calculated by the user. If the option for calculating the regions is selected, then the upscaling parameters have to be specified.
The two options for specifying sub-domains to the program exist.

‘PC Analysis for sensitivity and volume cutoffs’ is selected if the probability perturbation is to be done within sub-domains. This option performs internally within Pro-HMS a principal component decomposition of the sensitivity matrix, and then applies volume cutoffs for the sub-domains that are entered by the user in fraction.

If the ‘File for Sub-domains’ is selected, a file with user generated sub-domain indices has to be loaded. That file has to have one column only with the region indices. The name always to be ‘RegionIndices.txt’.

Example format of ‘RegionIndices.txt’:

```
-9999
1
1
1
1
1
2
-3
```
For more information on this format, refer to Appendix A. Also, refer to the file format of ‘hmissim.par’, which is related to this file, for the correct file format.

If you don’t want to use sub-domain perturbation but desire to perturb all regions of the reservoir, the option ‘Do not use Sub-domains’ is selected.
To internally compute the sub-domains, Pro-HMS uses an ensemble of realizations generated by sequential indicator simulation. The number of realizations in the ensemble has to be specified.

Note: The characteristics of the sub-domains could be quite different depending on the size of the ensemble used to calculate the sensitivities. Engineering judgment and prior knowledge of the nature of geological uncertainty have to be used to determine the optimal size of the ensemble.

The second option is the duration of the flow simulation to be performed for delineating the zones. For instance, if the production data is available for a duration of 1000 days, the user may specify that the sub-domains be delineated on the basis of the full duration of production.

Note: Depending on the nature of the problem and sensitivities of the history match to reservoir parameters, the sub-domains may be delineated on the basis of flow simulations for a reduced duration.
In order to speed up the domain delineation process, the sensitivities are computed using the upscaled ensemble of realizations. The original dimensions of the ensemble realizations as well as the upscaled dimensions are specified.

The flow simulation data file is also specified consistent with the upscaled grid specification.
Probability perturbation parameters and options such as the number of inner and outer iterations to be used by the Markov chain process are specified in this section.
The maximum number of inner and outer iterations for the optimization procedure has to be specified. The inner loop is the Dekker-Brent loop and the outer loop is for global convergence. The default (based on several trial cases) is ‘3’ for maximum inner iterations and ‘4’ for maximum outer iterations.
The simulator to be used for the history matching process as well as the simulation data file is specified in Section 5.
Any commercial simulator can be specified provided there is no requirement to execute the simulator only through a dedicated GUI. The corresponding simulation data file has to be input. The selection of simulation parameters to best represent field conditions is at the discretion of the user. The grid dimensions of the reservoir in the data file should be consistent with the grid specification for the indicator simulation models.

Note: A different simulator data file has to be specified for the sub-domain delineation procedure that has the upscaled grid specification.
Click ‘Save Parameter Files’ button to save the information input using the GUI. Click ‘Run’ to start the history matching process.
Nomenclature

$z_1, z_2$ Two pieces of realizations constitutes a new realization, Eq. (2.1)

$\alpha_i$ Weights, Eq. (2.2)

$f$ Objective function, Eq. (3.1)

$x, y, z$ History matching parameters, Eq. (3.1)

$P_n$ Pressure response at $n$-th gridblock ($i=1, 2, \cdots, n$), Eq. (4.1)

$n$ Number of gridblocks, Eq. (4.1)

$u$ Location vector, Eq. (5.2)

$k(u)$ Attribute random variable at location $u$, Eq. (5.2)

$I(u, z_i)$ Indicator variable at location $u$ corresponding to a threshold $z_i$, Eq. (5.2)

$n$ Neighboring data to be conditioned, Eq. (5.3)

$p_i$ Prior probability corresponding to $z_i$, Eq. (5.3)

$r_D$ Dynamic parameter controlling probability of transitioning from current category to the next category, Eq. (5.4)

$l$ Markov chain outer iteration counter, Eq. (5.4)

$\Delta OF$ Objective function quantifying the degree of deviation between target response and simulated response, Eq. (5.5)

$k$ Permeability, Eqs. (7.1), (7.2), (7.3)

$\phi_{IP}$ Interparticle porosity, Eqs. (7.1), (7.2), (7.3)
References


Liu, W., Cao, J., Mezzatesta A.G., and Zhu, P., “Parallel Reservoir Simulation on Shared and Distributed Memory System.” SPE 64797, paper presented at the SPE International Oil and Gas Conference and Exhibition in China held in Beijing, China, 7–10 November (2000).


Scheevel, J. R., and Payrazyan, K., “Principal component analysis applied to 3D seismic data for reservoir property estimation”, Formation evaluation and reservoir
geology, SPE annual technical conference and exhibition, Houston TX, 3-6 October (1999).


